pandas: powerful Python data analysis toolkit

Release 0.23.1

Wes McKinney & PyData Development Team

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## 4 Package overview

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pandas: powerful Python data analysis toolkit, Release 0.23.1

PDF Version
Zipped HTML

Date: Jun 12, 2018 Version: 0.23.1

Binary Installers: https://pypi.org/project/pandas
Source Repository: http://github.com/pandas-dev/pandas
Issues & Ideas: https://github.com/pandas-dev/pandas/issues
Q&A Support: http://stackoverflow.com/questions/tagged/pandas
Developer Mailing List: http://groups.google.com/group/pydata

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

1.1 v0.23.1

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

What’s new in v0.23.1

- **Fixed Regressions**
- **Performance Improvements**
- **Bug Fixes**

1.1.1 Fixed Regressions

Comparing Series with datetime.date

We’ve reverted a 0.23.0 change to comparing a `Series` holding datetimes and a `datetime.date` object (GH21152). In pandas 0.22 and earlier, comparing a Series holding datetimes and `datetime.date` objects would coerce the `datetime.date` to a datetime before comparing. This was inconsistent with Python, NumPy, and `DatetimeIndex`, which never consider a datetime and `datetime.date` equal.

In 0.23.0, we unified operations between DatetimeIndex and Series, and in the process changed comparisons between a Series of datetimes and `datetime.date` without warning.

We’ve temporarily restored the 0.22.0 behavior, so datetimes and dates may again compare equal, but restore the 0.23.0 behavior in a future release.

To summarize, here’s the behavior in 0.22.0, 0.23.0, 0.23.1:

```python
# 0.22.0... Silently coerce the datetime.date
>>> Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0    True
1   False
dtype: bool

# 0.23.0... Do not coerce the datetime.date
>>> Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
(continues on next page)
```
In addition, ordering comparisons will raise a TypeError in the future.

Other Fixes

- Reverted the ability of to_sql() to perform multivalue inserts as this caused regression in certain cases (GH21103). In the future this will be made configurable.

- Fixed regression in the DatetimeIndex.date and DatetimeIndex.time attributes in case of timezone-aware data: DatetimeIndex.time returned a tz-aware time instead of tz-naive (GH21267) and DatetimeIndex.date returned incorrect date when the input date has a non-UTC timezone (GH21230).

- Fixed regression in pandas.io.json.json_normalize() when called with None values in nested levels in JSON, and to not drop keys with value as None (GH21158, GH21356).

- Bug in to_csv() causes encoding error when compression and encoding are specified (GH21241, GH21118)

- Bug preventing pandas from being importable with -OO optimization (GH21071)

- Bug in Categorical.fillna() incorrectly raising a TypeError when value the individual categories are iterable and value is an iterable (GH21097, GH19788)

- Fixed regression in constructors coercing NA values like None to strings when passing dtype=str (GH21083)

- Regression in pivot_table() where an ordered Categorical with missing values for the pivot’s index would give a mis-aligned result (GH21133)

- Fixed regression in merging on boolean index/columns (GH21119).

1.1.2 Performance Improvements

- Improved performance of CategoricalIndex.is_monotonic_increasing(), CategoricalIndex.is_monotonic_decreasing() and CategoricalIndex.is_monotonic() (GH21025)

- Improved performance of CategoricalIndex.is_unique() (GH21107)

1.1.3 Bug Fixes

Groupby/Resample/Rolling
• Bug in `DataFrame.agg()` where applying multiple aggregation functions to a `DataFrame` with duplicated column names would cause a stack overflow (GH21063)

• Bug in `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` where the fill within a grouping would not always be applied as intended due to the implementations’ use of a non-stable sort (GH21207)

• Bug in `pandas.core.groupby.GroupBy.rank()` where results did not scale to 100% when specifying `method='dense' and pct=True`

• Bug in `pandas.DataFrame.rolling()` and `pandas.Series.rolling()` which incorrectly accepted a 0 window size rather than raising (GH21286)

Data-type specific

• Bug in `Series.str.replace()` where the method throws `TypeError` on Python 3.5.2 (:issue: 21078)

• Bug in `Timedelta` where passing a float with a unit would prematurely round the float precision (issue: 14156)

• Bug in `pandas.testing.assert_index_equal()` which raised `AssertionError` incorrectly, when comparing two `CategoricalIndex` objects with param `check_categorical=False` (GH19776)

Sparse

• Bug in `SparseArray.shape` which previously only returned the shape `SparseArray.sp_values` (GH21126)

Indexing

• Bug in `Series.reset_index()` where appropriate error was not raised with an invalid level name (GH20925)

• Bug in `interval_range()` when `start/periods` or `end/periods` are specified with float `start` or `end` (GH21161)

• Bug in `MultiIndex.set_names()` where error raised for a `MultiIndex` with `nlevels == 1` (GH21149)

• Bug in `IntervalIndex` constructors where creating an `IntervalIndex` from categorical data was not fully supported (GH21243, issue:21253)

• Bug in `MultiIndex.sort_index()` which was not guaranteed to sort correctly with `level=1`; this was also causing data misalignment in particular `DataFrame.stack()` operations (GH20994, GH20945, GH21052)

Plotting

• New keywords (sharex, sharey) to turn on/off sharing of x/y-axis by subplots generated with pandas.DataFrame().groupby().boxplot() (:issue: 20968)

I/O

• Bug in IO methods specifying `compression='zip'` which produced uncompressed zip archives (GH17778, GH21144)

• Bug in `DataFrame.to_stata()` which prevented exporting DataFrames to buffers and most file-like objects (GH21041)

• Bug in `read_stata()` and `StataReader` which did not correctly decode utf-8 strings on Python 3 from Stata 14 files (dta version 118) (GH21244)

• Bug in IO JSON `read_json()` reading empty JSON schema with `orient='table'` back to `DataFrame` caused an error (GH21287)
Reshaping

- Bug in `concat()` where error was raised in concatenating `Series` with numpy scalar and tuple names (GH21015)
- Bug in `concat()` warning message providing the wrong guidance for future behavior (GH21101)

Other

- Tab completion on `Index` in IPython no longer outputs deprecation warnings (GH21125)
- Bug preventing pandas being used on Windows without C++ redistributable installed (GH21106)

1.2 v0.23.0 (May 15, 2018)

This is a major release from 0.22.0 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Round-trippable JSON format with 'table' orient.
- Instantiation from dicts respects order for Python 3.6+.
- Dependent column arguments for `assign`.
- Merging / sorting on a combination of columns and index levels.
- Extending Pandas with custom types.
- Excluding unobserved categories from `groupby`.
- Changes to make output shape of `DataFrame.apply` consistent.

Check the API Changes and deprecations before updating.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Plan for dropping Python 2.7 for more.

What’s new in v0.23.0

- New features
  - JSON read/write round-trippable with `orient='table'`
  - `.assign()` accepts dependent arguments
  - `Merging on a combination of columns and index levels`
  - `Sorting by a combination of columns and index levels`
  - `Extending Pandas with Custom Types (Experimental)`
  - New observed keyword for excluding unobserved categories in `groupby`
  - `Rolling/Expanding.apply()` accepts `raw=False` to pass a `Series` to the function
  - `DataFrame.interpolate` has gained the `limit_area` kwarg
  - `get_dummies` now supports `dtype` argument
- Timedelta mod method
- .rank() handles inf values when NaN are present
- Series.str.cat has gained the join kwarg
- DataFrame.astype performs column-wise conversion to Categorical
- Other Enhancements

• Backwards incompatible API changes
  - Dependencies have increased minimum versions
  - Instantiation from dicts preserves dict insertion order for python 3.6+
  - Deprecate Panel
  - pandas.core.common removals
  - Changes to make output of DataFrame.apply consistent
  - Concatenation will no longer sort
  - Build Changes
  - Index Division By Zero Fills Correctly
  - Extraction of matching patterns from strings
  - Default value for the ordered parameter of CategoricalDtype
  - Better pretty-printing of DataFrames in a terminal
  - Datetimelike API Changes
  - Other API Changes

• Deprecations

• Removal of prior version deprecations/changes

• Performance Improvements

• Documentation Changes

• Bug Fixes
  - Categorical
  - Datetimelike
  - Timedelta
  - Timezones
  - Offsets
  - Numeric
  - Strings
  - Indexing
  - MultiIndex
  - I/O
  - Plotting
1.2.1 New features

1.2.1.1 JSON read/write round-trippable with orient='table'

A DataFrame can now be written to and subsequently read back via JSON while preserving metadata through usage of the orient='table' argument (see GH18912 and GH9146). Previously, none of the available orient values guaranteed the preservation of dtypes and index names, amongst other metadata.
foo     int64
bar     object
baz     datetime64[ns]
qux     category
dtype: object

Please note that the string `index` is not supported with the round trip format, as it is used by default in `write_json` to indicate a missing index name.

```
In [8]: df.index.name = 'index'
In [9]: df.to_json('test.json', orient='table')
In [10]: new_df = pd.read_json('test.json', orient='table')
In [11]: new_df
Out[11]:
   foo  bar  baz  qux
0  1    a  2018-01-01  a
1  2    b  2018-01-02  b
2  3    c  2018-01-03  c
3  4    d  2018-01-04  c
```

1.2.1.2 `assign()` accepts dependent arguments

The `DataFrame.assign()` now accepts dependent keyword arguments for python version later than 3.6 (see also PEP 468). Later keyword arguments may now refer to earlier ones if the argument is a callable. See the documentation here (GH14207)

```
In [13]: df = pd.DataFrame({'A': [1, 2, 3]})
In [14]: df
Out[14]:
   A
0  1
1  2
2  3
In [15]: df.assign(B=df.A, C=lambda x:[x['A'] + x['B']])
      A  B  C
0  1  1  2
1  2  2  4
2  3  3  6
```
**Warning:** This may subtly change the behavior of your code when you’re using `.assign()` to update an existing column. Previously, callables referring to other variables being updated would get the “old” values.

Previous Behavior:

```python
In [2]: df = pd.DataFrame({"A": [1, 2, 3]})

In [3]: df.assign(A=lambda df: df.A + 1, C=lambda df: df.A * -1)
Out[3]:
   A   C
0  2  -1
1  3  -2
2  4  -3
```

New Behavior:

```python
In [16]: df.assign(A=df.A+1, C=lambda df: df.A* -1)
Out[16]:
   A   C
0  2  -2
1  3  -3
2  4  -4
```

### 1.2.1.3 Merging on a combination of columns and index levels

Strings passed to `DataFrame.merge()` as the `on`, `left_on`, and `right_on` parameters may now refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes. See the [Merge on columns and levels documentation section](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.merge.html). (GH14355)

```python
In [17]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [18]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                        'B': ['B0', 'B1', 'B2', 'B3'],
                        'key2': ['K0', 'K1', 'K0', 'K1'],
                        index=left_index)

In [19]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [20]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                         'D': ['D0', 'D1', 'D2', 'D3'],
                         'key2': ['K0', 'K0', 'K0', 'K1'],
                         index=right_index)

In [21]: left.merge(right, on=['key1', 'key2'])
Out[21]:
   A   B   key2   C   D
key1
K0 A0 B0 K0 C0 D0
K1 A2 B2 K0 C1 D1
K2 A3 B3 K1 C3 D3
```
1.2.1.4 Sorting by a combination of columns and index levels

Strings passed to `DataFrame.sort_values()` as the `by` parameter may now refer to either column names or index level names. This enables sorting `DataFrame` instances by a combination of index levels and columns without resetting indexes. See the Sorting by Indexes and Values documentation section. (GH14353)

```python
In [22]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2), ('b', 2), ('b', 1), ('b', 1)])
In [23]: idx.names = ['first', 'second']

# Build DataFrame
In [24]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)}, index=idx)
In [25]: df_multi
Out[25]:
   A
first  second
a     1      6
      2      5
      2      4
b     2      3
      1      2
      1      1

# Sort by 'second' (index) and 'A' (column)
In [26]: df_multi.sort_values(by=['second', 'A'])
```

1.2.1.5 Extending Pandas with Custom Types (Experimental)

Pandas now supports storing array-like objects that aren’t necessarily 1-D NumPy arrays as columns in a DataFrame or values in a Series. This allows third-party libraries to implement extensions to NumPy’s types, similar to how pandas implemented categoricals, datetimes with timezones, periods, and intervals.

As a demonstration, we’ll use cyberpandas, which provides an `IPArray` type for storing ip addresses.

```python
In [1]: from cyberpandas import IPArray
In [2]: values = IPArray([...
          ...: 0,
          ...: 3232235777,
          ...: 425407664526415407174021557757643572
```
IPArray isn’t a normal 1-D NumPy array, but because it’s a pandas \ pandas.api.extension.ExtensionArray, it can be stored properly inside pandas’ containers.

```
In [3]: ser = pd.Series(values)
In [4]: ser
Out[4]:
0     0.0.0.0
1     192.168.1.1
2   2001:db8:85a3::8a2e:370:7334
dtype: ip
```

Notice that the dtype is ip. The missing value semantics of the underlying array are respected:

```
In [5]: ser.isna()
Out[5]:
0    True
1   False
2   False
dtype: bool
```

For more, see the extension types documentation. If you build an extension array, publicize it on our ecosystem page.

### 1.2.1.6 New observed keyword for excluding unobserved categories in groupby

Grouping by a categorical includes the unobserved categories in the output. When grouping by multiple categorical columns, this means you get the cartesian product of all the categories, including combinations where there are no observations, which can result in a large number of groups. We have added a keyword observed to control this behavior, it defaults to observed=False for backward-compatibility. (GH14942, GH8138, GH15217, GH17594, GH8669, GH20583, GH20902)

```
In [27]: cat1 = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "z"], ordered=True)
In [28]: cat2 = pd.Categorical(["c", "d", "c", "d"], categories=["c", "d", "y"], ordered=True)
In [29]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})
In [30]: df['C'] = ['foo', 'bar'] * 2
In [31]: df
Out[31]:
     A  B values  C
0    a  c     1  foo
1    a  d     2  bar
2    b  c     3  foo
3    b  d     4  bar
```

To show all values, the previous behavior:
In [32]: df.groupby(['A', 'B', 'C'], observed=False).count()
Out[32]:
          values
A  B  C
a  c  bar  NaN
foo  1.0
    d  bar  1.0
    foo  NaN
y  bar  NaN
    foo  NaN
b  c  bar  NaN
... ... ...
y  foo  NaN
z  c  bar  NaN
    foo  NaN
d  bar  NaN
    foo  NaN
y  bar  NaN
    foo  NaN
[18 rows x 1 columns]

To show only observed values:

In [33]: df.groupby(['A', 'B', 'C'], observed=True).count()
Out[33]:
          values
A  B  C
a  c  foo  1
    d  bar  1
b  c  foo  1
    d  bar  1

For pivoting operations, this behavior is already controlled by the dropna keyword:

In [34]: cat1 = pd.Categorical(['a', 'a', 'b', 'b'],
                             categories=['a', 'b', 'z'], ordered=True)
                      ...
In [35]: cat2 = pd.Categorical(['c', 'd', 'c', 'd'],
                             categories=['c', 'd', 'y'], ordered=True)
                      ...
In [36]: df = DataFrame({'A': cat1, 'B': cat2, 'values': [1, 2, 3, 4]})
In [37]: df
Out[37]:
          A  B  values
0   a  c   1
1   a  d   2
2   b  c   3
3   b  d   4

In [38]: pd.pivot_table(df, values='values', index=['A', 'B'],
                      dropna=True)
                      ....
Out[38]:
(continues on next page)
values
A B
a c 1
d 2
b c 3
d 4

In [39]: pd.pivot_table(df, values='values', index=['A', 'B'],
                   dropna=False)

Out[39]:
          values
A  B
a  c 1.0
d  2.0
y  NaN
b  c 3.0
d  4.0
y  NaN
z  NaN
d  NaN
y  NaN

1.2.1.7 Rolling/Expanding.apply() accepts raw=False to pass a Series to the function

Series.rolling().apply(), DataFrame.rolling().apply(), Series.expanding().
apply(), and DataFrame.expanding().apply() have gained a raw=None parameter. This is similar to
DataFame.apply(). This parameter, if True allows one to send a np.ndarray to the applied function. If
False a Series will be passed. The default is None, which preserves backward compatibility, so this will default
to True, sending an np.ndarray. In a future version the default will be changed to False, sending a Series.
(GH5071, GH20584)

In [40]: s = pd.Series(np.arange(5), np.arange(5) + 1)

In [41]: s
Out[41]:
  0  1
  1  2
  2  3
  3  4
  4  5
dtype: int64

Pass a Series:

In [42]: s.rolling(2, min_periods=1).apply(lambda x: x.iloc[-1], raw=False)
Out[42]:
  0  0
  1  1
  2  2
  3  3
  4  4
dtype: float64
Mimic the original behavior of passing an array:

```python
In [43]: s.rolling(2, min_periods=1).apply(lambda x: x[-1], raw=True)
Out[43]:
1  0.0
2  1.0
3  2.0
4  3.0
5  4.0
dtype: float64
```

### 1.2.1.8 DataFrame.interpolate has gained the limit_area kwarg

`DataFrame.interpolate()` has gained a `limit_area` parameter to allow further control of which NaNs are replaced. Use `limit_area='inside'` to fill only NaNs surrounded by valid values or use `limit_area='outside'` to fill only NaNs outside the existing valid values while preserving those inside. ([GH16284](https://github.com/pandas-dev/pandas/pull/16284)) See the [full documentation here](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.interpolate.html).

```python
In [44]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13, np.nan, np.nan])
In [45]: ser
Out[45]:
0   NaN
1   NaN
2    5.0
3   NaN
4   NaN
5   NaN
6   13.0
7   NaN
8   NaN
dtype: float64
```

Fill one consecutive inside value in both directions

```python
In [46]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[46]:
0   NaN
1   NaN
2    5.0
3    7.0
4   NaN
5    11.0
6   13.0
7   NaN
8   NaN
dtype: float64
```

Fill all consecutive outside values backward

```python
In [47]: ser.interpolate(limit_direction='backward', limit_area='outside')
Out[47]:
0    5.0
1    5.0
2    5.0
```

(continues on next page)
Fill all consecutive outside values in both directions

```python
In [48]: ser.interpolate(limit_direction='both', limit_area='outside')
Out[48]:
0  5.0
1  5.0
2  5.0
3  NaN
4  NaN
5  NaN
6  13.0
7  13.0
8  13.0
dtype: float64
```

### 1.2.1.9 `get_dummies` now supports `dtype` argument

The `get_dummies()` now accepts a `dtype` argument, which specifies a dtype for the new columns. The default remains `uint8`. (GH18330)

```python
In [49]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4], 'c': [5, 6]})
In [50]: pd.get_dummies(df, columns=['c']).dtypes
Out[50]:
a int64
b int64
c_5 uint8
c_6 uint8
dtype: object
```

```python
In [51]: pd.get_dummies(df, columns=['c'], dtype=bool).dtypes
Out[51]:
a int64
b int64
c_5 bool
c_6 bool
dtype: object
```

### 1.2.1.10 Timedelta mod method

`mod (%)` and `divmod` operations are now defined on `Timedelta` objects when operating with either timedelta-like or with numeric arguments. See the documentation here. (GH19365)

```python
In [52]: td = pd.Timedelta(hours=37)
```

(continues on next page)
1.2.1.11 `.rank()` handles `inf` values when `NaN` are present

In previous versions, `.rank()` would assign `inf` elements `NaN` as their ranks. Now ranks are calculated properly. (GH6945)

In [54]: s = pd.Series([-np.inf, 0, 1, np.nan, np.inf])
In [55]: s
Out[55]:
0 -inf
1 0.000000
2 1.000000
3 NaN
4 inf
dtype: float64
Previous Behavior:
In [11]: s.rank()
Out[11]:
0 1.0
1 2.0
2 3.0
3 NaN
4 NaN
dtype: float64
Current Behavior:
In [56]: s.rank()
Out[56]:
0 1.0
1 2.0
2 3.0
3 NaN
4 4.0
dtype: float64
Furthermore, previously if you rank `inf` or `-inf` values together with `NaN` values, the calculation won't distinguish `NaN` from infinity when using 'top' or 'bottom' argument.

In [57]: s = pd.Series([np.nan, np.nan, -np.inf, -np.inf])
In [58]: s
Out[58]:
0 NaN
1 NaN
2 -inf
3 -inf
dtype: float64
Previous Behavior:
In [15]: s.rank(na_option='top')
Out[15]:
      0  2.5
      1  2.5
      2  2.5
      3  2.5
dtype: float64

Current Behavior:

In [59]: s.rank(na_option='top')
Out[59]:
      0  1.5
      1  1.5
      2  3.5
      3  3.5
dtype: float64

These bugs were squashed:

- Bug in DataFrame.rank() and Series.rank() when method='dense' and pct=True in which percentile ranks were not being used with the number of distinct observations (GH15630)
- Bug in Series.rank() and DataFrame.rank() when ascending='False' failed to return correct ranks for infinity if NaN were present (GH19538)
- Bug in DataFrameGroupBy.rank() where ranks were incorrect when both infinity and NaN were present (GH20561)

1.2.1.12 Series.str.cat has gained the join kwarg

Previously, Series.str.cat() did not – in contrast to most of pandas – align Series on their index before concatenation (see GH18657). The method has now gained a keyword join to control the manner of alignment, see examples below and here.

In v.0.23 join will default to None (meaning no alignment), but this default will change to 'left' in a future version of pandas.

In [60]: s = pd.Series(['a', 'b', 'c', 'd'])
In [61]: t = pd.Series(['b', 'd', 'e', 'c'], index=[1, 3, 4, 2])
In [62]: s.str.cat(t)
Out[62]:
     0   ab
     1   bd
     2   ce
     3   dc

dtype: object

In [63]: s.str.cat(t, join='left', na_rep='-')
Out[63]:
     0   a-
     1   bb
     2   cc
     3   dd

dtype: object
Furthermore, `Series.str.cat()` now works for CategoricalIndex as well (previously raised a ValueError; see GH20842).

### 1.2.1.13 DataFrame.astype performs column-wise conversion to Categorical

`DataFrame.astype()` can now perform column-wise conversion to Categorical by supplying the string 'category' or a CategoricalDtype. Previously, attempting this would raise a NotImplemente_ERROR. See the Object Creation section of the documentation for more details and examples. (GH12860, GH18099)

Supplying the string 'category' performs column-wise conversion, with only labels appearing in a given column set as categories:

```
In [64]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))
In [65]: df = df.astype('category')
In [66]: df['A'].dtype
Out[66]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)
In [67]: df['B'].dtype
Out[67]: CategoricalDtype(categories=['b', 'c', 'd'], ordered=False)
```

Supplying a CategoricalDtype will make the categories in each column consistent with the supplied dtype:

```
In [68]: from pandas.api.types import CategoricalDtype
In [69]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))
In [70]: cdt = CategoricalDtype(categories=list('abcd'), ordered=True)
In [71]: df = df.astype(cdt)
In [72]: df['A'].dtype
Out[72]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
In [73]: df['B'].dtype
Out[73]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
```

### 1.2.1.14 Other Enhancements

- Unary + now permitted for Series and DataFrame as numeric operator (GH16073)
- Better support for to_excel() output with the xlsxwriter engine. (GH16149)
- `pandas.tseries.frequencies.to_offset()` now accepts leading ‘+’ signs e.g. ‘+1h’. (GH18171)
- `MultiIndex.unique()` now supports the level= argument, to get unique values from a specific index level (GH17896)
- `pandas.io.formats.style.Styler` now has method hide_index() to determine whether the index will be rendered in output (GH14194)
- `pandas.io.formats.style.Styler` now has method hide_columns() to determine whether columns will be hidden in output (GH14194)
• Improved wording of `ValueError` raised in `to_datetime()` when `unit=` is passed with a non-convertible value (GH14350)

• `Series.fillna()` now accepts a Series or a dict as a value for a categorical dtype (GH17033)

• `pandas.read_clipboard()` updated to use qtpy, falling back to PyQt5 and then PyQt4, adding compatibility with Python3 and multiple python-qt bindings (GH17722)

• Improved wording of `ValueError` raised in `read_csv()` when the `usecols` argument cannot match all columns. (GH17301)

• `DataFrame.corrwith()` now silently drops non-numeric columns when passed a Series. Before, an exception was raised (GH18570).

• `IntervalIndex` now supports time zone aware `Interval` objects (GH18537, GH18538)

• `Series() / DataFrame()` tab completion also returns identifiers in the first level of a `MultiIndex()` (GH16326)

• `read_excel()` has gained the `nrows` parameter (GH16645)

• `DataFrame.append()` can now in more cases preserve the type of the calling dataframe’s columns (e.g. if both are `CategoricalIndex`) (GH18359)

• `DataFrame.to_json()` and `Series.to_json()` now accept an index argument which allows the user to exclude the index from the JSON output (GH17394)

• `IntervalIndex.to_tuples()` has gained the `na_tuple` parameter to control whether NA is returned as a tuple of NA, or NA itself (GH18756)

• `Categorical.rename_categories`, `CategoricalIndex.rename_categories` and `Series.cat.rename_categories` can now take a callable as their argument (GH18862)

• `Interval` and `IntervalIndex` have gained a `length` attribute (GH18789)

• `Resampler` objects now have a functioning `pipe` method. Previously, calls to `pipe` were diverted to the `mean` method (GH17905).

• `is_scalar()` now returns `True` for `DateOffset` objects (GH18943).

• `DataFrame.pivot()` now accepts a list for the `values=` kwarg (GH17160).

• Added `pandas.api.extensions.register_dataframe_accessor()`, `pandas.api.extensions.register_series_accessor()`, and `pandas.api.extensions.register_index_accessor()`, accessor for libraries downstream of pandas to register custom accessors like `.cat` on pandas objects. See Registering Custom Accessors for more (GH14781).

• `IntervalIndex.astype` now supports conversions between subtypes when passed an `IntervalDtype` (GH19197)

• `IntervalIndex` and its associated constructor methods (`from_arrays`, `from_breaks`, `from_tuples`) have gained a `dtype` parameter (GH19262)

• Added `pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing()` and `pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing()` (GH17015)

• For subclassed `DataFrames`, `DataFrame.apply()` will now preserve the `Series` subclass (if defined) when passing the data to the applied function (GH19822)

• `DataFrame.from_dict()` now accepts a `columns` argument that can be used to specify the column names when `orient='index'` is used (GH18529)

• Added option `display.html.use_mathjax` so MathJax can be disabled when rendering tables in Jupyter notebooks (GH19856, GH19824)
• **DataFrame.replace()** now supports the `method` parameter, which can be used to specify the replacement method when `to_replace` is a scalar, list or tuple and `value` is None (GH19632)

• **Timestamp.month_name()**, **DatetimeIndex.month_name()**, and **Series.dt.month_name()** are now available (GH12805)

• **Timestamp.day_name()** and **DatetimeIndex.day_name()** are now available to return day names with a specified locale (GH12806)

• **DataFrame.to_sql()** now performs a multivalue insert if the underlying connection supports `itk` rather than inserting row by row. SQLAlchemy dialects supporting multivalue inserts include: `mysql`, `postgresql`, `sqlite` and any dialect with `supports_multivalues_insert` (GH14315, GH8953)

• **read_html()** now accepts a `displayed_only` keyword argument to controls whether or not hidden elements are parsed (True by default) (GH20027)

• **read_html()** now reads all `<tbody>` elements in a `<table>`, not just the first. (GH20690)

• **quantile()** and **quantile()** now accept the `interpolation` keyword, `linear` by default (GH20497)

• zip compression is supported via `compression=zip` in **DataFrame.to_pickle()**, **Series.to_pickle()**, **DataFrame.to_csv()**, **Series.to_csv()**, **DataFrame.to_json()**, **Series.to_json()**. (GH17778)

• WeekOfMonth constructor now supports `n=0` (GH20517).

• **DataFrame** and **Series** now support matrix multiplication (`@`) operator (GH10259) for Python>=3.5

• Updated **DataFrame.to_gbq()** and **pandas.read_gbq()** signature and documentation to reflect changes from the Pandas-GBQ library version 0.4.0. Adds intersphinx mapping to Pandas-GBQ library. (GH20564)

• Added new writer for exporting Stata dta files in version 117, **StataWriter117**. This format supports exporting strings with lengths up to 2,000,000 characters (GH16450)

• **to_hdf()** and **read_hdf()** now accept an `errors` keyword argument to control encoding error handling (GH20835)

• **cut()** has gained the `duplicates='raise' | 'drop'` option to control whether to raise on duplicated edges (GH20947)

• **date_range()**, **timedelta_range()**, and **interval_range()** now return a linearly spaced index if `start`, `stop`, and `periods` are specified, but `freq` is not. (GH20808, GH20983, GH20976)

### 1.2.2 Backwards incompatible API changes

#### 1.2.2.1 Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15184). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
<th>Issue</th>
</tr>
</thead>
<tbody>
<tr>
<td>python-dateutil</td>
<td>2.5.0</td>
<td>X</td>
<td>GH15184</td>
</tr>
<tr>
<td>openpyxl</td>
<td>2.4.0</td>
<td></td>
<td>GH15184</td>
</tr>
<tr>
<td>beautifulsoup4</td>
<td>4.2.1</td>
<td></td>
<td>GH20082</td>
</tr>
<tr>
<td>setuptools</td>
<td>24.2.0</td>
<td></td>
<td>GH20698</td>
</tr>
</tbody>
</table>
1.2.2.2 Instantiation from dicts preserves dict insertion order for python 3.6+

Until Python 3.6, dicts in Python had no formally defined ordering. For Python version 3.6 and later, dicts are ordered by insertion order, see PEP 468. Pandas will use the dict’s insertion order, when creating a Series or DataFrame from a dict and you’re using Python version 3.6 or higher. (GH19884)

Previous Behavior (and current behavior if on Python < 3.6):

```python
pd.Series({'Income': 2000,
           'Expenses': -1500,
           'Taxes': -200,
           'Net result': 300})
```

Expenses -1500
Income 2000
Net result 300
Taxes -200
dtype: int64

Note the Series above is ordered alphabetically by the index values.

New Behavior (for Python >= 3.6):

```python
In [74]: pd.Series({'Income': 2000,
                 'Expenses': -1500,
                 'Taxes': -200,
                 'Net result': 300})
```

Out[74]:
Income 2000
Expenses -1500
Taxes -200
Net result 300
dtype: int64

Notice that the Series is now ordered by insertion order. This new behavior is used for all relevant pandas types (Series, DataFrame, SparseSeries and SparseDataFrame).

If you wish to retain the old behavior while using Python >= 3.6, you can use .sort_index():

```python
In [75]: pd.Series({'Income': 2000,
                 'Expenses': -1500,
                 'Taxes': -200,
                 'Net result': 300}).sort_index()
```

Out[75]:
Expenses -1500
Income 2000
Net result 300
Taxes -200
dtype: int64

1.2.2.3 Deprecate Panel

Panel was deprecated in the 0.20.x release, showing as a DeprecationWarning. Using Panel will now show a FutureWarning. The recommended way to represent 3-D data are with a MultiIndex on a DataFrame via the to_frame() or with the xarray package. Pandas provides a to_xarray() method to automate this conversion. For more details see Deprecate Panel documentation. (GH13563, GH18324).
In [76]: p = tm.makePanel()

In [77]: p
Out[77]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

Convert to a MultiIndex DataFrame

In [78]: p.to_frame()
Out[78]:
<table>
<thead>
<tr>
<th>major</th>
<th>minor</th>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1.474071</td>
<td>-0.964980</td>
<td>-1.197071</td>
</tr>
<tr>
<td>A</td>
<td></td>
<td>0.781836</td>
<td>1.846883</td>
<td>-0.858447</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>2.353925</td>
<td>-1.717693</td>
<td>0.384316</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td>-0.744471</td>
<td>0.901805</td>
<td>0.476720</td>
</tr>
<tr>
<td>D</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.064034</td>
<td>-0.845696</td>
<td>-1.066969</td>
</tr>
<tr>
<td>A</td>
<td></td>
<td>-1.071357</td>
<td>-1.328865</td>
<td>0.306996</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>0.583787</td>
<td>0.888782</td>
<td>1.574159</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td>0.758527</td>
<td>1.171216</td>
<td>0.473424</td>
</tr>
<tr>
<td>D</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-1.282782</td>
<td>-1.340896</td>
<td>-0.303421</td>
</tr>
<tr>
<td>A</td>
<td></td>
<td>0.441153</td>
<td>1.682706</td>
<td>-0.028665</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>0.221471</td>
<td>0.228440</td>
<td>1.588931</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td>1.729689</td>
<td>0.520260</td>
<td>-0.242861</td>
</tr>
</tbody>
</table>

Convert to an xarray DataArray

In [79]: p.to_xarray()
Out[79]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
array([[ 1.474071, 0.781836, 2.353925, -0.744471],
       [-0.064034, -1.071357, 0.583787, 0.758527],
       [-1.282782, 0.441153, 0.221471, 1.729689]],
[[ 1.846883, -1.717693, 0.901805],
 [-0.845696, -1.328865, 0.888782, 1.171216],
 [-1.340896, 1.682706, 0.228444, 0.520262]],
[[ -0.964980, 1.846883, -1.717693, 0.901805],
 [-0.845696, -1.328865, 0.888782, 1.171216],
 [-1.340896, 1.682706, 0.228444, 0.520262]],
[[ -0.964980, 1.846883, -1.717693, 0.901805],
 [-0.845696, -1.328865, 0.888782, 1.171216],
 [-1.340896, 1.682706, 0.228444, 0.520262]])
Coordinates:
* items    (items) object 'ItemA' 'ItemB' 'ItemC'
* major_axis (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
* minor_axis (minor_axis) object 'A' 'B' 'C' 'D'

1.2.2.4 pandas.core.common removals

The following error & warning messages are removed from pandas.core.common (GH13634, GH19769):

- PerformanceWarning
- UnsupportedFunctionCall
• UnsortedIndexError
• AbstractMethodError

These are available from import from pandas.errors (since 0.19.0).

1.2.2.5 Changes to make output of DataFrame.apply consistent

DataFrame.apply() was inconsistent when applying an arbitrary user-defined-function that returned a list-like with axis=1. Several bugs and inconsistencies are resolved. If the applied function returns a Series, then pandas will return a DataFrame; otherwise a Series will be returned, this includes the case where a list-like (e.g. tuple or list is returned) (GH16353, GH17437, GH17970, GH17348, GH17892, GH18573, GH17602, GH18775, GH18901, GH18919).

In [80]: df = pd.DataFrame(np.tile(np.arange(3), 6).reshape(6, -1) + 1, columns=['A', 'B', 'C'])
In [81]: df
Out[81]:
   A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

Previous Behavior: if the returned shape happened to match the length of original columns, this would return a DataFrame. If the return shape did not match, a Series with lists was returned.

In [3]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[3]:
    A  B  C
0  [1, 2]  3
1 [1, 2]  2
2 [1, 2]  3
3 [1, 2]  3
4 [1, 2]  3
5 [1, 2]  3

In [4]: df.apply(lambda x: [1, 2], axis=1)
Out[4]:
   0  [1, 2]
   1  [1, 2]
   2  [1, 2]
   3  [1, 2]
   4  [1, 2]
   5  [1, 2]
dtype: object

New Behavior: When the applied function returns a list-like, this will now always return a Series.

In [82]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[82]:
   0  [1, 2, 3]
   1  [1, 2, 3]
   2  [1, 2, 3]
To have expanded columns, you can use `result_type='expand'`

```
In [84]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='expand')
```

```
     0  1  2  3
 0  0  1  2  3
 1  1  2  3
 2  1  2  3
 3  1  2  3
 4  1  2  3
 5  1  2  3
```

To broadcast the result across the original columns (the old behaviour for list-likes of the correct length), you can use `result_type='broadcast'`. The shape must match the original columns.

```
In [85]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='broadcast')
```

```
     A  B  C
 0  0  1  2  3
 1  1  2  3
 2  1  2  3
 3  1  2  3
 4  1  2  3
 5  1  2  3
```

Returning a `Series` allows one to control the exact return structure and column names:

```
In [86]: df.apply(lambda x: Series([1, 2, 3], index=['D', 'E', 'F']), axis=1)
```

```
     D  E  F
 0  0  1  2  3
 1  1  2  3
 2  1  2  3
 3  1  2  3
 4  1  2  3
 5  1  2  3
```
1.2.2.6 Concatenation will no longer sort

In a future version of pandas pandas.concat() will no longer sort the non-concatenation axis when it is not already aligned. The current behavior is the same as the previous (sorting), but now a warning is issued when sort is not specified and the non-concatenation axis is not aligned (GH4588).

```python
In [87]: df1 = pd.DataFrame({'a': [1, 2], 'b': [1, 2]}, columns=['b', 'a'])
In [88]: df2 = pd.DataFrame({'a': [4, 5]})
In [89]: pd.concat([df1, df2])
Out[89]:
   a  b
0  1  1.0
1  2  2.0
0  4  NaN
1  5  NaN
```
To keep the previous behavior (sorting) and silence the warning, pass sort=True

```python
In [90]: pd.concat([df1, df2], sort=True)
Out[90]:
   a  b
0  1  1.0
1  2  2.0
0  4  NaN
1  5  NaN
```
To accept the future behavior (no sorting), pass sort=False

Note that this change also applies to DataFrame.append(), which has also received a sort keyword for controlling this behavior.

1.2.2.7 Build Changes

- Building pandas for development now requires cython >= 0.24 (GH18613)
- Building from source now explicitly requires setuptools in setup.py (GH18113)
- Updated conda recipe to be in compliance with conda-build 3.0+ (GH18002)

1.2.2.8 Index Division By Zero Fills Correctly

Division operations on Index and subclasses will now fill division of positive numbers by zero with np.inf, division of negative numbers by zero with -np.inf and 0 / 0 with np.nan. This matches existing Series behavior. (GH19322, GH19347)

Previous Behavior:

```python
In [6]: index = pd.Int64Index([-1, 0, 1])
In [7]: index / 0
Out[7]: Int64Index([0, 0, 0], dtype='int64')
```
# Previous behavior yielded different results depending on the type of zero in the divisor
(continues on next page)
Current Behavior:

```
In [91]: index = pd.Int64Index([-1, 0, 1])

# division by zero gives -infinity where negative, +infinity where positive, and NaN
for 0 / 0
In [92]: index / 0
Out[92]: Float64Index([-inf, nan, inf], dtype='float64')

# The result of division by zero should not depend on whether the zero is int or float
In [93]: index = pd.UInt64Index([0, 1])

In [94]: index / np.array([0, 0], dtype=np.uint64)
Out[94]: Float64Index([nan, inf], dtype='float64')

In [95]: index = pd.UInt64Index([0, 1])

In [96]: pd.RangeIndex(1, 5) / 0
ZeroDivisionError: integer division or modulo by zero
```

### 1.2.2.9 Extraction of matching patterns from strings

By default, extracting matching patterns from strings with `str.extract()` used to return a `Series` if a single group was being extracted (a `DataFrame` if more than one group was extracted). As of Pandas 0.23.0 `str.extract()` always returns a `DataFrame`, unless `expand` is set to `False`. Finally, `None` was an accepted value for the `expand` parameter (which was equivalent to `False`), but now raises a `ValueError`. (GH11386)

Previous Behavior:

```
In [1]: s = pd.Series(['number 10', '12 eggs'])

In [2]: extracted = s.str.extract('.*(\d\d).*')

In [3]: extracted
Out [3]:
0   10
1   12
dtype: object

In [4]: type(extracted)
Out [4]:
pandas.core.series.Series
```

---

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New Behavior:

```
In [97]: s = pd.Series(['number 10', '12 eggs'])
In [98]: extracted = s.str.extract('.*(\d\d).*')
In [99]: extracted
Out[99]:
   0  10
   1  12
```

To restore previous behavior, simply set `expand` to `False`:

```
In [101]: s = pd.Series(['number 10', '12 eggs'])
In [102]: extracted = s.str.extract('.*(\d\d).*', expand=False)
In [103]: extracted
Out[103]:
   0  10
   1  12
dtype: object
```

1.2.2.10 Default value for the `ordered` parameter of `CategoricalDtype`

The default value of the `ordered` parameter for `CategoricalDtype` has changed from `False` to `None` to allow updating of categories without impacting `ordered`. Behavior should remain consistent for downstream objects, such as `Categorical` (GH18790).

In previous versions, the default value for the `ordered` parameter was `False`. This could potentially lead to the `ordered` parameter unintentionally being changed from `True` to `False` when users attempt to update categories if `ordered` is not explicitly specified, as it would silently default to `False`. The new behavior for `ordered=None` is to retain the existing value of `ordered`.

New Behavior:

```
In [105]: from pandas.api.types import CategoricalDtype
In [106]: cat = pd.Categorical(list('abcaba'), ordered=True, categories=list('cba'))
In [107]: cat
Out[107]:
[a, b, c, a, b, a]
Categories (3, object): [c < b < a]
In [108]: cdt = CategoricalDtype(categories=list('cbad'))
In [109]: cat.astype(cdt)
```

(continues on next page)
Notice in the example above that the converted Categorical has retained ordered=True. Had the default value for ordered remained as False, the converted Categorical would have become unordered, despite ordered=False never being explicitly specified. To change the value of ordered, explicitly pass it to the new dtype, e.g. CategoricalDtype(categories=list('cbad'), ordered=False).

Note that the unintentional conversion of ordered discussed above did not arise in previous versions due to separate bugs that prevented astype from doing any type of category to category conversion (GH10696, GH18593). These bugs have been fixed in this release, and motivated changing the default value of ordered.

1.2.2.11 Better pretty-printing of DataFrames in a terminal

Previously, the default value for the maximum number of columns was pd.options.display.max_columns=20. This meant that relatively wide data frames would not fit within the terminal width, and pandas would introduce line breaks to display these 20 columns. This resulted in an output that was relatively difficult to read:

If Python runs in a terminal, the maximum number of columns is now determined automatically so that the printed data frame fits within the current terminal width (pd.options.display.max_columns=0) (GH17023). If Python runs as a Jupyter kernel (such as the Jupyter QtConsole or a Jupyter notebook, as well as in many IDEs), this value cannot be inferred automatically and is thus set to 20 as in previous versions. In a terminal, this results in a much nicer output:
1.2.2.12 Datetimelike API Changes

- The default `Timedelta` constructor now accepts an ISO 8601 Duration string as an argument (GH19040)

- Subtracting `NaT` from a `Series` with `dtype='datetime64[ns]'` returns a `Series` with `dtype='timedelta64[ns]'` instead of `dtype='datetime64[ns]'` (GH18808)

- Addition or subtraction of `NaT` from `TimedeltaIndex` will return `TimedeltaIndex` instead of `DatetimeIndex` (GH19124)

- `TimedeltaIndex.shift()` and `TimedeltaIndex.shift()` will now raise `NullFrequencyError` (which subclasses `ValueError`, which was raised in older versions) when the index object frequency is `None` (GH19147)

- Addition and subtraction of `NaN` from a `Series` with `dtype='timedelta64[ns]'` will raise a `TypeError` instead of treating the `NaN` as `NaT` (GH19274)

- `NaT` division with `datetime.timedelta` will now return `NaN` instead of raising (GH17876)
**Operations between a** *Series* **with** dtype='datetime64[ns]' **and a** *PeriodIndex* **will correctly raise** TypeError (GH18850)

• **Subtraction of** *Series* **with timezone-aware** dtype='datetime64[ns]' **with mis-matched timezones will raise** TypeError **instead of** ValueError (GH18817)

• **Timestamp** will no longer silently ignore unused or invalid tz or tzinfo keyword arguments (GH17690)

• **Timestamp** will no longer silently ignore invalid freq arguments (GH5168)

• CacheableOffset and WeekDay are no longer available in the pandas.tseries.offsets module (GH17830)

• pandas.tseries.frequencies.get_freq_group() and pandas.tseries.frequencies.DAYS are removed from the public API (GH18034)

• *Series.truncate()* and *DataFrame.truncate()* will raise a **ValueError** if the index is not sorted instead of an unhelpful **KeyError** (GH17935)

• *Series.first* and *DataFrame.first* will now raise a **TypeError** rather than **NotImplementedError** when index is not a **DatetimeIndex** (GH20725).

• *Series.last* and *DataFrame.last* will now raise a **TypeError** rather than **NotImplementedError** when index is not a **DatetimeIndex** (GH20725).

• Restricted DateOffset keyword arguments. Previously, DateOffset subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176, GH18226).

• *pandas.merge()* provides a more informative error message when trying to merge on timezone-aware and timezone-naive columns (GH15800)

• For **DatetimeIndex** and **TimedeltaIndex** with freq=None, addition or subtraction of integer-dtyped array or Index will raise **NullFrequencyError** instead of **TypeError** (GH19895)

• **Timestamp** constructor now accepts a **nanosecond** keyword or positional argument (GH18898)

• **DatetimeIndex** will now raise an **AttributeError** when the tz attribute is set after instantiation (GH3746)

• **DatetimeIndex** with a **pytz** timezone will now return a consistent pytz timezone (GH18595)

### 1.2.2.13 Other API Changes

• **Series.astype()** and **Index.astype()** with an incompatible dtype will now raise a **TypeError** rather than a **ValueError** (GH18231)

• Series construction with an object dtyped tz-aware datetime and dtype=object specified, will now return an object dtyped Series, previously this would infer the datetime dtype (GH18231)

• A **Series** of dtype=category constructed from an empty dict will now have categories of dtype=object rather than dtype=float64, consistently with the case in which an empty list is passed (GH18515)

• All-NaN levels in a MultiIndex are now assigned float rather than object dtype, promoting consistency with Index (GH17929).

• Levels names of a MultiIndex (when not None) are now required to be unique: trying to create a MultiIndex with repeated names will raise a **ValueError** (GH18872)

• Both construction and renaming of Index/MultiIndex with non-hashable name/names will now raise **TypeError** (GH20527)
- `Index.map()` can now accept `Series` and dictionary input objects (GH12756, GH18482, GH18509).
- `DataFrame.unstack()` will now default to filling with `np.nan` for object columns. (GH12815)
- `IntervalIndex` constructor will raise if the `closed` parameter conflicts with how the input data is inferred to be closed (GH18421)
- Inserting missing values into indexes will work for all types of indexes and automatically insert the correct type of missing value (NaN, NaT, etc.) regardless of the type passed in (GH18295)
- When created with duplicate labels, `MultiIndex` now raises a `ValueError`. (GH17464)
- `Series.fillna()` now raises a `TypeError` instead of a `ValueError` when passed a list, tuple or `DataFrame` as a value (GH18293)
- `pandas.DataFrame.merge()` no longer casts a float column to object when merging on int and float columns (GH16572)
- `pandas.merge()` now raises a `ValueError` when trying to merge on incompatible data types (GH9780)
- The default NA value for `UInt64Index` has changed from 0 to NaN, which impacts methods that mask with NA, such as `UInt64Index.where()` (GH18398)
- Refactored `setup.py` to use `find_packages` instead of explicitly listing out all subpackages (GH18535)
- Rearranged the order of keyword arguments in `read_excel()` to align with `read_csv()` (GH16672)
- `wide_to_long()` previously kept numeric-like suffixes as object dtype. Now they are cast to numeric if possible (GH17627)
- In `read_excel()`, the `comment` argument is now exposed as a named parameter (GH18735)
- The options `html.border` and `mode.use_inf_as_null` were deprecated in prior versions, these will now show `FutureWarning` rather than a `DeprecationWarning` (GH19003)
- `IntervalIndex` and `IntervalDtype` no longer support categorical, object, and string subtypes (GH19016)
- `IntervalDtype` now returns `True` when compared against 'interval' regardless of subtype, and `IntervalDtype.name` now returns 'interval' regardless of subtype (GH18980)
- `KeyError` now raises instead of `ValueError` in `drop()`, `drop()`, `drop()`, `drop()` when dropping a non-existent element in an axis with duplicates (GH19186)
- `Series.to_csv()` now accepts a `compression` argument that works in the same way as the `compression` argument in `DataFrame.to_csv()` (GH18958)
- Set operations (union, difference...) on `IntervalIndex` with incompatible index types will now raise a `TypeError` rather than a `ValueError` (GH19329)
- `DateOffset` objects render more simply, e.g. `<DateOffset: days=1>` instead of `<DateOffset: kwds={'days': 1}>` (GH19403)
- `Categorical.fillna` now validates its value and method keyword arguments. It now raises when both or none are specified, matching the behavior of `Series.fillna()` (GH19682)
- `pd.to_datetime('today')` now returns a datetime, consistent with `pd.Timestamp('today')`; previously `pd.to_datetime('today')` returned a `.normalized()` datetime (GH19935)
- `Series.str.replace()` now takes an optional `regex` keyword which, when set to `False`, uses literal string replacement rather than regex replacement (GH16808)
- `DatetimeIndex.strftime()` and `PeriodIndex.strftime()` now return an `Index` instead of a numpy array to be consistent with similar accessors (GH20127)
• Constructing a Series from a list of length 1 no longer broadcasts this list when a longer index is specified (GH19714, GH20391).

• DataFrame.to_dict() with orient='index' no longer casts int columns to float for a DataFrame with only int and float columns (GH18580)

• A user-defined-function that is passed to Series.rolling().aggregate(), DataFrame.rolling().aggregate(), or its expanding cousins, will now always be passed a Series, rather than a np.array; .apply() only has the raw keyword, see here. This is consistent with the signatures of .aggregate() across pandas (GH20584)

• Rolling and Expanding types raise NotImplementedError upon iteration (GH11704).

1.2.3 Deprecations

• Series.from_array and SparseSeries.from_array are deprecated. Use the normal constructor Series(...) and SparseSeries(...) instead (GH18213).

• DataFrame.as_matrix is deprecated. Use DataFrame.values instead (GH18458).

• Series.asobject, DatetimeIndex.asobject, PeriodIndex.asobject and TimeDeltaIndex.asobject have been deprecated. Use .astype(object) instead (GH18572)

• Grouping by a tuple of keys now emits a FutureWarning and is deprecated. In the future, a tuple passed to 'by' will always refer to a single key that is the actual tuple, instead of treating the tuple as multiple keys. To retain the previous behavior, use a list instead of a tuple (GH18314)

• Series.valid is deprecated. Use Series.dropna() instead (GH18800).

• read_excel() has deprecated the skip_footer parameter. Use skipfooter instead (GH18836)

• ExcelFile.parse() has deprecated sheetname in favor of sheet_name for consistency with read_excel() (GH18920).

• The is_copy attribute is deprecated and will be removed in a future version (GH18801).

• IntervalIndex.from_intervals is deprecated in favor of the IntervalIndex constructor (GH19263)

• DataFrame.from_items is deprecated. Use DataFrame.from_dict() instead, or DataFrame.from_dict(OrderedDict()) if you wish to preserve the key order (GH17320, GH17312)

• Indexing a MultiIndex or a FloatIndex with a list containing some missing keys will now show a FutureWarning, which is consistent with other types of indexes (GH17758).

• The broadcast parameter of .apply() is deprecated in favor of result_type='broadcast' (GH18577)

• The reduce parameter of .apply() is deprecated in favor of result_type='reduce' (GH18577)

• The order parameter of factorize() is deprecated and will be removed in a future release (GH19727)

• Timestamp.weekday_name, DatetimeIndex.weekday_name, and Series.dt.weekday_name are deprecated in favor of Timestamp.day_name(), DatetimeIndex.day_name(), and Series.dt.day_name() (GH12806)

• pandas.tseries.plotting.tsplot is deprecated. Use Series.plot() instead (GH18627)

• Index.summary() is deprecated and will be removed in a future version (GH18217)

• NDFrame.get_ftype_counts() is deprecated and will be removed in a future version (GH18243)
• The convert_datetime64 parameter in DataFrame.to_records() has been deprecated and will be removed in a future version. The NumPy bug motivating this parameter has been resolved. The default value for this parameter has also changed from True to None (GH18160).

• Series.rolling().apply(), DataFrame.rolling().apply(), Series.expanding().apply(), and DataFrame.expanding().apply() have deprecated passing an np.array by default. One will need to pass the new raw parameter to be explicit about what is passed (GH20584).

• The data, base, strides, flags and itemsize properties of the Series and Index classes have been deprecated and will be removed in a future version (GH20419).

• DatetimeIndex.offset is deprecated. Use DatetimeIndex.freq instead (GH20716).

• Floor division between an integer ndarray and a Timedelta is deprecated. Divide by Timedelta.value instead (GH19761).

• Setting PeriodIndex.freq (which was not guaranteed to work correctly) is deprecated. Use PeriodIndex.asfreq() instead (GH20678).

• Index.get_duplicates() is deprecated and will be removed in a future version (GH20239).

• The previous default behavior of negative indices in Categorical.take is deprecated. In a future version it will change from meaning missing values to meaning positional indices from the right. The future behavior is consistent with Series.take() (GH20664).

• Passing multiple axes to the axis parameter in DataFrame.dropna() has been deprecated and will be removed in a future version (GH20987).

1.2.4 Removal of prior version deprecations/changes

• Warnings against the obsolete usage Categorical(codes, categories), which were emitted for instance when the first two arguments to Categorical() had different dtypes, and recommended the use of Categorical.from_codes, have now been removed (GH8074).

• The levels and labels attributes of a MultiIndex can no longer be set directly (GH4039).

• pd.tseries.util.pivot_annual has been removed (deprecated since v0.19). Use pivot_table instead (GH18370).

• pd.tseries.util.isleapyear has been removed (deprecated since v0.19). Use .is_leap_year property in Datetime-likes instead (GH18370).

• pd.ordered_merge has been removed (deprecated since v0.19). Use pd.merge_ordered instead (GH18459).

• The SparseList class has been removed (GH14007).

• The pandas.io.wb and pandas.io.data stub modules have been removed (GH13735).

• Categorical.from_array has been removed (GH13854).

• The freq and how parameters have been removed from the rolling/expanding/ewm methods of DataFrame and Series (deprecated since v0.18). Instead, resample before calling the methods. (GH18601 & GH18668).

• DatetimeIndex.to_datetime, Timestamp.to_datetime, PeriodIndex.to_datetime, and Index.to_datetime have been removed (GH8254, GH14096, GH14113).

• read_csv() has dropped the skip_footer parameter (GH13386).

• read_csv() has dropped the as_recarray parameter (GH13373).

• read_csv() has dropped the buffer_lines parameter (GH13360).
- `read_csv()` has dropped the `compact_ints` and `use_unsigned` parameters (GH13323)
- The `Timestamp` class has dropped the `offset` attribute in favor of `freq` (GH13593)
- The `Series`, `Categorical`, and `Index` classes have dropped the `reshape` method (GH13012)
- `pandas.tseries.frequencies.get_standard_freq` has been removed in favor of `pandas.tseries.frequencies.to_offset(freq).rule_code` (GH13874)
- The `freqstr` keyword has been removed from `pandas.tseries.frequencies.to_offset` in favor of `freq` (GH13874)
- The `Panel4D` and `PanelND` classes have been removed (GH13776)
- The `Panel` class has dropped the `to_long` and `toLong` methods (GH19077)
- The options `display.line_with` and `display.height` are removed in favor of `display.width` and `display.max_rows` respectively (GH4391, GH19107)
- The `labels` attribute of the `Categorical` class has been removed in favor of `Categorical.codes` (GH7768)
- The `flavor` parameter have been removed from `func.to_sql` method (GH13611)
- The modules `pandas.tools.hashing` and `pandas.util.hashing` have been removed (GH16223)
- The top-level functions `pd.rolling_*`, `pd.expanding_*` and `pd.ewm_*` have been removed (Deprecated since v0.18). Instead, use the `DataFrame/Series` methods `rolling`, `expanding` and `ewm` (GH18723)
- Imports from `pandas.core.common` for functions such as `is_datetime64_dtype` are now removed. These are located in `pandas.api.types` (GH13634, GH19769)
- The `infer_dst` keyword in `Series.tz_localize()`, `DatetimeIndex.tz_localize()` and `DatetimeIndex` have been removed. `infer_dst=True` is equivalent to `ambiguous='infer'`, and `infer_dst=False` to `ambiguous='raise'` (GH7963).
- When `.resample()` was changed from an eager to a lazy operation, like `.groupby()` in v0.18.0, we put in place compatibility (with a `FutureWarning`), so operations would continue to work. This is now fully removed, so a `Resampler` will no longer forward compat operations (GH20554)
- Remove long deprecated `axis=None` parameter from `.replace()` (GH20271)

### 1.2.5 Performance Improvements

- Indexers on `Series` or `DataFrame` no longer create a reference cycle (GH17956)
- Added a keyword argument, `cache`, to `to_datetime()` that improved the performance of converting duplicate datetime arguments (GH11665)
- `DateOffset` arithmetic performance is improved (GH18218)
- Converting a `Series` of `Timedelta` objects to days, seconds, etc... sped up through vectorization of underlying methods (GH18092)
- Improved performance of `.map()` with a `Series/dict` input (GH15081)
- The overridden `Timedelta` properties of days, seconds and microseconds have been removed, leveraging their built-in Python versions instead (GH18242)
- `Series` construction will reduce the number of copies made of the input data in certain cases (GH17449)
- Improved performance of `Series.dt.date()` and `DatetimeIndex.date()` (GH18058)
- Improved performance of `Series.dt.time()` and `DatetimeIndex.time()` (GH18461)
• Improved performance of `IntervalIndex.symmetric_difference()` (GH18475)

• Improved performance of `DatetimeIndex` and `Series` arithmetic operations with Business-Month and Business-Quarter frequencies (GH18489)

• `Series() / DataFrame()` tab completion limits to 100 values, for better performance. (GH18587)

• Improved performance of `DataFrame.median()` with `axis=1` when bottleneck is not installed (GH16468)

• Improved performance of `MultiIndex.get_loc()` for large indexes, at the cost of a reduction in performance for small ones (GH18519)

• Improved performance of `MultiIndex.remove_unused_levels()` when there are no unused levels, at the cost of a reduction in performance when there are (GH19289)

• Improved performance of `Index.get_loc()` for non-unique indexes (GH19478)

• Improved performance of pairwise `.rolling()` and `.expanding()` with `.cov()` and `.corr()` operations (GH17917)

• Improved performance of `pandas.core.groupby.GroupBy.rank()` (GH15779)

• Improved performance of variable `.rolling()` on `.min()` and `.max()` (GH19521)

• Improved performance of `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` (GH11296)

• Improved performance of `pandas.core.groupby.GroupBy.any()` and `pandas.core.groupby.GroupBy.all()` (GH15435)

• Improved performance of `pandas.core.groupby.GroupBy.pct_change()` (GH19165)

• Improved performance of `Series.isin()` in the case of categorical dtypes (GH20003)

• Improved performance of `getattr(Series, attr)` when the Series has certain index types. This manifested in slow printing of large Series with a `DatetimeIndex` (GH19764)

• Fixed a performance regression for `GroupBy.nth()` and `GroupBy.last()` with some object columns (GH19283)

• Improved performance of `pandas.core.arrays.Categorical.from_codes()` (GH18501)

### 1.2.6 Documentation Changes

Thanks to all of the contributors who participated in the Pandas Documentation Sprint, which took place on March 10th. We had about 500 participants from over 30 locations across the world. You should notice that many of the API docstrings have greatly improved.

There were too many simultaneous contributions to include a release note for each improvement, but this GitHub search should give you an idea of how many docstrings were improved.

Special thanks to Marc Garcia for organizing the sprint. For more information, read the NumFOCUS blogpost recapping the sprint.

• Changed spelling of “numpy” to “NumPy”, and “python” to “Python”. (GH19017)

• Consistency when introducing code samples, using either colon or period. Rewrote some sentences for greater clarity, added more dynamic references to functions, methods and classes. (GH18941, GH18948, GH18973, GH19017)

• Added a reference to `DataFrame.assign()` in the concatenate section of the merging documentation (GH18665)
1.2.7 Bug Fixes

1.2.7.1 Categorical

**Warning:** A class of bugs were introduced in pandas 0.21 with `CategoricalDtype` that affects the correctness of operations like `merge`, `concat`, and indexing when comparing multiple unordered `Categorical` arrays that have the same categories, but in a different order. We highly recommend upgrading or manually aligning your categories before doing these operations.

- Bug in `Categorical.equals` returning the wrong result when comparing two unordered `Categorical` arrays with the same categories, but in a different order (GH16603)
- Bug in `pandas.api.types.union_categoricals()` returning the wrong result when for unordered categoricals with the categories in a different order. This affected `pandas.concat()` with Categorical data (GH19096).
- Bug in `pandas.merge()` returning the wrong result when joining on an unordered `Categorical` that had the same categories but in a different order (GH19551)
- Bug in `CategoricalIndex.get_indexer()` returning the wrong result when target was an unordered `Categorical` that had the same categories as self but in a different order (GH19551)
- Bug in `Index.astype()` with a categorical dtype where the resultant index is not converted to a `CategoricalIndex` for all types of index (GH18630)
- Bug in `Series.astype()` and `Categorical.astype()` where an existing categorical data does not get updated (GH10696, GH18593)
- Bug in `Series.str.split()` with expand=True incorrectly raising an IndexError on empty strings (GH20002).
- Bug in `Index` constructor with dtype=`CategoricalDtype(...)` where categories and ordered are not maintained (GH19032)
- Bug in `Series` constructor with scalar and dtype=`CategoricalDtype(...)` where categories and ordered are not maintained (GH19565)
- Bug in `Categorical.__iter__` not converting to Python types (GH19909)
- Bug in `pandas.factorize()` returning the unique codes for the uniques. This now returns a Categorical with the same dtype as the input (GH19721)
- Bug in `pandas.factorize()` including an item for missing values in the uniques return value (GH19721)
- Bug in `Series.take()` with categorical data interpreting -1 in `indices` as missing value markers, rather than the last element of the Series (GH20664)

1.2.7.2 Datetimelike

- Bug in `Series.__sub__()` subtracting a non-nanosecond `np.datetime64` object from a `Series` gave incorrect results (GH7996)
- Bug in `DatetimeIndex, TimedeltaIndex` addition and subtraction of zero-dimensional integer arrays gave incorrect results (GH19012)
• Bug in DatetimeIndex and TimedeltaIndex where adding or subtracting an array-like of DateOffset objects either raised (np.array, pd.Index) or broadcast incorrectly (pd.Series) (GH18849)

• Bug in Series.__add__() adding Series with dtype timedelta64[ns] to a timezone-aware DatetimeIndex incorrectly dropped timezone information (GH13905)

• Adding a Period object to a datetime or Timestamp object will now correctly raise a TypeError (GH17983)

• Bug in Timestamp where comparison with an array of Timestamp objects would result in a RecursionError(GH15183)

• Bug in Series floor-division where operating on a scalar timedelta raises an exception (GH18846)

• Bug in DatetimeIndex where the repr was not showing high-precision time values at the end of a day (e.g., 23:59:59.999999999) (GH19030)

• Bug in .astype() to non-ns timedelta units would hold the incorrect dtype (GH19176, GH19223, GH12425)

• Bug in subtracting Series from NaT incorrectly returning NaT (GH19158)

• Bug in Series.truncate() which raises TypeError with a monotonic PeriodIndex (GH17717)

• Bug in pct_change() using periods and freq returned different length outputs (GH7292)

• Bug in comparison of DatetimeIndex against None or datetime.date objects raising TypeError for != comparisons instead of all-False and all-True, respectively (GH19301)

• Bug in Timestamp and to_datetime() where a string representing a barely out-of-bounds timestamp would be incorrectly rounded down instead of raising OutOfBoundsDatetime (GH19382)

• Bug in Timestamp.floor() DatetimeIndex.floor() where time stamps far in the future and past were not rounded correctly (GH19206)

• Bug in to_datetime() where passing an out-of-bounds datetime with errors='coerce' and utc=True would raise OutOfBoundsDatetime instead of parsing to NaT (GH19612)

• Bug in DatetimeIndex and TimedeltaIndex addition and subtraction where name of the returned object was not always set consistently. (GH19744)

• Bug in DatetimeIndex and TimedeltaIndex addition and subtraction where operations with numpy arrays raised TypeError (GH19847)

• Bug in DatetimeIndex and TimedeltaIndex where setting the freq attribute was not fully supported (GH20678)

1.2.7.3 Timedelta

• Bug in Timedelta.__mul__() where multiplying by NaT returned NaT instead of raising a TypeError (GH19819)

• Bug in Series with dtype='timedelta64[ns]' where addition or subtraction of TimedeltaIndex had results cast to dtype='int64' (GH17250)

• Bug in Series with dtype='timedelta64[ns]' where addition or subtraction of TimedeltaIndex could return a Series with an incorrect name (GH19043)

• Bug in Timedelta.__floordiv__() and Timedelta.__rfloordiv__() dividing by many incompatible numpy objects was incorrectly allowed (GH18846)

• Bug where dividing a scalar timedelta-like object with TimedeltaIndex performed the reciprocal operation (GH19125)
• Bug in TimedeltaIndex where division by a Series would return a TimedeltaIndex instead of a Series (GH19042)

• Bug in Timedelta.__add__(), Timedelta.__sub__() where adding or subtracting a np.timedelta64 object would return another np.timedelta64 instead of a Timedelta (GH19738)

• Bug in Timedelta.__floordiv__(), Timedelta.__rfloordiv__() where operating with a Tick object would raise a TypeError instead of returning a numeric value (GH19738)

• Bug in Period.asfreq() where periods near datetime(1, 1, 1) could be converted incorrectly (GH19643, GH19834)

• Bug in Timedelta.total_seconds() causing precision errors, for example Timedelta('30S').total_seconds() == 30.000000000000004 (GH19458)

• Bug in Timedelta.__rmod__() where operating with a numpy.timedelta64 returned a timedelta64 object instead of a Timedelta (GH19820)

• Multiplication of TimedeltaIndex by TimedeltaIndex will now raise TypeError instead of raising ValueError in cases of length mis-match (GH19333)

• Bug in indexing a TimedeltaIndex with a np.timedelta64 object which was raising a TypeError (GH20393)

1.2.7.4 Timezones

• Bug in creating a Series from an array that contains both tz-naive and tz-aware values will result in a Series whose dtype is tz-aware instead of object (GH16406)

• Bug in comparison of timezone-aware DatetimeIndex against NaT incorrectly raising TypeError (GH19276)

• Bug in DatetimeIndex.astype() when converting between timezone aware dtypes, and converting from timezone aware to naive (GH18951)

• Bug in comparing DatetimeIndex, which failed to raise TypeError when attempting to compare timezone-aware and timezone-naive datetimelike objects (GH18162)

• Bug in localization of a naive, datetime string in a Series constructor with a datetime64[ns, tz] dtype (GH174151)

• Timestamp.replace() will now handle Daylight Savings transitions gracefully (GH18319)

• Bug in tz-aware DatetimeIndex where addition/subtraction with a TimedeltaIndex or array with dtype='timedelta64[ns]' was incorrect (GH17558)

• Bug in DatetimeIndex.insert() where inserting NaT into a timezone-aware index incorrectly raised (GH16357)

• Bug in DataFrame constructor, where tz-aware Datetimeindex and a given column name will result in an empty DataFrame (GH19157)

• Bug in Timestamp.tz_localize() where localizing a timestamp near the minimum or maximum valid values could overflow and return a timestamp with an incorrect nanosecond value (GH12677)

• Bug when iterating over DatetimeIndex that was localized with fixed timezone offset that rounded nanosecond precision to microseconds (GH19603)

• Bug in DataFrame.diff() that raised an IndexError with tz-aware values (GH18578)

• Bug in melt() that converted tz-aware dtypes to tz-naive (GH15785)
• Bug in `DataFrame.count()` that raised an `ValueError`, if `DataFrame.dropna()` was called for a single column with timezone-aware values. (GH13407)

1.2.7.5 Offsets

• Bug in `WeekOfMonth` and `Week` where addition and subtraction did not roll correctly (GH18510, GH18672, GH18864)
• Bug in `WeekOfMonth` and `LastWeekOfMonth` where default keyword arguments for constructor raised `ValueError` (GH19142)
• Bug in `FY5253Quarter`, `LastWeekOfMonth` where rollback and rollforward behavior was inconsistent with addition and subtraction behavior (GH18854)
• Bug in `FY5253` where `datetime` addition and subtraction incremented incorrectly for dates on the year-end but not normalized to midnight (GH18854)
• Bug in `FY5253` where date offsets could incorrectly raise an `AssertionError` in arithmetic operations (GH14774)

1.2.7.6 Numeric

• Bug in `Series` constructor with an int or float list where specifying `dtype=str`, `dtype='str'` or `dtype='U'` failed to convert the data elements to strings (GH16605)
• Bug in `Index` multiplication and division methods where operating with a `Series` would return an `Index` object instead of a `Series` object (GH19042)
• Bug in the `DataFrame` constructor in which data containing very large positive or very large negative numbers was causing `OverflowError` (GH18584)
• Bug in `Index` constructor with `dtype='uint64'` where int-like floats were not coerced to `UInt64Index` (GH18400)
• Bug in `DataFrame` flex arithmetic (e.g. `df.add(other, fill_value=foo)`) with a `fill_value` other than `None` failed to raise `NotImplementedError` in corner cases where either the frame or `other` has length zero (GH19522)
• Multiplication and division of numeric-dtyped `Index` objects with timedelta-like scalars returns `TimedeltaIndex` instead of raising `TypeError` (GH19333)
• Bug where `NaN` was returned instead of `0` by `Series.pct_change()` and `DataFrame.pct_change()` when `fill_method` is not `None` (GH19873)

1.2.7.7 Strings

• Bug in `Series.str.get()` with a dictionary in the values and the index not in the keys, raising `KeyError` (GH20671)

1.2.7.8 Indexing

• Bug in `Index` construction from list of mixed type tuples (GH18505)
• Bug in `Index.drop()` when passing a list of both tuples and non-tuples (GH18304)
• Bug in `DataFrame.drop()`, `Panel.drop()`, `Series.drop()`, `Index.drop()` where no `KeyError` is raised when dropping a non-existent element from an axis that contains duplicates (GH19186)
• Bug in indexing a datetimelike Index that raised ValueError instead of IndexError (GH18386).
• `Index.to_series()` now accepts index and name kwargs (GH18699)
• `DatetimeIndex.to_series()` now accepts index and name kwargs (GH18699)
• Bug in indexing non-scalar value from Series having non-unique Index will return value flattened (GH17610)
• Bug in indexing with iterator containing only missing keys, which raised no error (GH20748)
• Fixed inconsistency in `.ix` between list and scalar keys when the index has integer dtype and does not include the desired keys (GH20753)
• Bug in `__setitem__` when indexing a DataFrame with a 2-d boolean ndarray (GH18582)
• Bug in `str.extractall` when there were no matches empty Index was returned instead of appropriate MultiIndex (GH19034)
• Bug in `IntervalIndex` where empty and purely NA data was constructed inconsistently depending on the construction method (GH18421)
• Bug in `IntervalIndex.symmetric_difference()` where the symmetric difference with a non-IntervalIndex did not raise (GH18475)
• Bug in `IntervalIndex` where set operations that returned an empty IntervalIndex had the wrong dtype (GH19101)
• Bug in `DataFrame.drop_duplicates()` where no KeyError is raised when passing in columns that don’t exist on the DataFrame (GH19726)
• Bug in `Index` subclasses constructors that ignore unexpected keyword arguments (GH19348)
• Bug in `Index.difference()` when taking difference of an Index with itself (GH20040)
• Bug in `DataFrame.first_valid_index()` and `DataFrame.last_valid_index()` in presence of entire rows of NaNs in the middle of values (GH20499).
• Bug in `IntervalIndex` where some indexing operations were not supported for overlapping or non-monotonic uint64 data (GH20636)
• Bug in `Series.is_unique` where extraneous output in stderr is shown if Series contains objects with `__ne__` defined (GH20661)
• Bug in `.loc` assignment with a single-element list-like incorrectly assigns as a list (GH19474)
• Bug in partial string indexing on a Series/DataFrame with a monotonic decreasing DatetimeIndex (GH19362)
• Bug in performing in-place operations on a DataFrame with a duplicate Index (GH17105)
• Bug in `IntervalIndex.get_loc()` and `IntervalIndex.get_indexer()` when used with an `IntervalIndex` containing a single interval (GH17284, GH20921)
• Bug in `.loc` with a uint64 indexer (GH20722)

1.2.7.9 MultiIndex

• Bug in MultiIndex.__contains__() where non-tuple keys would return True even if they had been dropped (GH19027)
• Bug in `MultiIndex.set_labels()` which would cause casting (and potentially clipping) of the new labels if the level argument is not 0 or a list like `[0, 1, ...]` (GH19057)
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- Bug in `MultiIndex.get_level_values()` which would return an invalid index on level of ints with missing values (GH17924)
- Bug in `MultiIndex.unique()` when called on empty `MultiIndex` (GH20568)
- Bug in `MultiIndex.unique()` which would not preserve level names (GH20570)
- Bug in `MultiIndex.remove_unused_levels()` which would fill nan values (GH18417)
- Bug in `MultiIndex.from_tuples()` which would fail to take zipped tuples in python3 (GH18434)
- Bug in `MultiIndex.get_loc()` which would fail to automatically cast values between float and int (GH18818, GH15994)
- Bug in `MultiIndex.get_loc()` which would cast boolean to integer labels (GH19086)
- Bug in `MultiIndex.get_loc()` which would fail to locate keys containing NaN (GH18485)
- Bug in `MultiIndex.get_loc()` in large `MultiIndex`, would fail when levels had different dtypes (GH18520)
- Bug in indexing where nested indexers having only numpy arrays are handled incorrectly (GH19686)

1.2.7.10 I/O

- `read_html()` now rewinds seekable IO objects after parse failure, before attempting to parse with a new parser. If a parser errors and the object is non-seekable, an informative error is raised suggesting the use of a different parser (GH17975)
- `DataFrame.to_html()` now has an option to add an id to the leading `<table>` tag (GH8496)
- Bug in `read_msgpack()` with a non existent file is passed in Python 2 (GH15296)
- Bug in `read_csv()` where a `MultiIndex` with duplicate columns was not being mangled appropriately (GH18062)
- Bug in `read_csv()` where missing values were not being handled properly when keep_default_na=False with dictionary na_values (GH19227)
- Bug in `read_csv()` causing heap corruption on 32-bit, big-endian architectures (GH20785)
- Bug in `read_sas()` where a file with 0 variables gave an AttributeError incorrectly. Now it gives an EmptyDataError (GH18184)
- Bug in `DataFrame.to_latex()` where pairs of braces meant to serve as invisible placeholders were escaped (GH18667)
- Bug in `DataFrame.to_latex()` where a NaN in a `MultiIndex` would cause an IndexError or incorrect output (GH14249)
- Bug in `DataFrame.to_latex()` where a non-string index-level name would result in an AttributeError (GH19981)
- Bug in `DataFrame.to_latex()` where the combination of an index name and the index_names=False option would result in incorrect output (GH18326)
- Bug in `DataFrame.to_parquet()` where a `MultiIndex` with an empty string as its name would result in incorrect output (GH18669)
- Bug in `DataFrame.to_parquet()` where missing space characters caused wrong escaping and produced non-valid latex in some cases (GH20859)
- Bug in `read_json()` where large numeric values were causing an OverflowError (GH18842)
- Bug in `DataFrame.to_parquet()` where an exception was raised if the write destination is S3 (GH19134)
- *Interval* now supported in `DataFrame.to_excel()` for all Excel file types (GH19242)
- *Timedelta* now supported in `DataFrame.to_excel()` for all Excel file types (GH19242, GH9155, GH19900)
- Bug in `pandas.io.stata.StataReader.value_labels()` raising an `AttributeError` when called on very old files. Now returns an empty dict (GH19417)
- Bug in `read_pickle()` when unpickling objects with *TimedeltaIndex* or *Float64Index* created with pandas prior to version 0.20 (GH19939)
- Bug in `pandas.io.json.json_normalize()` where subrecords are not properly normalized if any subrecords values are `NoneType` (GH20030)
- Bug in `usecols` parameter in `read_csv()` where error is not raised correctly when passing a string. (GH20529)
- Bug in `HDFStore.keys()` when reading a file with a softlink causes exception (GH20523)
- Bug in `HDFStore.select_column()` where a key which is not a valid store raised an `AttributeError` instead of a `KeyError` (GH17912)

### 1.2.7.11 Plotting

- Better error message when attempting to plot but `matplotlib` is not installed (GH19810).
- `DataFrame.plot()` now raises a `ValueError` when the `x` or `y` argument is improperly formed (GH18671)
- Bug in `DataFrame.plot()` when `x` and `y` arguments given as positions caused incorrect referenced columns for line, bar and area plots (GH20056)
- Bug in formatting tick labels with `datetime.time()` and fractional seconds (GH18478).
- `Series.plot.kde()` has exposed the args `ind` and `bw_method` in the docstring (GH18461). The argument `ind` may now also be an integer (number of sample points).
- `DataFrame.plot()` now supports multiple columns to the `y` argument (GH19699)

### 1.2.7.12 Groupby/Resample/Rolling

- Bug when grouping by a single column and aggregating with a class like `list` or `tuple` (GH18079)
- Fixed regression in `DataFrame.groupby()` which would not emit an error when called with a tuple key not in the index (GH18798)
- Bug in `DataFrame.resample()` which silently ignored unsupported (or mistyped) options for `label`, `closed` and `convention` (GH19303)
- Bug in `DataFrame.groupby()` where tuples were interpreted as lists of keys rather than as keys (GH17979, GH18249)
- Bug in `DataFrame.groupby()` where aggregation by `first/last/min/max` was causing timestamps to lose precision (GH19526)
- Bug in `DataFrame.transform()` where particular aggregation functions were being incorrectly cast to match the `dtype(s)` of the grouped data (GH19200)
- Bug in `DataFrame.groupby()` passing the `on=` kwarg, and subsequently using `.apply()` (GH17813)
- Bug in `DataFrame.resample() .aggregate` not raising a `KeyError` when aggregating a non-existent column (GH16766, GH19566)
• Bug in `DataFrameGroupBy.cumsum()` and `DataFrameGroupBy.cumprod()` when `skipna` was passed (GH19806)
• Bug in `DataFrame.resample()` that dropped timezone information (GH13238)
• Bug in `DataFrame.groupby()` where transformations using `np.all` and `np.any` were raising a `ValueError` (GH20653)
• Bug in `DataFrame.resample()` where `ffill`, `bfill`, `pad`, `backfill`, `fillna`, `interpolate`, and `asfreq` were ignoring `loffset`. (GH20744)
• Bug in `DataFrame.groupby()` when applying a function that has mixed data types and the user supplied function can fail on the grouping column (GH20949)
• Bug in `DataFrameGroupBy.rolling().apply()` where operations performed against the associated `DataFrameGroupBy` object could impact the inclusion of the grouped item(s) in the result (GH14013)

1.2.7.13 Sparse

• Bug in which creating a `SparseDataFrame` from a dense `Series` or an unsupported type raised an uncontrolled exception (GH19374)
• Bug in `SparseDataFrame.to_csv` causing exception (GH19384)
• Bug in `SparseSeries.memory_usage` which caused segfault by accessing non sparse elements (GH19368)
• Bug in constructing a `SparseArray`: if `data` is a scalar and `index` is defined it will coerce to `float64` regardless of scalar’s dtype. (GH19163)

1.2.7.14 Reshaping

• Bug in `DataFrame.merge()` where referencing a `CategoricalIndex` by name, where the `by` kwarg would `KeyError` (GH20777)
• Bug in `DataFrame.stack()` which fails trying to sort mixed type levels under Python 3 (GH18310)
• Bug in `DataFrame.unstack()` which casts int to float if `columns` is a `MultiIndex` with unused levels (GH17845)
• Bug in `DataFrame.unstack()` which raises an error if `index` is a `MultiIndex` with unused labels on the unstacked level (GH18562)
• Fixed construction of a `Series` from a dict containing `NaN` as key (GH18480)
• Fixed construction of a `DataFrame` from a dict containing `NaN` as key (GH18455)
• Disabled construction of a `Series` where `len(index) > len(data) = 1`, which previously would broadcast the data item, and now raises a `ValueError` (GH18819)
• Suppressed error in the construction of a `DataFrame` from a dict containing scalar values when the corresponding keys are not included in the passed index (GH18600)
• Fixed (changed from `object` to `float64`) dtype of `DataFrame` initialized with axes, no data, and `dtype=int` (GH19646)
• Bug in `Series.rank()` where `Series` containing `NaT` modifies the `Series` inplace (GH18521)
• Bug in `cut()` which fails when using readonly arrays (GH18773)
• Bug in `DataFrame.pivot_table()` which fails when the `aggfunc` arg is of type string. The behavior is now consistent with other methods like `agg` and `apply` (GH18713)
• Bug in `DataFrame.merge()` in which merging using `Index` objects as vectors raised an Exception (GH19038)

• Bug in `DataFrame.stack()`, `DataFrame.unstack()`, `Series.unstack()` which were not returning subclasses (GH15563)

• Bug in timezone comparisons, manifesting as a conversion of the index to UTC in `.concat()` (GH18523)

• Bug in `concat()` when concatenating sparse and dense series it returns only a `SparseDataFrame`. Should be a `DataFrame`. (GH18914, GH18686, and GH16874)

• Improved error message for `DataFrame.merge()` when there is no common merge key (GH19427)

• Bug in `DataFrame.join()` which does an `outer` instead of a `left` join when being called with multiple DataFrames and some have non-unique indices (GH19624)

• `Series.rename()` now accepts `axis` as a kwarg (GH18589)

• Bug in `rename()` where an `Index` of same-length tuples was converted to a MultiIndex (GH19497)

• Comparisons between `Series` and `Index` would return a `Series` with an incorrect name, ignoring the `Index`'s name attribute (GH19582)

• Bug in `qcut()` where datetime and timedelta data with `NaT` present raised a `ValueError` (GH19768)

• Bug in `DataFrame.iterrows()`, which would inferences strings not compliant to ISO8601 to datetimes (GH19671)

• Bug in `Series` constructor with `Categorical` where a `ValueError` is not raised when an index of different length is given (GH19342)

• Bug in `DataFrame.astype()` where column metadata is lost when converting to categorical or a dictionary of dtypes (GH19920)

• Bug in `cut()` and `qcut()` where timezone information was dropped (GH19872)

• Bug in `Series` constructor with a `dtype=str`, previously raised in some cases (GH19853)

• Bug in `get_dummies()`, and `select_dtypes()`, where duplicate column names caused incorrect behavior (GH20848)

• Bug in `isna()`, which cannot handle ambiguous typed lists (GH20675)

• Bug in `concat()` which raises an error when concatenating TZ-aware dataframes and all-NaT dataframes (GH12396)

• Bug in `concat()` which raises an error when concatenating empty TZ-aware series (GH18447)

1.2.7.15 Other

• Improved error message when attempting to use a Python keyword as an identifier in a `numexpr` backed query (GH18221)

• Bug in accessing a `pandas.get_option()`, which raised `KeyError` rather than `OptionError` when looking up a non-existant option key in some cases (GH19789)

• Bug in `testing.assert_series_equal()` and `testing.assert_frame_equal()` for Series or DataFrames with differing unicode data (GH20503)
1.3 v0.22.0 (December 29, 2017)

This is a major release from 0.21.1 and includes a single, API-breaking change. We recommend that all users upgrade to this version after carefully reading the release note (singular!).

1.3.1 Backwards incompatible API changes

Pandas 0.22.0 changes the handling of empty and all-NA sums and products. The summary is that

- The sum of an empty or all-NA Series is now 0
- The product of an empty or all-NA Series is now 1
- We’ve added a min_count parameter to .sum() and .prod() controlling the minimum number of valid values for the result to be valid. If fewer than min_count non-NA values are present, the result is NA. The default is 0. To return NaN, the 0.21 behavior, use min_count=1.

Some background: In pandas 0.21, we fixed a long-standing inconsistency in the return value of all-NA series depending on whether or not bottleneck was installed. See Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN. At the same time, we changed the sum and prod of an empty Series to also be NaN.

Based on feedback, we’ve partially reverted those changes.

1.3.1.1 Arithmetic Operations

The default sum for empty or all-NA Series is now 0.

```
pandas 0.21.x
```

```
In [1]: pd.Series([]).sum()
Out[1]: nan

In [2]: pd.Series([np.nan]).sum()
Out[2]: nan
```

```
pandas 0.22.0
```

```
In [1]: pd.Series([]).sum()
Out[1]: 0.0

In [2]: pd.Series([np.nan]).sum()
Out[2]: 0.0
```

The default behavior is the same as pandas 0.20.3 with bottleneck installed. It also matches the behavior of NumPy’s np.nansum on empty and all-NA arrays.

To have the sum of an empty series return NaN (the default behavior of pandas 0.20.3 without bottleneck, or pandas 0.21.x), use the min_count keyword.

```
In [3]: pd.Series([]).sum(min_count=1)
Out[3]: nan
```

Thanks to the skipna parameter, the .sum on an all-NA Series is conceptually the same as the .sum of an empty one with skipna=True (the default).

```
In [4]: pd.Series([np.nan]).sum(min_count=1)  # skipna=True by default
Out[4]: nan
```
The `min_count` parameter refers to the minimum number of *non-null* values required for a non-NA sum or product. `Series.prod()` has been updated to behave the same as `Series.sum()`, returning 1 instead.

```python
In [5]: pd.Series([]).prod()
Out [5]: 1.0

In [6]: pd.Series([np.nan]).prod()
Out [6]: 1.0

In [7]: pd.Series([]).prod(min_count=1)
Out [7]: nan
```

These changes affect `DataFrame.sum()` and `DataFrame.prod()` as well. Finally, a few less obvious places in pandas are affected by this change.

### 1.3.1.2 Grouping by a Categorical

Grouping by a `Categorical` and summing now returns 0 instead of NaN for categories with no observations. The product now returns 1 instead of NaN.

**pandas 0.21.x**

```python
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out [9]:
   a  3.0
   b  NaN
dtype: float64
```

**pandas 0.22**

```python
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out [9]:
   a  3
   b  0
dtype: int64
```

To restore the 0.21 behavior of returning NaN for unobserved groups, use `min_count>=1`.

```python
In [10]: pd.Series([1, 2]).groupby(grouper).sum(min_count=1)
Out [10]:
   a  3.0
   b  NaN
dtype: float64
```

### 1.3.1.3 Resample

The sum and product of all-NA bins has changed from NaN to 0 for sum and 1 for product.

**pandas 0.21.x**

---

**1.3. v0.22.0 (December 29, 2017)**
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
                   index=pd.date_range('2017', periods=4))
In [12]: s.resample('2d').sum()

Out[12]:
2017-01-01  2.0
2017-01-03  NaN
Freq: 2D, dtype: float64

To restore the 0.21 behavior of returning NaN, use min_count>=1.

In [13]: s.resample('2d').sum(min_count=1)

Out[13]:
2017-01-01  2.0
2017-01-03  NaN
dtype: float64

In particular, upsampling and taking the sum or product is affected, as upsampling introduces missing values even if the original series was entirely valid.

pandas 0.21.x

In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])
In [15]: pd.Series([1, 2], index=idx).resample('12H').sum()

Out[15]:
2017-01-01 00:00:00  1.0
2017-01-01 12:00:00  NaN
2017-01-02 00:00:00  2.0
Freq: 12H, dtype: float64

pandas 0.22.0

In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])
In [15]: pd.Series([1, 2], index=idx).resample("12H").sum()

Out[15]:
2017-01-01 00:00:00  1

Once again, the min_count keyword is available to restore the 0.21 behavior.

```python
In [16]: pd.Series([1, 2], index=idx).resample("12H").sum(min_count=1)
Out[16]:
2017-01-01 00:00:00 1.0
2017-01-01 12:00:00 NaN
2017-01-02 00:00:00 2.0
Freq: 12H, dtype: float64
```

### 1.3.1.4 Rolling and Expanding

Rolling and expanding already have a min_periods keyword that behaves similar to min_count. The only case that changes is when doing a rolling or expanding sum with min_periods=0. Previously this returned NaN, when fewer than min_periods non-NA values were in the window. Now it returns 0.

**pandas 0.21.1**

```python
In [17]: s = pd.Series([np.nan, np.nan])
In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
   0    NaN
   1    NaN
dtype: float64
```

**pandas 0.22.0**

```python
In [17]: s = pd.Series([np.nan, np.nan])
In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
   0  0.0
   1  0.0
dtype: float64
```

The default behavior of min_periods=None, implying that min_periods equals the window size, is unchanged.

### 1.3.2 Compatibility

If you maintain a library that should work across pandas versions, it may be easiest to exclude pandas 0.21 from your requirements. Otherwise, all your sum() calls would need to check if the Series is empty before summing.

With setuptools, in your setup.py use:

```python
install_requires=['pandas!=0.21.*', ...]
```

With conda, use

```bash
requirements:
  run:
    - pandas !=0.21.0, !=0.21.1
```
Note that the inconsistency in the return value for all-NA series is still there for pandas 0.20.3 and earlier. Avoiding pandas 0.21 will only help with the empty case.

1.4 v0.21.1 (December 12, 2017)

This is a minor bug-fix release in the 0.21.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

• Temporarily restore matplotlib datetime plotting functionality. This should resolve issues for users who implicitly relied on pandas to plot datetimes with matplotlib. See here.

• Improvements to the Parquet IO functions introduced in 0.21.0. See here.

What’s new in v0.21.1

• Restore Matplotlib datetime Converter Registration
• New features
  – Improvements to the Parquet IO functionality
  – Other Enhancements
• Deprecations
• Performance Improvements
• Bug Fixes
  – Conversion
  – Indexing
  – I/O
  – Plotting
  – Groupby/Resample/Rolling
  – Reshaping
  – Numeric
  – Categorical
  – String

1.4.1 Restore Matplotlib datetime Converter Registration

Pandas implements some matplotlib converters for nicely formatting the axis labels on plots with datetime or Period values. Prior to pandas 0.21.0, these were implicitly registered with matplotlib, as a side effect of import pandas.

In pandas 0.21.0, we required users to explicitly register the converter. This caused problems for some users who relied on those converters being present for regular matplotlib.pyplot plotting methods, so we’re temporarily reverting that change; pandas 0.21.1 again registers the converters on import, just like before 0.21.0.
We’ve added a new option to control the converters: `pd.options.plotting.matplotlib.register_converters`. By default, they are registered. Toggling this to `False` removes pandas’ formatters and restore any converters we overwrote when registering them (GH18301).

We’re working with the matplotlib developers to make this easier. We’re trying to balance user convenience (automatically registering the converters) with import performance and best practices (importing pandas shouldn’t have the side effect of overwriting any custom converters you’ve already set). In the future we hope to have most of the date-time formatting functionality in matplotlib, with just the pandas-specific converters in pandas. We’ll then gracefully deprecate the automatic registration of converters in favor of users explicitly registering them when they want them.

### 1.4.2 New features

#### 1.4.2.1 Improvements to the Parquet IO functionality

- `DataFrame.to_parquet()` will now write non-default indexes when the underlying engine supports it. The indexes will be preserved when reading back in with `read_parquet()` (GH18581).
- `read_parquet()` now allows to specify the columns to read from a parquet file (GH18154)
- `read_parquet()` now allows to specify kwargs which are passed to the respective engine (GH18216)

#### 1.4.2.2 Other Enhancements

- `Timestamp.timestamp()` is now available in Python 2.7. (GH17329)
- `Grouper` and `TimeGrouper` now have a friendly repr output (GH18203).

### 1.4.3 Deprecations

- `pandas.tseries.register` has been renamed to `pandas.plotting.register_matplotlib_converters()` (GH18301)

### 1.4.4 Performance Improvements

- Improved performance of plotting large series/dataframes (GH18236).

### 1.4.5 Bug Fixes

#### 1.4.5.1 Conversion

- Bug in `TimedeltaIndex` subtraction could incorrectly overflow when NaT is present (GH17791)
- Bug in `DatetimeIndex` subtracting datetimelike from DatetimeIndex could fail to overflow (GH18020)
- Bug in `IntervalIndex.copy()` when copying and `IntervalIndex` with non-default `closed` (GH18339)
- Bug in `DataFrame.to_dict()` where columns of datetime that are tz-aware were not converted to required arrays when used with `orient='records'`, raising `TypeError` (GH18372)
- Bug in `DateTimeIndex` and `date_range()` where mismatching tz-aware start and end timezones would not raise an err if `end.tzinfo` is None (GH18431)
- Bug in `Seriesfillna()` which raised when passed a long integer on Python 2 (GH18159).
1.4.5.2 Indexing

- Bug in a boolean comparison of a `datetime.datetime` and a `datetime64[ns]` dtype Series (GH17965)
- Bug where a `MultiIndex` with more than a million records was not raising `AttributeError` when trying to access a missing attribute (GH18165)
- Bug in `IntervalIndex` constructor when a list of intervals is passed with non-default `closed` (GH18334)
- Bug in `Index.putmask` when an invalid mask passed (GH18368)
- Bug in masked assignment of a `timedelta64[ns]` dtype Series, incorrectly coerced to float (GH18493)

1.4.5.3 I/O

- Bug in class: `~pandas.io.stata.StataReader` not converting date/time columns with display formatting addressed (GH17990). Previously columns with display formatting were normally left as ordinal numbers and not converted to datetime objects.
- Bug in `read_csv()` when reading a compressed UTF-16 encoded file (GH18071)
- Bug in `read_csv()` for handling null values in index columns when specifying `na_filter=False` (GH5239)
- Bug in `read_csv()` when reading numeric category fields with high cardinality (GH18186)
- Bug in `DataFrame.to_csv()` when the table had `MultiIndex` columns, and a list of strings was passed in for `header` (GH5539)
- Bug in parsing integer datetime-like columns with specified format in `read_sql` (GH17855).
- Bug in `DataFrame.to_msgpack()` when serializing data of the `numpy.bool_` datatype (GH18390)
- Bug in `read_json()` not decoding when reading line delimited JSON from S3 (GH17200)
- Bug in `pandas.io.json.json_normalize()` to avoid modification of `meta` (GH18610)
- Bug in `to_latex()` where repeated multi-index values were not printed even though a higher level index differed from the previous row (GH14484)
- Bug when reading NaN-only categorical columns in `HDFStore` (GH18413)
- Bug in `DataFrame.to_latex()` with `longtable=True` where a latex multicolumn always spanned over three columns (GH17959)

1.4.5.4 Plotting

- Bug in `DataFrame.plot()` and `Series.plot()` with `DatetimeIndex` where a figure generated by them is not pickleable in Python 3 (GH18439)

1.4.5.5 Groupby/Resample/Rolling

- Bug in `DataFrame.resample(...).apply(...)` when there is a callable that returns different columns (GH15169)
- Bug in `DataFrame.resample(...)` when there is a time change (DST) and resampling frequency is 12h or higher (GH15549)
- Bug in `pd.DataFrameGroupBy.count()` when counting over a datetimelike column (GH13393)
- Bug in `rolling.var` where calculation is inaccurate with a zero-valued array (GH18430)
1.4.5.6 Reshaping

- Error message in `pd.merge_asof()` for key datatype mismatch now includes datatype of left and right key (GH18068)
- Bug in `pd.concat` when empty and non-empty DataFrames or Series are concatenated (GH18178 GH18187)
- Bug in `DataFrame.filter(...)` when unicode is passed as a condition in Python 2 (GH13101)
- Bug when merging empty DataFrames when `np.seterr(divide='raise')` is set (GH17776)

1.4.5.7 Numeric

- Bug in `pd.Series.rolling.skew()` and `rolling.kurt()` with all equal values has floating issue (GH18044)

1.4.5.8 Categorical

- Bug in `DataFrame.astype()` where casting to 'category' on an empty DataFrame causes a segmentation fault (GH18004)
- Error messages in the testing module have been improved when items have different `CategoricalDtype` (GH18069)
- `CategoricalIndex` can now correctly take a `pd.api.types.CategoricalDtype` as its dtype (GH18116)
- Bug in `Categorical.unique()` returning read-only codes array when all categories were NaN (GH18051)
- Bug in `DataFrame.groupby(axis=1)` with a `CategoricalIndex` (GH18432)

1.4.5.9 String

- `Series.str.split()` will now propagate NaN values across all expanded columns instead of None (GH18450)

1.5 v0.21.0 (October 27, 2017)

This is a major release from 0.20.3 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Integration with Apache Parquet, including a new top-level `read_parquet()` function and `DataFrame.to_parquet()` method, see here.
- New user-facing `pandas.api.types.CategoricalDtype` for specifying categoricals independent of the data, see here.
- The behavior of `sum` and `prod` on all-NaN Series/DataFrames is now consistent and no longer depends on whether bottleneck is installed, and `sum` and `prod` on empty Series now return NaN instead of 0, see here.
- Compatibility fixes for pypy, see here.
- Additions to the `drop`, `reindex` and `rename` API to make them more consistent, see here.
- Addition of the new methods `DataFrame.infer_objects` (see here) and `GroupBy.pipe` (see here).
- Indexing with a list of labels, where one or more of the labels is missing, is deprecated and will raise a KeyError in a future version, see here.

Check the API Changes and deprecations before updating.

What’s new in v0.21.0

- New features
  - Integration with Apache Parquet file format
  - `infer_objects` type conversion
  - Improved warnings when attempting to create columns
  - `drop` now also accepts index/columns keywords
  - `rename`, `reindex` now also accept axis keyword
  - `CategoricalDtype` for specifying categoricals
  - `GroupBy` objects now have a `pipe` method
  - `Categorical.rename_categories` accepts a dict-like
  - Other Enhancements
- Backwards incompatible API changes
  - Dependencies have increased minimum versions
  - Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN
  - Indexing with a list with missing labels is Deprecated
  - NA naming Changes
  - Iteration of Series[Index will now return Python scalars
  - Indexing with a Boolean Index
  - `PeriodIndex` resampling
  - Improved error handling during item assignment in pd.eval
  - Dtype Conversions
  - `MultiIndex` Constructor with a Single Level
  - UTC Localization with Series
  - Consistency of Range Functions
  - No Automatic Matplotlib Converters
  - Other API Changes
- Deprecations
  - `Series.select` and `DataFrame.select`
  - `Series.argmax` and `Series.argmin`
- Removal of prior version deprecations/changes
- Performance Improvements
• Documentation Changes
• Bug Fixes
  – Conversion
  – Indexing
  – I/O
  – Plotting
  – Groupby/Resample/Rolling
  – Sparse
  – Reshaping
  – Numeric
  – Categorical
  – PyPy
  – Other

1.5.1 New features

1.5.1.1 Integration with Apache Parquet file format

Integration with Apache Parquet, including a new top-level `read_parquet()` and `DataFrame.to_parquet()` method, see here (GH15838, GH17438).

Apache Parquet provides a cross-language, binary file format for reading and writing data frames efficiently. Parquet is designed to faithfully serialize and de-serialize `DataFrame`s, supporting all of the pandas dtypes, including extension dtypes such as datetime with timezones.

This functionality depends on either the `pyarrow` or `fastparquet` library. For more details, see see the IO docs on Parquet.

1.5.1.2 `infer_objects` type conversion

The `DataFrame.infer_objects()` and `Series.infer_objects()` methods have been added to perform dtype inference on object columns, replacing some of the functionality of the deprecated `convert_objects` method. See the documentation here for more details. (GH11221)

This method only performs soft conversions on object columns, converting Python objects to native types, but not any coercive conversions. For example:

```python
In [1]: df = pd.DataFrame({'A': [1, 2, 3],
                      ...:                      'B': np.array([1, 2, 3], dtype='object'),
                      ...:                      'C': ['1', '2', '3']})

In [2]: df.dtypes
Out[2]:
A    int64
B    object
C    object
```

(continues on next page)
1.5.1.3 Improved warnings when attempting to create columns

New users are often puzzled by the relationship between column operations and attribute access on DataFrame instances (GH7175). One specific instance of this confusion is attempting to create a new column by setting an attribute on the DataFrame:

```
In[1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In[2]: df.two = [4, 5, 6]
```

This does not raise any obvious exceptions, but also does not create a new column:

```
In[3]: df
Out[3]:
   one
 0  1.0
 1  2.0
 2  3.0
```

Setting a list-like data structure into a new attribute now raises a UserWarning about the potential for unexpected behavior. See Attribute Access.

1.5.1.4 drop now also accepts index/columns keywords

The drop() method has gained index/columns keywords as an alternative to specifying the axis. This is similar to the behavior of reindex (GH12392).

For example:
In [7]: df = pd.DataFrame(np.arange(8).reshape(2,4),
...:                     columns=['A', 'B', 'C', 'D'])
...:

In [8]: df
Out[8]:
    A  B  C  D
0  0  1  2  3
1  4  5  6  7

In [9]: df.drop(['B', 'C'], axis=1)
Out[9]:
   A  D
0  0  3
1  4  7

# the following is now equivalent
In [10]: df.drop(columns=['B', 'C'])
Out[10]:
   A  D
0  0  3
1  4  7

1.5.1.5 rename, reindex now also accept axis keyword

The DataFrame.rename() and DataFrame.reindex() methods have gained the axis keyword to specify
the axis to target with the operation (GH12392).

Here’s rename:

In [11]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})

In [12]: df.rename(str.lower, axis='columns')
Out[12]:
   a  b
0  1  4
1  2  5
2  3  6

In [13]: df.rename(id, axis='index')
Out[13]:
   A  B
4501685568  1  4
4501685600  2  5
4501685632  3  6

And reindex:

In [14]: df.reindex(['A', 'B', 'C'], axis='columns')
Out[14]:
   A  B  C
0  1  4  NaN
1  2  5  NaN
2  3  6  NaN

(continues on next page)
The “index, columns” style continues to work as before.

We highly encourage using named arguments to avoid confusion when using either style.

1.5.1.6 CategoricalDtype for specifying categorical values

pandas.api.types.CategoricalDtype has been added to the public API and expanded to include the categories and ordered attributes. A CategoricalDtype can be used to specify the set of categories and orderedness of an array, independent of the data. This can be useful for example, when converting string data to a Categorical (GH14711, GH15078, GH16015, GH17643):

```python
In [18]: from pandas.api.types import CategoricalDtype
In [19]: s = pd.Series(['a', 'b', 'c', 'a'])  # strings
In [20]: dtype = CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
In [21]: s.astype(dtype)
```

```
Out[21]:
0    a
1    b
2    c
3    a
dtype: category
Categories (4, object): [a < b < c < d]
```

One place that deserves special mention is in `read_csv()`. Previously, with `dtype={'col': 'category'}`, the returned values and categories would always be strings.

```python
In [22]: data = 'A,B
a,1
b,2
c,3'
In [23]: pd.read_csv(StringIO(data), dtype={'B': 'category'}).B.cat.categories
```

```
Index(['1', '2', '3'], dtype='object')
```
Notice the “object” dtype.

With a `CategoricalDtype` of all numerics, datetimes, or timedeltas, we can automatically convert to the correct type

```python
In [24]: dtype = {'B': CategoricalDtype([1, 2, 3])}
In [25]: pd.read_csv(StringIO(data), dtype=dtype).B.cat.categories
Out[25]: Int64Index([1, 2, 3], dtype='int64')
```

The values have been correctly interpreted as integers.

The `.dtype` property of a `Categorical`, `CategoricalIndex` or a `Series` with categorical type will now return an instance of `CategoricalDtype`. While the repr has changed, `str(CategoricalDtype())` is still the string 'category'. We’ll take this moment to remind users that the `preferred` way to detect categorical data is to use `pandas.api.types.is_categorical_dtype()`, and not `str(dtype) == 'category'`.

See the `CategoricalDtype docs` for more.

### 1.5.1.7 GroupBy objects now have a pipe method

GroupBy objects now have a `pipe` method, similar to the one on DataFrame and Series, that allow for functions that take a GroupBy to be composed in a clean, readable syntax. (GH17871)

For a concrete example on combining `.groupby` and `.pipe`, imagine having a DataFrame with columns for stores, products, revenue and sold quantity. We’d like to do a groupwise calculation of prices (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable.

First we set the data:

```python
In [26]: import numpy as np
In [27]: n = 1000
In [28]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
                      ....:                     'Product': np.random.choice(['Product_1', 'Product_2',
                      ....:                                      'Product_3'], n),
                      ....:                     'Revenue': (np.random.random(n)*50+10).round(2),
                      ....:                     'Quantity': np.random.randint(1, 10, size=n)})
In [29]: df.head(2)
Out[29]:
        Store    Product  Revenue  Quantity
0  Store_1  Product_3   54.28       3
1  Store_2  Product_2   30.91       1
```

Now, to find prices per store/product, we can simply do:

```python
In [30]: (df.groupby('Store', 'Product')
    ....:     .pipe(lambda grp: grp.Revenue.sum()/grp.Quantity.sum())
    ....:     .unstack().round(2)
    ....:)
Out[30]:
          Product_1  Product_2  Product_3
Store
0  Store_1       5.43       3.00       1.80
1  Store_2       3.09       3.09       3.09
```

(continues on next page)
Store_1 6.37 6.98 7.49
Store_2 7.60 7.01 7.13

See the documentation for more.

### 1.5.1.8 `Categorical.rename_categories` accepts a dict-like

`rename_categories()` now accepts a dict-like argument for `new_categories`. The previous categories are looked up in the dictionary’s keys and replaced if found. The behavior of missing and extra keys is the same as in `DataFrame.rename()`.

```python
In [31]: c = pd.Categorical(['a', 'a', 'b'])
In [32]: c.rename_categories({"a": "eh", "b": "bee"})
Out[32]:
[eh, eh, bee]
Categories (2, object): [eh, bee]
```

**Warning:** To assist with upgrading pandas, `rename_categories` treats `Series` as list-like. Typically, `Series` are considered to be dict-like (e.g. in `.rename`, `.map`). In a future version of pandas `rename_categories` will change to treat them as dict-like. Follow the warning message’s recommendations for writing future-proof code.

```python
In [33]: c.rename_categories(pd.Series([0, 1], index=['a', 'c']))
```

**FutureWarning:** Treating Series 'new_categories' as a list-like and using the values. In a future version, 'rename_categories' will treat Series like a dictionary.

For dict-like, use 'new_categories.to_dict()' For list-like, use 'new_categories.values'.

```python
Out[33]:
[0, 0, 1]
Categories (2, int64): [0, 1]
```

### 1.5.1.9 Other Enhancements

**New functions or methods**

- `nearest()` is added to support nearest-neighbor upsampling (GH17496).
- `Index` has added support for a `to_frame` method (GH15230).

**New keywords**

- Added a `skipna` parameter to `infer_dtype()` to support type inference in the presence of missing values (GH17059).
- `Series.to_dict()` and `DataFrame.to_dict()` now support an `into` keyword which allows you to specify the `collections.Mapping` subclass that you would like returned. The default is `dict`, which is backwards compatible. (GH16122)
- `Series.set_axis()` and `DataFrame.set_axis()` now support the `inplace` parameter. (GH14636)
• `Series.to_pickle()` and `DataFrame.to_pickle()` have gained a protocol parameter (GH16252). By default, this parameter is set to `HIGHEST_PROTOCOL`.

• `read_feather()` has gained the `nthreads` parameter for multi-threaded operations (GH16359).

• `DataFrame.clip()` and `Series.clip()` have gained an inplace argument. (GH15388)

• `crosstab()` has gained a `margins_name` parameter to define the name of the row / column that will contain the totals when `margins=True`. (GH15972)

• `read_json()` now accepts a `chunksize` parameter that can be used when `lines=True`. If `chunksize` is passed, `read_json` now returns an iterator which reads in `chunksize` lines with each iteration. (GH17048)

• `read_json()` and `to_json()` now accept a `compression` argument which allows them to transparently handle compressed files. (GH17798)

Various enhancements

• Improved the import time of pandas by about 2.25x. (GH16764)

• Support for PEP 519 – Adding a file system path protocol on most readers (e.g. `read_csv()`) and writers (e.g. `DataFrame.to_csv()`). (GH13823)

• Added a `__fspath__` method to `pd.HDFStore`, `pd.ExcelFile`, and `pd.ExcelWriter` to work properly with the file system path protocol (GH13823).

• The `validate` argument for `merge()` now checks whether a merge is one-to-one, one-to-many, many-to-one, or many-to-many. If a merge is found to not be an example of specified merge type, an exception of type `MergeError` will be raised. For more, see here (GH16270)

• Added support for PEP 518 (`pyproject.toml`) to the build system (GH16745)

• `RangeIndex.append()` now returns a `RangeIndex` object when possible (GH16212)

• `Series.rename_axis()` and `DataFrame.rename_axis()` with `inplace=True` now return None while renaming the axis inplace. (GH15704)

• `api.types.infer_dtype()` now infers decimals. (GH15690)

• `DataFrame.select_dtypes()` now accepts scalar values for include/exclude as well as list-like. (GH16855)

• `date_range()` now accepts ‘YS’ in addition to ‘AS’ as an alias for start of year. (GH9313)

• `date_range()` now accepts ‘Y’ in addition to ‘A’ as an alias for end of year. (GH9313)

• `DataFrame.add_prefix()` and `DataFrame.add_suffix()` now accept strings containing the ‘%’ character. (GH17151)

• Read/write methods that infer compression (`read_csv()`, `read_table()`, `read_pickle()`, and `to_pickle()`) can now infer from path-like objects, such as `pathlib.Path`. (GH17206)

• `read_sas()` now recognizes much more of the most frequently used date (datetime) formats in SAS7BDAT files. (GH15871)

• `DataFrame.items()` and `Series.items()` are now present in both Python 2 and 3 and is lazy in all cases. (GH13918, GH17213)

• `pandas.io.formats.style.Styler.where()` has been implemented as a convenience for `pandas.io.formats.style.Styler.applymap()`. (GH17474)

• `MultiIndex.is_monotonic_decreasing()` has been implemented. Previously returned `False` in all cases. (GH16554)
• `read_excel()` raises `ImportError` with a better message if `xlrd` is not installed. (GH17613)

• `DataFrame.assign()` will preserve the original order of `**kwargs` for Python 3.6+ users instead of sorting the column names. (GH14207)

• `Series.reindex(), DataFrame.reindex(), Index.get_indexer()` now support list-like argument for `tolerance`. (GH17367)

### 1.5.2 Backwards incompatible API changes

#### 1.5.2.1 Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15206, GH15543, GH15214). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numpy</td>
<td>1.9.0</td>
<td>X</td>
</tr>
<tr>
<td>Matplotlib</td>
<td>1.4.3</td>
<td></td>
</tr>
<tr>
<td>Scipy</td>
<td>0.14.0</td>
<td></td>
</tr>
<tr>
<td>Bottleneck</td>
<td>1.0.0</td>
<td></td>
</tr>
</tbody>
</table>

Additionally, support has been dropped for Python 3.4 (GH15251).

#### 1.5.2.2 Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN

**Note:** The changes described here have been partially reverted. See the `v0.22.0 Whatsnew` for more.

The behavior of `sum` and `prod` on all-NaN Series/DataFrames no longer depends on whether `bottleneck` is installed, and return value of `sum` and `prod` on an empty Series has changed (GH9422, GH15507).

Calling `sum` or `prod` on an empty or all-NaN Series, or columns of a DataFrame, will result in NaN. See the docs.

```
In [33]: s = Series([np.nan])
```

Previously WITHOUT `bottleneck` installed:

```
In [2]: s.sum()
Out[2]: np.nan
```

Previously WITH `bottleneck`:

```
In [2]: s.sum()
Out[2]: 0.0
```

New Behavior, without regard to the bottleneck installation:

```
In [34]: s.sum()
Out[34]: 0.0
```

Note that this also changes the sum of an empty `Series`. Previously this always returned 0 regardless of a `bottlenck` installation:
but for consistency with the all-NaN case, this was changed to return NaN as well:

```
In [35]: pd.Series([]).sum()
Out[35]: 0.0
```

### 1.5.2.3 Indexing with a list with missing labels is Deprecated

Previously, selecting with a list of labels, where one or more labels were missing would always succeed, returning NaN for missing labels. This will now show a `FutureWarning`. In the future this will raise a `KeyError` (GH15747). This warning will trigger on a DataFrame or a Series for using `.loc[]` or `[[[]]` when passing a list-of-labels with at least 1 missing label. See the deprecation docs.

```
In [36]: s = pd.Series([1, 2, 3])
In [37]: s
Out[37]:
0  1
1  2
2  3
dtype: int64

Previous Behavior
```

```
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1  2.0
2  3.0
3  NaN
dtype: float64

Current Behavior
```

```
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to `.loc[]` with any missing label will raise
KeyError in the future, you can use `.reindex()` as an alternative.

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
˓

listlike
```

```
Out[4]:
1  2.0
2  3.0
3  NaN
dtype: float64

The idiomatic way to achieve selecting potentially not-found elements is via `.reindex()`

```
In [38]: s.reindex([1, 2, 3])
Out[38]:
1  2.0
2  3.0
```
Selection with all keys found is unchanged.

```
In [39]: s.loc[[1, 2]]
Out[39]:
  1   2
  2   3
dtype: int64
```

### 1.5.2.4 NA naming Changes

In order to promote more consistency among the pandas API, we have added additional top-level functions `isna()` and `notna()` that are aliases for `isnull()` and `notnull()`. The naming scheme is now more consistent with methods like `.dropna()` and `.fillna()`. Furthermore in all cases where `.isnull()` and `.notnull()` methods are defined, these have additional methods named `.isna()` and `.notna()`, these are included for classes Categorical, Index, Series, and DataFrame. (GH15001).

The configuration option `pd.options.mode.use_inf_as_null` is deprecated, and `pd.options.mode.use_inf_as_na` is added as a replacement.

### 1.5.2.5 Iteration of Series/Index will now return Python scalars

Previously, when using certain iteration methods for a Series with dtype int or float, you would receive a numpy scalar, e.g. `np.int64`, rather than a Python `int`. Issue (GH10904) corrected this for `Series.tolist()` and `list(Series)`. This change makes all iteration methods consistent, in particular, for `__iter__()` and `.map()'; note that this only affects int/float dtypes. (GH13236, GH13258, GH14216).

```
In [40]: s = pd.Series([1, 2, 3])
In [41]: s
Out[41]:
  0  1
  1  2
  2  3
dtype: int64
```

Previously:

```
In [2]: type(list(s)[0])
Out[2]: numpy.int64
```

New Behaviour:

```
In [42]: type(list(s)[0])
Out[42]: int
```

Furthermore this will now correctly box the results of iteration for `DataFrame.to_dict()` as well.

```
In [43]: d = {'a':[1], 'b':['b']}
In [44]: df = pd.DataFrame(d)
```
Previously:

In [8]: type(df.to_dict()['a'][0])
Out[8]: numpy.int64

New Behaviour:

In [45]: type(df.to_dict()['a'][0])
Out[45]: int

1.5.2.6 Indexing with a Boolean Index

Previously when passing a boolean Index to .loc, if the index of the Series/DataFrame had boolean labels, you would get a label based selection, potentially duplicating result labels, rather than a boolean indexing selection (where True selects elements), this was inconsistent how a boolean numpy array indexed. The new behavior is to act like a boolean numpy array indexer. (GH17738)

Previous Behavior:

In [46]: s = pd.Series([1, 2, 3], index=[False, True, False])
In [47]: s
Out[47]:
False 1
True 2
False 3
dtype: int64
In [59]: s.loc[pd.Index([True, False, True])]
Out[59]:
True 2
False 1
False 3
True 2
dtype: int64

Current Behavior

In [48]: s.loc[pd.Index([True, False, True])]
Out[48]:
False 1
False 3
dtype: int64

Furthermore, previously if you had an index that was non-numeric (e.g. strings), then a boolean Index would raise a KeyError. This will now be treated as a boolean indexer.

Previously Behavior:

In [49]: s = pd.Series([1,2,3], index=['a', 'b', 'c'])
In [50]: s
Out[50]:
a  1
b  2
c  3
dtype: int64
In [39]: s.loc[pd.Index([True, False, True])]
KeyError: "None of [Index([True, False, True], dtype='object')] are in the [index]"

Current Behavior

In [51]: s.loc[pd.Index([True, False, True])]
Out[51]:
a  1
b  3
dtype: int64

1.5.2.7 PeriodIndex resampling

In previous versions of pandas, resampling a Series/DataFrame indexed by a PeriodIndex returned a
DatetimeIndex in some cases (GH12884). Resampling to a multiplied frequency now returns a PeriodIndex
(GH15944). As a minor enhancement, resampling a PeriodIndex can now handle NaT values (GH13224)

Previous Behavior:

In [1]: pi = pd.period_range('2017-01', periods=12, freq='M')
In [2]: s = pd.Series(np.arange(12), index=pi)
In [3]: resampled = s.resample('2Q').mean()
In [4]: resampled
Out[4]:
2017-03-31  1.0
2017-09-30  5.5
2018-03-31 10.0
Freq: 2Q-DEC, dtype: float64
In [5]: resampled.index
Out[5]: DatetimeIndex(['2017-03-31', '2017-09-30', '2018-03-31'], dtype=
˓→'datetime64[ns]', freq='2Q-DEC')

New Behavior:

In [52]: pi = pd.period_range('2017-01', periods=12, freq='M')
In [53]: s = pd.Series(np.arange(12), index=pi)
In [54]: resampled = s.resample('2Q').mean()
In [55]: resampled
Out[55]:
2017Q1  2.5
2017Q3  8.5
Freq: 2Q-DEC, dtype: float64
In [56]: resampled.index
Out[56]: PeriodIndex(['2017Q1', '2017Q3'], dtype='period[2Q-DEC]', freq='2Q-DEC')

Upsampling and calling .ohlc() previously returned a Series, basically identical to calling .asfreq(). OHLC
upsampling now returns a DataFrame with columns open, high, low and close (GH13083). This is consistent
with downsampling and DatetimeIndex behavior.
Previous Behavior:

```
In [1]: pi = pd.PeriodIndex(start='2000-01-01', freq='D', periods=10)
In [2]: s = pd.Series(np.arange(10), index=pi)
In [3]: s.resample('H').ohlc()
Out[3]:
2000-01-01 00:00 0.0 ...
2000-01-10 23:00 NaN
Freq: H, Length: 240, dtype: float64
```

```
In [4]: s.resample('M').ohlc()
Out[4]:
open high low close
2000-01 0   9   0   9
```

New Behavior:

```
In [57]: pi = pd.PeriodIndex(start='2000-01-01', freq='D', periods=10)
In [58]: s = pd.Series(np.arange(10), index=pi)
In [59]: s.resample('H').ohlc()
Out[59]:
open high low close
2000-01-01 00:00 0.0 0.0 0.0 0.0
2000-01-01 01:00 NaN NaN NaN NaN
2000-01-01 02:00 NaN NaN NaN NaN
2000-01-01 03:00 NaN NaN NaN NaN
2000-01-01 04:00 NaN NaN NaN NaN
2000-01-01 05:00 NaN NaN NaN NaN
2000-01-01 06:00 NaN NaN NaN NaN
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Previously, if you attempted the following expression, you would get a not very helpful error message:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
IndexError: only integers, slices (":") or ellipsis ("...")
and integer or boolean arrays are valid indices
```

This is a very long way of saying numpy arrays don’t support string-item indexing. With this change, the error message is now this:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
ValueError: Cannot assign expression output to target
```

It also used to be possible to evaluate expressions inplace, even if there was no item assignment:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
Out[4]: 3
```

However, this input does not make much sense because the output is not being assigned to the target. Now, a `ValueError` will be raised when such an input is passed in:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
...
ValueError: Cannot operate inplace if there is no assignment
```

### 1.5.2.9 Dtype Conversions

Previously assignments, `.where()` and `.fillna()` with a `bool` assignment, would coerce to same the type (e.g. `int` / `float`), or raise for datetimelikes. These will now preserve the bools with `object` dtypes. *(GH16821).*

```
In [62]: s = Series([1, 2, 3])
```

```
In [5]: s[1] = True
```

```
In [6]: s
Out[6]:
0     1
1     1
2     3
dtype: int64
```

New Behavior

```
In [63]: s[1] = True
```

```
In [64]: s
Out[64]:
0     1
1    True
2     3
dtype: object
```
Previously, as assignment to a datetimelike with a non-datetimelike would coerce the non-datetime-like item being assigned (GH14145).

```python
In [65]: s = pd.Series([pd.Timestamp('2011-01-01'), pd.Timestamp('2012-01-01')])
In [1]: s[1] = 1
In [2]: s
Out[2]:
0 2011-01-01 00:00:00.000000000
1 1970-01-01 00:00:00.000000001
dtype: datetime64[ns]
```

These now coerce to object dtype.

```python
In [66]: s[1] = 1
In [67]: s
Out[67]:
0 2011-01-01 00:00:00
1 1
dtype: object
```

- Inconsistent behavior in `.where()` with datetimelikes which would raise rather than coerce to object (GH16402)
- Bug in assignment against int64 data with np.ndarray with float64 dtype may keep int64 dtype (GH14001)

### 1.5.2.10 MultiIndex Constructor with a Single Level

The MultiIndex constructors no longer squeezes a MultiIndex with all length-one levels down to a regular Index. This affects all the MultiIndex constructors. (GH17178)

Previous behavior:

```python
In [2]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[2]: Index(['a', 'b'], dtype='object')
```

Length 1 levels are no longer special-cased. They behave exactly as if you had length 2+ levels, so a `MultiIndex` is always returned from all of the MultiIndex constructors:

```python
In [68]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[68]: MultiIndex(levels=[['a', 'b']],
                     labels=[[0, 1]])
```

### 1.5.2.11 UTC Localization with Series

Previously, `to_datetime()` did not localize datetime Series data when utc=True was passed. Now, `to_datetime()` will correctly localize Series with a datetime64[ns, UTC] dtype to be consistent with how list-like and Index data are handled. (GH6415).

Previous Behavior
In [69]: s = Series(['20130101 00:00:00'] * 3)
In [12]: pd.to_datetime(s, utc=True)
Out[12]:
0  2013-01-01
1  2013-01-01
2  2013-01-01
dtype: datetime64[ns]

New Behavior
In [70]: pd.to_datetime(s, utc=True)
Out[70]:
0  2013-01-01 00:00:00+00:00
1  2013-01-01 00:00:00+00:00
2  2013-01-01 00:00:00+00:00
dtype: datetime64[ns, UTC]

Additionally, DataFrames with datetime columns that were parsed by `read_sql_table()` and `read_sql_query()` will also be localized to UTC only if the original SQL columns were timezone aware datetime columns.

1.5.2.12 Consistency of Range Functions

In previous versions, there were some inconsistencies between the various range functions: `date_range()`, `bdate_range()`, `period_range()`, `timedelta_range()`, and `interval_range()`.(GH17471).

One of the inconsistent behaviors occurred when the `start`, `end` and `period` parameters were all specified, potentially leading to ambiguous ranges. When all three parameters were passed, `interval_range` ignored the period parameter, `period_range` ignored the end parameter, and the other range functions raised. To promote consistency among the range functions, and avoid potentially ambiguous ranges, `interval_range` and `period_range` will now raise when all three parameters are passed.

Previous Behavior:
In [2]: pd.interval_range(start=0, end=4, periods=6)
Out[2]: IntervalIndex([(0, 1], (1, 2], (2, 3])
        closed='right',
        dtype='interval[int64]')
In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
Out[3]: PeriodIndex(['2017Q1', '2017Q2', '2017Q3', '2017Q4', '2018Q1', '2018Q2'],
        dtype='period[Q-DEC]', freq='Q-DEC')

New Behavior:
In [2]: pd.interval_range(start=0, end=4, periods=6)
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be specified
In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be specified
Additionally, the endpoint parameter `end` was not included in the intervals produced by `interval_range`. However, all other range functions include `end` in their output. To promote consistency among the range functions, `interval_range` will now include `end` as the right endpoint of the final interval, except if `freq` is specified in a way which skips `end`.

**Previous Behavior:**

```python
In [4]: pd.interval_range(start=0, end=4)
Out[4]:
IntervalIndex([(0, 1], (1, 2], (2, 3]],
               closed='right',
               dtype='interval[int64]')
```

**New Behavior:**

```python
In [71]: pd.interval_range(start=0, end=4)
Out[71]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4]],
               closed='right',
               dtype='interval[int64]')
```

### 1.5.2.13 No Automatic Matplotlib Converters

Pandas no longer registers our `date`, `time`, `datetime`, `datetime64`, and `Period` converters with matplotlib when pandas is imported. Matplotlib plot methods (``plt.plot``), will not nicely format the x-axis for `DatetimeIndex` or `PeriodIndex` values. You must explicitly register these methods:

Pandas built-in `Series.plot` and `DataFrame.plot` will register these converters on first-use (GH17710).

**Note:** This change has been temporarily reverted in pandas 0.21.1, for more details see [here](#).

### 1.5.2.14 Other API Changes

- The Categorical constructor no longer accepts a scalar for the `categories` keyword. (GH16022)
- Accessing a non-existent attribute on a closed `HDFStore` will now raise an `AttributeError` rather than a `ClosedFileError` (GH16301)
- `read_csv()` now issues a `UserWarning` if the `names` parameter contains duplicates (GH17095)
- `read_csv()` now treats 'null' and 'n/a' strings as missing values by default (GH16471, GH16078)
- Pandas' `HDFStore`’s string representation is now faster and less detailed. For the previous behavior, use `pandas.HDFStore.info()` (GH16503).
- Compression defaults in HDF stores now follow pytables standards. Default is no compression and if `complib` is missing and `complevel` > 0 `zlib` is used (GH15943)
- `Index.get_indexer_non_unique()` now returns a `ndarray` indexer rather than an `Index`; this is consistent with `Index.get_indexer()` (GH16819)
- Removed the `@slow` decorator from `pandas.util.testing`, which caused issues for some downstream packages’ test suites. Use `@pytest.mark.slow` instead, which achieves the same thing (GH16850)
- Moved definition of `MergeError` to the `pandas.errors` module.
• The signature of `Series.set_axis()` and `DataFrame.set_axis()` has been changed from `set_axis(axis, labels)` to `set_axis(labels, axis=0)`, for consistency with the rest of the API. The old signature is deprecated and will show a `FutureWarning` (GH14636)

• `Series.argmin()` and `Series.argmax()` will now raise a `TypeError` when used with object dtypes, instead of a `ValueError` (GH13595)

• `Period` is now immutable, and will now raise an `AttributeError` when a user tries to assign a new value to the `ordinal` or `freq` attributes (GH17116).

• `to_datetime()` when passed a tz-aware `origin=` kwarg will now raise a more informative `ValueError` rather than a `TypeError` (GH16842)

• `to_datetime()` now raises a `ValueError` when format includes `%W` or `%U` without also including day of the week and calendar year (GH16774)

• Renamed non-functional `index` to `index_col` in `read_stata()` to improve API consistency (GH16342)

• Bug in `DataFrame.drop()` caused boolean labels `False` and `True` to be treated as labels 0 and 1 respectively when dropping indices from a numeric index. This will now raise a `ValueError` (GH16877)

• Restricted DateOffset keyword arguments. Previously, DateOffset subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176)

1.5.3 Deprecations

• `DataFrame.from_csv()` and `Series.from_csv()` have been deprecated in favor of `read_csv()` (GH4191)

• `read_excel()` has deprecated `sheetname` in favor of `sheet_name` for consistency with `.to_excel()` (GH10559).

• `read_excel()` has deprecated `parse_cols` in favor of `usecols` for consistency with `read_csv()` (GH4988)

• `read_csv()` has deprecated the `tupleize_cols` argument. Column tuples will always be converted to a MultiIndex (GH17060)

• `DataFrame.to_csv()` has deprecated the `tupleize_cols` argument. Multi-index columns will be always written as rows in the CSV file (GH17060)

• The `convert` parameter has been deprecated in the `.take()` method, as it was not being respected (GH16948)

• `pd.options.html.border` has been deprecated in favor of `pd.options.display.html.border` (GH15793).

• `SeriesGroupBy.nth()` has deprecated `True` in favor of `'all'` for its kwarg `dropna` (GH11038).

• `DataFrame.as_blocks()` is deprecated, as this is exposing the internal implementation (GH17302)

• `pd.TimeGrouper` is deprecated in favor of `pandas.Grouper` (GH16747)

• `cdate_range` has been deprecated in favor of `bdate_range()`, which has gained `weekmask` and `holidays` parameters for building custom frequency date ranges. See the documentation for more details (GH17596)

• passing categories or ordered kwargs to `Series.astype()` is deprecated, in favor of passing a `CategoricalDtype` (GH17636)

• `.get_value` and `.set_value` on `Series`, `DataFrame`, `Panel`, `SparseSeries`, and `SparseDataFrame` are deprecated in favor of using `.iat[]` or `.at[]` accessors (GH15269)
• Passing a non-existent column in `.to_excel(..., columns=)` is deprecated and will raise a `KeyError` in the future (GH17295)

• `raise_on_error` parameter to `Series.where()`, `Series.mask()`, `DataFrame.where()`, `DataFrame.mask()` is deprecated, in favor of `errors=` (GH14968)

• Using `DataFrame.rename_axis()` and `Series.rename_axis()` to alter index or column `labels` is now deprecated in favor of using `.rename.rename_axis` may still be used to alter the name of the index or columns (GH17833).

• `reindex_axis()` has been deprecated in favor of `reindex()`. See here for more (GH17833).

### 1.5.3.1 Series.select and DataFrame.select

The `Series.select()` and `DataFrame.select()` methods are deprecated in favor of using `df.loc[labels.map(crit)]` (GH12401)

```
In [72]: df = DataFrame({'A': [1, 2, 3]}, index=['foo', 'bar', 'baz'])

In [3]: df.select(lambda x: x in ['bar', 'baz'])
FutureWarning: select is deprecated and will be removed in a future release. You can use .loc[crit] as a replacement
Out[3]:
    A
bar 2
baz 3
```

```
In [73]: df.loc[df.index.map(lambda x: x in ['bar', 'baz'])]
Out[73]:
    A
bar 2
baz 3
```

### 1.5.3.2 Series.argmax and Series.argmin

The behavior of `Series.argmax()` and `Series.argmin()` have been deprecated in favor of `Series.idxmax()` and `Series.idxmin()`, respectively (GH16830).

For compatibility with NumPy arrays, `pd.Series` implements `argmax` and `argmin`. Since pandas 0.13.0, `argmax` has been an alias for `pandas.Series.idxmax()`, and `argmin` has been an alias for `pandas.Series.idxmin()`. They return the `label` of the maximum or minimum, rather than the `position`.

We’ve deprecated the current behavior of `Series.argmax` and `Series.argmin`. Using either of these will emit a `FutureWarning`. Use `Series.idxmax()` if you want the label of the maximum. Use `Series.values.argmax()` if you want the position of the maximum. Likewise for the minimum. In a future release `Series.argmax` and `Series.argmin` will return the position of the maximum or minimum.

### 1.5.4 Removal of prior version deprecations/changes

• `read_excel()` has dropped the `has_index_names` parameter (GH10967)

• The `pd.options.display.height` configuration has been dropped (GH3663)

• The `pd.options.display.line_width` configuration has been dropped (GH2881)

• The `pd.options.display.mpl_style` configuration has been dropped (GH12190)
• Index has dropped the `.sym_diff()` method in favor of `.symmetric_difference()` (GH12591)
• Categorical has dropped the `.order()` and `.sort()` methods in favor of `.sort_values()` (GH12882)
• `eval()` and `DataFrame.eval()` have changed the default of inplace from None to False (GH11149)
• The function `get_offset_name` has been dropped in favor of the `.freqstr` attribute for an offset (GH11834)
• pandas no longer tests for compatibility with hdf5-files created with pandas < 0.11 (GH17404).

1.5.5 Performance Improvements

• Improved performance of instantiating `SparseDataFrame` (GH16773)
• `Series.dt` no longer performs frequency inference, yielding a large speedup when accessing the attribute (GH17210)
• Improved performance of `set_categories()` by not materializing the values (GH17508)
• `Timestamp.microsecond` no longer re-computes on attribute access (GH17331)
• Improved performance of the `CategoricalIndex` for data that is already categorical dtype (GH17513)
• Improved performance of `RangeIndex.min()` and `RangeIndex.max()` by using `RangeIndex` properties to perform the computations (GH17607)

1.5.6 Documentation Changes

• Several `NaT` method docstrings (e.g. `NaT.ctime()`) were incorrect (GH17327)
• The documentation has had references to versions < v0.17 removed and cleaned up (GH17442, GH17442, GH17404 & GH17504)

1.5.7 Bug Fixes

1.5.7.1 Conversion

• Bug in assignment against datetime-like data with `int` may incorrectly convert to datetime-like (GH14145)
• Bug in assignment against `int64` data with `np.ndarray` with `float64` dtype may keep `int64` dtype (GH14001)
• Fixed the return type of `IntervalIndex.is_non_overlapping_monotonic` to be a Python bool for consistency with similar attributes/methods. Previously returned `numpy.bool_`. (GH17237)
• Bug in `IntervalIndex.is_non_overlapping_monotonic` when intervals are closed on both sides and overlap at a point (GH16560)
• Bug in `Series.fillna()` returns frame when `inplace=True` and `value` is dict (GH16156)
• Bug in `Timestamp.weekday_name` returning a UTC-based weekday name when localized to a timezone (GH17354)
• Bug in `Timestamp.replace` when replacing `tzinfo` around DST changes (GH15683)
• Bug in `Timedelta` construction and arithmetic that would not propagate the `Overflow` exception (GH17367)
- Bug in `astype()` converting to object dtype when passed extension type classes (DateTimeTZDtype, CategoricalDtype) rather than instances. Now a TypeError is raised when a class is passed (GH17780).
- Bug in `to_numeric()` in which elements were not always being coerced to numeric when `errors='coerce'` (GH17007, GH17125)
- Bug in DataFrame and Series constructors where range objects are converted to int32 dtype on Windows instead of int64 (GH16804)

### 1.5.7.2 Indexing

- When called with a null slice (e.g. `df.iloc[:],`) the `.iloc` and `.loc` indexers return a shallow copy of the original object. Previously they returned the original object. (GH13873).
- When called on an unsorted MultiIndex, the `.loc` indexer now will raise UnsortedIndexError only if proper slicing is used on non-sorted levels (GH16734).
- Fixes regression in 0.20.3 when indexing with a string on a TimedeltaIndex (GH16896).
- Fixed TimedeltaIndex.get_loc() handling of np.timedelta64 inputs (GH16909).
- Fix MultiIndex.sort_index() ordering when ascending argument is a list, but not all levels are specified, or are in a different order (GH16934).
- Fixes bug where indexing with np.inf caused an OverflowError to be raised (GH16957)
- Bug in reindexing on an empty CategoricalIndex (GH16770)
- Fixes DataFrame.loc for setting with alignment and tz-aware DatetimeIndex (GH16889)
- Avoids IndexError when passing an Index or Series to .iloc with older numpy (GH17193)
- Allow unicode empty strings as placeholders in multilevel columns in Python 2 (GH17099)
- Bug in .iloc when used with inplace addition or assignment and an int indexer on a MultiIndex causing the wrong indexes to be read from and written to (GH17148)
- Bug in .isin() in which checking membership in empty Series objects raised an error (GH16991)
- Bug in CategoricalIndex reindexing in which specified indices containing duplicates were not being respected (GH17323)
- Bug in intersection of RangeIndex with negative step (GH17296)
- Bug in IntervalIndex where performing a scalar lookup fails for included right endpoints of non-overlapping monotonic decreasing indexes (GH16417, GH17271)
- Bug in DataFrame.first_valid_index() and DataFrame.last_valid_index() when no valid entry (GH17400)
- Bug in Series.rename() when called with a callable, incorrectly alters the name of the Series, rather than the name of the Index. (GH17407)
- Bug in String.str_get() raises IndexError instead of inserting NaNs when using a negative index. (GH17704)

### 1.5.7.3 I/O

- Bug in `read_hdf()` when reading a timezone aware index from fixed format HDFStore (GH17618)
- Bug in `read_csv()` in which columns were not being thoroughly de-duplicated (GH17060)
- Bug in `read_csv()` in which specified column names were not being thoroughly de-duplicated (GH17095)
• Bug in `read_csv()` in which non integer values for the header argument generated an unhelpful / unrelated error message (GH16338)
• Bug in `read_csv()` in which memory management issues in exception handling, under certain conditions, would cause the interpreter to segfault (GH14696, GH16798).
• Bug in `read_csv()` when called with `low_memory=False` in which a CSV with at least one column > 2GB in size would incorrectly raise a MemoryError (GH16798).
• Bug in `read_csv()` when called with a single-element list `header` would return a `DataFrame` of all NaN values (GH7757)
• Bug in `DataFrame.to_csv()` defaulting to ‘ascii’ encoding in Python 3, instead of ‘utf-8’ (GH17097)
• Bug in `read_stata()` where value labels could not be read when using an iterator (GH16923)
• Bug in `read_stata()` where the index was not set (GH16342)
• Bug in `read_html()` where import check fails when run in multiple threads (GH16928)
• Bug in `read_csv()` where automatic delimiter detection caused a TypeError to be thrown when a bad line was encountered rather than the correct error message (GH13374)
• Bug in `DataFrame.to_html()` with `notebook=True` where DataFrames with named indices or non-MultiIndex indices had undesired horizontal or vertical alignment for column or row labels, respectively (GH16792)
• Bug in `DataFrame.to_html()` in which there was no validation of the `justify` parameter (GH17527)
• Bug in `HDFStore.select()` when reading a contiguous mixed-data table featuring VLArray (GH17021)
• Bug in `to_json()` where several conditions (including objects with unprintable symbols, objects with deep recursion, overlapping labels) caused segfaults instead of raising the appropriate exception (GH14256)

**1.5.7.4 Plotting**

• Bug in plotting methods using `secondary_y` and `fontsize` not setting secondary axis font size (GH12565)
• Bug when plotting `timedelta` and `datetime` dtypes on y-axis (GH16953)
• Line plots no longer assume monotonic x data when calculating xlims, they show the entire lines now even for unsorted x data. (GH11310, GH11471)
• With matplotlib 2.0.0 and above, calculation of x limits for line plots is left to matplotlib, so that its new default settings are applied. (GH15495)
• Bug in `Series.plot.bar` or `DataFrame.plot.bar` with y not respecting user-passed color (GH16822)
• Bug causing `plotting.parallel_coordinates` to reset the random seed when using random colors (GH17525)

**1.5.7.5 Groupby/Resample/Rolling**

• Bug in `DataFrame.resample(...).size()` where an empty DataFrame did not return a Series (GH14962)
• Bug in `infer_freq()` causing indices with 2-day gaps during the working week to be wrongly inferred as business daily (GH16624)
• Bug in `.rolling(...).quantile()` which incorrectly used different defaults than `Series.quantile()` and `DataFrame.quantile()` (GH9413, GH16211)
• Bug in `groupby.transform()` that would coerce boolean dtypes back to float (GH16875)

• Bug in `Series.resample(...).apply()` where an empty `Series` modified the source index and did not return the name of a `Series` (GH14313)

• Bug in `.rolling(...).apply(...)` with a `DataFrame` with a `DatetimeIndex`, a window of a `timedelta`-convertible and `min_periods >= 1` (GH15305)

• Bug in `DataFrame.groupby` where index and column keys were not recognized correctly when the number of keys equaled the number of elements on the groupby axis (GH16859)

• Bug in `groupby.nunique()` with `TimeGrouper` which cannot handle `NaT` correctly (GH17575)

• Bug in `DataFrame.groupby` where a single level selection from a `MultiIndex` unexpectedly sorts (GH17537)

• Bug in `DataFrame.groupby` where spurious warning is raised when `Grouper` object is used to override ambiguous column name (GH17383)

• Bug in `TimeGrouper` differs when passes as a list and as a scalar (GH17530)

1.5.7.6 Sparse

• Bug in `SparseSeries` raises `AttributeError` when a dictionary is passed in as data (GH16905)

• Bug in `SparseDataFrame.fillna()` not filling all NaNs when frame was instantiated from SciPy sparse matrix (GH16112)

• Bug in `SparseSeries.unstack()` and `SparseDataFrame.stack()` (GH16614, GH15045)

• Bug in `make_sparse()` treating two numeric/boolean data, which have same bits, as same when array dtype is object (GH17574)

• `SparseArray.all()` and `SparseArray.any()` are now implemented to handle `SparseArray`, these were used but not implemented (GH17570)

1.5.7.7 Reshaping

• Joining/Merging with a non unique `PeriodIndex` raised a `TypeError` (GH16871)

• Bug in `crosstab()` where non-aligned series of integers were casted to float (GH17005)

• Bug in merging with categorical dtypes with datetimelikes incorrectly raised a `TypeError` (GH16900)

• Bug when using `isin()` on a large object series and large comparison array (GH16012)

• Fixes regression from 0.20, `Series.aggregate()` and `DataFrame.aggregate()` allow dictionaries as return values again (GH16741)

• Fixes dtype of result with integer dtype input, from `pivot_table()` when called with `margins=True` (GH17013)

• Bug in `crosstab()` where passing two `Series` with the same name raised a `KeyError` (GH13279)

• `Series.argmin()`, `Series.argmax()`, and their counterparts on `DataFrame` and groupby objects work correctly with floating point data that contains infinite values (GH13595).

• Bug in `unique()` where checking a tuple of strings raised a `TypeError` (GH17108)

• Bug in `concat()` where order of result index was unpredictable if it contained non-comparable elements (GH17344)

1.5. v0.21.0 (October 27, 2017)
• Fixes regression when sorting by multiple columns on a `datetime64` dtype `Series` with `NaT` values (GH16836)
• Bug in `pivot_table()` where the result’s columns did not preserve the categorical dtype of `columns` when `dropna` was `False` (GH17842)
• Bug in `DataFrame.drop_duplicates` where dropping with non-unique column names raised a `ValueError` (GH17836)
• Bug in `unstack()` which, when called on a list of levels, would discard the `fillna` argument (GH13971)
• Bug in the alignment of `range` objects and other list-likes with `DataFrame` leading to operations being performed row-wise instead of column-wise (GH17901)

1.5.7.8 Numeric

• Bug in `.clip()` with `axis=1` and a list-like for `threshold` is passed; previously this raised `ValueError` (GH15390)
• `Series.clip()` and `DataFrame.clip()` now treat `NA` values for upper and lower arguments as `None` instead of raising `ValueError` (GH17276).

1.5.7.9 Categorical

• Bug in `Series.isin()` when called with a categorical (GH16639)
• Bug in the categorical constructor with empty values and categories causing the `.categories` to be an empty `Float64Index` rather than an empty `Index` with object dtype (GH17248)
• Bug in categorical operations with `Series.cat` not preserving the original `Series`’ name (GH17509)
• Bug in `DataFrame.merge()`.cat failing for categorical columns with boolean/int data types (GH17187)
• Bug in constructing a `Categorical/CategoricalDtype` when the specified `categories` are of categorical type (GH17884).

1.5.7.10 PyPy

• Compatibility with PyPy in `read_csv()` with `usecols=[<unsorted ints>]` and `read_json()` (GH17351)
• Split tests into cases for CPython and PyPy where needed, which highlights the fragility of index matching with `float('nan')`, `np.nan` and `NAT` (GH17351)
• Fix `DataFrame.memory_usage()` to support PyPy. Objects on PyPy do not have a fixed size, so an approximation is used instead (GH17228)

1.5.7.11 Other

• Bug where some inplace operators were not being wrapped and produced a copy when invoked (GH12962)
• Bug in `eval()` where the `inplace` parameter was being incorrectly handled (GH16732)
1.6 v0.20.3 (July 7, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

What’s new in v0.20.3

- **Bug Fixes**
  - Conversion
  - Indexing
  - I/O
  - Plotting
  - Reshaping
  - Categorical

1.6.1 Bug Fixes

- Fixed a bug in failing to compute rolling computations of a column-MultiIndexed DataFrame (GH16789, GH16825)
- Fixed a pytest marker failing downstream packages’ tests suites (GH16680)

1.6.1.1 Conversion

- Bug in pickle compat prior to the v0.20.x series, when UTC is a timezone in a Series/DataFrame/Index (GH16608)
- Bug in Series construction when passing a Series with dtype='category' (GH16524).
- Bug in DataFrame.astype() when passing a Series as the dtype kwarg. (GH16717).

1.6.1.2 Indexing

- Bug in Float64Index causing an empty array instead of None to be returned from .get(np.nan) on a Series whose index did not contain any NaNs (GH8569)
- Bug in MultiIndex.isin causing an error when passing an empty iterable (GH16777)
- Fixed a bug in a slicing DataFrame/Series that have a TimedeltaIndex (GH16637)

1.6.1.3 I/O

- Bug in read_csv() in which files weren’t opened as binary files by the C engine on Windows, causing EOF characters mid-field, which would fail (GH16039, GH16559, GH16675)
- Bug in read_hdf() in which reading a Series saved to an HDF file in ‘fixed’ format fails when an explicit mode='r' argument is supplied (GH16583)
• Bug in `DataFrame.to_latex()` where `bold_rows` was wrongly specified to be `True` by default, whereas in reality row labels remained non-bold whatever parameter provided. (GH16707)
• Fixed an issue with `DataFrame.style()` where generated element ids were not unique (GH16780)
• Fixed loading a `DataFrame` with a `PeriodIndex, from a format='fixed' HDFStore, in Python 3, that was written in Python 2 (GH16781)

1.6.1.4 Plotting

• Fixed regression that prevented RGB and RGBA tuples from being used as color arguments (GH16233)
• Fixed an issue with `DataFrame.plot.scatter()` that incorrectly raised a `KeyError` when categorical data is used for plotting (GH16199)

1.6.1.5 Reshaping

• `PeriodIndex / TimedeltaIndex.join` was missing the `sort=` kwarg (GH16541)
• Bug in joining on a `MultiIndex` with a `category` dtype for a level (GH16627).
• Bug in `merge()` when merging/joining with multiple categorical columns (GH16767)

1.6.1.6 Categorical

• Bug in `DataFrame.sort_values` not respecting the `kind` parameter with categorical data (GH16793)

1.7 v0.20.2 (June 4, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

What’s new in v0.20.2

• Enhancements
• Performance Improvements
• Bug Fixes
  – Conversion
  – Indexing
  – I/O
  – Plotting
  – Groupby/Resample/Rolling
  – Sparse
  – Reshaping
  – Numeric
  – Categorical
1.7.1 Enhancements

- Series provides a `to_latex` method (GH16180)
- A new groupby method `ngroup()`, parallel to the existing `cumcount()`, has been added to return the group order (GH11642); see here.

1.7.2 Performance Improvements

- Performance regression fix when indexing with a list-like (GH16285)
- Performance regression fix for MultiIndexes (GH16319, GH16346)
- Improved performance of `.clip()` with scalar arguments (GH15400)
- Improved performance of groupby with categorical groupers (GH16413)
- Improved performance of `MultiIndex.remove_unused_levels()` (GH16556)

1.7.3 Bug Fixes

- Silenced a warning on some Windows environments about “tput: terminal attributes: No such device or address” when detecting the terminal size. This fix only applies to python 3 (GH16496)
- Bug in using `pathlib.Path` or `py.path.local` objects with io functions (GH16291)
- Bug in `Index.symmetric_difference()` on two equal MultiIndex’s, results in a `TypeError` (GH13490)
- Bug in `DataFrame.update()` with `overwrite=False` and `NaN` values (GH15593)
- Passing an invalid engine to `read_csv()` now raises an informative `ValueError` rather than `UnboundLocalError`. (GH16511)
- Bug in `unique()` on an array of tuples (GH16519)
- Bug in `cut()` when labels are set, resulting in incorrect label ordering (GH16459)
- Fixed a compatibility issue with IPython 6.0’s tab completion showing deprecation warnings on Categoricals (GH16409)

1.7.3.1 Conversion

- Bug in `to_numeric()` in which empty data inputs were causing a segfault of the interpreter (GH16302)
- Silence numpy warnings when broadcasting `DataFrame` to `Series` with comparison ops (GH16378, GH16306)
1.7.3.2 Indexing

- Bug in `DataFrame.reset_index(level=)` with single level index (GH16263)
- Bug in partial string indexing with a monotonic, but not strictly-monotonic, index incorrectly reversing the slice bounds (GH16515)
- Bug in `MultiIndex.remove_unused_levels()` that would not return a `MultiIndex` equal to the original. (GH16556)

1.7.3.3 I/O

- Bug in `read_csv()` when comment is passed in a space delimited text file (GH16472)
- Bug in `read_csv()` not raising an exception with nonexistent columns in `usecols` when it had the correct length (GH14671)
- Bug that would force importing of the clipboard routines unnecessarily, potentially causing an import error on startup (GH16288)
- Bug that raised `IndexError` when HTML-rendering an empty `DataFrame` (GH15953)
- Bug in `read_csv()` in which tarfile object inputs were raising an error in Python 2.x for the C engine (GH16530)
- Bug where `DataFrame.to_html()` ignored the `index_names` parameter (GH16493)
- Bug where `pd.read_hdf()` returns numpy strings for index names (GH13492)
- Bug in `HDFStore.select_as_multiple()` where start/stop arguments were not respected (GH16209)

1.7.3.4 Plotting

- Bug in `DataFrame.plot` with a single column and a list-like color (GH3486)
- Bug in `plot` where `NaT` in `DatetimeIndex` results in `Timestamp.min` (GH12405)
- Bug in `DataFrame.boxplot` where `figsize` keyword was not respected for non-grouped boxplots (GH11959)

1.7.3.5 Groupby/Resample/Rolling

- Bug in creating a time-based rolling window on an empty `DataFrame` (GH15819)
- Bug in `rolling.cov()` with offset window (GH16058)
- Bug in `.resample()` and `.groupby()` when aggregating on integers (GH16361)

1.7.3.6 Sparse

- Bug in construction of `SparseDataFrame from scipy.sparse.dok_matrix` (GH16179)
1.7.3.7 Reshaping

- Bug in `DataFrame.stack` with unsorted levels in `MultiIndex` columns (GH16323)
- Bug in `pd.wide_to_long()` where no error was raised when `i` was not a unique identifier (GH16382)
- Bug in `Series.isin(..)` with a list of tuples (GH16394)
- Bug in construction of a `DataFrame` with mixed dtypes including an all-NaT column. (GH16395)
- Bug in `DataFrame.agg()` and `Series.agg()` with aggregating on non-callable attributes (GH16405)

1.7.3.8 Numeric

- Bug in `.interpolate()`, where `limit_direction` was not respected when `limit=None` (default) was passed (GH16282)

1.7.3.9 Categorical

- Fixed comparison operations considering the order of the categories when both categoricals are unordered (GH16014)

1.7.3.10 Other

- Bug in `DataFrame.drop()` with an empty-list with non-unique indices (GH16270)

1.8 v0.20.1 (May 5, 2017)

This is a major release from 0.19.2 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- New `.agg()` API for `Series/DataFrame` similar to the groupby-rolling-resample API’s, see [here](#)  
- Integration with the `feather-format`, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see [here](#).  
- The `.ix` indexer has been deprecated, see [here](#)  
- `Panel` has been deprecated, see [here](#)  
- Addition of an `IntervalIndex` and `Interval` scalar type, see [here](#)  
- Improved user API when grouping by index levels in `.groupby()`, see [here](#)  
- Improved support for `UInt64` dtypes, see [here](#)  
- A new orient for JSON serialization, `orient='table'`, that uses the Table Schema spec and that gives the possibility for a more interactive repr in the Jupyter Notebook, see [here](#)  
- Experimental support for exporting styled DataFrames (`DataFrame.style`) to Excel, see [here](#)  
- Window binary corr/cov operations now return a MultiIndexed `DataFrame` rather than a `Panel`, as `Panel` is now deprecated, see [here](#)  
- Support for S3 handling now uses `s3fs`, see [here](#)
Google BigQuery support now uses the pandas-gbq library, see here

**Warning:** Pandas has changed the internal structure and layout of the codebase. This can affect imports that are not from the top-level pandas.* namespace, please see the changes here.

Check the API Changes and deprecations before updating.

**Note:** This is a combined release for 0.20.0 and and 0.20.1. Version 0.20.1 contains one additional change for backwards-compatibility with downstream projects using pandas’ utils routines. (GH16250)

### What’s new in v0.20.0

- **New features**
  - `agg` API for DataFrame/Series
  - `dtype` keyword for data I/O
  - `.to_datetime()` has gained an `origin` parameter
  - Groupby Enhancements
  - Better support for compressed URLs in `read_csv`
  - Pickle file I/O now supports compression
  - `UInt64` Support Improved
  - `GroupBy` on Categoricals
  - `Table Schema` Output
  - SciPy sparse matrix from/to `SparseDataFrame`
  - Excel output for styled DataFrames
  - IntervalIndex
  - Other Enhancements

- **Backwards incompatible API changes**
  - Possible incompatibility for HDF5 formats created with pandas < 0.13.0
  - Map on Index types now return other Index types
  - Accessing datetime fields of Index now return Index
  - `pd.unique` will now be consistent with extension types
  - `S3` File Handling
  - Partial String Indexing Changes
  - Concat of different float dtypes will not automatically upcast
  - Pandas Google BigQuery support has moved
  - Memory Usage for Index is more Accurate
  - `DataFrame.sort_index` changes
1.8.1 New features

1.8.1.1 agg API for DataFrame/Series

Series & DataFrame have been enhanced to support the aggregation API. This is a familiar API from groupby, window operations, and resampling. This allows aggregation operations in a concise way by using `agg()` and
transform(). The full documentation is here (GH1623).

Here is a sample

```python
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
                  index=pd.date_range('1/1/2000', periods=10))

In [2]: df.iloc[3:7] = np.nan

In [3]: df
Out[3]:
       A     B     C
2000-01-01 1.682600 0.413582 1.689516
2000-01-02 -2.099110 -1.180182 1.595661
2000-01-03 -0.419048 0.522165 -1.208946
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 0.955435 -0.133009 2.011466
2000-01-09 0.578780 0.897126 -0.980013
2000-01-10 -0.045748 0.361601 -0.208039
```

One can operate using string function names, callables, lists, or dictionaries of these.

Using a single function is equivalent to .apply.

```python
In [4]: df.agg('sum')
Out[4]:
       A     B     C
A   0.652908 0.881282 2.899645
dtype: float64
```

Multiple aggregations with a list of functions.

```python
In [5]: df.agg(['sum', 'min'])
Out[5]:
          A      B      C
sum  0.652908 0.881282 2.899645
min -2.099110 -1.180182 -1.208946
```

Using a dict provides the ability to apply specific aggregations per column. You will get a matrix-like output of all of the aggregators. The output has one column per unique function. Those functions applied to a particular column will be NaN:

```python
In [6]: df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
Out[6]:
          A      B
max   NaN  0.897126
min -2.099110 -1.180182
sum  0.652908 NaN
```

The API also supports a.transform() function for broadcasting results.

```python
In [7]: df.transform(['abs', lambda x: x - x.min()])
Out[7]:
```
When presented with mixed dtypes that cannot be aggregated, `.agg()` will only take the valid aggregations. This is similar to how groupby `.agg()` works. (GH15015)

```python
In [8]: df = pd.DataFrame({'A': [1, 2, 3],
                      'B': [1., 2., 3.],
                      'C': ['foo', 'bar', 'baz'],
                      'D': pd.date_range('20130101', periods=3))

In [9]: df.dtypes
Out[9]:
A   int64
B   float64
C     object
D  datetime64[ns]
dtype: object

In [10]: df.agg({'min': 'min', 'sum': 'sum'})
Out[10]:
          A   B   C   D
min   1.0  1.0  bar  2013-01-01
sum  6.0  6.0  foobar baz   NaT
```

### 1.8.1.2 dtype keyword for data IO

The 'python' engine for `read_csv()`, as well as the `read_fwf()` function for parsing fixed-width text files and `read_excel()` for parsing Excel files, now accept the `dtype` keyword argument for specifying the types of specific columns (GH14295). See the `io docs` for more information.

```python
In [11]: data = "a b
1 2
3 4"

In [12]: pd.read_fwf(StringIO(data)).dtypes
Out[12]:
a   int64
b   int64
dtype: object

In [13]: pd.read_fwf(StringIO(data), dtype={'a':'float64', 'b':'object'}).dtypes
Out[13]:
a   float64
b     object
dtype: object
```
1.8.1.3  `.to_datetime()` has gained an `origin` parameter

`to_datetime()` has gained a new parameter, `origin`, to define a reference date from where to compute the resulting timestamps when parsing numerical values with a specific `unit` specified. (GH11276, GH11745)

For example, with 1960-01-01 as the starting date:

```python
In [14]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[14]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype='datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00, which is commonly called 'unix epoch' or POSIX time. This was the previous default, so this is a backward compatible change.

```python
In [15]: pd.to_datetime([1, 2, 3], unit='D')
Out[15]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype='datetime64[ns]', freq=None)
```

1.8.1.4  Groupby Enhancements

Strings passed to `DataFrame.groupby()` as the `by` parameter may now reference either column names or index level names. Previously, only column names could be referenced. This allows to easily group by a column and index level at the same time. (GH5677)

```python
In [16]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
                   ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
In [17]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])
In [18]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
                           'B': np.arange(8)},
                           index=index)
In [19]: df
Out[19]:
   A B
first second
bar   one 1 0
      two 1 1
      baz one 1 2
      two 1 3
      foo one 2 4
      two 2 5
      qux one 3 6
      two 3 7
In [20]: df.groupby(['second', 'A']).sum()
```

(continues on next page)
1.8.1.5 Better support for compressed URLs in read_csv

The compression code was refactored (GH12688). As a result, reading dataframes from URLs in read_csv() or read_table() now supports additional compression methods: xz, bz2, and zip (GH14570). Previously, only gzip compression was supported. By default, compression of URLs and paths are now inferred using their file extensions. Additionally, support for bz2 compression in the python 2 C-engine improved (GH14874).

In [21]: url = 'https://github.com/{repo}/raw/{branch}/{path}'.format(  
           ....:     repo = 'pandas-dev/pandas',  
           ....:     branch = 'master',  
           ....:     path = 'pandas/tests/io/parser/data/salaries.csv.bz2',  
           ....: )  
           ....:  
In [22]: df = pd.read_table(url, compression='infer')  # default, infer compression  
In [23]: df = pd.read_table(url, compression='bz2')  # explicitly specify compression  
In [24]: df.head(2)  
Out[24]:  
<table>
<thead>
<tr>
<th></th>
<th>S</th>
<th>X</th>
<th>E</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>13876</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>11608</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

1.8.1.6 Pickle file I/O now supports compression

read_pickle(), DataFrame.to_pickle() and Series.to_pickle() can now read from and write to compressed pickle files. Compression methods can be an explicit parameter or be inferred from the file extension. See the docs here.

In [25]: df = pd.DataFrame({  
            ....:     'A': np.random.randn(1000),  
            ....:     'B': 'foo',  
            ....:     'C': pd.date_range('20130101', periods=1000, freq='s')})  
            ....:  
Using an explicit compression type

In [26]: df.to_pickle("data.pkl.compress", compression="gzip")  
In [27]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")  
In [28]: rt.head()  
Out[28]:  
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.578227</td>
<td>foo</td>
<td>2013-01-01 00:00:00</td>
</tr>
<tr>
<td>-0.230575</td>
<td>foo</td>
<td>2013-01-01 00:00:01</td>
</tr>
<tr>
<td>0.695530</td>
<td>foo</td>
<td>2013-01-01 00:00:02</td>
</tr>
<tr>
<td>-0.466001</td>
<td>foo</td>
<td>2013-01-01 00:00:03</td>
</tr>
<tr>
<td>-0.154972</td>
<td>foo</td>
<td>2013-01-01 00:00:04</td>
</tr>
</tbody>
</table>
The default is to infer the compression type from the extension (compression='infer'):

```
In [29]: df.to_pickle("data.pkl.gz")
In [30]: rt = pd.read_pickle("data.pkl.gz")
In [31]: rt.head()
Out[31]:
   A   B          C
0  1.578227  foo  2013-01-01 00:00:00
1  0.230575  foo  2013-01-01 00:00:01
2  0.695530  foo  2013-01-01 00:00:02
3  0.466001  foo  2013-01-01 00:00:03
4 -0.154972  foo  2013-01-01 00:00:04
```

```
In [32]: df["A"].to_pickle("s1.pkl.bz2")
In [33]: rt = pd.read_pickle("s1.pkl.bz2")
In [34]: rt.head()
Out[34]:
   0  1.578227
   1  0.230575
   2  0.695530
   3  0.466001
   4 -0.154972
Name: A, dtype: float64
```

### 1.8.1.7 UInt64 Support Improved

Pandas has significantly improved support for operations involving unsigned, or purely non-negative, integers. Previously, handling these integers would result in improper rounding or data-type casting, leading to incorrect results. Notably, a new numerical index, `UInt64Index`, has been created (GH14937)

```
In [35]: idx = pd.UInt64Index([1, 2, 3])
In [36]: df = pd.DataFrame({'A': ['a', 'b', 'c']}, index=idx)
In [37]: df.index
Out[37]: UInt64Index([1, 2, 3], dtype='uint64')
```

- Bug in converting object elements of array-like objects to unsigned 64-bit integers (GH4471, GH14982)
- Bug in `Series.unique()` in which unsigned 64-bit integers were causing overflow (GH14721)
- Bug in `DataFrame` construction in which unsigned 64-bit integer elements were being converted to objects (GH14881)
- Bug in `pd.read_csv()` in which unsigned 64-bit integer elements were being improperly converted to the wrong data types (GH14983)
- Bug in `pd.unique()` in which unsigned 64-bit integers were causing overflow (GH14915)
- Bug in `pd.value_counts()` in which unsigned 64-bit integers were being erroneously truncated in the output (GH14934)
1.8.1.8 GroupBy on Categoricals

In previous versions, `.groupby(..., sort=False)` would fail with a `ValueError` when grouping on a categorical series with some categories not appearing in the data. (GH13179)

```python
In [38]: chromosomes = np.r_[np.arange(1, 23).astype(str), ['X', 'Y']]

In [39]: df = pd.DataFrame(
   ....:   {'A': np.random.randint(100),
   ....:    'B': np.random.randint(100),
   ....:    'C': np.random.randint(100),
   ....:    'chromosomes': pd.Categorical(np.random.choice(chromosomes, 100),
   ....:                                     categories=chromosomes,
   ....:                                     ordered=True))

In [40]: df
Out[40]:
   A  B  C  chromosomes
  0  80 36  94       12
  1  80 36  94       X
  2  80 36  94       19
  3  80 36  94       22
  4  80 36  94       17
  5  80 36  94        6
  6  80 36  94       13
   ...  ...  ...  ...  
 93  80 36  94       21
 94  80 36  94       20
 95  80 36  94       11
 96  80 36  94       16
 97  80 36  94       21
 98  80 36  94       18
 99  80 36  94        8

[100 rows x 4 columns]
```

**Previous Behavior:**

```python
In [3]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
---------------------------------------------------------------------------
ValueError: items in new_categories are not the same as in old categories
```

**New Behavior:**

```python
In [41]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
Out[41]:
      A  B  C
  chromosomes
     2  320 144 376
     3  400 180 470
     4  240 108 282
     5  240 108 282
     6  400 180 470
     7  400 180 470
     8  480 216 564
    ...  ...  ...  ...
    19  400 180 470

(continues on next page)
### 1.8.1.9 Table Schema Output

The new `orient` 'table' for `DataFrame.to_json()` will generate a Table Schema compatible string representation of the data.

```python
In [42]: df = pd.DataFrame(
    ....:     {'A': [1, 2, 3],
    ....:      'B': ['a', 'b', 'c'],
    ....:      'C': pd.date_range('2016-01-01', freq='d', periods=3),
    ....:     }, index=pd.Index(range(3), name='idx'))

In [43]: df
Out[43]:
   A  B         C
idx  
0  1  a 2016-01-01
1  2  b 2016-01-02
2  3  c 2016-01-03

In [44]: df.to_json(orient='table')

"schema": {"fields": [{"name": "idx", "type": "integer"}, ]
  , {"name": "A", "type": "integer"}, ]
  , {"name": "B", "type": "string"}, ]
  , {"name": "C", "type": "datetime"}, ]
  , "primaryKey": ["idx"], ]
  , "pandas_version": "0.20.0"}, ]
  , "data": [{"idx": 0,"A": 1,"B": "a", ]
  , "C": "2016-01-01T00:00:00.000Z"}, ]
  , {"idx": 1,"A": 2,"B": "b", ]
  , "C": "2016-01-02T00:00:00.000Z"}, ]
  , {"idx": 2,
```

See [IO: Table Schema for more information.](#)

Additionally, the repr for DataFrame and Series can now publish this JSON Table schema representation of the Series or DataFrame if you are using IPython (or another frontend like nteract using the Jupyter messaging protocol). This gives frontends like the Jupyter notebook and nteract more flexibility in how they display pandas objects, since they have more information about the data. You must enable this by setting the `display.html.table_schema` option to `True`.

### 1.8.1.10 SciPy sparse matrix from/to SparseDataFrame

Pandas now supports creating sparse dataframes directly from `scipy.sparse.spmatrix` instances. See the [documentation](#) for more information. (GH4343)

All sparse formats are supported, but matrices that are not in the `COOrdinate` format will be converted, copying data as needed.
In [45]: from scipy.sparse import csr_matrix

In [46]: arr = np.random.random(size=(1000, 5))

In [47]: arr[arr < .9] = 0

In [48]: sp_arr = csr_matrix(arr)

In [49]: sp_arr

Out[49]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
with 521 stored elements in Compressed Sparse Row format>

In [50]: sdf = pd.SparseDataFrame(sp_arr)

In [51]: sdf

Out[51]:
          0        1        2        3        4
0  NaN   NaN   NaN   NaN  NaN  NaN
1  NaN   NaN   NaN 0.955103   NaN  NaN
2  NaN   NaN   NaN 0.900469   NaN  NaN
3  NaN   NaN   NaN   NaN   NaN  NaN
4  NaN  0.924771   NaN   NaN   NaN  NaN
5  NaN   NaN   NaN   NaN   NaN  NaN
6  NaN   NaN   NaN   NaN   NaN  NaN
...      ...      ...      ...      ...  ...
993  NaN   NaN   NaN   NaN   NaN  NaN
994  NaN   NaN   NaN  0.972191   NaN  NaN
995  NaN  0.979898  0.97901   NaN   NaN  NaN
996  NaN   NaN   NaN   NaN   NaN  NaN
997  NaN   NaN   NaN   NaN   NaN  NaN
998  NaN   NaN   NaN   NaN   NaN  NaN
999  NaN   NaN   NaN   NaN   NaN  NaN

[1000 rows x 5 columns]

To convert a SparseDataFrame back to sparse SciPy matrix in COO format, you can use:

In [52]: sdf.to_coo()

Out[52]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
with 521 stored elements in COOrdinate format>

1.8.1.11 Excel output for styled DataFrames

Experimental support has been added to export DataFrame.style formats to Excel using the openpyxl engine. (GH15530)

For example, after running the following, styled.xlsx renders as below:
In [56]: df.iloc[0, 2] = np.nan

In [57]: df

Out[57]:
     A    B         C   D         E
0  1.0  1.329212  NaN  -0.316280  -0.990810
1  2.0  -1.070816 -1.438713  0.564417   0.295722
2  3.0   1.626404  0.219565  0.678805   1.889273
3  4.0   0.961538  0.104011  -0.481165   0.850229
4  5.0   1.453425  1.057737  0.165562   0.515018
5  6.0   1.336936  0.562861  1.392855  -0.063328
6  7.0   0.121668  1.207603  -0.002040   1.627796
7  8.0   0.354493  1.037528  -0.385684   0.519818
8  9.0   1.666583  1.325963  1.428984  -2.089354
9 10.0  -0.129820  0.631523  -0.586538   0.290720

In [58]: styled = df.style.
....:     applymap(lambda val: 'color: %s' % 'red' if val < 0 else 'black').
....:     highlight_max()
....:

In [59]: styled.to_excel('styled.xlsx', engine='openpyxl')

See the Style documentation for more detail.

1.8.1.12 IntervalIndex

pandas has gained an `IntervalIndex` with its own `dtype`, `interval` as well as the `Interval` scalar type. These allow first-class support for interval notation, specifically as a return type for the categories in `cut()` and `qcut()`. The `IntervalIndex` allows some unique indexing, see the docs. (GH7640, GH8625)
Warning: These indexing behaviors of the IntervalIndex are provisional and may change in a future version of pandas. Feedback on usage is welcome.

Previous behavior:

The returned categories were strings, representing Intervals

```
In [1]: c = pd.cut(range(4), bins=2)
In [2]: c
Out[2]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3], (1.5, 3]
Categories (2, object): [(-0.003, 1.5] < (1.5, 3]]
In [3]: c.categories
Out[3]: Index(['(-0.003, 1.5]', '(1.5, 3]'], dtype='object')
```

New behavior:

```
In [60]: c = pd.cut(range(4), bins=2)
In [61]: c
Out[61]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
In [62]: c.categories
Out[62]: IntervalIndex([(-0.003, 1.5], (1.5, 3.0]
                           closed='right',
                           dtype='interval[float64]')
```

Furthermore, this allows one to bin other data with these same bins, with NaN representing a missing value similar to other dtypes.

```
In [63]: pd.cut([0, 3, 1, 1], bins=c.categories)
Out[63]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
```

An IntervalIndex can also be used in Series and DataFrame as the index.

```
In [64]: df = pd.DataFrame({'A': range(4),
                               'B': pd.cut([0, 3, 1, 1], bins=c.categories)})
In [65]: df.set_index('B')
Out[65]:
       A
       B
    (-0.003, 1.5]  0
          (1.5, 3.0]  1
        (-0.003, 1.5]  2
           (-0.003, 1.5]  3
```
Selecting via a specific interval:

```
In [66]: df.loc[pd.Interval(1.5, 3.0)]
Out[66]:
A   1
Name: (1.5, 3.0], dtype: int64
```

Selecting via a scalar value that is contained in the intervals.

```
In [67]: df.loc[0]
Out[67]:
       A
(-0.003, 1.5]  0
(-0.003, 1.5]  2
(-0.003, 1.5]  3
```

### 1.8.1.13 Other Enhancements

- `DataFrame.rolling()` now accepts the parameter `closed='right'|'left'|'both'|'neither'` to choose the rolling window-endpoint closedness. See the documentation (GH13965)
- Integration with the feather-format, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see here.
- `Series.str.replace()` now accepts a callable, as replacement, which is passed to `re.sub` (GH15055)
- `Series.str.replace()` now accepts a compiled regular expression as a pattern (GH15446)
- `Series.sort_index` accepts parameters `kind` and `na_position` (GH13589, GH14444)
- `DataFrame` and `DataFrame.groupby()` have gained a `nunique()` method to count the distinct values over an axis (GH14336, GH15197).
- `DataFrame` has gained a `melt()` method, equivalent to `pd.melt()`, for unpivoting from a wide to long format (GH12640).
- `pd.read_excel()` now preserves sheet order when using `sheetname=None` (GH9930)
- Multiple offset aliases with decimal points are now supported (e.g. 0.5min is parsed as 30s) (GH8419)
- `.isnull()` and `.notnull()` have been added to `Index` object to make them more consistent with the `Series` API (GH15300)
- New `UnsortedIndexError` (subclass of `KeyError`) raised when indexing/slicing into an unsorted `MultiIndex` (GH11897). This allows differentiation between errors due to lack of sorting or an incorrect key. See here
- `MultiIndex` has gained a `.to_frame()` method to convert to a `DataFrame` (GH12397)
- `pd.cut` and `pd.qcut` now support `datetime64` and `timedelta64` dtypes (GH14714, GH14798)
- `pd.qcut` has gained the `duplicates='raise'/'drop'` option to control whether to raise on duplicated edges (GH7751)
- `Series` provides a `to_excel` method to output Excel files (GH8825)
- The `usecols` argument in `pd.read_csv()` now accepts a callable function as a value (GH14154)
- The `skiprows` argument in `pd.read_csv()` now accepts a callable function as a value (GH10882)
- The `nrows` and `chunksize` arguments in `pd.read_csv()` are supported if both are passed (GH6774, GH15755)
• DataFrame.plot now prints a title above each subplot if suplots=True and title is a list of strings (GH14753)

• DataFrame.plot can pass the matplotlib 2.0 default color cycle as a single string as color parameter, see here. (GH15516)

• Series.interpolate() now supports timedelta as an index type with method='time' (GH6424)

• Addition of a level keyword to DataFrame/Series.rename to rename labels in the specified level of a MultiIndex (GH4160).

• DataFrame.reset_index() will now interpret a tuple index.name as a key spanning across levels of columns, if this is a MultiIndex (GH16164)

• Timedelta.isoformat method added for formatting Timedeltas as an ISO 8601 duration. See the Timedelta docs (GH15136)

• .select_dtypes() now allows the string datetimetz to generically select datetimes with tz (GH14910)

• The .to_latex() method will now accept multicol and multirow arguments to use the accompanying LaTeX enhancements

• pd.merge_asof() gained the option direction='backward'|'forward'|'nearest' (GH14887)

• Series/DataFrame.asfreq() have gained a fill_value parameter, to fill missing values (GH3715).

• Series/DataFrame.resample.asfreq have gained a fill_value parameter, to fill missing values during resampling (GH3715).

• pandas.util.hash_pandas_object() has gained the ability to hash a MultiIndex (GH15224)

• Series/DataFrame.squeeze() have gained the axis parameter. (GH15339)

• DataFrame.to_excel() has a new freeze_panes parameter to turn on Freeze Panes when exporting to Excel (GH15160)

• pd.read_html() will parse multiple header rows, creating a MultiIndex header. (GH13434).

• HTML table output skips colspan or rowspan attribute if equal to 1. (GH15403)

• pandas.io.formats.style.Styler template now has blocks for easier extension, see the example notebook (GH15649)

• Styler.render() now accepts **kwargs to allow user-defined variables in the template (GH15649)

• Compatibility with Jupyter notebook 5.0; MultiIndex column labels are left-aligned and MultiIndex row-labels are top-aligned (GH15379)

• TimedeltaIndex now has a custom date-tick formatter specifically designed for nanosecond level precision (GH8711)

• pd.api.types.union_categoricals gained the ignore_ordered argument to allow ignoring the ordered attribute of unioned categoricals (GH13410). See the categorical union docs for more information.

• DataFrame.to_latex() and DataFrame.to_string() now allow optional header aliases. (GH15536)

• Re-enable the parse_dates keyword of pd.read_excel() to parse string columns as dates (GH14326)

• Added .empty property to subclasses of Index. (GH15270)

• Enabled floor division for Timedelta and TimedeltaIndex (GH15828)

• pandas.io.json.json_normalize() gained the option errors='ignore'|'raise'; the default is errors='raise' which is backward compatible. (GH14583)
• pandas.io.json.json_normalize() with an empty list will return an empty DataFrame (GH15534)

• pandas.io.json.json_normalize() has gained a sep option that accepts str to separate joined fields; the default is “.”, which is backward compatible. (GH14883)

• MultiIndex.remove_unused_levels() has been added to facilitate removing unused levels. (GH15694)

• pd.read_csv() will now raise a ParserError error whenever any parsing error occurs (GH15913, GH15925)

• pd.read_csv() now supports the error_bad_lines and warn_bad_lines arguments for the Python parser (GH15925)

• The display.show_dimensions option can now also be used to specify whether the length of a Series should be shown in its repr (GH7117).

• parallel_coordinates() has gained a sort_labels keyword argument that sorts class labels and the colors assigned to them (GH15908)

• Options added to allow one to turn on/off using bottleneck and numexpr, see here (GH16157)

• DataFrame.style.bar() now accepts two more options to further customize the bar chart. Bar alignment is set with align='left'|'mid'|'zero', the default is “left”, which is backward compatible; You can now pass a list of color=[color_negative, color_positive]. (GH14757)

1.8.2 Backwards incompatible API changes

1.8.2.1 Possible incompatibility for HDF5 formats created with pandas < 0.13.0

pd.TimeSeries was deprecated officially in 0.17.0, though has already been an alias since 0.13.0. It has been dropped in favor of pd.Series. (GH15098).

This may cause HDF5 files that were created in prior versions to become unreadable if pd.TimeSeries was used. This is most likely to be for pandas < 0.13.0. If you find yourself in this situation. You can use a recent prior version of pandas to read in your HDF5 files, then write them out again after applying the procedure below.

```
In [2]: s = pd.TimeSeries([1,2,3], index=pd.date_range('20130101', periods=3))

In [3]: s
Out[3]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64

In [4]: type(s)
Out[4]: pandas.core.series.TimeSeries

In [5]: s = pd.Series(s)

In [6]: s
Out[6]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64
```
In [7]: `type(s)`
Out[7]: pandas.core.series.Series

### 1.8.2.2 Map on Index types now return other Index types

map on an Index now returns an Index, not a numpy array (GH12766)

<table>
<thead>
<tr>
<th>In</th>
<th>Code</th>
<th>Out</th>
</tr>
</thead>
<tbody>
<tr>
<td>[68]</td>
<td><code>idx = Index([1, 2])</code></td>
<td><code>idx</code></td>
</tr>
<tr>
<td>[69]</td>
<td><code>idx</code></td>
<td><code>Int64Index([1, 2], dtype='int64')</code></td>
</tr>
<tr>
<td>[70]</td>
<td><code>mi = MultiIndex.from_tuples([(1, 2), (2, 4)])</code></td>
<td><code>mi</code></td>
</tr>
<tr>
<td>[71]</td>
<td><code>mi</code></td>
<td><code>MultiIndex(levels=[[1, 2], [2, 4]], labels=[[0, 1], [0, 1]])</code></td>
</tr>
</tbody>
</table>

Previous Behavior:

<table>
<thead>
<tr>
<th>In</th>
<th>Code</th>
<th>Out</th>
</tr>
</thead>
<tbody>
<tr>
<td>[5]</td>
<td><code>idx.map(lambda x: x * 2)</code></td>
<td><code>array([2, 4])</code></td>
</tr>
<tr>
<td>[6]</td>
<td><code>idx.map(lambda x: (x, x * 2))</code></td>
<td><code>array([(1, 2), (2, 4)], dtype=object)</code></td>
</tr>
<tr>
<td>[7]</td>
<td><code>mi.map(lambda x: x)</code></td>
<td><code>array([(1, 2), (2, 4)], dtype=object)</code></td>
</tr>
<tr>
<td>[8]</td>
<td><code>mi.map(lambda x: x[0])</code></td>
<td><code>array([1, 2])</code></td>
</tr>
</tbody>
</table>

New Behavior:

<table>
<thead>
<tr>
<th>In</th>
<th>Code</th>
<th>Out</th>
</tr>
</thead>
<tbody>
<tr>
<td>[72]</td>
<td><code>idx.map(lambda x: x * 2)</code></td>
<td><code>Int64Index([2, 4], dtype='int64')</code></td>
</tr>
<tr>
<td>[73]</td>
<td><code>idx.map(lambda x: (x, x * 2))</code></td>
<td><code>MultiIndex(levels=[[1, 2], [2, 4]], labels=[[0, 1], [0, 1]])</code></td>
</tr>
<tr>
<td>[74]</td>
<td><code>mi.map(lambda x: x)</code></td>
<td><code>MultiIndex(levels=[[1, 2], [2, 4]], labels=[[0, 1], [0, 1]])</code></td>
</tr>
<tr>
<td>[75]</td>
<td><code>mi.map(lambda x: x[0])</code></td>
<td><code>Int64Index([1, 2], dtype='int64')</code></td>
</tr>
</tbody>
</table>

map on a Series with datetime64 values may return int64 dtypes rather than int32
1.8.2.3 Accessing datetime fields of Index now return Index

The datetime-related attributes (see here for an overview) of DatetimeIndex, PeriodIndex and TimedeltaIndex previously returned numpy arrays. They will now return a new Index object, except in the case of a boolean field, where the result will still be a boolean ndarray. (GH15022)

Previous behaviour:

```
In [1]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')
In [2]: idx.hour
Out[2]: array([ 0, 10, 20, 6, 16], dtype=int32)
```

New Behavior:

```
In [79]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')
In [80]: idx.hour
Out[80]: Int64Index([0, 10, 20, 6, 16], dtype='int64')
```

This has the advantage that specific Index methods are still available on the result. On the other hand, this might have backward incompatibilities: e.g. compared to numpy arrays, Index objects are not mutable. To get the original ndarray, you can always convert explicitly using np.asarray(idx.hour).

1.8.2.4 pd.unique will now be consistent with extension types

In prior versions, using Series.unique() and pandas.unique() on Categorical and tz-aware data-types would yield different return types. These are now made consistent. (GH15903)
• Datetime tz-aware

Previous behaviour:

```python
# Series
In [5]: pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
                 pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[5]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
              dtype=object)

In [6]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
                           pd.Timestamp('20160101', tz='US/Eastern')]))
Out[6]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

# Index
In [7]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
               pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[7]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]',
                      freq=None)

In [8]: pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
                         pd.Timestamp('20160101', tz='US/Eastern')]))
Out[8]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]',
                      freq=None)
```

New Behavior:

```python
# Series, returns an array of Timestamp tz-aware
In [81]: pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
                 ....: pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[81]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
              dtype=object)

In [82]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
                         ....: pd.Timestamp('20160101', tz='US/Eastern')]))
Out[82]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
              dtype=object)

# Index, returns a DatetimeIndex
In [83]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
              ....: pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[83]: DatetimeIndex(['2016-01-01 05:00:00-05:00'], dtype='datetime64[ns, US/Eastern]',
                      freq=None)

In [84]: pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
                         ....: pd.Timestamp('20160101', tz='US/Eastern')]))
Out[84]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]',
                      freq=None)
```

• Categoricals

Previous behaviour:
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
In [1]: pd.Series(list('baabc'), dtype='category').unique()
Out[1]:
{'b', 'a', 'c'}
Categories (3, object): [b, a, c]

In [2]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[2]:
array(['b', 'a', 'c'], dtype=object)
```

New Behavior:

```python
# returns a Categorical
In [85]: pd.Series(list('baabc'), dtype='category').unique()
Out[85]:
{'b', 'a', 'c'}
Categories (3, object): [b, a, c]

In [86]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[86]:
{'b', 'a', 'c'}
Categories (3, object): [b, a, c]
```

### 1.8.2.5 S3 File Handling

pandas now uses s3fs for handling S3 connections. This shouldn’t break any code. However, since s3fs is not a required dependency, you will need to install it separately, like boto in prior versions of pandas. (GH11915).

### 1.8.2.6 Partial String Indexing Changes

**DatetimeIndex Partial String Indexing** now works as an exact match, provided that string resolution coincides with index resolution, including a case when both are seconds (GH14826). See *Slice vs. Exact Match* for details.

```python
In [87]: df = DataFrame({'a': [1, 2, 3]}, DatetimeIndex(['2011-12-31 23:59:59', '2012-01-01 00:00:00', '2012-01-01 00:00:01']))

Previous Behavior:

In [4]: df['2011-12-31 23:59:59']
Out[4]:
a
2011-12-31 23:59:59 1

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]:
2011-12-31 23:59:59 1
Name: a, dtype: int64

New Behavior:

In [4]: df['2011-12-31 23:59:59']
KeyError: '2011-12-31 23:59:59'

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]: 1
```

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1.8.2.7 Concat of different float dtypes will not automatically upcast

Previously, `concat` of multiple objects with different float dtypes would automatically upcast results to a dtype of float64. Now the smallest acceptable dtype will be used (GH13247)

```
In [88]: df1 = pd.DataFrame(np.array([1.0], dtype=np.float32, ndmin=2))
In [89]: df1.dtypes
Out[89]:
0   float32
dtype: object
In [90]: df2 = pd.DataFrame(np.array([np.nan], dtype=np.float32, ndmin=2))
In [91]: df2.dtypes
Out[91]:
0   float32
dtype: object
```

Previous Behavior:

```
In [7]: pd.concat([df1, df2]).dtypes
Out[7]:
0   float64
dtype: object
```

New Behavior:

```
In [92]: pd.concat([df1, df2]).dtypes
Out[92]:
0   float32
dtype: object
```

1.8.2.8 Pandas Google BigQuery support has moved

pandas has split off Google BigQuery support into a separate package pandas-gbq. You can `conda install pandas-gbq -c conda-forge` or `pip install pandas-gbq` to get it. The functionality of `read_gbq()` and `DataFrame.to_gbq()` remain the same with the currently released version of pandas-gbq=0.1.4. Documentation is now hosted here (GH15347)

1.8.2.9 Memory Usage for Index is more Accurate

In previous versions, showing `.memory_usage()` on a pandas structure that has an index, would only include actual index values and not include structures that facilitated fast indexing. This will generally be different for `Index` and `MultiIndex` and less-so for other index types. (GH15237)

Previous Behavior:

```
In [8]: index = Index(['foo', 'bar', 'baz'])
In [9]: index.memory_usage(deep=True)
Out[9]: 180
In [10]: index.get_loc('foo')
Out[10]: 0
```

(continues on next page)
In [11]: index.memory_usage(deep=True)
Out[11]: 180

New Behavior:

In [8]: index = Index(['foo', 'bar', 'baz'])
In [9]: index.memory_usage(deep=True)
Out[9]: 180
In [10]: index.get_loc('foo')
Out[10]: 0
In [11]: index.memory_usage(deep=True)
Out[11]: 260

1.8.2.10 DataFrame.sort_index changes

In certain cases, calling `.sort_index()` on a MultiIndexed DataFrame would return the same DataFrame without seeming to sort. This would happen with a lexsorted, but non-monotonic levels. (GH15622, GH15687, GH14015, GH13431, GH15797)

This is unchanged from prior versions, but shown for illustration purposes:

In [93]: df = DataFrame(np.arange(6), columns=['value'], index=MultiIndex.from_product([list('BA'), range(3)])
In [94]: df
Out[94]:
   value
0   B  0
   1  1
   2  2
0   A  0
   1  4
   2  5

In [95]: df.index.is_lexsorted()
Out[95]: False
In [96]: df.index.is_monotonic
Out[96]: False

Sorting works as expected

In [97]: df.sort_index()
Out[97]:
   value
   A  0  3
   1  4
   2  5
   B  0  0
   1  1
   2  2
In [98]: df.sort_index().index.is_lexsorted()
Out[98]: True

However, this example, which has a non-monotonic 2nd level, doesn’t behave as desired.

In [100]: df = pd.DataFrame(
    .....:     {'value': [1, 2, 3, 4]},
    .....:     index=pd.MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
    .....:     labels=[[0, 0, 1, 1], [0, 1, 0, 1]])

In [101]: df
Out[101]:
   value
  a bb  1
  aa  2
  b bb  3
  aa  4

Previous Behavior:

In [11]: df.sort_index()
Out[11]:
   value
  a bb  1
  aa  2
  b bb  3
  aa  4

In [14]: df.sort_index().index.is_lexsorted()
Out[14]: True

In [15]: df.sort_index().index.is_monotonic
Out[15]: False

New Behavior:

In [102]: df.sort_index()
Out[102]:
   value
  a aa  2
  bb  1
  b aa  4
  bb  3

In [103]: df.sort_index().index.is_lexsorted()
Out[103]: True

In [104]: df.sort_index().index.is_monotonic
Out[104]: True
1.8.2.11 Groupby Describe Formatting

The output formatting of `groupby.describe()` now labels the `describe()` metrics in the columns instead of the index. This format is consistent with `groupby.agg()` when applying multiple functions at once. (GH4792)

Previous Behavior:

```python
In [1]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})
In [2]: df.groupby('A').describe()
Out[2]:
         B
A  count 2.000000
    mean 1.500000
    std  0.707107
    min  1.000000
   25%  1.250000
   50%  1.500000
   75%  1.750000
   max  2.000000

In [3]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
```

New Behavior:

```python
In [105]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})
In [106]: df.groupby('A').describe()
Out[106]:
         B
A  count 2.000000
    mean 1.500000
    std  0.707107
    min  1.000000
   25%  1.250000
   50%  1.500000
   75%  1.750000
   max  2.000000

In [107]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
```

→

```python
In [107]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
```
### 1.8.2.12 Window Binary Corr/Cov operations return a MultiIndex DataFrame

A binary window operation, like `.corr()` or `.cov()`, when operating on a `.rolling()`, `.expanding()`, or `.ewm()` object, will now return a 2-level MultiIndexed DataFrame rather than a `Panel`, as `Panel` is now deprecated, see here. These are equivalent in function, but a MultiIndexed DataFrame enjoys more support in pandas. See the section on *Windowed Binary Operations* for more information. (GH15677)

```python
In [108]: np.random.seed(1234)

In [109]: df = pd.DataFrame(np.random.rand(100, 2),
                      columns=pd.Index(['A', 'B'], name='bar),
                      index=pd.date_range('20160101',
                      periods=100, freq='D', name='foo'))

In [110]: df.tail()
Out[110]:
   bar  A  B
foo 2016-04-05 0.640880 0.126205
     2016-04-06 0.171465 0.737086
     2016-04-07 0.127029 0.369650
     2016-04-08 0.604334 0.103104
     2016-04-09 0.802374 0.945553

Previous Behavior:

```python
In [2]: df.rolling(12).corr()
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 100 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: 2016-01-01 00:00:00 to 2016-04-09 00:00:00
Major_axis axis: A to B
Minor_axis axis: A to B
```

New Behavior:

```python
In [111]: res = df.rolling(12).corr()

In [112]: res.tail()
Out[112]:
   bar  A  B
foo 2016-04-07 B -0.132090 1.000000
     2016-04-08 A 1.000000 -0.145775
     B -0.145775 1.000000
     2016-04-09 A 1.000000 0.119645
     B 0.119645 1.000000

Retrieving a correlation matrix for a cross-section

```python
In [113]: df.rolling(12).corr().loc['2016-04-07']
Out[113]:
   bar  A  B
foo 2016-04-07 A 1.000000 -0.13209
     B -0.13209 1.000000
```
1.8.2.13 HDFStore where string comparison

In previous versions most types could be compared to string column in a HDFStore usually resulting in an invalid comparison, returning an empty result frame. These comparisons will now raise a TypeError (GH15492)

```
In [114]: df = pd.DataFrame({'unparsed_date': ['2014-01-01', '2014-01-01']})
In [115]: df.to_hdf('store.h5', 'key', format='table', data_columns=True)
In [116]: df.dtypes
Out[116]:
unparsed_date    object
dtype: object

Previous Behavior:
```

```
In [4]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
File "<string>", line 1
  (unparsed_date > 1970-01-01 00:00:01.388552400)
    ^
SyntaxError: invalid token

New Behavior:
```

```
In [18]: ts = pd.Timestamp('2014-01-01')
In [19]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
```

1.8.2.14 Index.intersection and inner join now preserve the order of the left Index

Index.intersection() now preserves the order of the calling Index (left) instead of the other Index (right) (GH15582). This affects inner joins, DataFrame.join() and merge(), and the .align method.

- Index.intersection

```
In [117]: left = pd.Index([2, 1, 0])
In [118]: left
Out[118]: Int64Index([2, 1, 0], dtype='int64')
In [119]: right = pd.Index([1, 2, 3])
In [120]: right
Out[120]: Int64Index([1, 2, 3], dtype='int64')
```

Previous Behavior:

```
In [4]: left.intersection(right)
Out[4]: Int64Index([1, 2], dtype='int64')
```

New Behavior:

```
In [121]: left.intersection(right)
Out[121]: Int64Index([2, 1], dtype='int64')
```
• DataFrame.join and pd.merge

```
In [122]: left = pd.DataFrame({'a': [20, 10, 0]}, index=[2, 1, 0])
In [123]: left
Out[123]:
   a
2  20
1  10
0  0
In [124]: right = pd.DataFrame({'b': [100, 200, 300]}, index=[1, 2, 3])
In [125]: right
Out[125]:
   b
1  100
2  200
3  300
```

Previous Behavior:
```
In [4]: left.join(right, how='inner')
Out[4]:
   a  b
1  10 100
2  20 200
```

New Behavior:
```
In [126]: left.join(right, how='inner')
Out[126]:
   a  b
2  20 200
1  10 100
```

### 1.8.2.15 Pivot Table always returns a DataFrame

The documentation for `pivot_table()` states that a `DataFrame` is always returned. Here a bug is fixed that allowed this to return a `Series` under certain circumstance. (GH4386)

```
in [127]: df = DataFrame({'col1': [3, 4, 5],
.....:               'col2': ['C', 'D', 'E'],
.....:               'col3': [1, 3, 9]})

in [128]: df
Out[128]:
     col1 col2 col3
0      3    C   1
1      4    D   3
2      5    E   9
```
In [2]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[2]:
     col3 col2
1   C    3
3   D    4
9   E    5
Name: col1, dtype: int64

New Behavior:

In [129]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[129]:
     col1
   col3 col2
1   C    3
3   D    4
9   E    5

1.8.2.16 Other API Changes

- numexpr version is now required to be >= 2.4.6 and it will not be used at all if this requisite is not fulfilled (GH15213).
- CParserError has been renamed to ParserError in pd.read_csv() and will be removed in the future (GH12665)
- SparseArray.cumsum() and SparseSeries.cumsum() will now always return SparseArray and SparseSeries respectively (GH12855)
- DataFrame.applymap() with an empty DataFrame will return a copy of the empty DataFrame instead of a Series (GH8222)
- Series.map() now respects default values of dictionary subclasses with a __missing__ method, such as collections.Counter (GH15999)
- .loc has compat with .ix for accepting iterators, and NamedTuples (GH15120)
- interpolate() and fillna() will raise a ValueError if the limit keyword argument is not greater than 0. (GH9217)
- pd.read_csv() will now issue a ParserWarning whenever there are conflicting values provided by the dialect parameter and the user (GH14898)
- pd.read_csv() will now raise a ValueError for the C engine if the quote character is larger than than one byte (GH11592)
- inplace arguments now require a boolean value, else a ValueError is thrown (GH14189)
- pandas.api.types.is_datetime64_ns_dtype will now report True on a tz-aware dtype, similar to pandas.api.types.is_datetime64_any_dtype
- DataFrame.asof() will return a null filled Series instead the scalar NaN if a match is not found (GH15118)
- Specific support for copy.copy() and copy.deepcopy() functions on NDFrame objects (GH15444)
- Series.sort_values() accepts a one element list of bool for consistency with the behavior of DataFrame.sort_values() (GH15604)
- .merge() and .join() on category dtype columns will now preserve the category dtype when possible (GH10409)
• SparseDataFrame.default_fill_value will be 0, previously was nan in the return from pd.get_dummies(..., sparse=True) (GH15594)

• The default behaviour of Series.str.match has changed from extracting groups to matching the pattern. The extracting behaviour was deprecated since pandas version 0.13.0 and can be done with the Series.str.extract method (GH5224). As a consequence, the as_indexer keyword is ignored (no longer needed to specify the new behaviour) and is deprecated.

• NaT will now correctly report False for datetimelike boolean operations such as is_month_start (GH15781)

• NaT will now correctly return np.nan for Timedelta and Period accessors such as days and quarter (GH15782)

• NaT will now returns NaT for tz_localize and tz_convert methods (GH15830)

• DataFrame and Panel constructors with invalid input will now raise ValueError rather than PandasError, if called with scalar inputs and not axes (GH15541)

• DataFrame and Panel constructors with invalid input will now raise ValueError rather than pandas.core.common.PandasError, if called with scalar inputs and not axes; The exception PandasError is removed as well. (GH15541)

• The exception pandas.core.common.AmbiguousIndexError is removed as it is not referenced (GH15541)

1.8.3 Reorganization of the library: Privacy Changes

1.8.3.1 Modules Privacy Has Changed

Some formerly public python/c/c++/cython extension modules have been moved and/or renamed. These are all removed from the public API. Furthermore, the pandas.core, pandas.compat, and pandas.util top-level modules are now considered to be PRIVATE. If indicated, a deprecation warning will be issued if you reference thses modules. (GH12588)
Some new subpackages are created with public functionality that is not directly exposed in the top-level namespace: pandas.errors, pandas.plotting and pandas.testing (more details below). Together with pandas.api.types and certain functions in the pandas.io and pandas.tseries submodules, these are now the public subpackages.

Further changes:

- The function `union_categoricals()` is now importable from pandas.api.types, formerly from pandas.types.concat (GH15998)
- The type import pandas.tslib.NaTType is deprecated and can be replaced by using `type(pandas.NaT)` (GH16146)
- The public functions in pandas.tools.hashing deprecated from that locations, but are now importable from pandas.util (GH16223)
- The modules in pandas.util: decorators, print_versions, doctools, validators, depr_module are now private. Only the functions exposed in pandas.util itself are public (GH16223)

### 1.8.3.2 pandas.errors

We are adding a standard public module for all pandas exceptions & warnings pandas.errors. (GH14800). Previously these exceptions & warnings could be imported from pandas.core.common or pandas.io.common. These exceptions and warnings will be removed from the *.common locations in a future release. (GH15541)

The following are now part of this API:

```python
['DtypeWarning',
'EmptyDataError',
'OutOfBoundsDatetime',
'ParserError',
...
(continues on next page)
```
1.8.3.3 pandas.testing

We are adding a standard module that exposes the public testing functions in pandas.testing (GH9895). Those functions can be used when writing tests for functionality using pandas objects.

The following testing functions are now part of this API:

- `testing.assert_frame_equal()`
- `testing.assert_series_equal()`
- `testing.assert_index_equal()`

1.8.3.4 pandas.plotting

A new public pandas.plotting module has been added that holds plotting functionality that was previously in either pandas.tools.plotting or in the top-level namespace. See the deprecations sections for more details.

1.8.3.5 Other Development Changes

- Building pandas for development now requires cython >= 0.23 (GH14831)
- Require at least 0.23 version of cython to avoid problems with character encodings (GH14699)
- Switched the test framework to use pytest (GH13097)
- Reorganization of tests directory layout (GH14854, GH15707).

1.8.4 Deprecations

1.8.4.1 Deprecate .ix

The .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers. .ix offers a lot of magic on the inference of what the user wants to do. To wit, .ix can decide to index positionally OR via labels, depending on the data type of the index. This has caused quite a bit of user confusion over the years. The full indexing documentation is here. (GH14218)

The recommended methods of indexing are:

- .loc if you want to label index
- .iloc if you want to positionally index.

Using .ix will now show a DeprecationWarning with a link to some examples of how to convert code here.

```python
In [130]: df = pd.DataFrame({'A': [1, 2, 3],
                      'B': [4, 5, 6]},
                      index=list('abc'))
```

(continues on next page)
Previous Behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: df ix[[0, 2], 'A']
```

```
Out[3]:
a 1
Name: A, dtype: int64
```

Using `.loc`. Here we will select the appropriate indexes from the index, then use label indexing.

```
In [132]: df.loc[df.index[[0, 2]], 'A']
```

```
Out[132]:
a 1
c 3
Name: A, dtype: int64
```

Using `.iloc`. Here we will get the location of the ‘A’ column, then use positional indexing to select things.

```
In [133]: df.iloc[[0, 2], df.columns.get_loc('A')]
```

```
Out[133]:
a 1
c 3
Name: A, dtype: int64
```

## 1.8.4.2 Deprecate Panel

Panel is deprecated and will be removed in a future version. The recommended way to represent 3-D data are with a MultiIndex on a DataFrame via the `to_frame()` or with the xarray package. Pandas provides a `to_xarray()` method to automate this conversion. For more details see Deprecate Panel documentation. (GH13563).

```
In [134]: p = tm.makePanel()
```

```
In [135]: p
```

```
Out[135]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

Convert to a MultiIndex DataFrame

```
In [136]: p.to_frame()
```

```
Out[136]:
           ItemA  ItemB  ItemC
major minor
2000-01-03 A  0.628776 -1.409432  0.209395
```
Convert to an xarray DataArray

```python
In [137]: p.to_xarray()
Out[137]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
array([[[ 0.628776, 0.988138, -0.938153, -0.223019],
       [ 0.186494, -0.072608, -1.239072, 2.123692],
       [ 0.952478, -0.550603, 0.139683, 0.122273]],
      [[-1.409432, -1.347533, 1.272395, -0.591863],
       [ 1.422986, 0.363565, -1.449567, -0.414505],
       [-2.147855, -0.014752, -1.195524, -1.425795]],
      [[ 0.209395, -0.896581, -0.161137, -1.051539],
       [-0.592886, 1.104352, 0.889157, -0.319561],
       [-1.473116, -0.43155 , 0.288377, -0.619993]])
Coordinates:
* items (items) object 'ItemA' 'ItemB' 'ItemC'
* major_axis (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
* minor_axis (minor_axis) object 'A' 'B' 'C' 'D'
```

1.8.4.3 Deprecate groupby.agg() with a dictionary when renaming

The `.groupby(..).agg(..), .rolling(..).agg(..), and .resample(..).agg(..)` syntax can accept a variable of inputs, including scalars, list, and a dict of column names to scalars or lists. This provides a useful syntax for constructing multiple (potentially different) aggregations.

However, `.agg(..)` can also accept a dict that allows ‘renaming’ of the result columns. This is a complicated and confusing syntax, as well as not consistent between `Series` and `DataFrame`. We are deprecating this ‘renaming’ functionality.

- We are deprecating passing a dict to a grouped/rolled/resampled `Series`. This allowed one to rename the resulting aggregation, but this had a completely different meaning than passing a dictionary to a grouped `DataFrame`, which accepts column-to-aggregations.

- We are deprecating passing a dict-of-dicts to a grouped/rolled/resampled `DataFrame` in a similar manner.

This is an illustrative example:

```python
In [138]: df = pd.DataFrame({'A': [1, 1, 1, 2, 2],
                       'B': range(5),
                       'C': range(5))
```
Here is a typical useful syntax for computing different aggregations for different columns. This is a natural, and useful syntax. We aggregate from the dict-to-list by taking the specified columns and applying the list of functions. This returns a MultiIndex for the columns (this is not deprecated).

```
In [140]: df.groupby('A').agg({'B': 'sum', 'C': 'min'})
Out[140]:
         B  C
A
1  3  0
2  7  3
```

Here’s an example of the first deprecation, passing a dict to a grouped Series. This is a combination aggregation & renaming:

```
In [6]: df.groupby('A').B.agg({'foo': 'count'})
FutureWarning: using a dict on a Series for aggregation is deprecated and will be removed in a future version
Out[6]:
    foo
   A
   1  3
   2  2
```

You can accomplish the same operation, more idiomatically by:

```
In [141]: df.groupby('A').B.agg({'count'}).rename(columns={'count': 'foo'})
Out[141]:
   foo
   A
   1  3
   2  2
```

Here’s an example of the second deprecation, passing a dict-of-dict to a grouped DataFrame:

```
In [23]: (df.groupby('A')
   ...:     .agg({'B': {'foo': 'sum'}, 'C': {'bar': 'min'}}))
FutureWarning: using a dict with renaming is deprecated and will be removed in a future version
Out[23]:
         B  C  foo  bar
A
1  3  0  0
2  7  3  3
```
You can accomplish nearly the same by:

```python
In [142]: (df.groupby('A')
.......: .agg({'B': 'sum', 'C': 'min'})
.......: .rename(columns={'B': 'foo', 'C': 'bar'})
.......: )
Out[142]:
   foo  bar
A
1  3  0
2  7  3
```

### 1.8.4.4 Deprecate .plotting

The `pandas.tools.plotting` module has been deprecated, in favor of the top level `pandas.plotting` module. All the public plotting functions are now available from `pandas.plotting` (GH12548).

Furthermore, the top-level `pandas.scatter_matrix` and `pandas.plot_params` are deprecated. Users can import these from `pandas.plotting` as well.

Previous script:

```python
pd.tools.plotting.scatter_matrix(df)
pd.scatter_matrix(df)
```

Should be changed to:

```python
pd.plotting.scatter_matrix(df)
```

### 1.8.4.5 Other Deprecations

- `SparseArray.to_dense()` has deprecated the `fill` parameter, as that parameter was not being respected (GH14647)
- `SparseSeries.to_dense()` has deprecated the `sparse_only` parameter (GH14647)
- `Series.repeat()` has deprecated the `reps` parameter in favor of `repeats` (GH12662)
- The `Series` constructor and `.astype` method have deprecated accepting timestamp dtypes without a frequency (e.g. `np.datetime64`) for the `dtype` parameter (GH15524)
- `Index.repeat()` and `MultiIndex.repeat()` have deprecated the `n` parameter in favor of `repeats` (GH12662)
- `Categorical.searchsorted()` and `Series.searchsorted()` have deprecated the `v` parameter in favor of `value` (GH12662)
- `TimedeltaIndex.searchsorted()`, `DatetimeIndex.searchsorted()`, and `PeriodIndex.searchsorted()` have deprecated the key parameter in favor of `value` (GH12662)
- `DataFrame.astype()` has deprecated the `raise_on_error` parameter in favor of `errors` (GH14878)
- `Series.sortlevel` and `DataFrame.sortlevel` have been deprecated in favor of `Series.sort_index` and `DataFrame.sort_index` (GH15099)
- importing `concat` from `pandas.tools.merge` has been deprecated in favor of imports from the `pandas` namespace. This should only affect explicit imports (GH15358)
- Series/DataFrame/Panel.consolidate() been deprecated as a public method. (GH15483)
- The as_indexer keyword of Series.str.match() has been deprecated (ignored keyword) (GH15257).
- The following top-level pandas functions have been deprecated and will be removed in a future version (GH13790, GH15940)
  - pd.pnow(), replaced by Period.now()
  - pd.Term, is removed, as it is not applicable to user code. Instead use in-line string expressions in the where clause when searching in HDFStore
  - pd.Expr, is removed, as it is not applicable to user code.
  - pd.match(), is removed.
  - pd.groupby(), replaced by using the .groupby() method directly on a Series/DataFrame
  - pd.get_store(), replaced by a direct call to pd.HDFStore(...)
- is_any_int_dtype, is_floating_dtype, and is_sequence are deprecated from pandas.api.types (GH16042)

1.8.5 Removal of prior version deprecations/changes

- The pandas.rpy module is removed. Similar functionality can be accessed through the rpy2 project. See the R interfacing docs for more details.
- The pandas.io.ga module with a google-analytics interface is removed (GH11308). Similar functionality can be found in the Google2Pandas package.
- pd.to_datetime and pd.to_timedelta have dropped the coerce parameter in favor of errors (GH13602)
- pandas.stats.fama_macbeth, pandas.stats.ols, pandas.stats.plm and pandas.stats.var, as well as the top-level pandas.fama_macbeth and pandas.ols routines are removed. Similar functionality can be found in the statsmodels package. (GH11898)
- The TimeSeries and SparseTimeSeries classes, aliases of Series and SparseSeries, are removed (GH10890, GH15098).
- Series.is_time_series is dropped in favor of Series.index.is_all_dates (GH15098)
- The deprecated  irow, icol, iget and iget_value methods are removed in favor of iloc and iat as explained here (GH10711).
- The deprecated DataFrame.iterkv() has been removed in favor of DataFrame.iteritems() (GH10711)
- The Categorical constructor has dropped the name parameter (GH10632)
- Categorical has dropped support for NaN categories (GH10748)
- The take_last parameter has been dropped from duplicated(), drop_duplicates(), nlargest(), and nsmallest() methods (GH10236, GH10792, GH10920)
- Series, Index, and DataFrame have dropped the sort and order methods (GH10726)
- Where clauses in pytables are only accepted as strings and expressions types and not other data-types (GH12027)
- DataFrame has dropped the combineAdd and combineMult methods in favor of add and mul respectively (GH10735)
1.8.6 Performance Improvements

- Improved performance of `pd.wide_to_long()` (GH14779)
- Improved performance of `pd.factorize()` by releasing the GIL with `object` dtype when inferred as strings (GH14859, GH16057)
- Improved performance of timeseries plotting with an irregular DatetimeIndex (or with `compat_x=True`) (GH15073).
- Improved performance of `groupby().cummin()` and `groupby().cummax()` (GH15048, GH15109, GH15561, GH15635)
- Improved performance and reduced memory when indexing with a `MultiIndex` (GH15245)
- When reading buffer object in `read_sas()` method without specified format, filepath string is inferred rather than buffer object. (GH14947)
- Improved performance of `.rank()` for categorical data (GH15498)
- Improved performance when using `.unstack()` (GH15503)
- Improved performance of merge/join on category columns (GH10409)
- Improved performance of `drop_duplicates()` on `bool` columns (GH12963)
- Improve performance of `pd.core.groupby.GroupBy.apply` when the applied function used the `.name` attribute of the group DataFrame (GH15062).
- Improved performance of `iloc` indexing with a list or array (GH15504).
- Improved performance of `Series.sort_index()` with a monotonic index (GH15694)
- Improved performance in `pd.read_csv()` on some platforms with buffered reads (GH16039)

1.8.7 Bug Fixes

1.8.7.1 Conversion

- Bug in `Timestamp.replace` now raises `TypeError` when incorrect argument names are given; previously this raised `ValueError` (GH15240)
- Bug in `Timestamp.replace` with `compat` for passing long integers (GH15030)
- Bug in `Timestamp` returning UTC based time/date attributes when a timezone was provided (GH13303, GH6538)
- Bug in `Timestamp` incorrectly localizing timezones during construction (GH11481, GH15777)
- Bug in `TimedeltaIndex` addition where overflow was being allowed without error (GH14816)
- Bug in `TimedeltaIndex` raising a `ValueError` when boolean indexing with `loc` (GH14946)
- Bug in catching an overflow in `Timestamp + Timedelta/Offset` operations (GH15126)
- Bug in `DatetimeIndex.round()` and `Timestamp.round()` floating point accuracy when rounding by milliseconds or less (GH14440, GH15578)
- Bug in `astype()` where `inf` values were incorrectly converted to integers. Now raises error now with `astype()` for `Series` and `DataFrames` (GH14265)
- Bug in `DataFrame(..).apply(to_numeric)` when values are of type `decimal.Decimal` (GH14827)
- Bug in `describe()` when passing a numpy array which does not contain the median to the `percentiles` keyword argument (GH14908)
- Cleaned up `PeriodIndex` constructor, including raising on floats more consistently (GH13277)
- Bug in using `__deepcopy__` on empty NDFrame objects (GH15370)
- Bug in `.replace()` may result in incorrect dtypes. (GH12747, GH15765)
- Bug in `Series.replace` and `DataFrame.replace` which failed on empty replacement dicts (GH15289)
- Bug in `Series.replace` which replaced a numeric by string (GH15743)
- Bug in `Index` construction with `NaN` elements and integer dtype specified (GH15187)
- Bug in `Series` construction with a datetimetz (GH14928)
- Bug in `Series.dt.round()` inconsistent behaviour on `NaT`'s with different arguments (GH14940)
- Bug in `Series` constructor when both `copy=True` and `dtype` arguments are provided (GH15125)
- Incorrect dtyped `Series` was returned by comparison methods (e.g., `lt`, `gt`, ...) against a constant for an empty `DataFrame` (GH15077)
- Bug in `Series.ffill()` with mixed dtypes containing tz-aware datetimes. (GH14956)
- Bug in `DataFrame.fillna()` where the argument `downcast` was ignored when `fillna` value was of type dict (GH15277)
- Bug in `.asfreq()`, where frequency was not set for empty `Series` (GH14320)
- Bug in `DataFrame` construction with nulls and datetimes in a list-like (GH15869)
- Bug in `DataFrame.fillna()` with tz-aware datetimes (GH15855)
- Bug in `is_string_dtype, is_timedelta64_ns_dtype, and is_string_like_dtype` in which an error was raised when `None` was passed in (GH15941)
- Bug in the return type of `pd.unique` on a `Categorical`, which was returning an ndarray and not a `Categorical` (GH15903)
- Bug in `Index.to_series()` where the index was not copied (and so mutating later would change the original), (GH15949)
- Bug in indexing with partial string indexing with a len-1 `DataFrame` (GH16071)
- Bug in `Series` construction where passing invalid dtype didn’t raise an error. (GH15520)

### 1.8.7.2 Indexing

- Bug in `Index` power operations with reversed operands (GH14973)
- Bug in `DataFrame.sort_values()` when sorting by multiple columns where one column is of type `int64` and contains `NaT` (GH14922)
- Bug in `DataFrame.reindex()` in which `method` was ignored when passing columns (GH14992)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a `Series` indexer (GH14730, GH15424)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a numpy array (GH15434)
- Bug in `Series.asof` which raised if the series contained all `np.nan` (GH15713)
- Bug in `.at` when selecting from a tz-aware column (GH15822)
- Bug in `Series.where()` and `DataFrame.where()` where array-like conditionals were being rejected (GH15414)
• Bug in `Series.where()` where TZ-aware data was converted to float representation (GH15701)
• Bug in `.loc` that would not return the correct dtype for scalar access for a DataFrame (GH11617)
• Bug in output formatting of a `MultiIndex` when names are integers (GH12223, GH15262)
• Bug in `Categorical.searchsorted()` where alphabetical instead of the provided categorical order was used (GH14522)
• Bug in `Series.iloc` where a `Categorical` object for list-like indexes input was returned, where a `Series` was expected. (GH14580)
• Bug in `DataFrame.isin` comparing datetimelike to empty frame (GH15473)
• Bug in `.reset_index()` when an all NaN level of a `MultiIndex` would fail (GH6322)
• Bug in `.reset_index()` when raising error for index name already present in `MultiIndex` columns (GH16120)
• Bug in creating a `MultiIndex` with tuples and not passing a list of names; this will now raise `ValueError` (GH15110)
• Bug in the HTML display with a `MultiIndex` and truncation (GH14882)
• Bug in the display of `.info()` where a qualifier (+) would always be displayed with a `MultiIndex` that contains only non-strings (GH15245)
• Bug in `pd.concat()` where the names of `MultiIndex` of resulting DataFrame are not handled correctly when None is presented in the names of `MultiIndex` of input DataFrame (GH15787)
• Bug in `DataFrame.sort_index()` and `Series.sort_index()` where na_position doesn’t work with a `MultiIndex` (GH14784, GH16604)
• Bug in `pd.concat()` when combining objects with a `CategoricalIndex` (GH16111)
• Bug in indexing with a scalar and a `CategoricalIndex` (GH16123)

### 1.8.7.3 I/O

• Bug in `pd.to_numeric()` in which float and unsigned integer elements were being improperly casted (GH14941, GH15005)
• Bug in `pd.read_fwf()` where the skiprows parameter was not being respected during column width inference (GH11256)
• Bug in `pd.read_csv()` in which the dialect parameter was not being verified before processing (GH14898)
• Bug in `pd.read_csv()` in which missing data was being improperly handled with `usecols` (GH6710)
• Bug in `pd.read_csv()` in which a file containing a row with many columns followed by rows with fewer columns would cause a crash (GH14125)
• Bug in `pd.read_csv()` for the C engine where `usecols` were being indexed incorrectly with `parse_dates` (GH14792)
• Bug in `pd.read_csv()` with `parse_dates` when multiline headers are specified (GH15376)
• Bug in `pd.read_csv()` with `float_precision='round_trip'` which caused a segfault when a text entry is parsed (GH15140)
• Bug in `pd.read_csv()` when an index was specified and no values were specified as null values (GH15835)
• Bug in `pd.read_csv()` in which certain invalid file objects caused the Python interpreter to crash (GH15337)
- Bug in `pd.read_csv()` in which invalid values for `nrows` and `chunksize` were allowed (GH15767)
- Bug in `pd.read_csv()` for the Python engine in which unhelpful error messages were being raised when parsing errors occurred (GH15910)
- Bug in `pd.read_csv()` in which the `skipfooter` parameter was not being properly validated (GH15925)
- Bug in `pd.to_csv()` in which there was numeric overflow when a timestamp index was being written (GH15982)
- Bug in `pd.util.hashing.hash_pandas_object()` in which hashing of categoricals depended on the ordering of categories, instead of just their values. (GH15143)
- Bug in `.to_json()` where `lines=True` and contents (keys or values) contain escaped characters (GH15096)
- Bug in `.to_json()` causing single byte ascii characters to be expanded to four byte unicode (GH15344)
- Bug in `.to_json()` for the C engine where rollover was not correctly handled for case where frac is odd and `diff` is exactly 0.5 (GH15716, GH15864)
- Bug in `pd.read_json()` for Python 2 where `lines=True` and contents contain non-ascii unicode characters (GH15132)
- Bug in `pd.read_msgpack()` in which `Series` categoricals were being improperly processed (GH14901)
- Bug in `pd.read_msgpack()` which did not allow loading of a dataframe with an index of type `CategoricalIndex` (GH15487)
- Bug in `pd.read_msgpack()` when deserializing a `CategoricalIndex` (GH15487)
- Bug in `DataFrame.to_records()` with converting a `DatetimeIndex` with a timezone (GH13937)
- Bug in `DataFrame.to_records()` which failed with unicode characters in column names (GH11879)
- Bug in `.to_sql()` when writing a `DataFrame` with numeric index names (GH15404).
- Bug in `DataFrame.to_html()` with `index=False` and `max_rows` raising in `IndexError` (GH14998)
- Bug in `pd.read_hdf()` passing a `Timestamp` to the `where` parameter with a non date column (GH15492)
- Bug in `DataFrame.to_stata()` and StataWriter which produces incorrectly formatted files to be produced for some locales (GH13856)
- Bug in StataReader and StataWriter which allows invalid encodings (GH15723)
- Bug in the Series repr not showing the length when the output was truncated (GH15962).

### 1.8.7.4 Plotting

- Bug in `DataFrame.hist` where `plt.tight_layout` caused an `AttributeError` (use matplotlib >= 2.0.1) (GH9351)
- Bug in `DataFrame.boxplot` where `fontsize` was not applied to the tick labels on both axes (GH15108)
- Bug in the date and time converters pandas registers with matplotlib not handling multiple dimensions (GH16026)
- Bug in `pd.scatter_matrix()` could accept either `color` or `c`, but not both (GH14855)
1.8.7.5 Groupby/Resample/Rolling

- Bug in `.groupby(..).resample()` when passed the on= kwarg. (GH15021)
- Properly set __name__ and __qualname__ for Groupby.* functions (GH14620)
- Bug in GroupBy.get_group() failing with a categorical grouper (GH15155)
- Bug in `.groupby(...).rolling(...)` when on is specified and using a DatetimeIndex (GH15130, GH13966)
- Bug in groupby operations with timedelta64 when passing numeric_only=False (GH5724)
- Bug in groupby.apply() coercing object dtypes to numeric types, when not all values were numeric (GH14423, GH15421, GH15670)
- Bug in resample, where a non-string loffset argument would not be applied when resampling a timeseries (GH13218)
- Bug in DataFrame.groupby().describe() when grouping on Index containing tuples (GH14848)
- Bug in groupby().nunique() with a datetimelike-grouper where bins counts were incorrect (GH13453)
- Bug in groupby.transform() that would coerce the resultant dtypes back to the original (GH10972, GH11444)
- Bug in groupby.agg() incorrectly localizing timezone on datetime (GH15426, GH10668, GH13046)
- Bug in `.rolling/expanding()` functions where count() was not counting np.Inf, nor handling object dtypes (GH12541)
- Bug in `.rolling()` where pd.Timedelta or datetime.timedelta was not accepted as a window argument (GH15440)
- Bug in Rolling.quantile function that caused a segmentation fault when called with a quantile value outside of the range [0, 1] (GH15463)
- Bug in DataFrame.resample().median() if duplicate column names are present (GH14233)

1.8.7.6 Sparse

- Bug in SparseSeries.reindex on single level with list of length 1 (GH15447)
- Bug in repr-formatting a SparseDataFrame after a value was set on (a copy of) one of its series (GH15488)
- Bug in SparseDataFrame construction with lists not coercing to dtype (GH15682)
- Bug in sparse array indexing in which indices were not being validated (GH15863)

1.8.7.7 Reshaping

- Bug in `pd.merge_asof()` where left_index or right_index caused a failure when multiple by was specified (GH15676)
- Bug in `pd.merge_asof()` where left_index/right_index together caused a failure when tolerance was specified (GH15135)
- Bug in DataFrame.pivot_table() where dropna=True would not drop all-NaN columns when the columns was a category dtype (GH15193)
- Bug in `pd.melt()` where passing a tuple value for value_vars caused a TypeError (GH15348)
• Bug in `pd.pivot_table()` where no error was raised when values argument was not in the columns (GH14938)

• Bug in `pd.concat()` in which concatenating with an empty dataframe with `join='inner'` was being improperly handled (GH15328)

• Bug with `sort=True` in `DataFrame.join` and `pd.merge` when joining on indexes (GH15582)

• Bug in `DataFrame.nsmallest` and `DataFrame.nlargest` where identical values resulted in duplicated rows (GH15297)

• Bug in `pandas.pivot_table()` incorrectly raising `UnicodeError` when passing unicode input for margins keyword (GH13292)

1.8.7.8 Numeric

• Bug in `.rank()` which incorrectly ranks ordered categories (GH15420)

• Bug in `.corr()` and `.cov()` where the column and index were the same object (GH14617)

• Bug in `.mode()` where `mode` was not returned if was only a single value (GH15714)

• Bug in `pd.cut()` with a single bin on an all 0s array (GH15428)

• Bug in `pd.qcut()` with a single quantile and an array with identical values (GH15431)

• Bug in `pandas.tools.utils.cartesian_product()` with large input can cause overflow on windows (GH15265)

• Bug in `.eval()` which caused multiline evals to fail with local variables not on the first line (GH15342)

1.8.7.9 Other

• Compat with SciPy 0.19.0 for testing on `.interpolate()` (GH15662)

• Compat for 32-bit platforms for `.qcut/cut`; bins will now be int64 dtype (GH14866)

• Bug in interactions with Qt when a QtApplication already exists (GH14372)

• Avoid use of np.finfo() during import pandas removed to mitigate deadlock on Python GIL misuse (GH14641)

1.9 v0.19.2 (December 24, 2016)

This is a minor bug-fix release in the 0.19.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

• Compatibility with Python 3.6

• Added a Pandas Cheat Sheet. (GH13202)

What’s new in v0.19.2

• Enhancements

• Performance Improvements
1.9.1 Enhancements

The `pd.merge_asof()`, added in 0.19.0, gained some improvements:

- `pd.merge_asof()` gained `left_index/right_index` and `left_by/right_by` arguments (GH14253)
- `pd.merge_asof()` can take multiple columns in `by` parameter and has specialized dtypes for better performance (GH13936)

1.9.2 Performance Improvements

- Performance regression with `PeriodIndex` (GH14822)
- Performance regression in indexing with `getitem` (GH14930)
- Improved performance of `.replace()` (GH12745)
- Improved performance `Series` creation with a datetime index and dictionary data (GH14894)

1.9.3 Bug Fixes

- Compat with python 3.6 for pickling of some offsets (GH14685)
- Compat with python 3.6 for some indexing exception types (GH14684, GH14689)
- Compat with python 3.6 for deprecation warnings in the test suite (GH14681)
- Compat with python 3.6 for `Timestamp` pickles (GH14689)
- Compat with `dateutil==2.6.0`; segfault reported in the testing suite (GH14621)
- Allow nanoseconds in `Timestamp.replace` as a kwarg (GH14621)
- Bug in `pd.read_csv` in which aliasing was being done for `na_values` when passed in as a dictionary (GH14203)
- Bug in `pd.read_csv` in which column indices for a dict-like `na_values` were not being respected (GH14203)
- Bug in `pd.read_csv` where reading files fails, if the number of headers is equal to the number of lines in the file (GH14515)
- Bug in `pd.read_csv` for the Python engine in which an unhelpful error message was being raised when multi-char delimiters were not being respected with quotes (GH14582)
- Fix bugs (GH14734, GH13654) in `pd.read_sas` and `pandas.io.sas.sas7bdat.SAS7BDATReader` that caused problems when reading a SAS file incrementally.
- Bug in `pd.read_csv` for the Python engine in which an unhelpful error message was being raised when `skipfooter` was not being respected by Python’s CSV library (GH13879)
- Bug in `.fillna()` in which timezone aware datetime64 values were incorrectly rounded (GH14872)
- Bug in `.groupby(..., sort=True)` of a non-lexsorted MultiIndex when grouping with multiple levels (GH14776)
- Bug in `pd.cut` with negative values and a single bin (GH14652)
• Bug in `pd.to_numeric` where a 0 was not unsigned on a `downcast='unsigned'` argument (GH14401)
• Bug in plotting regular and irregular timeseries using shared axes (`sharex=True` or `ax.twinx()`) (GH13341, GH14322).
• Bug in not propagating exceptions in parsing invalid datetimes, noted in python 3.6 (GH14561)
• Bug in resampling a `DatetimeIndex` in local TZ, covering a DST change, which would raise `AmbiguousTimeError` (GH14682)
• Bug in indexing that transformed `RecursionError` into `KeyError` or `IndexingError` (GH14554)
• Bug in `HDFStore` when writing a `MultiIndex` when using `data_columns=True` (GH14435)
• Bug in `HDFStore.append()` when writing a `Series` and passing a `min_itemsize` argument containing a value for the index (GH14142)
• Bug when writing to a `HDFStore` in `table` format with a `min_itemsize` value for the index and without asking to append (GH10381)
• Bug in `Series.groupby.nunique()` raising an `IndexError` for an empty `Series` (GH12553)
• Bug in `DataFrame.nlargest` and `DataFrame.nsmallest` when the index had duplicate values (GH13412)
• Bug in clipboard functions on linux with python2 with unicode and separators (GH13747)
• Bug in clipboard functions on Windows 10 and python 3 (GH14362, GH12807)
• Bug in `.to_clipboard()` and Excel compat (GH12529)
• Bug in `DataFrame.combine_first()` for integer columns (GH14687).
• Bug in `pd.read_csv()` in which the `dtype` parameter was not being respected for empty data (GH14712)
• Bug in `pd.read_csv()` in which the `nrows` parameter was not being respected for large input when using the C engine for parsing (GH7626)
• Bug in `pd.merge_asof()` could not handle timezone-aware `DatetimeIndex` when a tolerance was specified (GH14844)
• Explicit check in `to_stata` and `StataWriter` for out-of-range values when writing doubles (GH14618)
• Bug in `.plot(kind='kde')` which did not drop missing values to generate the KDE Plot, instead generating an empty plot. (GH14821)
• Bug in `unstack()` if called with a list of column(s) as an argument, regardless of the dtypes of all columns, they get coerced to object (GH11847)

1.10 v0.19.1 (November 3, 2016)

This is a minor bug-fix release from 0.19.0 and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

<table>
<thead>
<tr>
<th>What’s new in v0.19.1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance Improvements</strong></td>
</tr>
<tr>
<td><strong>Bug Fixes</strong></td>
</tr>
</tbody>
</table>
1.10.1 Performance Improvements

- Fixed performance regression in factorization of Period data (GH14338)
- Fixed performance regression in Series.asof(where) when where is a scalar (GH14461)
- Improved performance in DataFrame.asof(where) when where is a scalar (GH14461)
- Improved performance in .to_json() when lines=True (GH14408)
- Improved performance in certain types of loc indexing with a MultiIndex (GH14551).

1.10.2 Bug Fixes

- Source installs from PyPI will now again work without cython installed, as in previous versions (GH14204)
- Compat with Cython 0.25 for building (GH14496)
- Fixed regression where user-provided file handles were closed in read_csv (c engine) (GH14418).
- Fixed regression in DataFrame.quantile when missing values where present in some columns (GH14357).
- Fixed regression in Index.difference where the freq of a DatetimeIndex was incorrectly set (GH14323)
- Added back pandas.core.common.array_equivalent with a deprecation warning (GH14555).
- Bug in pd.read_csv for the C engine in which quotation marks were improperly parsed in skipped rows (GH14459)
- Bug in pd.read_csv for Python 2.x in which Unicode quote characters were no longer being respected (GH14477)
- Fixed regression in Index.append when categorical indices were appended (GH14545).
- Fixed regression in pd.DataFrame where constructor fails when given dict with None value (GH14381)
- Fixed regression in DatetimeIndex._maybe_cast_slice_bound when index is empty (GH14354).
- Bug in localizing an ambiguous timezone when a boolean is passed (GH14402)
- Bug in TimedeltaIndex addition with a Datetime-like object where addition overflow in the negative direction was not being caught (GH14068, GH14453)
- Bug in string indexing against data with object Index may raise AttributeError (GH14424)
- Correctly raise ValueError on empty input to pd.eval() and df.query() (GH13139)
- Bug in RangeIndex.intersection when result is a empty set (GH14364).
- Bug in groupby-transform broadcasting that could cause incorrect dtype coercion (GH14457)
- Bug in Series.__setitem__ which allowed mutating read-only arrays (GH14359).
- Bug in DataFrame.insert where multiple calls with duplicate columns can fail (GH14291)
- pd.merge() will raise ValueError with non-boolean parameters in passed boolean type arguments (GH14434)
- Bug in Timestamp where dates very near the minimum (1677-09) could underflow on creation (GH14415)
- Bug in pd.concat where names of the keys were not propagated to the resulting MultiIndex (GH14252)
- Bug in pd.concat where axis cannot take string parameters 'rows' or 'columns' (GH14369)
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- Bug in pd.concat with dataframes heterogeneous in length and tuple keys (GH14438)
- Bug in MultiIndex.set_levels where illegal level values were still set after raising an error (GH13754)
- Bug in DataFrame.to_json where lines=True and a value contained a } character (GH14391)
- Bug in df.groupby causing an AttributeError when grouping a single index frame by a column and the index level (GH14327)
- Bug in df.groupby where TypeError raised when pd.Grouper(key=...) is passed in a list (GH14334)
- Bug in pd.pivot_table may raise TypeError or ValueError when index or columns is not scalar and values is not specified (GH14380)

1.11 v0.19.0 (October 2, 2016)

This is a major release from 0.18.1 and includes number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `merge_asof()` for asof-style time-series joining, see here
- `.rolling()` is now time-series aware, see here
- `read_csv()` now supports parsing Categorical data, see here
- A function union_categorical() has been added for combining categoricals, see here
- PeriodIndex now has its own period dtype, and changed to be more consistent with other Index classes. See here
- Sparse data structures gained enhanced support of int and bool dtypes, see here
- Comparison operations with Series no longer ignores the index, see here for an overview of the API changes.
- Introduction of a pandas development API for utility functions, see here.
- Deprecation of Panel4D and PanelND. We recommend to represent these types of n-dimensional data with the xarray package.
- Removal of the previously deprecated modules pandas.io.data, pandas.io.wb, pandas.tools.rplot.

Warning: pandas >= 0.19.0 will no longer silence numpy ufunc warnings upon import, see here.

What’s new in v0.19.0

- **New features**
  - `merge_asof` for asof-style time-series joining
  - `.rolling()` is now time-series aware
  - `read_csv` has improved support for duplicate column names
  - `read_csv` supports parsing Categorical directly
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- Categorical Concatenation
- Semi-Month Offsets
- New Index methods
- Google BigQuery Enhancements
- Fine-grained numpy errstate
- `get_dummies` now returns integer dtypes
- Downcast values to smallest possible dtype in `to_numeric`
- `pandas development API`
- Other enhancements

- **API changes**
  - `Series.tolist()` will now return Python types
  - `Series` operators for different indexes
    - Arithmetic operators
    - Comparison operators
    - Logical operators
    - Flexible comparison methods
  - `Series` type promotion on assignment
  - `.to_datetime()` changes
  - Merging changes
  - `.describe()` changes
  - **Period changes**
    - `PeriodIndex` now has `period` dtype
    - `Period('NaT')` now returns `pd.NaT`
    - `PeriodIndex.values` now returns array of `Period` object
  - `Index` + / – no longer used for set operations
  - `Index.difference` and `.symmetric_difference` changes
  - `Index.unique` consistently returns `Index`
  - `MultiIndex constructors, groupby and set_index` preserve categorical dtypes
  - `read_csv` will progressively enumerate chunks
  - Sparse Changes
    - `int64` and `bool` support enhancements
    - Operators now preserve dtypes
    - Other sparse fixes
  - `Indexer` dtype changes
  - Other API Changes
1.11.1 New features

1.11.1.1 merge_asof for asof-style time-series joining

A long-time requested feature has been added through the `merge_asof()` function, to support asof style joining of time-series (GH1870, GH13695, GH13709, GH13902). Full documentation is here.

The `merge_asof()` performs an asof merge, which is similar to a left-join except that we match on nearest key rather than equal keys.

```python
In [1]: left = pd.DataFrame({'a': [1, 5, 10],
...:                       'left_val': ['a', 'b', 'c']})
...:
In [2]: right = pd.DataFrame({'a': [1, 2, 3, 6, 7],
...:                          'right_val': [1, 2, 3, 6, 7]})
...

In [3]: left
Out[3]:
   a  left_val
0  1      a
1  5      b
2 10     c

In [4]: right
Out[4]:
   a  right_val
0  1       1
1  2       2
2  3       3
3  6       6
4  7       7

We typically want to match exactly when possible, and use the most recent value otherwise.

```python
In [5]: pd.merge_asof(left, right, on='a')
Out[5]:
   a  left_val  right_val
0  1      a       1
1  5      b       3
2 10     c       7
```

We can also match rows ONLY with prior data, and not an exact match.

```python
In [6]: pd.merge_asof(left, right, on='a', allow_exact_matches=False)
Out[6]:
   a  left_val  right_val
```
In a typical time-series example, we have trades and quotes and we want to asof-join them. This also illustrates using the by parameter to group data before merging.

```python
In [7]: trades = pd.DataFrame(
   ...:     {'time': pd.to_datetime(['20160525 13:30:00.023',
   ...:                            '20160525 13:30:00.038',
   ...:                            '20160525 13:30:00.048',
   ...:                            '20160525 13:30:00.048',
   ...:                            '20160525 13:30:00.048']),
   ...:     'ticker': ['MSFT', 'MSFT',
   ...:                'GOOG', 'GOOG', 'AAPL'],
   ...:     'price': [51.95, 51.95,
   ...:                720.77, 720.92, 98.00],
   ...:     'quantity': [75, 155,
   ...:                   100, 100, 100]},
   ...: columns=['time', 'ticker', 'price', 'quantity'])

In [8]: quotes = pd.DataFrame(
   ...:     {'time': pd.to_datetime(['20160525 13:30:00.023',
   ...:                              '20160525 13:30:00.023',
   ...:                              '20160525 13:30:00.030',
   ...:                              '20160525 13:30:00.041',
   ...:                              '20160525 13:30:00.048',
   ...:                              '20160525 13:30:00.049',
   ...:                              '20160525 13:30:00.072',
   ...:                              '20160525 13:30:00.075']),
   ...:     'ticker': ['GOOG', 'MSFT', 'MSFT',
   ...:                'MSFT', 'GOOG', 'AAPL', 'GOOG',
   ...:                'MSFT'],
   ...:     'bid': [720.50, 51.95, 51.97, 51.99,
   ...:               720.50, 97.99, 720.50, 52.01],
   ...:     'ask': [720.93, 51.96, 51.98, 52.00,
   ...:               720.93, 98.01, 720.88, 52.03],
   ...: columns=['time', 'ticker', 'bid', 'ask'])
```

```
In [9]: trades
Out[9]:
   time  ticker  price  quantity
0  2016-05-25 13:30:00.023  MSFT   51.95     75
1  2016-05-25 13:30:00.038  MSFT   51.95    155
2  2016-05-25 13:30:00.048  GOOG  720.77     100
3  2016-05-25 13:30:00.048  GOOG  720.92     100
4  2016-05-25 13:30:00.048  AAPL   98.00     100
```

```
In [10]: quotes
Out[10]:
   time  ticker  bid  ask
0  2016-05-25 13:30:00.023  GOOG  720.50  720.93
1  2016-05-25 13:30:00.023  MSFT   51.95   51.96
```

An asof merge joins on the `on` typically a datetimelike field, which is ordered, and in this case we are using a grouper in the `by` field. This is like a left-outer join, except that forward filling happens automatically taking the most recent non-NaN value.

In [11]: pd.merge_asof(trades, quotes,
        ....:     on='time',
        ....:     by='ticker')
        ....:
Out[11]:
        time ticker price quantity bid ask
       0 2016-05-25 13:30:00.023 MSFT 51.95 75 51.95 51.96
       1 2016-05-25 13:30:00.038 MSFT 51.95 155 51.97 51.98
       2 2016-05-25 13:30:00.048 GOOG 720.77 100 720.50 720.93
       3 2016-05-25 13:30:00.048 GOOG 720.92 100 720.50 720.93
       4 2016-05-25 13:30:00.048 AAPL 98.00 100 NaN NaN

This returns a merged DataFrame with the entries in the same order as the original left passed DataFrame (`trades` in this case), with the fields of the `quotes` merged.

1.11.1.2 `.rolling()` is now time-series aware

`.rolling()` objects are now time-series aware and can accept a time-series offset (or convertible) for the `window` argument (GH13327, GH12995). See the full documentation here.

In [12]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
        ....:     index=pd.date_range('20130101 09:00:00', periods=5, freq='s'))
        ....:
In [13]: dft
Out[13]:
          B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 2.0
2013-01-01 09:00:03 NaN
2013-01-01 09:00:04 4.0

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

In [14]: dft.rolling(2).sum()
Out[14]:
          B
2013-01-01 09:00:00 NaN
2013-01-01 09:00:01 NaN
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 NaN
2013-01-01 09:00:04 NaN

(continues on next page)
In [15]: dft.rolling(2, min_periods=1).sum()

      B
2013-01-01 09:00:00 0.0  
2013-01-01 09:00:01 1.0  
2013-01-01 09:00:02 3.0  
2013-01-01 09:00:03 2.0  
2013-01-01 09:00:04 4.0

Specifying an offset allows a more intuitive specification of the rolling frequency.

In [16]: dft.rolling('2s').sum()
Out[16]:
      B
2013-01-01 09:00:00 0.0  
2013-01-01 09:00:01 1.0  
2013-01-01 09:00:02 3.0  
2013-01-01 09:00:03 2.0  
2013-01-01 09:00:04 4.0

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

In [17]: dft = DataFrame({'B': [0, 1, 2, np.nan, 4]},
                   index = pd.Index([pd.Timestamp('20130101 09:00:00'),
                                      pd.Timestamp('20130101 09:00:02'),
                                      pd.Timestamp('20130101 09:00:03'),
                                      pd.Timestamp('20130101 09:00:05'),
                                      pd.Timestamp('20130101 09:00:06')],
                                      name='foo'))

In [18]: dft
Out[18]:
      B
foo 2013-01-01 09:00:00 0.0  
     2013-01-01 09:00:02 1.0  
     2013-01-01 09:00:03 2.0  
     2013-01-01 09:00:05 NaN  
     2013-01-01 09:00:06 4.0

In [19]: dft.rolling(2).sum()

      B
foo 2013-01-01 09:00:00 NaN  
     2013-01-01 09:00:02 1.0  
     2013-01-01 09:00:03 3.0  
     2013-01-01 09:00:05 NaN  
     2013-01-01 09:00:06 NaN

Using the time-specification generates variable windows for this sparse data.
Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```python
In [21]: dft = dft.reset_index()
In [22]: dft
Out[22]:
   foo  B
0  2013-01-01 09:00:00  0.0
1  2013-01-01 09:00:02  1.0
2  2013-01-01 09:00:03  2.0
3  2013-01-01 09:00:05  NaN
4  2013-01-01 09:00:06  4.0
```

```
In [23]: dft.rolling('2s', on='foo').sum()
Out[23]:
  foo  B
0  2013-01-01 09:00:00  0.0
1  2013-01-01 09:00:02  1.0
2  2013-01-01 09:00:03  3.0
3  2013-01-01 09:00:05  NaN
4  2013-01-01 09:00:06  4.0
```

### 1.11.1.3 `read_csv` has improved support for duplicate column names

Duplicate column names are now supported in `read_csv()` whether they are in the file or passed in as the `names` parameter (GH7160, GH9424)

```python
In [24]: data = '0,1,2
3,4,5'
In [25]: names = ['a', 'b', 'a']
```

**Previous behavior:**

```python
In [2]: pd.read_csv(StringIO(data), names=names)
Out[2]:
   a  b  a
0  2  1  2
1  5  4  5
```

The first `a` column contained the same data as the second `a` column, when it should have contained the values `[0, 3]`.

**New behavior:**
11.1.4 read_csv supports parsing Categorical directly

The read_csv() function now supports parsing a Categorical column when specified as a dtype (GH10153). Depending on the structure of the data, this can result in a faster parse time and lower memory usage compared to converting to Categorical after parsing. See the io docs here.

Individual columns can be parsed as a Categorical using a dict specification

Note: The resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the to_numeric() function, or as appropriate, another converter such as to_datetime().

11.  v0.19.0 (October 2, 2016)
1.11.1.5 Categorical Concatenation

- A function `union_categoricals()` has been added for combining categoricals, see [Unioning Categoricals](GH13361, GH13763, GH13846, GH14173)

```python
In [37]: from pandas.api.types import union_categoricals
In [38]: a = pd.Categorical(['b', 'c'])
In [39]: b = pd.Categorical(['a', 'b'])
In [40]: union_categoricals([a, b])
Out[40]:
[b, c, a, b]
Categories (3, object): [b, c, a]
```

- `concat` and `append` now can concat category dtypes with different categories as object dtype (GH13524)

```python
In [41]: s1 = pd.Series(['a', 'b'], dtype='category')
In [42]: s2 = pd.Series(['b', 'c'], dtype='category')
```

Previous behavior:

```python
In [1]: pd.concat([s1, s2])
ValueError: incompatible categories in categorical concat
```

New behavior:

```python
In [43]: pd.concat([s1, s2])
Out[43]:
```

(continues on next page)
1.11.1.6 Semi-Month Offsets

Pandas has gained new frequency offsets, `SemiMonthEnd` (‘SM’) and `SemiMonthBegin` (‘SMS’). These provide date offsets anchored (by default) to the 15th and end of month, and 15th and 1st of month respectively. (GH1543)

```python
In [44]: from pandas.tseries.offsets import SemiMonthEnd, SemiMonthBegin

SemiMonthEnd:

In [45]: Timestamp('2016-01-01') + SemiMonthEnd()
Out[45]: Timestamp('2016-01-15 00:00:00')

In [46]: pd.date_range('2015-01-01', freq='SM', periods=4)
                   dtype='datetime64[ns]', freq='SM-15')

SemiMonthBegin:

In [47]: Timestamp('2016-01-01') + SemiMonthBegin()
Out[47]: Timestamp('2016-01-15 00:00:00')

In [48]: pd.date_range('2015-01-01', freq='SMS', periods=4)
                     dtype='datetime64[ns]', freq='SMS-15')

Using the anchoring suffix, you can also specify the day of month to use instead of the 15th.

```
In [49]: pd.date_range('2015-01-01', freq='SMS-16', periods=4)
Out[49]: DatetimeIndex(['2015-01-01', '2015-01-16', '2015-02-01', '2015-02-16'],
                     dtype='datetime64[ns]', freq='SMS-16')

In [50]: pd.date_range('2015-01-01', freq='SM-14', periods=4)
                     dtype='datetime64[ns]', freq='SM-14')
```

1.11.1.7 New Index methods

The following methods and options are added to `Index`, to be more consistent with the `Series` and `DataFrame` API.

Index now supports the `.where()` function for same shape indexing (GH13170)

```
In [51]: idx = pd.Index(['a', 'b', 'c'])

In [52]: idx.where([True, False, True])
Out[52]: Index(['a', nan, 'c'], dtype='object')
```
Index now supports `.dropna()` to exclude missing values (GH6194)

```
In [53]: idx = pd.Index([1, 2, np.nan, 4])
In [54]: idx.dropna()
Out[54]: Float64Index([1.0, 2.0, 4.0], dtype='float64')
```

For MultiIndex, values are dropped if any level is missing by default. Specifying `how='all'` only drops values where all levels are missing.

```
In [55]: midx = pd.MultiIndex.from_arrays([[[1, 2, np.nan, 4],
                                            [1, 2, np.nan, np.nan]]])
In [56]: midx
Out[56]: MultiIndex(levels=[[1, 2, 4], [1, 2]],
                   labels=[[0, 1, -1, 2], [0, 1, -1, -1]])
In [57]: midx.dropna()
```

Index now supports `.str.extractall()` which returns a DataFrame, see the docs here (GH10008, GH13156)

```
In [59]: idx = pd.Index(["a1a2", "b1", "c1"])
In [60]: idx.str.extractall("[ab](?!P<digit>|d)")
Out[60]:
    digit  match
   ---  ----
    0    1
    1    2
    1    1
```

Index.astype() now accepts an optional boolean argument `copy`, which allows optional copying if the requirements on dtype are satisfied (GH13209)

1.11.1.8 Google BigQuery Enhancements

- The `read_gbq()` method has gained the `dialect` argument to allow users to specify whether to use BigQuery’s legacy SQL or BigQuery’s standard SQL. See the docs for more details (GH13615).
- The `to_gbq()` method now allows the DataFrame column order to differ from the destination table schema (GH11359).
1.11.1.9 Fine-grained numpy errstate

Previous versions of pandas would permanently silence numpy’s ufunc error handling when pandas was imported. Pandas did this in order to silence the warnings that would arise from using numpy ufuncs on missing data, which are usually represented as NaNs. Unfortunately, this silenced legitimate warnings arising in non-pandas code in the application. Starting with 0.19.0, pandas will use the numpy.errstate context manager to silence these warnings in a more fine-grained manner, only around where these operations are actually used in the pandas codebase. (GH13109, GH13145)

After upgrading pandas, you may see new RuntimeWarnings being issued from your code. These are likely legitimate, and the underlying cause likely existed in the code when using previous versions of pandas that simply silenced the warning. Use numpy.errstate around the source of the RuntimeWarning to control how these conditions are handled.

1.11.1.10 get_dummies now returns integer dtypes

The pd.get_dummies function now returns dummy-encoded columns as small integers, rather than floats (GH8725). This should provide an improved memory footprint.

Previous behavior:

```
In [1]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[1]:
a    float64
b    float64
c    float64
dtype: object
```

New behavior:

```
In [61]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[61]:
a    uint8
b    uint8
c    uint8
dtype: object
```

1.11.1.11 Downcast values to smallest possible dtype in to_numeric

pd.to_numeric() now accepts a downcast parameter, which will downcast the data if possible to smallest specified numerical dtype (GH13352)

```
In [62]: s = ['1', 2, 3]

In [63]: pd.to_numeric(s, downcast='unsigned')
Out[63]: array([1, 2, 3], dtype=uint8)

In [64]: pd.to_numeric(s, downcast='integer')
Out[64]: array([1, 2, 3], dtype=int8)
```
1.11.1.12 pandas development API

As part of making pandas API more uniform and accessible in the future, we have created a standard sub-package of pandas, `pandas.api` to hold public API's. We are starting by exposing type introspection functions in `pandas.api.types`. More sub-packages and officially sanctioned API's will be published in future versions of pandas (GH13147, GH13634)

The following are now part of this API:

```
In [65]: import pprint
In [66]: from pandas.api import types
In [67]: funcs = [ f for f in dir(types) if not f.startswith('_') ]
In [68]: pprint.pprint(funcs)

['CategoricalDtype',
'DatetimeTZDtype',
'IntervalDtype',
'PeriodDtype',
'infer_dtype',
'is_any_int_dtype',
'is_array_like',
'is_bool',
'is_bool_dtype',
'is_categorical',
'is_categorical_dtype',
'is_complex',
'is_complex_dtype',
'is_datetime64_any_dtype',
'is_datetime64_dtype',
'is_datetime64_ns_dtype',
'is_datetime64tz_dtype',
'is_datetimeetz',
'is_dict_like',
'is_dtype_equal',
'is_extension_type',
'is_file_like',
'is_float',
'is_float_dtype',
'is_floating_dtype',
'is_hashable',
'is_int64_dtype',
'is_integer',
'is_integer_dtype',
'is_interval',
'is_interval_dtype',
'is_iterator',
'is_list_like',
'is_named_tuple',
'is_number',
'is_numeric_dtype',
'is_object_dtype',
'is_period',
'is_period_dtype',
'is_re',
'is_re_compilable',
'is_scalar',
```

(continues on next page)
'is_sequence',
'is_signed_integer_dtype',
'is_sparse',
'is_string_dtype',
'is_timedelta64_dtype',
'is_timedelta64_ns_dtype',
'is_unsigned_integer_dtype',
'pandas_dtype',
'union_categoricals']

Note: Calling these functions from the internal module pandas.core.common will now show a
DeprecationWarning (GH13990)

1.11.1.13 Other enhancements

• Timestamp can now accept positional and keyword parameters similar to
datetime.datetime() (GH10758, GH11630)

In [69]: pd.Timestamp(2012, 1, 1)
Out[69]: Timestamp('2012-01-01 00:00:00')

In [70]: pd.Timestamp(year=2012, month=1, day=1, hour=8, minute=30)
Out[70]: Timestamp('2012-01-01 08:30:00 →')

• The .resample() function now accepts a on= or level= parameter for resampling on a datetimelike column or MultiIndex level (GH13500)

In [71]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W',
                             periods=5),
                        ....:          'a': np.arange(5),
                        ....:          index=pd.MultiIndex.from_arrays([
                        ....:              [1,2,3,4,5],
                        ....:              pd.date_range('2015-01-01', freq='W',
                        ....:                  periods=5)],
                        ....:          names=['v','d']))

In [72]: df
Out[72]:

   date  a
  ---  ---
   v  d
  1 2015-01-04  2015-01-04  0
  2 2015-01-11  2015-01-11  1
  3 2015-01-18  2015-01-18  2
  4 2015-01-25  2015-01-25  3
  5 2015-02-01  2015-02-01  4

In [73]: df.resample('M', on='date').sum()
   →
   a
date

(continues on next page)
• The `.get_credentials()` method of `GbqConnector` can now first try to fetch the application default credentials. See the docs for more details (GH13577).

• The `.tz_localize()` method of `DatetimeIndex` and `Timestamp` has gained the `errors` keyword, so you can potentially coerce nonexistent timestamps to NaT. The default behavior remains to raising a `NonExistentTimeError` (GH13057).

• `.to_hdf/read_hdf()` now accept path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path (GH11773).

• The `pd.read_csv()` with `engine='python'` has gained support for the `decimal` (GH12933), `na_filter` (GH13321) and the `memory_map` option (GH13381).

• Consistent with the Python API, `pd.read_csv()` will now interpret `+inf` as positive infinity (GH13274).

• The `pd.read_html()` has gained support for the `na_values`, `converters`, `keep_default_na` options (GH13461).

• `Categorical.astype()` now accepts an optional boolean argument `copy`, effective when `dtype` is categorical (GH13209).

• `DataFrame` has gained the `.asof()` method to return the last non-NaN values according to the selected subset (GH13358).

• The `DataFrame` constructor will now respect key ordering if a list of `OrderedDict` objects are passed in (GH13304).

• `pd.read_html()` has gained support for the `decimal` option (GH12907).

• `Series` has gained the properties `.is_monotonic`, `.is_monotonic_increasing`, `.is_monotonic_decreasing`, similar to `Index` (GH13336).

• `DataFrame.to_sql()` now allows a single value as the SQL type for all columns (GH11886).

• `Series.append` now supports the `ignore_index` option (GH13677).

• `.to_stata()` and `StataWriter` can now write variable labels to Stata dta files using a dictionary to make column names to labels (GH13535, GH13536).

• `.to_stata()` and `StataWriter` will automatically convert `datetime64[ns]` columns to Stata format `%tc`, rather than raising a `ValueError` (GH12259).

• `read_stata()` and `StataReader` raise with a more explicit error message when reading Stata files with repeated value labels when `convert_categoricals=True` (GH13923).

• `DataFrame.style` will now render sparsified MultiIndexes (GH11655).

• `DataFrame.style` will now show column level names (e.g. `DataFrame.columns.names`) (GH13775).

• `DataFrame` has gained support to re-order the columns based on the values in a row using `df.sort_values(by='...', axis=1)` (GH10806).
In [75]: df = pd.DataFrame({'A': [2, 7], 'B': [3, 5], 'C': [4, 8]},
    index=['row1', 'row2'])

In [76]: df
Out[76]:
   A  B  C
row1 2  3  4
row2 7  5  8

In [77]: df.sort_values(by='row2', axis=1)

Out[77]:
   B  A  C
row1 3  2  4
row2 5  7  8

- Added documentation to I/O regarding the perils of reading in columns with mixed dtypes and how to handle it (GH13746)
- `to_html()` now has a `border` argument to control the value in the opening `<table>` tag. The default is the value of the `html.border` option, which defaults to 1. This also affects the notebook HTML repr, but since Jupyter’s CSS includes a border-width attribute, the visual effect is the same. (GH11563).
- Raise `ImportError` in the sql functions when `sqlalchemy` is not installed and a connection string is used (GH11920).
- Compatibility with matplotlib 2.0. Older versions of pandas should also work with matplotlib 2.0 (GH13333)
- `Timestamp`, `Period`, `DatetimeIndex`, `PeriodIndex` and `.dt` accessor have gained a `.is_leap_year` property to check whether the date belongs to a leap year. (GH13727)
- `astype()` will now accept a dict of column name to data types mapping as the `dtype` argument. (GH12086)
- The `pd.read_json` and `DataFrame.to_json` has gained support for reading and writing json lines with the `lines` option see `Line delimited json` (GH9180)
- `read_excel()` now supports the `true_values` and `false_values` keyword arguments (GH13347)
- `groupby()` will now accept a scalar and a single-element list for specifying `level` on a non-MultiIndex grouper. (GH13907)
- Non-convertible dates in an excel date column will be returned without conversion and the column will be `object` dtype, rather than raising an exception (GH10001).
- `pd.Timedelta(None)` is now accepted and will return `NaT`, mirroring `pd.Timestamp` (GH13687)
- `pd.read_stata()` can now handle some format 111 files, which are produced by SAS when generating Stata dta files (GH11526)
- `Series` and `Index` now support `divmod` which will return a tuple of series or indices. This behaves like a standard binary operator with regards to broadcasting rules (GH14208).

### 1.11.2 API changes

#### 1.11.2.1 `Series.tolist()` will now return Python types

`Series.tolist()` will now return Python types in the output, mimicking NumPy `.tolist()` behavior (GH10904)
In [78]: s = pd.Series([1,2,3])

Previous behavior:

In [7]: type(s.tolist()[0])
Out[7]:
<class 'numpy.int64'>

New behavior:

In [79]: type(s.tolist()[0])
Out[79]:
int

1.11.2.2 Series operators for different indexes

Following Series operators have been changed to make all operators consistent, including DataFrame (GH1134, GH4581, GH13538)

• Series comparison operators now raise `ValueError` when index are different.
• Series logical operators align both index of left and right hand side.

**Warning:** Until 0.18.1, comparing Series with the same length, would succeed even if the .index are different (the result ignores .index). As of 0.19.0, this will raises `ValueError` to be more strict. This section also describes how to keep previous behavior or align different indexes, using the flexible comparison methods like .eq.

As a result, Series and DataFrame operators behave as below:

**Arithmetic operators**

Arithmetic operators align both index (no changes).

In [80]: s1 = pd.Series([1, 2, 3], index=list('ABC'))
In [81]: s2 = pd.Series([2, 2, 2], index=list('ABD'))
In [82]: s1 + s2
Out[82]:
     A  3.0
     B  4.0
     C  NaN
     D  NaN
dtype: float64

In [83]: df1 = pd.DataFrame([1, 2, 3], index=list('ABC'))
In [84]: df2 = pd.DataFrame([2, 2, 2], index=list('ABD'))
In [85]: df1 + df2
Out[85]:
     A  0
     A  3.0
(continues on next page)
Comparison operators

Comparison operators raise `ValueError` when `.index` are different.

**Previous Behavior (Series):**

Series compared values ignoring the `.index` as long as both had the same length:

```
In [1]: s1 == s2
Out[1]:
A   False
B    True
C    False
dtype: bool
```

**New behavior (Series):**

```
In [2]: s1 == s2
Out[2]:
ValueError: Can only compare identically-labeled Series objects
```

**Note:** To achieve the same result as previous versions (compare values based on locations ignoring `.index`), compare both `.values`.

```
In [86]: s1.values == s2.values
Out[86]: array([False,   True,  False], dtype=bool)
```

If you want to compare `Series` aligning its `.index`, see flexible comparison methods section below:

```
In [87]: s1.eq(s2)
Out[87]:
A   False
B    True
C    False
D    False
dtype: bool
```

**Current Behavior (DataFrame, no change):**

```
In [3]: df1 == df2
Out[3]:
ValueError: Can only compare identically-labeled DataFrame objects
```

Logical operators

Logical operators align both `.index` of left and right hand side.

**Previous behavior (Series), only left hand side index was kept:**
In [4]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [5]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [6]: s1 & s2
Out[6]:
A   True
B   False
C   False
dtype: bool

New behavior (Series):

In [88]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [89]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [90]: s1 & s2
Out[90]:
A   True
B   False
C   False
D   False
dtype: bool

Note: Series logical operators fill a NaN result with False.

Note: To achieve the same result as previous versions (compare values based on only left hand side index), you can use reindex_like:

In [91]: s1 & s2.reindex_like(s1)
Out[91]:
A    True
B    False
C    False
dtype: bool

Current Behavior (DataFrame, no change):

In [92]: df1 = pd.DataFrame([True, False, True], index=list('ABC'))
In [93]: df2 = pd.DataFrame([True, True, True], index=list('ABD'))
In [94]: df1 & df2
Out[94]:
     0
A  True
B  False
C  NaN
D  NaN
**Flexible comparison methods**

Series flexible comparison methods like `eq`, `ne`, `le`, `lt`, `ge` and `gt` now align both `index`. Use these operators if you want to compare two Series which has the different `index`.

In [95]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])
In [96]: s2 = pd.Series([2, 2, 2], index=['b', 'c', 'd'])

In [97]: s1.eq(s2)
Out[97]:
a   False
b   True
c   False
d   False
dtype: bool

In [98]: s1.ge(s2)

Out[98]:
a   False
b   True
c   True
d   False
dtype: bool

Previously, this worked the same as comparison operators (see above).

### 1.11.2.3 Series type promotion on assignment

A Series will now correctly promote its dtype for assignment with incompat values to the current dtype (GH13234)

In [99]: s = pd.Series()

Previous behavior:

In [2]: s["a"] = pd.Timestamp("2016-01-01")
In [3]: s["b"] = 3.0
TypeError: invalid type promotion

New behavior:

In [100]: s["a"] = pd.Timestamp("2016-01-01")
In [101]: s["b"] = 3.0
In [102]: s
Out[102]:
    a    2016-01-01 00:00:00
    b      3
dtype: object

In [103]: s.dtype
Out[103]: dtype('O')
1.11.2.4 .to_datetime() changes

Previously if .to_datetime() encountered mixed integers/floats and strings, but no datetimes with errors='coerce' it would convert all to NaT.

**Previous behavior:**

```python
In [2]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[2]: DatetimeIndex(['NaT', 'NaT'], dtype='datetime64[ns]', freq=None)
```

**Current behavior:**

This will now convert integers/floats with the default unit of ns.

```python
In [104]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[104]: DatetimeIndex(['1970-01-01 00:00:00.000000001', 'NaT'], dtype='datetime64[ns]', freq=None)
```

**Bug fixes related to .to_datetime():**

- Bug in pd.to_datetime() when passing integers or floats, and no unit and errors='coerce' (GH13180).
- Bug in pd.to_datetime() when passing invalid datatypes (e.g. bool); will now respect the errors keyword (GH13176)
- Bug in pd.to_datetime() which overflowed on int8, and int16 dtypes (GH13451)
- Bug in pd.to_datetime() raise AttributeError with NaN and the other string is not valid when errors='ignore' (GH12424)
- Bug in pd.to_datetime() did not cast floats correctly when unit was specified, resulting in truncated datetime (GH13834)

1.11.2.5 Merging changes

Merging will now preserve the dtype of the join keys (GH8596)

```python
In [105]: df1 = pd.DataFrame({'key': [1], 'v1': [10]})
In [106]: df1
Out[106]:
   key  v1
0    1  10
In [107]: df2 = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})
In [108]: df2
Out[108]:
   key  v1
0    1  20
1    2  30
```

**Previous behavior:**

```python
In [5]: pd.merge(df1, df2, how='outer')
Out[5]:
   key  v1
0   1.0  10.0
(continues on next page)
New behavior:

We are able to preserve the join keys

```
In [109]: pd.merge(df1, df2, how='outer')
Out[109]:
   key  v1
0   1   10
1   2   30
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast, which is unchanged from previous.

```
In [111]: pd.merge(df1, df2, how='outer', on='key')
Out[111]:
   key  v1_x  v1_y
0   1    10.0  20
1   2    NaN   30
```

1.11.2.6 `.describe()` changes

Percentile identifiers in the index of a `.describe()` output will now be rounded to the least precision that keeps them distinct (GH13104)

```
In [113]: s = pd.Series([0, 1, 2, 3, 4])
In [114]: df = pd.DataFrame([0, 1, 2, 3, 4])
```

Previous behavior:

The percentiles were rounded to at most one decimal place, which could raise `ValueError` for a data frame if the percentiles were duplicated.
In [3]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])

Out[3]:
count  5.000000
mean  2.000000
std  1.581139
min  0.000000
0.0%  0.000400
0.1%  0.002000
0.1%  0.004000
50%  2.000000
99.9%  3.996000
100.0%  3.998000
100.0%  3.999600
max  4.000000
dtype: float64

In [4]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])

ValueError: cannot reindex from a duplicate axis

New behavior:

In [115]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])

Out[115]:
count  5.000000
mean  2.000000
std  1.581139
min  0.000000
0.01%  0.000400
0.05%  0.002000
0.1%  0.004000
50%  2.000000
99.9%  3.996000
99.95%  3.998000
99.99%  3.999600
max  4.000000
dtype: float64

In [116]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])

 ValueError: cannot reindex from a duplicate axis

Furthermore:
• Passing duplicated percentiles will now raise a `ValueError`.
• Bug in `.describe()` on a DataFrame with a mixed-dtype column index, which would previously raise a `TypeError` (GH13288)

1.11.2.7 Period changes

**PeriodIndex now has period dtype**

PeriodIndex now has its own period dtype. The period dtype is a pandas extension dtype like category or the *timezone aware dtype* (`datetime64[ns, tz]`) (GH13941). As a consequence of this change, `PeriodIndex` no longer has an integer dtype:

**Previous behavior:**

```
In [1]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')
In [2]: pi
Out[2]: PeriodIndex(['2016-08-01'], dtype='int64', freq='D')
In [3]: pd.api.types.is_integer_dtype(pi)
Out[3]: True
In [4]: pi.dtype
Out[4]: dtype('int64')
```

**New behavior:**

```
In [117]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')
In [118]: pi
Out[118]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')
In [119]: pd.api.types.is_integer_dtype(pi)
Out[119]: False
In [120]: pd.api.types.is_period_dtype(pi)
Out[120]: True
In [121]: pi.dtype
Out[121]: period[D]
In [122]: type(pi.dtype)
pandas.core.dtypes.dtypes.PeriodDtype
```

**Period('NaT') now returns pd.NaT**

Previously, `Period` has its own `Period('NaT')` representation different from `pd.NaT`. Now `Period('NaT')` has been changed to return `pd.NaT`. (GH12759, GH13582)

**Previous behavior:**
In [5]: pd.Period('NaT', freq='D')
Out[5]: Period('NaT', 'D')

New behavior:

These result in pd.NaT without providing freq option.

In [123]: pd.Period('NaT')
Out[123]: NaT
In [124]: pd.Period(None)
Out[124]: NaT

To be compatible with Period addition and subtraction, pd.NaT now supports addition and subtraction with int. Previously it raised ValueError.

Previous behavior:

In [5]: pd.NaT + 1
...:
ValueError: Cannot add integral value to Timestamp without freq.

New behavior:

In [125]: pd.NaT + 1
Out[125]: NaT
In [126]: pd.NaT - 1
Out[126]: NaT

PeriodIndex.values now returns array of Period object

.values is changed to return an array of Period objects, rather than an array of integers (GH13988).

Previous behavior:

In [6]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [7]: pi.values
array([492, 493])

New behavior:

In [127]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [128]: pi.values
Out[128]: array([Period('2011-01', 'M'), Period('2011-02', 'M')], dtype=object)

1.11.2.8 Index + / − no longer used for set operations

Addition and subtraction of the base Index type and of DatetimeIndex (not the numeric index types) previously performed set operations (set union and difference). This behavior was already deprecated since 0.15.0 (in favor using the specific .union() and .difference() methods), and is now disabled. When possible, + and − are now used for element-wise operations, for example for concatenating strings or subtracting datetimes (GH8227, GH14127).

Previous behavior:
In [1]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
FutureWarning: using '+' to provide set union with Indexes is deprecated, use '|' or .union()
Out[1]: Index(['a', 'b', 'c'], dtype='object')

**New behavior:** the same operation will now perform element-wise addition:

In [129]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
Out[129]: Index(['aa', 'bc'], dtype='object')

Note that numeric Index objects already performed element-wise operations. For example, the behavior of adding two integer Indexes is unchanged. The base Index is now made consistent with this behavior.

In [130]: pd.Index([1, 2, 3]) + pd.Index([2, 3, 4])
Out[130]: Int64Index([3, 5, 7], dtype='int64')

Further, because of this change, it is now possible to subtract two DatetimeIndex objects resulting in a TimedeltaIndex:

**Previous behavior:**

In [1]: pd.DatetimeIndex(['2016-01-01', '2016-01-02']) - pd.DatetimeIndex(['2016-01-02', '2016-01-03'])
FutureWarning: using '-' to provide set differences with datetimelike Indexes is deprecated, use .difference()
Out[1]: DatetimeIndex(['2016-01-01'], dtype='datetime64[ns]', freq=None)

**New behavior:**

In [131]: pd.DatetimeIndex(['2016-01-01', '2016-01-02']) - pd.DatetimeIndex(['2016-01-02', '2016-01-03'])
Out[131]: TimedeltaIndex(['-1 days', '-1 days'], dtype='timedelta64[ns]', freq=None)

1.11.2.9 Index.difference and .symmetric_difference changes

Index.difference and Index.symmetric_difference will now, more consistently, treat NaN values as any other values. (GH13514)

In [132]: idx1 = pd.Index([1, 2, 3, np.nan])
In [133]: idx2 = pd.Index([0, 1, np.nan])

**Previous behavior:**

In [3]: idx1.difference(idx2)
Out[3]: Float64Index([1.0, 2.0, 3.0], dtype='float64')
In [4]: idx1.symmetric_difference(idx2)
Out[4]: Float64Index([0.0, 1.0, 2.0, 3.0], dtype='float64')

**New behavior:**

In [134]: idx1.difference(idx2)
Out[134]: Float64Index([2.0, 3.0], dtype='float64')
In [135]: idx1.symmetric_difference(idx2)
Out[135]: Float64Index([0.0, 2.0, 3.0], dtype='float64')
1.11.2.10 **Index.unique** consistently returns `Index`

`Index.unique()` now returns unique values as an `Index` of the appropriate `dtype`. (GH13395). Previously, most `Index` classes returned `np.ndarray`, and `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex` returned `Index` to keep metadata like timezone.

**Previous behavior:**

```python
In [1]: pd.Index([1, 2, 3]).unique()
Out[1]: array([1, 2, 3])

In [2]: pd.DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], tz='Asia/Tokyo').unique()
Out[2]: DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
                      '2011-01-03 00:00:00+09:00'],
                      dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

**New behavior:**

```python
In [136]: pd.Index([1, 2, 3]).unique()
Out[136]: Int64Index([1, 2, 3], dtype='int64')

In [137]: pd.DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], tz='Asia/Tokyo').unique()
Out[137]: DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
                      '2011-01-03 00:00:00+09:00'],
                      dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

1.11.2.11 **MultiIndex constructors, groupby and set_index preserve categorical dtypes**

`MultiIndex.from_arrays` and `MultiIndex.from_product` will now preserve categorical `dtype` in `MultiIndex` levels (GH13743, GH13854).

```python
In [138]: cat = pd.Categorical(['a', 'b'], categories=list("bac"))

In [139]: lvll1 = ['foo', 'bar']

In [140]: midx = pd.MultiIndex.from_arrays([cat, lvll1])

In [141]: midx
Out[141]: MultiIndex(levels=[['b', 'a', 'c'], ['bar', 'foo']],
                  labels=[[1, 0], [1, 0]])
```

**Previous behavior:**

```python
In [4]: midx.levels[0]
Out[4]: Index(['b', 'a', 'c'], dtype='object')

In [5]: midx.get_level_values[0]
Out[5]: Index(['a', 'b'], dtype='object')
```
New behavior: the single level is now a `CategoricalIndex`:

```python
In [142]: midx.levels[0]
Out[142]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False, dtype='category')
In [143]: midx.get_level_values(0)
CategoricalIndex(['a', 'b'], categories=['b', 'a', 'c'], ordered=False, dtype='category')
```

An analogous change has been made to `MultiIndex.from_product`. As a consequence, `groupby` and `set_index` also preserve categorical dtypes in indexes:

```python
In [144]: df = pd.DataFrame({'A': [0, 1], 'B': [10, 11], 'C': cat})
In [145]: df_grouped = df.groupby(by=['A', 'C']).first()
In [146]: df_set_idx = df.set_index(['A', 'C'])
```

Previous behavior:

```python
In [11]: df_grouped.index.levels[1]
Out[11]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [12]: df_grouped.reset_index().dtypes
Out[12]:
A    int64
C    object
B   float64
dtype: object
In [13]: df_set_idx.index.levels[1]
Out[13]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [14]: df_set_idx.reset_index().dtypes
Out[14]:
A    int64
C    object
B    int64
dtype: object
```

New behavior:

```python
In [147]: df_grouped.index.levels[1]
Out[147]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False, name='C', dtype='category')
In [148]: df_grouped.reset_index().dtypes
Out[148]:
A    int64
C    category
B   float64
dtype: object
In [149]: df_set_idx.index.levels[1]
Out[149]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False, name='C', dtype='category')
```

(continues on next page)
1.11.2.12 read_csv will progressively enumerate chunks

When read_csv() is called with chunksize=n and without specifying an index, each chunk used to have an independently generated index from 0 to n-1. They are now given instead a progressive index, starting from 0 for the first chunk, from n for the second, and so on, so that, when concatenated, they are identical to the result of calling read_csv() without the chunksize= argument (GH12185).

```
In [151]: data = 'A,B
0,1
2,3
4,5
6,7'
```

**Previous behavior:**

```
In [2]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
```

```
Out[2]:
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
```

**New behavior:**

```
In [152]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
```

```
Out[152]:
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
```

1.11.2.13 Sparse Changes

These changes allow pandas to handle sparse data with more dtypes, and for work to make a smoother experience with data handling.

**int64 and bool support enhancements**

Sparse data structures now gained enhanced support of int64 and bool dtype (GH667, GH13849).

Previously, sparse data were float64 dtype by default, even if all inputs were of int or bool dtype. You had to specify dtype explicitly to create sparse data with int64 dtype. Also, fill_value had to be specified explicitly because the default was np.nan which doesn’t appear in int64 or bool data.
In [1]: pd.SparseArray([1, 2, 0, 0])
Out[1]:
[1.0, 2.0, 0.0, 0.0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

# specifying int64 dtype, but all values are stored in sp_values because
# fill_value default is np.nan
In [2]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[2]:
[1, 2, 0, 0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

In [3]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64, fill_value=0)
Out[3]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)

As of v0.19.0, sparse data keeps the input dtype, and uses more appropriate fill_value defaults (0 for int64
dtype, False for bool dtype).

In [153]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[153]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)

In [154]: pd.SparseArray([True, False, False, False])
Out[154]:
[True, False, False, False]
Fill: False
IntIndex
Indices: array([0], dtype=int32)

See the docs for more details.

Operators now preserve dtypes

- Sparse data structure now can preserve dtype after arithmetic ops (GH13848)

In [155]: s = pd.SparseSeries([0, 2, 0, 1], fill_value=0, dtype=np.int64)

In [156]: s.dtype
Out[156]: dtype('int64')

In [157]: s + 1
Out[157]:
0  1
1  3

(continues on next page)
Sparse data structure now support `astype` to convert internal `dtype` (GH13900)

```
2  1
3  2
dtype: int64
BlockIndex
Block locations: array([1, 3], dtype=int32)
Block lengths: array([1, 1], dtype=int32)
```

`astype` fails if data contains values which cannot be converted to specified `dtype`. Note that the limitation is applied to `fill_value` which default is `np.nan`.

```
In [158]: s = pd.SparseSeries([1., 0., 2., 0.], fill_value=0)
In [159]: s
Out[159]:
0  1.0
1  0.0
2  2.0
3  0.0
dtype: float64
BlockIndex
Block locations: array([0, 2], dtype=int32)
Block lengths: array([1, 1], dtype=int32)
In [160]: s.astype(np.int64)
```

Other sparse fixes

- Subclassed `SparseDataFrame` and `SparseSeries` now preserve class types when slicing or transposing. (GH13787)
- `SparseArray` with bool `dtype` now supports logical (bool) operators (GH14000)
- Bug in `SparseSeries` with `MultiIndex` [] indexing may raise `IndexError` (GH13144)
- Bug in `SparseSeries` with `MultiIndex` [] indexing result may have normal `Index` (GH13144)
- Bug in `SparseDataFrame` in which `axis=None` did not default to `axis=0` (GH13048)
- Bug in `SparseSeries` and `SparseDataFrame` creation with object `dtype` may raise `TypeError` (GH11633)
- Bug in SparseDataFrame doesn't respect passed SparseArray or SparseSeries 's dtype and fill_value (GH13866)
- Bug in SparseArray and SparseSeries don't apply ufunc to fill_value (GH13853)
- Bug in SparseSeries.abs incorrectly keeps negative fill_value (GH13853)
- Bug in single row slicing on multi-type SparseDataFrame s, types were previously forced to float (GH13917)
- Bug in SparseSeries slicing changes integer dtype to float (GH8292)
- Bug in SparseDataFarme comparison ops may raise TypeError (GH13001)
- Bug in SparseDataFarme.isnull raises ValueError (GH8276)
- Bug in SparseSeries representation with bool dtype may raise IndexError (GH13110)
- Bug in SparseSeries and SparseDataFrame of bool or int64 dtype may display its values like float64 dtype (GH13110)
- Bug in sparse indexing using SparseArray with bool dtype may return incorrect result (GH13985)
- Bug in SparseArray created from SparseSeries may lose dtype (GH13999)
- Bug in SparseSeries comparison with dense returns normal Series rather than SparseSeries (GH13999)

1.11.2.14 Indexer dtype changes

**Note:** This change only affects 64 bit python running on Windows, and only affects relatively advanced indexing operations

Methods such as Index.get_indexer that return an indexer array, coerce that array to a “platform int”, so that it can be directly used in 3rd party library operations like numpy.take. Previously, a platform int was defined as np.int_ which corresponds to a C integer, but the correct type, and what is being used now, is np.intp, which corresponds to the C integer size that can hold a pointer (GH3033, GH13972).

These types are the same on many platform, but for 64 bit python on Windows, np.int_ is 32 bits, and np.intp is 64 bits. Changing this behavior improves performance for many operations on that platform.

**Previous behavior:**

```
In [1]: i = pd.Index(['a', 'b', 'c'])
In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int32')
```

**New behavior:**

```
In [1]: i = pd.Index(['a', 'b', 'c'])
In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int64')
```
1.11.2.15 Other API Changes

- `Timestamp.to_pydatetime` will issue a `UserWarning` when `warn=True`, and the instance has a non-zero number of nanoseconds, previously this would print a message to stdout (GH14101).
- `Series.unique()` with datetime and timezone now returns return array of `Timestamp` with timezone (GH13565).
- `Panel.to_sparse()` will raise a `NotImplementedError` exception when called (GH13778).
- `Index.reshape()` will raise a `NotImplementedError` exception when called (GH12882).
- `.filter()` enforces mutual exclusion of the keyword arguments (GH12399).
- `eval`’s upcasting rules for `float32` types have been updated to be more consistent with NumPy’s rules. New behavior will not upcast to `float64` if you multiply a pandas `float32` object by a scalar float64 (GH12388).
- An `UnsupportedFunctionCall` error is now raised if NumPy ufuncs like `np.mean` are called on groupby or resample objects (GH12811).
- `__setitem__` will no longer apply a callable rhs as a function instead of storing it. Call `where` directly to get the previous behavior (GH13299).
- Calls to `.sample()` will respect the random seed set via `numpy.random.seed(n)` (GH13161)
- `Styler.apply` is now more strict about the outputs your function must return. For `axis=0` or `axis=1`, the output shape must be identical. For `axis=None`, the output must be a DataFrame with identical columns and index labels (GH13222).
- `Float64Index.astype(int)` will now raise `ValueError` if `Float64Index` contains NaN values (GH13149)
- `TimedeltaIndex.astype(int)` and `DatetimeIndex.astype(int)` will now return `Int64Index` instead of `np.array` (GH13209)
- Passing `Period` with multiple frequencies to normal `Index` now returns `Index` with `object` dtype (GH13664)
- `PeriodIndex.fillna` with `Period` has different freq now coerces to `object` dtype (GH13664)
- Faceted boxplots from `DataFrame.boxplot(by=col)` now return a `Series` when `return_type` is not `None`. Previously these returned an `OrderedDict`. Note that when `return_type=None`, the default, these still return a 2-D NumPy array (GH12216, GH7096).
- `pd.read_hdf` will now raise `ValueError` instead of `KeyError`, if a mode other than `r`, `r+` and `a` is supplied. (GH13623)
- `pd.read_csv()`, `pd.read_table()`, and `pd.read_hdf()` raise the built-in `FileNotFoundError` exception for Python 3.x when called on a nonexistent file; this is back-ported as `IOError` in Python 2.x (GH14086)
- More informative exceptions are passed through the csv parser. The exception type would now be the original exception type instead of `CParserError` (GH13562).
- `pd.read_csv()` in the C engine will now issue a `ParserWarning` or raise a `ValueError` when `sep` encoded is more than one character long (GH14065)
- `DataFrame.values` will now return `float64` with `DataFrame` of mixed `int64` and `uint64` dtypes, conforming to `np.find_common_type` (GH10364, GH13917)
- `.groupby().groups` will now return a dictionary of `Index` objects, rather than a dictionary of `np.ndarray` or lists (GH14293)
1.11.3 Deprecations

- **Series.reshape** and **Categorical.reshape** have been deprecated and will be removed in a subsequent release (GH12882, GH12882)
- **PeriodIndex.to_datetime** has been deprecated in favor of **PeriodIndex.to_timestamp** (GH8254)
- **Timestamp.to_datetime** has been deprecated in favor of **Timestamp.to_pydatetime** (GH8254)
- **Index.to_datetime** and **DatetimeIndex.to_datetime** have been deprecated in favor of **pd.to_datetime** (GH8254)
- **pandas.core.datetools** module has been deprecated and will be removed in a subsequent release (GH14094)
- **SparseList** has been deprecated and will be removed in a future version (GH13784)
- **DataFrame.to_html()** and **DataFrame.to_latex()** have dropped the **colSpace** parameter in favor of **col_space** (GH13857)
- **DataFrame.to_sql()** has deprecated the **flavor** parameter, as it is superfluous when SQLAlchemy is not installed (GH13611)
- Deprecated **read_csv** keywords:
  - **compact_ints** and **use_unsigned** have been deprecated and will be removed in a future version (GH13320)
  - **buffer_lines** has been deprecated and will be removed in a future version (GH13360)
  - **as_recarray** has been deprecated and will be removed in a future version (GH13373)
  - **skip_footer** has been deprecated in favor of **skipfooter** and will be removed in a future version (GH13349)
- **top-level pd.ordered_merge()** has been renamed to **pd.merge_ordered()** and the original name will be removed in a future version (GH13358)
- **Timestamp.offset** property (and named arg in the constructor), has been deprecated in favor of **freq** (GH12160)
- **pd.tseries.util.pivot_annual** is deprecated. Use **pivot_table** as alternative, an example is [here](GH736)
- **pd.tseries.util.isleapyear** has been deprecated and will be removed in a subsequent release. Datetime-likes now have a **is_leap_year** property (GH13727)
- **Panel4D** and **PanelND** constructors are deprecated and will be removed in a future version. The recommended way to represent these types of n-dimensional data are with the **xarray** package. Pandas provides a **to_xarray()** method to automate this conversion (GH13564).
- **pandas.tseries.frequencies.get_standard_freq** is deprecated. Use **pandas.tseries.frequencies.to_offset(freq).rule_code** instead (GH13874)
- **pandas.tseries.frequencies.to_offset's freqstr** keyword is deprecated in favor of **freq** (GH13874)
- **Categorical.from_array** has been deprecated and will be removed in a future version (GH13854)

1.11.4 Removal of prior version deprecations/changes

- The **SparsePanel** class has been removed (GH13778)
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- The `pd.sandbox` module has been removed in favor of the external library pandas-qt (GH13670)
- The `pandas.io.data` and `pandas.io.wb` modules are removed in favor of the pandas-datareader package (GH13724).
- The `pandas.tools.rplot` module has been removed in favor of the seaborn package (GH13855)
- `DataFrame.to_csv()` has dropped the `engine` parameter, as was deprecated in 0.17.1 (GH11274, GH13419)
- `DataFrame.to_dict()` has dropped the `outtype` parameter in favor of `orient` (GH13627, GH8486)
- `pd.Categorical` has dropped setting of the `ordered` attribute directly in favor of the `set_ordered` method (GH13671)
- `pd.Categorical` has dropped the `levels` attribute in favor of `categories` (GH8376)
- `DataFrame.to_sql()` has dropped the `mysql` option for the `flavor` parameter (GH13611)
- `Panel.shift()` has dropped the `lags` parameter in favor of `periods` (GH14041)
- `pd.Index` has dropped the `diff` method in favor of `difference` (GH13669)
- `pd.DataFrame` has dropped the `to_wide` method in favor of `to_panel` (GH14039)
- `Series.to_csv` has dropped the `nanRep` parameter in favor of `na_rep` (GH13804)
- `Series.xs, DataFrame.xs, Panel.xs, Panel.major_xs, and Panel.minor_xs` have dropped the `copy` parameter (GH13781)
- `str.split` has dropped the `return_type` parameter in favor of `expand` (GH13701)
- Removal of the legacy time rules (offset aliases), deprecated since 0.17.0 (this has been alias since 0.8.0) (GH13590, GH13868). Now legacy time rules raises ValueError. For the list of currently supported offsets, see here.
- The default value for the `return_type` parameter for `DataFrame.plot.box` and `Dataframe.boxplot` changed from None to "axes". These methods will now return a matplotlib axes by default instead of a dictionary of artists. See here (GH6581).
- The `tquery` and `uquery` functions in the `pandas.io.sql` module are removed (GH5950).

### 1.11.5 Performance Improvements

- Improved performance of sparse `IntIndex.intersect` (GH13082)
- Improved performance of sparse arithmetic with `BlockIndex` when the number of blocks are large, though recommended to use `IntIndex` in such cases (GH13082)
- Improved performance of `DataFrame.quantile()` as it now operates per-block (GH11623)
- Improved performance of float64 hash table operations, fixing some very slow indexing and groupby operations in python 3 (GH13166, GH13334)
- Improved performance of `DataFrameGroupBy.transform` (GH12737)
- Improved performance of `Index` and `Series.duplicated` (GH10235)
- Improved performance of `Index.difference` (GH12044)
- Improved performance of `RangeIndex.is_monotonic_increasing` and `is_monotonic_decreasing` (GH13749)
- Improved performance of datetime string parsing in `DatetimeIndex` (GH13692)
- Improved performance of hashing `Period` (GH12817)
• Improved performance of `pandas.factorize` of datetime with timezone (GH13750)
• Improved performance of by lazily creating indexing hashtables on larger Indexes (GH14266)
• Improved performance of `pandas.groupby.groups` (GH14293)
• Unnecessary materializing of a MultiIndex when introspecting for memory usage (GH14308)

### 1.11.6 Bug Fixes

- Bug in `pandas.groupby().shift()`, which could cause a segfault or corruption in rare circumstances when grouping by columns with missing values (GH13813)
- Bug in `pandas.groupby().cumsum()` calculating `cumprod` when `axis=1` (GH13994)
- Bug in `pandas.to_timedelta()` in which the `errors` parameter was not being respected (GH13613)
- Bug in `pandas.io.json.json_normalize()`, where non-ascii keys raised an exception (GH13213)
- Bug when passing a non-default-indexed Series as `xerr` or `yerr` in `.plot()` (GH11858)
- Bug in area plot draws legend incorrectly if subplot is enabled or legend is moved after plot (matplotlib 1.5.0 is required to draw area plot legend properly) (GH9161, GH13544)
- Bug in `pandas.DataFrame` assignment with an object-dtyped Index where the resultant column is mutable to the original object. (GH13352)
- Bug in `pandas.matplotlib.AutomaticFormatter`; this restores the second scaled formatting and re-adds micro-second scaled formatting (GH13131)
- Bug in selection from a `pandas.HDFStore` with a fixed format and/or start/stop specified will now return the selected range (GH8287)
- Bug in `pandas.Categorical.from_codes()` where an unhelpful error was raised when an invalid ordered parameter was passed in (GH14058)
- Bug in `pandas.Series` construction from a tuple of integers on windows not returning default dtype (int64) (GH13646)
- Bug in `pandas.TimedeltaIndex` addition with a Datetime-like object where addition overflow was not being caught (GH14068)
- Bug in `pandas.GroupBy.transform` with datetime values and missing groups (GH13191)
- Bug where empty `pandas.Series` were incorrectly coerced in datetime-like numeric operations (GH13844)
- Bug in `pandas.Categorical` constructor when passed a `Categorical` containing datetimes with timezones (GH14190)
- Bug in `pandas.Series.str.extractall()` with str index raises `ValueError` (GH13156)
- Bug in `pandas.Series.str.extractall()` with single group and quantifier (GH13382)
- Bug in `pandas.DatetimeIndex` and `pandas.Period` subtraction raises `ValueError` or `AttributeError` rather than `TypeError` (GH13078)
- Bug in `pandas.Index` and `pandas.Series` created with NaN and NaT mixed data may not have `datetime64` dtype (GH13324)
• Bug in `Index` and `Series` may ignore `np.datetime64('nat')` and `np.timedelta64('nat')` to infer dtype (GH13324)

• Bug in `PeriodIndex` and `Period` subtraction raises `AttributeError` (GH13071)

• Bug in `PeriodIndex` construction returning a `float64` index in some circumstances (GH13067)

• Bug in `.resample(..)` with a `PeriodIndex` not changing its `freq` appropriately when empty (GH13067)

• Bug in `.resample(..)` with a `PeriodIndex` not retaining its type or name with an empty DataFrame appropriately when empty (GH13212)

• Bug in `groupby(..).apply(..)` when the passed function returns scalar values per group (GH13468).

• Bug in `groupby(..).resample(..)` where passing some keywords would raise an exception (GH13235)

• Bug in `.tz_convert` on a tz-aware `DateTimeIndex` that relied on index being sorted for correct results (GH13066)

• Bug in `.tz_localize` with `dateutil.tz.tzlocal` may return incorrect result (GH13583)

• Bug in `DatetimeTZDtype` dtype with `dateutil.tz.tzlocal` cannot be regarded as valid dtype (GH13583)

• Bug in `pd.read_hdf()` where attempting to load an HDF file with a single dataset, that had one or more categorical columns, failed unless the key argument was set to the name of the dataset. (GH13231)

• Bug in `.rolling()` that allowed a negative integer window in construction of the `Rolling()` object, but would later fail on aggregation (GH13383)

• Bug in `Series` indexing with tuple-valued data and a numeric index (GH13509)

• Bug in printing `pd.DataFrame` where unusual elements with the `object` dtype were causing segfaults (GH13717)

• Bug in ranking `Series` which could result in segfaults (GH13445)

• Bug in various index types, which did not propagate the name of passed index (GH12309)

• Bug in `DatetimeIndex`, which did not honour the `copy=True` (GH13205)

• Bug in `DatetimeIndex.is_normalized` returns incorrectly for normalized date_range in case of local timezones (GH13459)

• Bug in `pd.concat` and `.append may coerces datetime64 and timedelta to object dtype containing python built-in datetime or timedelta rather than Timestamp or Timedelta` (GH13626)

• Bug in `PeriodIndex.append` may raises `AttributeError` when the result is object dtype (GH13221)

• Bug in `CategoricalIndex.append` may accept normal list (GH13626)

• Bug in `pd.concat` and `.append with the same timezone get reset to UTC` (GH7795)

• Bug in `Series` and `DataFrame .append raises AmbiguousTimeError` if data contains datetime near DST boundary (GH13366)

• Bug in `DataFrame.to_csv()` in which float values were being quoted even though quotations were specified for non-numeric values only (GH12922, GH13259)

• Bug in `DataFrame.describe()` raising `ValueError` with only boolean columns (GH1389)

• Bug in `MultiIndex` slicing where extra elements were returned when level is non-unique (GH12896)

• Bug in `.str.replace` does not raise TypeError for invalid replacement (GH13483)

• Bug in `MultiIndex.from_arrays` which didn’t check for input array lengths matching (GH13599)
• Bug in `cartesian_product` and `MultiIndex.from_product` which may raise with empty input arrays (GH12258)

• Bug in `pd.read_csv()` which may cause a segfault or corruption when iterating in large chunks over a stream/file under rare circumstances (GH13703)

• Bug in `pd.read_csv()` which caused errors to be raised when a dictionary containing scalars is passed in for `na_values` (GH12224)

• Bug in `pd.read_csv()` which caused BOM files to be incorrectly parsed by not ignoring the BOM (GH4793)

• Bug in `pd.read_csv()` with `engine='python'` which raised errors when a numpy array was passed in for `usecols` (GH12546)

• Bug in `pd.read_csv()` where the index columns were being incorrectly parsed when parsed as dates with a `thousands` parameter (GH14066)

• Bug in `pd.read_csv()` with `engine='python'` in which `NaN` values weren’t being detected after data was converted to numeric values (GH13314)

• Bug in `pd.read_csv()` in which the `nrows` argument was not properly validated for both engines (GH10476)

• Bug in `pd.read_csv()` with `engine='python'` in which `usecols` kwarg from being an empty set (GH13402)

• Bug in `pd.read_csv()` in the C engine where the NULL character was not being parsed as NULL (GH14012)

• Bug in `pd.read_csv()` with `engine='c'` in which `NULL quotechar` was not accepted even though `quoting` was specified as `None` (GH13411)

• Bug in `pd.read_csv()` with `engine='c'` in which fields were not properly cast to float when quoting was specified as non-numeric (GH13411)

• Bug in `pd.read_csv()` in Python 2.x with non-UTF8 encoded, multi-character separated data (GH3404)

• Bug in `pd.read_csv()`, where aliases for `utf-xx` (e.g. UTF-xx, UTF_xx, utf_xx) raised `UnicodeDecodeError` (GH13549)

• Bug in `pd.read_csv`, `pd.read_table`, `pd.read_fwf`, `pd.read_stata`, and `pd.read_sas` where files were opened by parsers but not closed if both `chunksize` and `iterator` were `None` (GH13940)

• Bug in `StataReader`, `StataWriter`, `XportReader` and `SAS7BDATReader` where a file was not properly closed when an error was raised. (GH13940)

• Bug in `pd.pivot_table()` where `margins_name` is ignored when `aggfunc` is a list (GH13354)

• Bug in `pd.Series.str.zfill`, `center`, `ljust`, `rjust`, and `pad` when passing non-integers, did not raise `TypeError` (GH13598)

• Bug in checking for any null objects in a `TimedeltaIndex`, which always returned `True` (GH13603)

• Bug in `Series` arithmetic raises `TypeError` if it contains datetime-like as `object` dtype (GH13043)
• Bug in Series.isnull() and Series.notnull() ignore Period('NaT') (GH13737)
• Bug in Series.fillna() and Series.dropna() don’t affect to Period('NaT') (GH13737)
• Bug in Series.fillna(value=np.nan) incorrectly raises KeyError on a category dtype typed Series (GH14021)
• Bug in extension dtype creation where the created types were not is/identical (GH13285)
• Bug in .resample(...) where incorrect warnings were triggered by IPython introspection (GH13618)
• Bug in NaT - Period raises AttributeError (GH13071)
• Bug in Series comparison may output incorrect result if rhs contains NaT (GH9005)
• Bug in Series and Index comparison may output incorrect result if it contains NaT with object dtype (GH13592)
• Bug in Period addition raises TypeError if Period is on right hand side (GH13069)
• Bug in pd and Series or Index comparison raises TypeError (GH13200)
• Bug in pd.set_eng_float_format() that would prevent NaN and Inf from formatting (GH11981)
• Bug in .unstack with Categorical dtype resets .ordered to True (GH13249)
• Clean some compile time warnings in datetime parsing (GH13607)
• Bug in factorize raises AmbiguousTimeError if data contains datetime near DST boundary (GH13750)
• Bug in .set_index raises AmbiguousTimeError if new index contains DST boundary and multi levels (GH12920)
• Bug in .shift raises AmbiguousTimeError if data contains datetime near DST boundary (GH13926)
• Bug in pd.read_hdf() returns incorrect result when a DataFrame with a categorical column and a query which doesn’t match any values (GH13792)
• Bug in .iloc when indexing with a non lex-sorted MultiIndex (GH13797)
• Bug in .loc when indexing with date strings in a reverse sorted DatetimeIndex (GH14316)
• Bug in Series comparison operators when dealing with zero dim NumPy arrays (GH13006)
• Bug in .combine_first may return incorrect dtype (GH7630, GH10567)
• Bug in groupby where apply returns different result depending on whether first result is None or not (GH12824)
• Bug in groupby(...).nth() where the group key is included inconsistently if called after .head() / .tail() (GH12839)
• Bug in .to_html, .to_latex and .to_string silently ignore custom datetime formatter passed through the formatters key word (GH10690)
• Bug in DataFrame.iterrows(), not yielding a Series subclass if defined (GH13977)
• Bug in pd.to_numeric when errors='coerce' and input contains non-hashable objects (GH13324)
• Bug in invalid Timedelta arithmetic and comparison may raise ValueError rather than TypeError (GH13624)
• Bug in invalid datetime parsing in to_datetime and DatetimeIndex may raise TypeError rather than ValueError (GH11169, GH11287)
• Bug in Index created with tz-aware Timestamp and mismatched tz option incorrectly coerces timezone (GH13692)
• Bug in `DatetimeIndex` with nanosecond frequency does not include timestamp specified with `end` (GH13672)
• Bug in `Series` when setting a slice with a `np.timedelta64` (GH14155)
• Bug in `Index` raises `OutOfBoundsDatetime` if datetime exceeds `datetime64[ns]` bounds, rather than coercing to object dtype (GH13663)
• Bug in `Index` may ignore specified `datetime64` or `timedelta64` passed as dtype (GH13981)
• Bug in `RangeIndex` can be created without no arguments rather than raises `TypeError` (GH13793)
• Bug in `.value_counts()` raises `OutOfBoundsDatetime` if data exceeds `datetime64[ns]` bounds (GH13663)
• Bug in `DatetimeIndex` may raise `OutOfBoundsDatetime` if input `np.datetime64` has other unit than `ns` (GH9114)
• Bug in `Series` creation with `np.datetime64` which has other unit than `ns` as object dtype results in incorrect values (GH13876)
• Bug in `resample` with timedelta data where data was casted to float (GH13119).
• Bug in `pd.isnull()` `pd.notnull()` raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
• Bug in `pd.merge()` may raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
• Bug in `HDFStore/read_hdf()` discarded `DatetimeIndex.name` if tz was set (GH13884)
• Bug in `Categorical.remove_unused_categories()` changes `.codes` dtype to platform int (GH13261)
• Bug in `groupby` with `as_index=False` returns all NaN’s when grouping on multiple columns including a categorical one (GH13204)
• Bug in `df.groupby(...)[...]` where getitem with `Int64Index` raised an error (GH13731)
• Bug in the CSS classes assigned to `DataFrame.style` for index names. Previously they were assigned "col_heading level<n> col<c>" where `n` was the number of levels + 1. Now they are assigned "index_name level<n>"`, where `n` is the correct level for that MultiIndex.
• Bug where `pd.read_gbq()` could throw `ImportError`: No module named discovery as a result of a naming conflict with another python package called `apiclient` (GH13454)
• Bug in `Index.union` returns an incorrect result with a named empty index (GH13432)
• Bugs in `Index.difference` and `DataFrame.join` raise in Python3 when using mixed-integer indexes (GH13432, GH12814)
• Bug in `subtract tz-aware datetime.datetime from tz-aware datetime64 series` (GH14088)
• Bug in `.to_excel()` when DataFrame contains a MultiIndex which contains a label with a NaN value (GH13511)
• Bug in invalid frequency offset string like “D1”, “-2-3H” may not raise `ValueError` (GH13930)
• Bug in `concat` and `groupby` for hierarchical frames with `RangeIndex` levels (GH13542).
• Bug in `Series.str.contains()` for Series containing only NaN values of object dtype (GH14171)
• Bug in `agg()` function on `groupby` dataframe changes dtype of `datetime64[ns]` column to `float64` (GH12821)
• Bug in using NumPy ufunc with PeriodIndex to add or subtract integer raise IncompatibleFrequency. Note that using standard operator like + or - is recommended, because standard operators use more efficient path (GH13980)

• Bug in operations on NaT returning float instead of datetime64[ns] (GH12941)

• Bug in Series flexible arithmetic methods (like .add()) raises ValueError when axis=None (GH13894)

• Bug in DataFrame.to_csv() with MultiIndex columns in which a stray empty line was added (GH6618)

• Bug in DatetimeIndex, TimedeltaIndex and PeriodIndex.equals() may return True when input isn't Index but contains the same values (GH13107)

• Bug in assignment against datetime with timezone may not work if it contains datetime near DST boundary (GH14146)

• Bug in pd.eval() and HDFStore query truncating long float literals with python 2 (GH14241)

• Bug in Index raises KeyError displaying incorrect column when column is not in the df and columns contains duplicate values (GH13822)

• Bug in Period and PeriodIndex creating wrong dates when frequency has combined offset aliases (GH13874)

• Bug in .to_string() when called with an integer line_width and index=False raises an UnboundLocalError exception because idx referenced before assignment.

• Bug in eval() where the resolvers argument would not accept a list (GH14095)

• Bugs in stack, get_dummies, make_axis_dummies which don’t preserve categorical dtypes in (multi)indexes (GH13854)

• PeriodIndex can now accept list and array which contains pd.NaT (GH13430)

• Bug in df.groupby where .median() returns arbitrary values if grouped dataframe contains empty bins (GH13629)

• Bug in Index.copy() where name parameter was ignored (GH13430)

1.12 v0.18.1 (May 3, 2016)

This is a minor bug-fix release from 0.18.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

• .groupby(...) has been enhanced to provide convenient syntax when working with .rolling(..), .expanding(..) and .resample(..) per group, see here

• pd.to_datetime() has gained the ability to assemble dates from a DataFrame, see here

• Method chaining improvements, see here.

• Custom business hour offset, see here.

• Many bug fixes in the handling of sparse, see here

• Expanded the Tutorials section with a feature on modern pandas, courtesy of @TomAugsburger. (GH13045).
What’s new in v0.18.1

- **New features**
  - Custom Business Hour
  - `.groupby(..) syntax with window and resample operations`
  - Method chaining improvements
    * `.where()` and `.mask()`
    * `.loc[]`, `.iloc[]`, `.ix[]`
    * [] indexing
  - Partial string indexing on `DateTimeIndex` when part of a `MultiIndex`
  - Assembling Datetimes
  - Other Enhancements

- **Sparse changes**

- **API changes**
  - `.groupby(..).nth()` changes
  - numpy function compatibility
  - Using `.apply` on groupby resampling
  - Changes in `read_csv` exceptions
  - `to_datetime` error changes
  - Other API changes
  - Deprecations

- **Performance Improvements**

- **Bug Fixes**

1.12.1 New features

1.12.1.1 Custom Business Hour

The `CustomBusinessHour` is a mixture of `BusinessHour` and `CustomBusinessDay` which allows you to specify arbitrary holidays. For details, see [Custom Business Hour](GH11514)

```python
In [1]: from pandas.tseries.offsets import CustomBusinessHour
In [2]: from pandas.tseries.holiday import USFederalHolidayCalendar
In [3]: bhour_us = CustomBusinessHour(calendar=USFederalHolidayCalendar())
```

Friday before MLK Day

```python
In [4]: dt = datetime(2014, 1, 17, 15)
```

(continues on next page)
Tuesday after MLK Day (Monday is skipped because it’s a holiday)

1.12.1.2 .groupby(..) syntax with window and resample operations

[groupby(..) has been enhanced to provide convenient syntax when working with .rolling(..), .expanding(..) and .resample(..) per group, see (GH12486, GH12738).

You can now use .rolling(..) and .expanding(..) as methods on groupbys. These return another deferred object (similar to what .rolling() and .expanding() do on ungrouped pandas objects). You can then operate on these RollingGroupby objects in a similar manner.

Previously you would have to do this to get a rolling window mean per-group:

```
                       'B': np.arange(40)})
In [8]: df.groupby('A').apply(lambda x: x.rolling(4).B.mean())
Out[9]:
     A
0   0  NaN
1   1  NaN
2   2  NaN
3   3  1.5
4   4  2.5
5   5  3.5
6   6  4.5
```

(continues on next page)
Now you can do:

```python
In [10]: df.groupby('A').rolling(4).B.mean()
Out[10]:
               B
A     1  0    NaN
     1    NaN
     2    NaN
     3   2.5
     4   3.5
     5   4.5
     6     ...
     3  33   NaN
     34  NaN
     35  33.5
     36  34.5
     37  35.5
     38  36.5
    39  37.5
Name: B, Length: 40, dtype: float64
```

For `.resample(..)` type of operations, previously you would have to:

```python
In [11]: df = pd.DataFrame({'date': pd.date_range(start='2016-01-01', periods=4, freq='W'),
                      'group': [1, 1, 2, 2],
                      'val': [5, 6, 7, 8]}).set_index('date')
In [12]: df.groupby('group').apply(lambda x: x.resample('1D').ffill())
Out[12]:
group  val
date
2016-01-03  1  5
2016-01-10  1  6
2016-01-17  2  7
2016-01-24  2  8
```

```python
In [13]: df.groupby('group').apply(lambda x: x.resample('1D').ffill())
Out[13]:
       group  val
date
1  2016-01-03  1  5
    2016-01-04  1  5
    2016-01-05  1  5
```
Now you can do:

```python
In [14]: df.groupby('group').resample('1D').ffill()
```

```console
Out[14]:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>group</td>
<td>val</td>
</tr>
<tr>
<td>1</td>
<td>date</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2016-01-03</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-04</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-05</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-06</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-07</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-08</td>
<td>1 5</td>
</tr>
<tr>
<td>1</td>
<td>2016-01-09</td>
<td>1 5</td>
</tr>
<tr>
<td>2</td>
<td>2016-01-18</td>
<td>2 7</td>
</tr>
<tr>
<td>2</td>
<td>2016-01-19</td>
<td>2 7</td>
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<td>2</td>
<td>2016-01-20</td>
<td>2 7</td>
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<td>2</td>
<td>2016-01-21</td>
<td>2 7</td>
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<tr>
<td>2</td>
<td>2016-01-22</td>
<td>2 7</td>
</tr>
<tr>
<td>2</td>
<td>2016-01-23</td>
<td>2 7</td>
</tr>
<tr>
<td>2</td>
<td>2016-01-24</td>
<td>2 8</td>
</tr>
</tbody>
</table>
```

[16 rows x 2 columns]

1.12.1.3 Method chaining improvements

The following methods/indexers now accept a callable. It is intended to make these more useful in method chains, see the documentation. (GH11485, GH12533)

- .where() and .mask()
- .loc[], .iloc[] and .ix[]
- [] indexing

.\where() and .mask()

These can accept a callable for the condition and other arguments.
In [15]: df = pd.DataFrame({'A': [1, 2, 3],
                     'B': [4, 5, 6],
                     'C': [7, 8, 9]})

In [16]: df.where(lambda x: x > 4, lambda x: x + 10)
Out[16]:
   A  B  C
0  11 14  7
1  12  5  8
2  13  6  9

.loc[], .iloc[], .ix[]

These can accept a callable, and a tuple of callable as a slicer. The callable can return a valid boolean indexer or anything which is valid for these indexer’s input.

# callable returns bool indexer
In [17]: df.loc[lambda x: x.A >= 2, lambda x: x.sum() > 10]
Out[17]:
   B  C
1  5  8
2  6  9

# callable returns list of labels
In [18]: df.loc[lambda x: [1, 2], lambda x: ['A', 'B']]
Out[18]:
   A  B
1  2  5
2  3  6

[] indexing

Finally, you can use a callable in [] indexing of Series, DataFrame and Panel. The callable must return a valid input for [] indexing depending on its class and index type.

In [19]: df[lambda x: 'A']
Out[19]:
   0   1
   1   2
   2   3
Name: A, dtype: int64

Using these methods / indexers, you can chain data selection operations without using temporary variable.

In [20]: bb = pd.read_csv('data/baseball.csv', index_col='id')
In [21]: (bb.groupby(['year', 'team'])
       ....: .sum()
       ....: .loc[lambda df: df.r > 100]
       ....: )
Out[21]:

(continues on next page)
1.12.1.4 Partial string indexing on DateTimeIndex when part of a MultiIndex

Partial string indexing now matches on DateTimeIndex when part of a MultiIndex (GH10331)

```python
In [22]: dft2 = pd.DataFrame(np.random.randn(20, 1),
                   columns=['A'],
                   index=pd.MultiIndex.from_product([pd.date_range('20130101','20130130',periods=10, freq='12H'), ['a', 'b']]))
```

```
In [23]: dft2
Out[23]:
     A
2013-01-01 00:00:00   0.156998
                  b  0.571455
2013-01-01 12:00:00   1.057633
                  b  0.791489
2013-01-02 00:00:00   0.524627
                  b  0.071878
2013-01-02 12:00:00   1.910759
                  b  0.749185
                  b -0.675521
2013-01-03 00:00:00   0.440266
                  b  0.688972
2013-01-03 12:00:00   0.276646
                  b  1.924533
                  b  0.749185
                  b -0.675521
2013-01-04 00:00:00   1.015405
                  b  0.749185
                  b -0.675521
2013-01-04 12:00:00   0.749185
                  b  0.688972
                  b  0.688972
                  b  0.688972
                  b  0.688972
                  b  1.924533
```

(continues on next page)
On other levels

In [25]: idx = pd.IndexSlice

In [26]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [27]: dft2

Out[27]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>2013-01-01 00:00:00 0.156998</td>
</tr>
<tr>
<td></td>
<td>2013-01-01 12:00:00 1.057633</td>
</tr>
<tr>
<td></td>
<td>2013-01-02 00:00:00 -0.524627</td>
</tr>
<tr>
<td></td>
<td>2013-01-02 12:00:00 1.910759</td>
</tr>
<tr>
<td></td>
<td>2013-01-03 00:00:00 0.513082</td>
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<tr>
<td></td>
<td>2013-01-03 12:00:00 1.043945</td>
</tr>
<tr>
<td></td>
<td>2013-01-04 00:00:00 1.459927</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>b</td>
<td>2013-01-02 12:00:00 0.787965</td>
</tr>
<tr>
<td></td>
<td>2013-01-03 00:00:00 -0.546416</td>
</tr>
<tr>
<td></td>
<td>2013-01-03 12:00:00 2.107785</td>
</tr>
<tr>
<td></td>
<td>2013-01-04 00:00:00 1.015405</td>
</tr>
<tr>
<td></td>
<td>2013-01-04 12:00:00 -0.675521</td>
</tr>
<tr>
<td></td>
<td>2013-01-05 00:00:00 0.688972</td>
</tr>
<tr>
<td></td>
<td>2013-01-05 12:00:00 1.924533</td>
</tr>
</tbody>
</table>

[20 rows x 1 columns]

In [28]: dft2.loc[idx[:, '2013-01-05'], :]

Out[28]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>2013-01-05 00:00:00 0.440266</td>
</tr>
<tr>
<td></td>
<td>2013-01-05 12:00:00 -0.276646</td>
</tr>
<tr>
<td>b</td>
<td>2013-01-05 00:00:00 0.688972</td>
</tr>
<tr>
<td></td>
<td>2013-01-05 12:00:00 1.924533</td>
</tr>
</tbody>
</table>

1.12.1.5 Assembling Datetimes

pd.to_datetime() has gained the ability to assemble datetimes from a passed in DataFrame or a dict. (GH8158).

In [29]: df = pd.DataFrame({'year': [2015, 2016],
                       'month': [2, 3],
                       'day': [4, 5],
                       'price': [1.2, 3.4]})
Assembling using the passed frame.

```python
In [31]: pd.to_datetime(df)
Out[31]:
0  2015-02-04 02:00:00
1  2016-03-05 03:00:00
dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```python
In [32]: pd.to_datetime(df[['year', 'month', 'day']])
Out[32]:
0  2015-02-04
1  2016-03-05
dtype: datetime64[ns]
```

### 1.12.1.6 Other Enhancements

- `pd.read_csv()` now supports `delim_whitespace=True` for the Python engine (GH12958)
- `pd.read_csv()` now supports opening ZIP files that contains a single CSV, via extension inference or explicit `compression='zip'` (GH12175)
- `pd.read_csv()` now supports opening files using xz compression, via extension inference or explicit `compression='xz'` is specified; xz compressions is also supported by `DataFrame.to_csv` in the same way (GH11852)
- `pd.read_msgpack()` now always gives writeable ndarrays even when compression is used (GH12359)
- `pd.read_msgpack()` now supports serializing and de-serializing categoricals with msgpack (GH12573)
- `.to_json()` now supports `NDFrames` that contain categorical and sparse data (GH10778)
- `interpolate()` now supports `method='akima'` (GH7588).
- `pd.read_excel()` now accepts path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path, in line with other `read_*` functions (GH12655)
- Added `.weekday_name` property as a component to `DatetimeIndex` and the `.dt` accessor. (GH11128)
- `Index.take` now handles `allow_fill` and `fill_value` consistently (GH12631)

```python
In [33]: idx = pd.Index([1., 2., 3., 4.], dtype='float')
# default, allow_fill=True, fill_value=None
In [34]: idx.take([2, -1])
Out[34]: Float64Index([3.0, 4.0], dtype='float64')
```
In [35]: idx.take([2, -1], fill_value=True)
Out[35]: Float64Index([3.0, nan], dtype='float64')

Index now supports .str.get_dummies() which returns MultiIndex, see Creating Indicator Variables (GH10008, GH10103)

In [36]: idx = pd.Index(['a|b', 'a|c', 'b|c'])
In [37]: idx.str.get_dummies('|')
Out[37]: MultiIndex(levels=[[0, 1], [0, 1], [0, 1]], labels=[[1, 1, 0], [1, 0, 1], [0, 1, 1]], names=['a', 'b', 'c'])

pd.crosstab() has gained a normalize argument for normalizing frequency tables (GH12569). Examples in the updated docs here.

.resample(..).interpolate() is now supported (GH12925)

.isin() now accepts passed sets (GH12988)

1.12.2 Sparse changes

These changes conform sparse handling to return the correct types and work to make a smoother experience with indexing.

SparseArray.take now returns a scalar for scalar input, SparseArray for others. Furthermore, it handles a negative indexer with the same rule as Index (GH10560, GH12796)

In [38]: s = pd.SparseArray([np.nan, np.nan, 1, 2, 3, np.nan, 4, 5, np.nan, 6])
In [39]: s.take(0)
Out[39]: nan
In [40]: s.take([1, 2, 3])

[1.0, 2.0]

Fill: nan

IntIndex
Indices: array([1, 2], dtype=int32)

• Bug in SparseSeries[] indexing with Ellipsis raises KeyEr (GH9467)
• Bug in SparseArray[] indexing with tuples are not handled properly (GH12966)
• Bug in SparseSeries.loc[] with list-like input raises TypeError (GH10560)
• Bug in SparseSeries.iloc[] with scalar input may raise IndexError (GH10560)
• Bug in SparseSeries.loc[], .iloc[] with slice returns SparseArray, rather than SparseSeries (GH10560)
• Bug in SparseDataFrame.loc[], .iloc[] may results in dense Series, rather than SparseSeries (GH12787)
• Bug in SparseArray addition ignores fill_value of right hand side (GH12910)
• Bug in SparseArray mod raises AttributeError (GH12910)
- Bug in `SparseArray` `pow` calculates `1 ** np.nan` as `np.nan` which must be `1` (GH12910)
- Bug in `SparseArray` comparison output may incorrect result or raise `ValueError` (GH12971)
- Bug in `SparseSeries.__repr__` raises `TypeError` when it is longer than `max_rows` (GH10560)
- Bug in `SparseSeries.shape` ignores `fill_value` (GH10452)
- Bug in `SparseSeries` and `SparseArray` may have different `dtype` from its dense values (GH12908)
- Bug in `SparseSeries.reindex` incorrectly handle `fill_value` (GH12797)
- Bug in `SparseArray.to_frame()` results in `DataFrame`, rather than `SparseDataFrame` (GH9850)
- Bug in `SparseSeries.value_counts()` does not count `fill_value` (GH6749)
- Bug in `SparseArray.to_dense()` does not preserve `dtype` (GH10648)
- Bug in `pd.concat()` of `SparseSeries` results in dense (GH10536)
- Bug in `pd.concat()` of `SparseDataFrame` incorrectly handle `fill_value` (GH9765)
- Bug in `pd.concat()` of `SparseDataFrame` may raise `AttributeError` (GH12174)
- Bug in `SparseArray.shift()` may raise `NameError` or `TypeError` (GH12908)

### 1.12.3 API changes

#### 1.12.3.1 `.groupby(..).nth()` changes

The index in `.groupby(..).nth()` output is now more consistent when the `as_index` argument is passed (GH11039):

```python
In [41]: df = DataFrame({'A' : ['a', 'b', 'a'],
.....:       'B' : [1, 2, 3]})
.....:

In [42]: df
Out[42]:
   A  B
0  a  1
1  b  2
2  a  3

Previous Behavior:

```python
In [3]: df.groupby('A', as_index=True)['B'].nth(0)
Out[3]:
   0  1
   1  2
Name: B, dtype: int64

In [4]: df.groupby('A', as_index=False)['B'].nth(0)
Out[4]:
   0  1
   1  2
Name: B, dtype: int64
```

New Behavior:
Furthermore, previously, a .groupby would always sort, regardless if sort=False was passed with .nth().

```
In [45]: np.random.seed(1234)
In [46]: df = pd.DataFrame(np.random.randn(100, 2), columns=['a', 'b'])
In [47]: df['c'] = np.random.randint(0, 4, 100)

Previous Behavior:
```
```
In [4]: df.groupby('c', sort=True).nth(1)
Out[4]:
   a   b
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

In [5]: df.groupby('c', sort=False).nth(1)
Out[5]:
   a   b
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524
```

New Behavior:
```
In [48]: df.groupby('c', sort=True).nth(1)
Out[48]:
   a   b
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

In [49]: df.groupby('c', sort=False).nth(1)
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-0.334077</td>
<td>0.002118</td>
</tr>
<tr>
<td>1</td>
<td>0.036142</td>
<td>-2.074978</td>
</tr>
<tr>
<td>2</td>
<td>-0.720589</td>
<td>0.887163</td>
</tr>
<tr>
<td>3</td>
<td>0.859588</td>
<td>-0.636524</td>
</tr>
</tbody>
</table>
```

(continues on next page)
2 -0.720589 0.887163
3 0.859588 -0.636524
0 -0.334077 0.002118
1 0.036142 -2.074978

1.12.3.2 numpy function compatibility

Compatibility between pandas array-like methods (e.g. \texttt{sum} and \texttt{take}) and their numpy counterparts has been greatly increased by augmenting the signatures of the pandas methods so as to accept arguments that can be passed in from numpy, even if they are not necessarily used in the pandas implementation (GH12644, GH12638, GH12687)

- \texttt{.searchsorted()} for Index and TimedeltaIndex now accept a \texttt{sorter} argument to maintain compatibility with numpy’s \texttt{searchsorted} function (GH12238)
- Bug in numpy compatibility of \texttt{np.round()} on a Series (GH12600)

An example of this signature augmentation is illustrated below:

In [50]: sp = pd.SparseDataFrame([1, 2, 3])

In [51]: sp
Out[51]:
   0  1
   1  2
   2  3

Previous behaviour:

In [2]: np.cumsum(sp, axis=0)
...: TypeError: cumsum() takes at most 2 arguments (4 given)

New behaviour:

In [52]: np.cumsum(sp, axis=0)
Out[52]:
   0  0
   1  1
   2  3

1.12.3.3 Using \texttt{.apply} on groupby resampling

Using \texttt{apply} on resampling groupby operations (using a \texttt{pd.TimeGrouper}) now has the same output types as similar \texttt{apply} calls on other groupby operations. (GH11742).

In [53]: df = pd.DataFrame({'date': pd.to_datetime(['10/10/2000', '11/10/2000']),
                          'value': [10, 13]})

In [54]: df
Out[54]:
   date  value  
0 10/10  10
1 11/10  13  

(continues on next page)
Previous behavior:

```python
In [1]: df.groupby(pd.TimeGrouper(key='date', freq='M')).apply(lambda x: x.value.˓→sum())
Out[1]:
...  
TypeError: cannot concatenate a non-NDFrame object
```

```python
# Output is a Series
In [2]: df.groupby(pd.TimeGrouper(key='date', freq='M')).apply(lambda x: x[['value']].sum())
Out[2]:
          date
2000-10-31 value 10
2000-11-30 value 13
dtype: int64
```

New Behavior:

```python
# Output is a Series
In [55]: df.groupby(pd.TimeGrouper(key='date', freq='M')).apply(lambda x: x.value.˓→sum())
Out[55]:
          date
2000-10-31  10
2000-11-30  13
Freq: M, dtype: int64
```

```python
# Output is a DataFrame
In [56]: df.groupby(pd.TimeGrouper(key='date', freq='M')).apply(lambda x: x[['value']].sum())
Out[56]:
value
date
2000-10-31  10
2000-11-30  13
```

### 1.12.3.4 Changes in `read_csv` exceptions

In order to standardize the `read_csv` API for both the `c` and `python` engines, both will now raise an `EmptyDataError`, a subclass of `ValueError`, in response to empty columns or header (GH12493, GH12506)

Previous behaviour:

```python
In [1]: df = pd.read_csv(StringIO(''), engine='c')
...  
ValueError: No columns to parse from file
```

```python
In [2]: df = pd.read_csv(StringIO(''), engine='python')
...  
StopIteration
```

New behaviour:
In [1]: df = pd.read_csv(StringIO(''), engine='c')
    ...
pandas.io.common.EmptyDataError: No columns to parse from file

In [2]: df = pd.read_csv(StringIO(''), engine='python')
    ...
pandas.io.common.EmptyDataError: No columns to parse from file

In addition to this error change, several others have been made as well:

  - **CParseError** now sub-classes **ValueError** instead of just a **Exception** (GH12551)
  - A **CParseError** is now raised instead of a generic **Exception** in **read_csv** when the **c** engine cannot parse a column (GH12506)
  - A **ValueError** is now raised instead of a generic **Exception** in **read_csv** when the **c** engine encounters a **NaN** value in an integer column (GH12506)
  - A **ValueError** is now raised instead of a generic **Exception** in **read_csv** when **true_values** is specified, and the **c** engine encounters an element in a column containing unencodable bytes (GH12506)
  - **pandas.parser.OverflowError** exception has been removed and has been replaced with Python’s built-in **OverflowError** exception (GH12506)
  - **pd.read_csv()** no longer allows a combination of strings and integers for the **usecols** parameter (GH12678)

### 1.12.3.5 to_datetime error changes

Bugs in **pd.to_datetime()** when passing a unit with convertible entries and **errors='coerce'** or non-convertible with **errors='ignore'**. Furthermore, an **OutOfBoundsDatetime** exception will be raised when an out-of-range value is encountered for that unit when **errors='raise'**. (GH11758, GH13052, GH13059)

Previous behaviour:

In [27]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[27]: NaT

In [28]: pd.to_datetime(11111111, unit='D', errors='ignore')
OverflowError: Python int too large to convert to C long

In [29]: pd.to_datetime(11111111, unit='D', errors='raise')
OverflowError: Python int too large to convert to C long

New behaviour:

In [2]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[2]: Timestamp('2014-12-31 16:31:00')

In [3]: pd.to_datetime(11111111, unit='D', errors='ignore')
Out[3]: 11111111

In [4]: pd.to_datetime(11111111, unit='D', errors='raise')
OutOfBoundsDatetime: cannot convert input with unit 'D'
1.12.3.6 Other API changes

- `.swaplevel()` for Series, DataFrame, Panel, and MultiIndex now features defaults for its first two parameters `i` and `j` that swap the two innermost levels of the index. (GH12934)
- `.searchsorted()` for Index and TimedeltaIndex now accept a `sorter` argument to maintain compatibility with numpy’s searchsorted function (GH12238)
- Period and PeriodIndex now raises IncompatibleFrequency error which inherits ValueError rather than raw ValueError (GH12615)
- Series.apply for category dtype now applies the passed function to each of the .categories (and not the .codes), and returns a category dtype if possible (GH12473)
- read_csv will now raise a TypeError if parse_dates is neither a boolean, list, or dictionary (matches the doc-string) (GH5636)
- The default for .query()/.eval() is now engine=None, which will use numexpr if it’s installed; otherwise it will fall back to the python engine. This mimics the pre-0.18.1 behavior if numexpr is installed (and which, previously, if numexpr was not installed, .query()/.eval() would raise). (GH12749)
- pd.show_versions() now includes pandas_datareader version (GH12740)
- Provide a proper __name__ and __qualname__ attributes for generic functions (GH12021)
- pd.concat(ignore_index=True) now uses RangeIndex as default (GH12695)
- pd.merge() and DataFrame.join() will show a UserWarning when merging/joining a single- with a multi-leveled dataframe (GH9455, GH12219)
- Compat with scipy > 0.17 for deprecated piecewise_polynomial interpolation method; support for the replacement from_derivatives method (GH12887)

1.12.3.7 Deprecations

- The method name Index.sym_diff() is deprecated and can be replaced by Index.symmetric_difference() (GH12591)
- The method name Categorical.sort() is deprecated in favor of Categorical.sort_values() (GH12882)

1.12.4 Performance Improvements

- Improved speed of SAS reader (GH12656, GH12961)
- Performance improvements in .groupby(..).cumcount() (GH11039)
- Improved memory usage in pd.read_csv() when using skiprows=an_integer (GH13005)
- Improved performance of DataFrame.to_sql when checking case sensitivity for tables. Now only checks if table has been created correctly when table name is not lower case. (GH12876)
- Improved performance of Period construction and time series plotting (GH12903, GH11831).
- Improved performance of .str.encode() and .str.decode() methods (GH13008)
- Improved performance of to_numeric if input is numeric dtype (GH12777)
- Improved performance of sparse arithmetic with IntIndex (GH13036)
1.12.5 Bug Fixes

- `usecols` parameter in `pd.read_csv` is now respected even when the lines of a CSV file are not even (GH12203)
- Bug in `groupby.transform(...)` when `axis=1` is specified with a non-monotonic ordered index (GH12713)
- Bug in `Period` and `PeriodIndex` creation raises `KeyError` if `freq="Minute"` is specified. Note that “Minute” freq is deprecated in v0.17.0, and recommended to use `freq="T"` instead (GH11854)
- Bug in `.resample(...) .count()` with a `PeriodIndex` always raising a `TypeError` (GH12774)
- Bug in `.resample(...)` with a `PeriodIndex` casting to a `DatetimeIndex` when empty (GH12868)
- Bug in `.resample(...)` with a `PeriodIndex` when resampling to an existing frequency (GH12770)
- Bug in printing data which contains `Period` with different `freq` raises `ValueError` (GH12615)
- Bug in `Series` construction with `Categorical` and `dtype='category'` is specified (GH12574)
- Bugs in concatenation with a coercable dtype was too aggressive, resulting in different dtypes in outputformatting when an object was longer than `display.max_rows` (GH12411, GH12045, GH11594, GH10571, GH12211)
- Bug in `float_format` option with option not being validated as a callable. (GH12706)
- Bug in `GroupBy.filter` when `dropna=False` and no groups fulfilled the criteria (GH12768)
- Bug in `__name__` of `.cum*` functions (GH12021)
- Bug in `.astype()` of a Float64Index/Int64Index to an Int64Index (GH12881)
- Bug in roundtripping an integer based index in `.to_json()/.read_json()` when `orient='index'` (the default) (GH12866)
- Bug in plotting `Categorical` dtypes cause error when attempting stacked bar plot (GH13019)
- Comp with `>=` numpy 1.11 for NaT comparisons (GH12969)
- Bug in `.drop()` with a non-unique MultiIndex. (GH12701)
- Bug in `.concat` of datetime tz-aware and naive DataFrames (GH12467)
- Bug in correctly raising a `ValueError` in `.resample(...).fillna(...)` when passing a non-string (GH12952)
- Bug fixes in various encoding and header processing issues in `pd.read_sas()` (GH12659, GH12654, GH12647, GH12809)
- Bug in `pd.crosstab()` where would silently ignore `aggfunc` if `values=None` (GH12569).
- Potential segfault in `DataFrame.to_json` when serialising `datetime.time` (GH11473).
- Potential segfault in `DataFrame.to_json` when attempting to serialise 0d array (GH11299).
- Segfault in `to_json` when attempting to serialise a `DataFrame` or `Series` with non-ndarray values; now supports serialization of `category`, `sparse`, and `datetime64[ns, tz]` dtypes (GH10778).
- Bug in `DataFrame.to_json` with unsupported dtype not passed to default handler (GH12554).
- Bug in `.align` not returning the sub-class (GH12983)
- Bug in `aligning a Series with a DataFrame` (GH13037)
- Bug in ABCPanel in which Panel4D was not being considered as a valid instance of this generic type (GH12810)
• Bug in consistency of .name on .groupby(...).apply(...) cases (GH12363)
• Bug in Timestamp.__repr__ that caused pprint to fail in nested structures (GH12622)
• Bug in Timedelta.min and Timedelta.max, the properties now report the true minimum/maximum timedeltas as recognized by pandas. See the documentation. (GH12727)
• Bug in .quantile() with interpolation may coerce to float unexpectedly (GH12772)
• Bug in .quantile() with empty Series may return scalar rather than empty Series (GH12772)
• Bug in .loc with out-of-bounds in a large indexer would raise IndexError rather than KeyError (GH12527)
• Bug in resampling when using a TimedeltaIndex and .asfreq(), would previously not include the final fencepost (GH12926)
• Bug in equality testing with a Categorical in a DataFrame (GH12564)
• Bug in GroupBy.first(), .last() returns incorrect row when TimeGrouper is used (GH7453)
• Bug in pd.read_csv() with the c engine when specifying skiprows with newlines in quoted items (GH10911, GH12775)
• Bug in DataFrame timezone lost when assigning tz-aware datetime Series with alignment (GH12981)
• Bug in .value_counts() when normalize=True and dropna=True where nulls still contributed to the normalized count (GH12558)
• Bug in Series.value_counts() loses name if its dtype is category (GH12835)
• Bug in Series.value_counts() loses timezone info (GH12835)
• Bug in Series.value_counts(normalize=True) with Categorical raises UnboundLocalError (GH12835)
• Bug in Panel.fillna() ignoring inplace=True (GH12633)
• Bug in pd.read_csv() when specifying names, usecols, and parse_dates simultaneously with the c engine (GH9755)
• Bug in pd.read_csv() when specifying delim_whitespace=True and lineterminator simultaneously with the c engine (GH12912)
• Bug in Series.rename, DataFrame.rename and DataFrame.rename_axis not treating Series as mappings to relabel (GH12623).
• Clean in .rolling.min and .rolling.max to enhance dtype handling (GH12373)
• Bug in groupby where complex types are coerced to float (GH12902)
• Bug in Series.map raises TypeError if its dtype is category or tz-aware datetime (GH12473)
• Bugs on 32bit platforms for some test comparisons (GH12972)
• Bug in index coercion when falling back from RangeIndex construction (GH12893)
• Better error message in window functions when invalid argument (e.g. a float window) is passed (GH12669)
• Bug in slicing subclassed DataFrame defined to return subclassed Series may return normal Series (GH11559)
• Bug in .str accessor methods may raise ValueError if input has name and the result is DataFrame or MultiIndex (GH12617)
• Bug in DataFrame.last_valid_index() and DataFrame.first_valid_index() on empty frames (GH12800)
• Bug in `CategoricalIndex.get_loc` returns different result from regular `Index` (GH12531)
• Bug in `PeriodIndex.resample` where name not propagated (GH12769)
• Bug in `date_range` closed keyword and timezones (GH12684).
• Bug in `pd.concat` raises `AttributeError` when input data contains tz-aware datetime and timedelta (GH12620)
• Bug in `pd.concat` did not handle empty `Series` properly (GH11082)
• Bug in `.plot.bar` alignment when `width` is specified with `int` (GH12979)
• Bug in `fill_value` is ignored if the argument to a binary operator is a constant (GH12723)
• Bug in `pd.read_html()` when using bs4 flavor and parsing table with a header and only one column (GH9178)
• Bug in `.pivot_table` when `margins=True` and `dropna=True` where nulls still contributed to margin count (GH12577)
• Bug in `.pivot_table` when `dropna=False` where table index/column names disappear (GH12133)
• Bug in `pd.crosstab()` when `margins=True` and `dropna=False` which raised (GH12642)
• Bug in `Series.name` when `name` attribute can be a hashable type (GH12610)
• Bug in `.describe()` resets categorical columns information (GH11558)
• Bug where `loffset` argument was not applied when calling `resample().count()` on a timeseries (GH12725)
• `pd.read_excel()` now accepts column names associated with keyword argument `names` (GH12870)
• Bug in `pd.to_numeric()` with `Index` returns `np.ndarray`, rather than `Index` (GH12777)
• Bug in `pd.to_numeric()` with datetime-like may raise `TypeError` (GH12777)
• Bug in `pd.to_numeric()` with scalar raises `ValueError` (GH12777)

1.13 v0.18.0 (March 13, 2016)

This is a major release from 0.17.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.18.0 no longer supports compatibility with Python version 2.6 and 3.3 (GH7718, GH11273)

Warning: numexpr version 2.4.4 will now show a warning and not be used as a computation back-end for pandas because of some buggy behavior. This does not affect other versions (>= 2.1 and >= 2.4.6). (GH12489)

Highlights include:

• Moving and expanding window functions are now methods on `Series` and `DataFrame`, similar to `.groupby`, see here.
• Adding support for a `RangeIndex` as a specialized form of the `Int64Index` for memory savings, see here.
• API breaking change to the `.resample` method to make it more `.groupby` like, see `here`.

• Removal of support for positional indexing with floats, which was deprecated since 0.14.0. This will now raise a `TypeError`, see `here`.

• The `.to_xarray()` function has been added for compatibility with the `xarray` package, see `here`.

• The `read_sas` function has been enhanced to read `sas7bdat` files, see `here`.

• Addition of the `.str.extractall()` method, and API changes to the `.str.extract()` method and `.str.cat()` method.

• `pd.test()` top-level nose test runner is available (GH4327).

Check the `API Changes` and `deprecations` before updating.

<table>
<thead>
<tr>
<th>What’s new in v0.18.0</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>New features</strong></td>
</tr>
<tr>
<td>– Window functions are now methods</td>
</tr>
<tr>
<td>– Changes to rename</td>
</tr>
<tr>
<td>– Range Index</td>
</tr>
<tr>
<td>– Changes to <code>str.extract</code></td>
</tr>
<tr>
<td>– Addition of <code>str.extractall</code></td>
</tr>
<tr>
<td>– Changes to <code>str.cat</code></td>
</tr>
<tr>
<td>– Datetimelike rounding</td>
</tr>
<tr>
<td>– Formatting of Integers in <code>FloatIndex</code></td>
</tr>
<tr>
<td>– Changes to dtype assignment behaviors</td>
</tr>
<tr>
<td>– <code>to_xarray</code></td>
</tr>
<tr>
<td>– Latex Representation</td>
</tr>
<tr>
<td>– <code>pd.read_sas()</code> changes</td>
</tr>
<tr>
<td>– Other enhancements</td>
</tr>
<tr>
<td><strong>Backwards incompatible API changes</strong></td>
</tr>
<tr>
<td>– <code>NaT</code> and <code>Timedelta</code> operations</td>
</tr>
<tr>
<td>– Changes to <code>msgpack</code></td>
</tr>
<tr>
<td>– Signature change for <code>.rank</code></td>
</tr>
<tr>
<td>– Bug in <code>QuarterBegin</code> with <code>n=0</code></td>
</tr>
<tr>
<td>– Resample API</td>
</tr>
<tr>
<td>* Downsampling</td>
</tr>
<tr>
<td>* Upsampling</td>
</tr>
<tr>
<td>* Previous API will work but with deprecations</td>
</tr>
<tr>
<td>– Changes to <code>eval</code></td>
</tr>
<tr>
<td>– Other API Changes</td>
</tr>
<tr>
<td>– Deprecations</td>
</tr>
</tbody>
</table>
1.13.1 New features

1.13.1.1 Window functions are now methods

Window functions have been refactored to be methods on Series/DataFrame objects, rather than top-level functions, which are now deprecated. This allows these window-type functions, to have a similar API to that of .groupby. See the full documentation here (GH11603, GH12373)

```python
In [1]: np.random.seed(1234)
In [2]: df = pd.DataFrame({'A': range(10), 'B': np.random.randn(10)})
In [3]: df
Out[3]:
   A  B
0  0  0.471435
1  1 -1.190976
2  2  1.432707
3  3 -0.312652
4  4 -0.720589
5  5  0.887163
6  6  0.859588
7  7 -0.636524
8  8  0.015696
9  9 -2.242685

Previous Behavior:

In [8]: pd.rolling_mean(df,window=3)
FutureWarning: pd.rolling_mean is deprecated for DataFrame and will be removed in a future version, replace with DataFrame.rolling(window=3,center=False).mean()
Out[8]:
   A  B
0 NaN NaN
1 NaN NaN
2  1  0.237722
3  2 -0.023640
4  3  0.133155
5  4 -0.048693
6  5  0.342054
7  6  0.370076
8  7  0.079587
9  8 -0.954504

New Behavior:

In [4]: r = df.rolling(window=3)
These show a descriptive repr

```
In [5]: r
Out[5]: Rolling [window=3,center=False,axis=0]
```

with tab-completion of available methods and properties.

```
In [9]: r.
   r.A    r.agg    r.apply    r.count    r.exclusions    r.max    r.
      -median    r.name    r.skew    r.sum
   r.B    r.aggregate    r.corr    r.cov    r.kurt    r.mean    r.
      -min    r.quantile    r.std    r.var
```

The methods operate on the Rolling object itself

```
In [6]: r.mean()
Out[6]:
   A   B
  0  NaN  NaN
  1  NaN  NaN
  2  1.0  0.237722
  3  2.0 -0.023640
  4  3.0  0.133155
  5  4.0 -0.048693
  6  5.0  0.342054
  7  6.0  0.370076
  8  7.0  0.079587
  9  8.0 -0.954504
```

They provide getitem accessors

```
In [7]: r['A'].mean()
Out[7]:
   A
  0  NaN
  1  NaN
  2  1.0
  3  2.0
  4  3.0
  5  4.0
  6  5.0
  7  6.0
  8  7.0
  9  8.0
Name: A, dtype: float64
```

And multiple aggregations

```
In [8]: r.agg({'A' : ['mean','std'],
   ...:    'B' : ['mean','std']})
Out[8]:
   A     B
  mean  std  mean  std
  0 NaN   NaN  NaN   NaN
  1 NaN   NaN  NaN   NaN
  2 1.0  1.0  0.237722 1.327364
  3 2.0  1.0 -0.023640 1.335505
  4 3.0  1.0  0.133155 1.143778
```

(continues on next page)
### 1.13.1.2 Changes to rename

Series.rename and NDFrame.rename_axis can now take a scalar or list-like argument for altering the Series or axis name, in addition to their old behaviors of altering labels. *(GH9494, GH11965)*

```
In [9]: s = pd.Series(np.random.randn(5))

In [10]: s.rename('newname')
Out[10]:
   0    1.150036
   1    0.991946
   2    0.953324
   3   -2.021255
   4   -0.334077
Name: newname, dtype: float64
```

```
In [11]: df = pd.DataFrame(np.random.randn(5, 2))

In [12]: (df.rename_axis("indexname")
       ....: .rename_axis("columns_name", axis="columns"))
   ....:
Out[12]:
   columns_name  0  1
   indexname
   0  0.002118  0.405453
   1  0.289092  1.321158
   2 -1.546906 -0.202646
   3 -0.655969  0.193421
   4  0.553439  1.318152
```

The new functionality works well in method chains. Previously these methods only accepted functions or dicts mapping a *label* to a new label. This continues to work as before for function or dict-like values.

### 1.13.1.3 Range Index

A RangeIndex has been added to the Int64Index sub-classes to support a memory saving alternative for common use cases. This has a similar implementation to the python range object (xrange in python 2), in that it only stores the start, stop, and step values for the index. It will transparently interact with the user API, converting to Int64Index if needed.

This will now be the default constructed index for NDFrame objects, rather than previous an Int64Index. *(GH939, GH12070, GH12071, GH12109, GH12888)*

Previous Behavior:

```
In [3]: s = pd.Series(range(1000))

In [4]: s.index
```

(continues on next page)
New Behavior:

In [6]: s.index.nbytes
Out[6]: 8000

1.13.1.4 Changes to str.extract

The \_str.extract\_ method takes a regular expression with capture groups, finds the first match in each subject string, and returns the contents of the capture groups (GH11386).

In v0.18.0, the expand argument was added to extract.

- expand=False: it returns a Series, Index, or DataFrame, depending on the subject and regular expression pattern (same behavior as pre-0.18.0).
- expand=True: it always returns a DataFrame, which is more consistent and less confusing from the perspective of a user.

Currently the default is expand=None which gives a FutureWarning and uses expand=False. To avoid this warning, please explicitly specify expand.

Extracting a regular expression with one group returns a Series if expand=False.

It returns a DataFrame with one column if expand=True.
Calling on an Index with a regex with exactly one capture group returns an Index if expand=False.

```
In [18]: s = pd.Series(['a1', 'b2', 'c3'], Index(['A11', 'B22', 'C33']))
In [19]: s.index
Out[19]: Index(['A11', 'B22', 'C33'], dtype='object')
In [20]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
```

It returns a DataFrame with one column if expand=True.

```
In [21]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
```

Calling on an Index with a regex with more than one capture group raises ValueError if expand=False.

```
>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

It returns a DataFrame if expand=True.

```
In [22]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
```

In summary, extract (expand=True) always returns a DataFrame with a row for every subject string, and a column for every capture group.

### 1.13.1.5 Addition of str.extractall

The str.extractall method was added (GH11386). Unlike extract, which returns only the first match.

```
In [23]: s = pd.Series(['ala2', 'b1', 'c1'], Index(['A', 'B', 'C']))
In [24]: s
Out[24]:
          A    B    C
datype: object
          a1   b1   c1
```
In [25]: s.str.extract("(?P<letter>[ab])(?P<digit>\d)", expand=False)

    letter digit
     A   a  1
     B   b  1
     C  NaN NaN

The `extractall` method returns all matches.

In [26]: s.str.extractall("(?P<letter>[ab])(?P<digit>\d)")

<table>
<thead>
<tr>
<th>letter</th>
<th>digit</th>
<th>match</th>
</tr>
</thead>
<tbody>
<tr>
<td>A 0</td>
<td>a</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>a</td>
<td>2</td>
</tr>
<tr>
<td>B 0</td>
<td>b</td>
<td>1</td>
</tr>
</tbody>
</table>

### 1.13.1.6 Changes to str.cat

The method `.str.cat()` concatenates the members of a `Series`. Before, if NaN values were present in the Series, calling `.str.cat()` on it would return NaN, unlike the rest of the Series. str.* API. This behavior has been amended to ignore NaN values by default. *(GH11435)*.

A new, friendlier `ValueError` is added to protect against the mistake of supplying the `sep` as an arg, rather than as a kwarg. *(GH11334)*.

In [27]: pd.Series(['a','b',np.nan,'c']).str.cat(sep=' ')

Out[27]: 'a b c'

In [28]: pd.Series(['a','b',np.nan,'c']).str.cat(sep=' ', na_rep='?')

Out[28]: 'a b ? c'

In [2]: pd.Series(['a','b',np.nan,'c']).str.cat(' ')

`ValueError: Did you mean to supply a `sep` keyword?`

### 1.13.1.7 Datetimelike rounding

`DatetimeIndex`, `Timestamp`, `TimedeltaIndex`, `Timedelta` have gained the `.round()`, `.floor()` and `.ceil()` method for datetimelike rounding, flooring and ceiling. *(GH4314, GH11963)*

Naive datetimes

In [29]: dr = pd.date_range('20130101 09:12:56.1234', periods=3)

In [30]: dr

Out[30]: DatetimeIndex(['2013-01-01 09:12:56.123400', '2013-01-02 09:12:56.123400', '2013-01-03 09:12:56.123400'], dtype='datetime64[ns]', freq='D')

In [31]: dr.round('s')
In addition, .round(), .floor() and .ceil() will be available thru the .dt accessor of Series.
In [42]: s = pd.Series(dr)

In [43]: s
Out[43]:
0  2013-01-01 09:12:56.123400-05:00
1  2013-01-02 09:12:56.123400-05:00
2  2013-01-03 09:12:56.123400-05:00
dtype: datetime64[ns, US/Eastern]

In [44]: s.dt.round('D')
Out[44]:
0 2013-01-01 00:00:00-05:00
1 2013-01-02 00:00:00-05:00
2 2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]

1.13.1.8 Formatting of Integers in FloatIndex

Integers in `FloatIndex`, e.g. 1., are now formatted with a decimal point and a 0 digit, e.g. 1.0 (GH11713) This change not only affects the display to the console, but also the output of IO methods like `.to_csv` or `.to_html`

Previous Behavior:

In [2]: s = pd.Series([1,2,3], index=np.arange(3.))

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

In [4]: s.index
Out[4]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

In [5]: print(s.to_csv(path=None))
0,1
1,2
2,3

New Behavior:

In [45]: s = pd.Series([1,2,3], index=np.arange(3.))

In [46]: s
Out[46]:
0.0  1
1.0  2
2.0  3
dtype: int64

In [47]: s.index
Out[47]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

(continues on next page)
In [48]: print(s.to_csv(path=None))
   → 0,1
   1.0,2
   2.0,3

1.13.1.9 Changes to dtype assignment behaviors

When a DataFrame’s slice is updated with a new slice of the same dtype, the dtype of the DataFrame will now remain
the same. (GH10503)

Previous Behavior:

In [5]: df = pd.DataFrame({
   'a': [0, 1, 1],
   'b': pd.Series([100, 200, 300], dtype='uint32')})
In [7]: df.dtypes
Out [7]:
   a int64
   b uint32
dtype: object
In [8]: ix = df['a'] == 1
In [9]: df.loc[ix, 'b'] = df.loc[ix, 'b']
In [11]: df.dtypes
Out [11]:
   a int64
   b int64
dtype: object

New Behavior:

In [49]: df = pd.DataFrame({
   'a': [0, 1, 1],
   'b': pd.Series([100, 200, 300], dtype='uint32')})
In [50]: df.dtypes
Out [50]:
   a int64
   b uint32
dtype: object
In [51]: ix = df['a'] == 1
In [52]: df.loc[ix, 'b'] = df.loc[ix, 'b']
In [53]: df.dtypes
Out [53]:
   a int64
   b uint32
dtype: object

When a DataFrame’s integer slice is partially updated with a new slice of floats that could potentially be downcasted
to integer without losing precision, the dtype of the slice will be set to float instead of integer.
Previous Behavior:

```python
In [4]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
                      columns=list('abc'),
                      index=[[4,4,8], [8,10,12]])

In [5]: df
Out[5]:
   a  b  c
4  8  1  2  3
10 4  5  6
8 12  7  8  9

In [7]: df.ix[4, 'c'] = np.array([0., 1.])

In [8]: df
Out[8]:
   a  b  c
4  8  1  2  0
10 4  5  1
8 12  7  8  9
```

New Behavior:

```python
In [54]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
                      columns=list('abc'),
                      index=[[4,4,8], [8,10,12]])

In [55]: df
Out[55]:
   a  b  c
4  8  1  2  3
10 4  5  6
8 12  7  8  9

In [56]: df.loc[4, 'c'] = np.array([0., 1.])

In [57]: df
Out[57]:
   a  b  c
4  8  1  2  0.0
10 4  5  1.0
8 12  7  8  9.0
```

1.13.1.10 to_xarray

In a future version of pandas, we will be deprecating Panel and other > 2 ndim objects. In order to provide for continuity, all **NDFrame** objects have gained the **.to_xarray()** method in order to convert to xarray objects, which has a pandas-like interface for > 2 ndim. (GH11972)

See the xarray full-documentation here.

```python
In [1]: p = Panel(np.arange(2*3*4).reshape(2,3,4))

In [2]: p.to_xarray()
Out[2]:
(continues on next page)
```

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1.13.1.11 Latex Representation

DataFrame has gained a \_repr\_latex\_() method in order to allow for conversion to latex in a ipython/jupyter notebook using nbconvert. (GH11778)

Note that this must be activated by setting the option pd.display.latex.repr=True (GH12182)

For example, if you have a jupyter notebook you plan to convert to latex using nbconvert, place the statement pd.display.latex.repr=True in the first cell to have the contained DataFrame output also stored as latex.

The options display.latex.escape and display.latex.longtable have also been added to the configuration and are used automatically by the to_latex method. See the available options docs for more info.

1.13.1.12 pd.read_sas() changes

read_sas has gained the ability to read SAS7BDAT files, including compressed files. The files can be read in entirety, or incrementally. For full details see here. (GH4052)

1.13.1.13 Other enhancements

- Handle truncated floats in SAS xport files (GH11713)
- Added option to hide index in Series.to_string (GH11729)
- read_excel now supports s3 urls of the format s3://bucketname/filename (GH11447)
- add support for AWS_S3_HOST env variable when reading from s3 (GH12198)
- A simple version of Panel.round() is now implemented (GH11763)
- For Python 3.x, round(DataFrame), round(Series), round(Panel) will work (GH11763)
- sys.getsizeof(obj) returns the memory usage of a pandas object, including the values it contains (GH11597)
- Series gained an is_unique attribute (GH11946)
- DataFrame.quantile and Series.quantile now accept interpolation keyword (GH10174).
- Added DataFrame.style.format for more flexible formatting of cell values (GH11692)
- DataFrame.select_dtypes now allows the np.float16 typecode (GH11990)
- pivot_table() now accepts most iterables for the values parameter (GH12017)
• Added Google BigQuery service account authentication support, which enables authentication on remote servers. (GH11881, GH12572). For further details see here

• HDFStore is now iterable: for k in store is equivalent to for k in store.keys() (GH12221).

• Add missing methods/fields to .dt for Period (GH8848)

• The entire codebase has been PEP-ified (GH12096)

1.13.2 Backwards incompatible API changes

• the leading whitespaces have been removed from the output of .to_string(index=False) method (GH11833)

• the out parameter has been removed from the Series.round() method. (GH11763)

• DataFrame.round() leaves non-numeric columns unchanged in its return, rather than raises. (GH11885)

• DataFrame.head(0) and DataFrame.tail(0) return empty frames, rather than self. (GH11937)

• Series.head(0) and Series.tail(0) return empty series, rather than self. (GH11937)

• to_msgpack and read_msgpack encoding now defaults to 'utf-8'. (GH12170)

• the order of keyword arguments to text file parsing functions (.read_csv(), .read_table(), .read_fwf()) changed to group related arguments. (GH11555)

• NaTType.isoformat now returns the string 'NaT' to allow the result to be passed to the constructor of Timestamp. (GH12300)

1.13.2.1 NaT and Timedelta operations

NaT and Timedelta have expanded arithmetic operations, which are extended to Series arithmetic where applicable. Operations defined for datetime64[ns] or timedelta64[ns] are now also defined for NaT (GH11564).

NaT now supports arithmetic operations with integers and floats.

```
In [58]: pd.NaT * 1
Out[58]: NaT

In [59]: pd.NaT * 1.5
Out[59]: NaT

In [60]: pd.NaT / 2
Out[60]: NaT

In [61]: pd.NaT * np.nan
Out[61]: NaT
```

NaT defines more arithmetic operations with datetime64[ns] and timedelta64[ns].

```
In [62]: pd.NaT / pd.NaT
Out[62]: nan

In [63]: pd.Timedelta('1s') / pd.NaT
Out[63]: nan
```

NaT may represent either a datetime64[ns] null or a timedelta64[ns] null. Given the ambiguity, it is treated as a timedelta64[ns], which allows more operations to succeed.
In [64]: pd.NaT + pd.NaT
Out[64]: NaT

# same as
In [65]: pd.Timedelta('1s') + pd.Timedelta('1s')
Out[65]: Timedelta('0 days 00:00:02')

as opposed to

In [3]: pd.Timestamp('19900315') + pd.Timestamp('19900315')
TypeError: unsupported operand type(s) for +: 'Timestamp' and 'Timestamp'

However, when wrapped in a Series whose dtype is datetime64[ns] or timedelta64[ns], the dtype information is respected.

In [1]: pd.Series([pd.NaT], dtype='<M8[ns]') + pd.Series([pd.NaT], dtype='<M8[ns]')
TypeError: can only operate on a datetimes for subtraction, but the operator [__add__] was passed

In [66]: pd.Series([pd.NaT], dtype='<m8[ns]') + pd.Series([pd.NaT], dtype='<m8[ns]')
Out[66]:
0    NaT
dtype: timedelta64[ns]

Timedelta division by floats now works.

In [67]: pd.Timedelta('1s') / 2.0
Out[67]: Timedelta('0 days 00:00:00.500000')

Subtraction by Timedelta in a Series by a Timestamp works (GH11925)

In [68]: ser = pd.Series(pd.timedelta_range('1 day', periods=3))

In [69]: ser
Out[69]:
0    1 days
1    2 days
2    3 days
dtype: timedelta64[ns]

In [70]: pd.Timestamp('2012-01-01') - ser
Out[70]:
0  2011-12-31
1  2011-12-30
2  2011-12-29
dtype: datetime64[ns]

NaT.isoformat() now returns 'NaT'. This change allows pd.Timestamp to rehydrate any timestamp like object from its isoformat (GH12300).

1.13.2.2 Changes to msgpack

Forward incompatible changes in msgpack writing format were made over 0.17.0 and 0.18.0; older versions of pandas cannot read files packed by newer versions (GH12129, GH10527)

Bugs in to_msgpack and read_msgpack introduced in 0.17.0 and fixed in 0.18.0, caused files packed in Python 2 unreadable by Python 3 (GH12142). The following table describes the backward and forward compat of msgpacks.
Warning:

<table>
<thead>
<tr>
<th>Packed with</th>
<th>Can be unpacked with</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-0.17 / Python 2</td>
<td>any</td>
</tr>
<tr>
<td>pre-0.17 / Python 3</td>
<td>any</td>
</tr>
<tr>
<td>0.17 / Python 2</td>
<td>• ==0.17 / Python 2</td>
</tr>
<tr>
<td></td>
<td>• &gt;=0.17 / any Python</td>
</tr>
<tr>
<td>0.17 / Python 3</td>
<td>&gt;=0.18 / any Python</td>
</tr>
<tr>
<td>0.18</td>
<td>&gt;= 0.18</td>
</tr>
</tbody>
</table>

0.18.0 is backward-compatible for reading files packed by older versions, except for files packed with 0.17 in Python 2, in which case only they can only be unpacked in Python 2.

1.13.2.3 Signature change for .rank

Series.rank and DataFrame.rank now have the same signature (GH11759)

Previous signature

```python
In [3]: pd.Series([0,1]).rank(method='average', na_option='keep', ascending=True, pct=False)
Out[3]:
   0 1
  1 2
dtype: float64

In [4]: pd.DataFrame([0,1]).rank(axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False)
Out[4]:
   0 1
  1 2
```

New signature

```python
In [71]: pd.Series([0,1]).rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)
       ....:
       ....:
Out[71]:
   0 1.0
   1 2.0
dtype: float64

In [72]: pd.DataFrame([0,1]).rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)
       ....:
       ....:
```

```python
\n\n\n\n\n\n\n\n\nOut[72]:
   0 1.0
   1 2.0
```
1.13.2.4 Bug in QuarterBegin with n=0

In previous versions, the behavior of the QuarterBegin offset was inconsistent depending on the date when the \( n \) parameter was 0. (GH11406)

The general semantics of anchored offsets for \( n=0 \) is to not move the date when it is an anchor point (e.g., a quarter start date), and otherwise roll forward to the next anchor point.

```
In [73]: d = pd.Timestamp('2014-02-01')
In [74]: d
Out[74]: Timestamp('2014-02-01 00:00:00')
In [75]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[75]: Timestamp('2014-02-01 00:00:00')
In [76]: d + pd.offsets.QuarterBegin(n=0, startingMonth=1)
Out[76]: Timestamp('2014-04-01 00:00:00')
```

For the QuarterBegin offset in previous versions, the date would be rolled backwards if date was in the same month as the quarter start date.

```
In [3]: d = pd.Timestamp('2014-02-15')
In [4]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[4]: Timestamp('2014-02-01 00:00:00')
```

This behavior has been corrected in version 0.18.0, which is consistent with other anchored offsets like MonthBegin and YearBegin.

```
In [77]: d = pd.Timestamp('2014-02-15')
In [78]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[78]: Timestamp('2014-05-01 00:00:00')
```

1.13.2.5 Resample API

Like the change in the window functions API \textit{above}, \texttt{.resample(...)} is changing to have a more groupby-like API. (GH11732, GH12702, GH12202, GH12332, GH12334, GH12348, GH12448).

```
In [79]: np.random.seed(1234)
In [80]: df = pd.DataFrame(np.random.rand(10,4),
......:       columns=list('ABCD'),
......:       index=pd.date_range('2010-01-01 09:00:00', periods=10,
.....:       freq='s'))
In [81]: df
Out[81]:
   A     B     C     D
0 0.19152 0.62211 0.43773 0.78536
1 0.77998 0.27260 0.27646 0.80187
2 0.95814 0.87593 0.35782 0.50099
3 0.68350 0.71270 0.37025 0.56119
4 0.19152 0.62211 0.43773 0.78536
5 0.77998 0.27260 0.27646 0.80187
6 0.95814 0.87593 0.35782 0.50099
7 0.68350 0.71270 0.37025 0.56119
8 0.19152 0.62211 0.43773 0.78536
9 0.77998 0.27260 0.27646 0.80187
(continues on next page)
Recent API

You would write a resampling operation that immediately evaluates. If a `how` parameter was not provided, it would default to `how='mean'`.

```
In [6]: df.resample('2s')
Out[6]:
          A         B         C         D
2010-01-01 09:00:00 0.485748 0.447351 0.357096 0.793615
2010-01-01 09:00:02 0.820801 0.794317 0.364034 0.531096
2010-01-01 09:00:04 0.433985 0.314582 0.424104 0.625733
2010-01-01 09:00:06 0.624988 0.609738 0.633165 0.612452
2010-01-01 09:00:08 0.510470 0.534317 0.573201 0.806949
```

You could also specify a `how` directly

```
In [7]: df.resample('2s', how='sum')
Out[7]:
          A         B         C         D
2010-01-01 09:00:00 0.971495 0.894701 0.714192 1.587231
2010-01-01 09:00:02 1.641602 1.588635 0.728068 1.062191
2010-01-01 09:00:04 0.867969 0.629165 0.633165 0.612452
2010-01-01 09:00:06 1.249976 1.219477 1.266330 1.224904
2010-01-01 09:00:08 1.020940 1.068634 1.146402 1.613897
```

New API

Now, you can write `.resample(..)` as a 2-stage operation like `.groupby(...)`, which yields a `Resampler`.

```
In [82]: r = df.resample('2s')
In [83]: r
Out[83]: DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left, label=left,
   →convention=start, base=0]
```

Downsampling

You can then use this object to perform operations. These are downsampling operations (going from a higher frequency to a lower one).

```
In [84]: r.mean()
Out[84]:
          A         B         C         D
2010-01-01 09:00:00 0.485748 0.447351 0.357096 0.793615
2010-01-01 09:00:02 0.820801 0.794317 0.364034 0.531096
2010-01-01 09:00:04 0.433985 0.314582 0.424104 0.625733
2010-01-01 09:00:06 0.624988 0.609738 0.633165 0.612452
2010-01-01 09:00:08 0.510470 0.534317 0.573201 0.806949
```
In [85]: r.sum()
Out[85]:

<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>0.971495</td>
<td>0.894701</td>
<td>0.714192</td>
<td>1.587231</td>
</tr>
<tr>
<td>1</td>
<td>1.641602</td>
<td>1.588635</td>
<td>0.728068</td>
<td>1.062191</td>
</tr>
<tr>
<td>2</td>
<td>0.867969</td>
<td>0.629165</td>
<td>0.848208</td>
<td>1.251465</td>
</tr>
<tr>
<td>3</td>
<td>1.249976</td>
<td>1.219477</td>
<td>1.266330</td>
<td>1.224904</td>
</tr>
<tr>
<td>4</td>
<td>1.020940</td>
<td>1.068634</td>
<td>1.146402</td>
<td>1.613897</td>
</tr>
</tbody>
</table>

Furthermore, resample now supportsgetitem operations to perform the resample on specific columns.

In [86]: r[['A','C']].mean()
Out[86]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.485748</td>
<td>0.357096</td>
</tr>
<tr>
<td>1</td>
<td>0.820801</td>
<td>0.364034</td>
</tr>
<tr>
<td>2</td>
<td>0.433985</td>
<td>0.424104</td>
</tr>
<tr>
<td>3</td>
<td>0.624988</td>
<td>0.633165</td>
</tr>
<tr>
<td>4</td>
<td>0.510470</td>
<td>0.573201</td>
</tr>
</tbody>
</table>

and .aggregate type operations.

In [87]: r.agg({'A' : 'mean', 'B' : 'sum'})
Out[87]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.485748</td>
<td>0.971495</td>
</tr>
<tr>
<td>1</td>
<td>0.820801</td>
<td>1.641602</td>
</tr>
<tr>
<td>2</td>
<td>0.433985</td>
<td>1.249976</td>
</tr>
<tr>
<td>3</td>
<td>0.624988</td>
<td>1.219477</td>
</tr>
<tr>
<td>4</td>
<td>0.510470</td>
<td>1.020940</td>
</tr>
</tbody>
</table>

These accessors can of course, be combined

In [88]: r[['A','B']].agg(['mean','sum'])
Out[88]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sum</td>
</tr>
<tr>
<td>0</td>
<td>0.485748</td>
<td>0.971495</td>
</tr>
<tr>
<td>1</td>
<td>0.820801</td>
<td>1.641602</td>
</tr>
<tr>
<td>2</td>
<td>0.433985</td>
<td>0.867969</td>
</tr>
<tr>
<td>3</td>
<td>0.624988</td>
<td>1.249976</td>
</tr>
<tr>
<td>4</td>
<td>0.510470</td>
<td>1.020940</td>
</tr>
</tbody>
</table>

**Upsampling**

Upsampling operations take you from a lower frequency to a higher frequency. These are now performed with theResampler objects with backfill(), ffill(), fillna() and asfreq() methods.

In [89]: s = pd.Series(np.arange(5,dtype='int64'),
                   index=date_range('2010-01-01', periods=5, freq='Q'))

In [90]: s
Out[90]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

(continues on next page)
Previously

```python
In [6]: s.resample('M', fill_method='ffill')
Out[6]:
2010-03-31 0
2010-04-30 0
2010-05-31 0
2010-06-30 1
2010-07-31 1
2010-08-31 1
2010-09-30 2
2010-10-31 2
2010-11-30 2
2010-12-31 3
2011-01-31 3
2011-02-28 3
2011-03-31 4
Freq: M, dtype: int64
```

New API

```python
In [91]: s.resample('M').ffill()
Out[91]:
2010-03-31 0
2010-04-30 0
2010-05-31 0
2010-06-30 1
2010-07-31 1
2010-08-31 1
2010-09-30 2
2010-10-31 2
2010-11-30 2
2010-12-31 3
2011-01-31 3
2011-02-28 3
2011-03-31 4
Freq: M, dtype: int64
```

**Note:** In the new API, you can either downsample OR upsample. The prior implementation would allow you to pass an aggregator function (like `mean`) even though you were upsampling, providing a bit of confusion.

**Previous API will work but with deprecations**

**Warning:** This new API for resample includes some internal changes for the prior-to-0.18.0 API, to work with a deprecation warning in most cases, as the resample operation returns a deferred object. We can intercept operations...
and just do what the (pre 0.18.0) API did (with a warning). Here is a typical use case:

```
In [4]: r = df.resample('2s')
```

```
In [6]: r*10
pandas/tseries/resample.py:80: FutureWarning: .resample() is now a deferred operation
use .resample(...).mean() instead of .resample(...)
```

```
Out[6]:
   A   B   C   D
2010-01-01 09:00:00 4.857476 4.473507 3.570960 7.936154
2010-01-01 09:00:02 8.208011 7.943173 3.640340 5.310957
2010-01-01 09:00:04 4.339846 3.145823 4.241039 6.257326
2010-01-01 09:00:06 6.249881 6.097384 6.331650 6.124518
2010-01-01 09:00:08 5.104699 5.343172 5.732009 8.069486
```

However, getting and assignment operations directly on a `Resampler` will raise a `ValueError`:

```
In [7]: r.iloc[0] = 5
ValueError: .resample() is now a deferred operation
use .resample(...).mean() instead of .resample(...)
```

There is a situation where the new API can not perform all the operations when using original code. This code is intending to resample every 2s, take the mean AND then take the min of those results.

```
In [4]: df.resample('2s').min()
```

```
Out[4]:
     A      B      C      D
2010-01-01  0.433985  0.314582  0.357096  0.531096
```

The new API will:

```
In [92]: df.resample('2s').mean().min()
```

```
Out[92]:
       A      B      C      D
2010-01-01  0.433985  0.314582  0.357096  0.531096
dtype: float64
```

The good news is the return dimensions will differ between the new API and the old API, so this should loudly raise an exception.

To replicate the original operation

```
In [93]: df.resample('2s').mean().min()
```

```
Out[93]:
     A      B      C      D
2010-01-01  0.433985  0.314582  0.357096  0.531096
dtype: float64
```
1.13.2.6 Changes to eval

In prior versions, new columns assignments in an `eval` expression resulted in an inplace change to the DataFrame. (GH9297, GH8664, GH10486)

```python
In [94]: df = pd.DataFrame({'a': np.linspace(0, 10, 5), 'b': range(5)})
```

```python
In [95]: df
Out[95]:
   a  b
0  0  0
1  2.5 1
2  5  2
3  7.5 3
4  10  4
```

```python
In [12]: df.eval('c = a + b')
```

```
FutureWarning: eval expressions containing an assignment currently default to operating inplace. This will change in a future version of pandas, use inplace=True to avoid this warning.
```

```python
In [13]: df
Out[13]:
   a  b  c
0  0  0  0
1  2.5 1  3.5
2  5  2  7
3  7.5 3 10.5
4  10  4 14
```

In version 0.18.0, a new `inplace` keyword was added to choose whether the assignment should be done inplace or return a copy.

```python
In [96]: df
Out[96]:
   a  b  c
0  0  0  0
1  2.5 1  3.5
2  5  2  7
3  7.5 3 10.5
4  10  4 14
```

```python
In [97]: df.eval('d = c - b', inplace=False)
```

```python
          a  b  c  d
0   0.0  0.0  0.0  0.0
1  2.5  1.5  3.5  2.5
2  5.0  2.0  7.0  5.0
3  7.5  3.5 10.5  7.5
4 10.0  4.0 14.0 10.0
```

```python
In [98]: df
```

(continues on next page)
In [99]: df.eval('d = c - b', inplace=True)

In [100]: df
Out[100]:
   a  b  c  d
0  0.0  0.0  0.0  0.0
1  2.5  1.0  3.5  2.5
2  5.0  2.0  7.0  5.0
3  7.5  3.0  10.5  7.5
4 10.0  4.0  14.0 10.0

Warning: For backwards compatibility, `inplace` defaults to `True` if not specified. This will change in a future version of pandas. If your code depends on an inplace assignment you should update to explicitly set `inplace=True`.

The `inplace` keyword parameter was also added the `query` method.

In [101]: df.query('a > 5')
Out[101]:
   a  b  c  d
3  7.5  3.0 10.5  7.5
4 10.0  4.0 14.0 10.0

In [102]: df.query('a > 5', inplace=True)

In [103]: df
Out[103]:
   a  b  c  d
3  7.5  3.0 10.5  7.5
4 10.0  4.0 14.0 10.0

Warning: Note that the default value for `inplace` in a `query` is `False`, which is consistent with prior versions.

eval has also been updated to allow multi-line expressions for multiple assignments. These expressions will be evaluated one at a time in order. Only assignments are valid for multi-line expressions.

In [104]: df
Out[104]:
   a  b  c  d
3  7.5  3.0 10.5  7.5
4 10.0  4.0 14.0 10.0

In [105]: df.eval(""
    .....: e = d + a
    .....: f = e - 22
    .....: g = f / 2.0"", inplace=True)

(continues on next page)
1.13.7 Other API Changes

- DataFrame.between_time and Series.between_time now only parse a fixed set of time strings. Parsing of date strings is no longer supported and raises a ValueError. (GH11818)

```python
In [106]: df
Out[106]:
       a    b    c   d    e   f   g
3  7.5  3.0  10.5  7.5 -7.0 -3.5
4 10.0  4.0  14.0  10.0 20.0 -2.0 -1.0
```

This will now raise.

```python
In [2]: s.between_time('20150101 07:00:00','20150101 09:00:00')
ValueError: Cannot convert arg ['20150101 07:00:00'] to a time.
```

- .memory_usage() now includes values in the index, as does memory_usage in .info() (GH11597)
- DataFrame.to_latex() now supports non-ascii encodings (eg utf-8) in Python 2 with the parameter encoding (GH7061)
- pandas.merge() and DataFrame.merge() will show a specific error message when trying to merge with an object that is not of type DataFrame or a subclass (GH12081)
- DataFrame.unstack and Series.unstack now take fill_value keyword to allow direct replacement of missing values when an unstack results in missing values in the resulting DataFrame. As an added benefit, specifying fill_value will preserve the data type of the original stacked data. (GH9746)
- As part of the new API for window functions and resampling, aggregation functions have been clarified, raising more informative error messages on invalid aggregations. (GH9052). A full set of examples are presented in groupby.
- Statistical functions for NDFrame objects (like sum(), mean(), min()) will now raise if non-numpy-compatible arguments are passed in for **kwargs (GH12301)
- .to_latex and .to_html gain a decimal parameter like .to_csv; the default is '.' (GH12031)
- More helpful error message when constructing a DataFrame with empty data but with indices (GH8020)
- .describe() will now properly handle bool dtype as a categorical (GH6625)
- More helpful error message with an invalid .transform with user defined input (GH10165)
- Exponentially weighted functions now allow specifying alpha directly (GH10789) and raise ValueError if parameters violate $0 < \alpha \leq 1$ (GH12492)
1.13.2.8 Deprecations

- The functions `pd.rolling_*`, `pd.expanding_*`, and `pd.ewm*` are deprecated and replaced by the corresponding method call. Note that the new suggested syntax includes all of the arguments (even if default) (GH11603)

```python
In [1]: s = pd.Series(range(3))
In [2]: pd.rolling_mean(s, window=2, min_periods=1)
FutureWarning: pd.rolling_mean is deprecated for Series and will be removed in a future version, replace with Series.rolling(min_periods=1, window=2, center=False).mean()
```

```output
Out[2]:
0 0.0
1 0.5
2 1.5
dtype: float64
```

```python
In [3]: pd.rolling_cov(s, s, window=2)
FutureWarning: pd.rolling_cov is deprecated for Series and will be removed in a future version, replace with Series.rolling(window=2).cov(other=<Series>)
```

```output
Out[3]:
0  NaN
1 0.5
2 0.5
dtype: float64
```

- The `freq` and `how` arguments to the `.rolling`, `.expanding`, and `.ewm` (new) functions are deprecated, and will be removed in a future version. You can simply resample the input prior to creating a window function. (GH11603).

For example, instead of `s.rolling(window=5, freq='D').max()` to get the max value on a rolling 5 Day window, one could use `s.resample('D').mean().rolling(window=5).max()`, which first resamples the data to daily data, then provides a rolling 5 day window.

- `pd.tseries.frequencies.get_offset_name` function is deprecated. Use offset’s `.freqstr` property as alternative (GH11192)

- `pandas.stats.fama_macbeth` routines are deprecated and will be removed in a future version (GH6077)

- `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var` routines are deprecated and will be removed in a future version (GH6077)

- Show a `FutureWarning` rather than a `DeprecationWarning` on using long-time deprecated syntax in `HDFStore.select`, where the `where` clause is not a string-like (GH12027)

- The `pandas.options.display.mpl_style` configuration has been deprecated and will be removed in a future version of pandas. This functionality is better handled by matplotlib’s style sheets (GH11783).

1.13.2.9 Removal of deprecated float indexers

In GH4892 indexing with floating point numbers on a non-`Float64Index` was deprecated (in version 0.14.0). In 0.18.0, this deprecation warning is removed and these will now raise a `TypeError`. (GH12165, GH12333)

```python
In [109]: s = pd.Series([1, 2, 3], index=[4, 5, 6])
In [110]: s
```

(continues on next page)
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```python
Out[110]:
4  1
5  2
6  3
dtype: int64
In [111]: s2 = pd.Series([1, 2, 3], index=list('abc'))

In [112]: s2
Out[112]:
a 1
b 2
c 3
dtype: int64
```

**Previous Behavior:**

```python
# this is label indexing
In [2]: s[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[2]: 2

# this is positional indexing
In [3]: s.iloc[1.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[3]: 2

# this is label indexing
In [4]: s.loc[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[4]: 2

# .ix would coerce 1.0 to the positional 1, and index
In [5]: s2.ix[1.0] = 10
FutureWarning: scalar indexers for index type Index should be integers and not floating point

In [6]: s2
Out[6]:
a 1
b 10
c 3
dtype: int64
```

**New Behavior:**

For iloc, getting & setting via a float scalar will always raise.

```python
In [3]: s.iloc[2.0]
TypeError: cannot do label indexing on <class 'pandas.indexes.numeric.Int64Index'> with these indexers [2.0] of <type 'float'>
```

Other indexers will coerce to a like integer for both getting and setting. The `FutureWarning` has been dropped for `.loc`, `.ix` and `[]`. 

1.13. v0.18.0 (March 13, 2016)
and setting

```python
In [115]: s_copy = s.copy()
In [116]: s_copy[5.0] = 10
In [117]: s_copy
Out[117]:
   4  1
   5 10
   6  3
   dtype: int64
In [118]: s_copy = s.copy()
In [119]: s_copy.loc[5.0] = 10
In [120]: s_copy
Out[120]:
   4  1
   5 10
   6  3
   dtype: int64
```

Positional setting with `.ix` and a float indexer will ADD this value to the index, rather than previously setting the value by position.

```python
In [3]: s2.ix[1.0] = 10
In [4]: s2
Out[4]:
    a  b  c
   --- --- ---
     1  2  3
   1.0 10
   dtype: int64
```

Slicing will also coerce integer-like floats to integers for a non-Float64Index.

```python
In [121]: s.loc[5.0:6]
Out[121]:
   5  2
   6  3
   dtype: int64
```

Note that for floats that are NOT coercible to ints, the label based bounds will be excluded

```python
In [122]: s.loc[5.1:6]
Out[122]:
   6  3
   dtype: int64
```

Float indexing on a Float64Index is unchanged.

---

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In [123]: s = pd.Series([1, 2, 3], index=np.arange(3.))
In [124]: s[1.0]
Out[124]: 2
In [125]: s[1.0:2.5]
Out[125]:
1.0  2
2.0  3
dtype: int64

1.13.2.10 Removal of prior version deprecations/changes

- Removal of `rolling_corr_pairwise` in favor of `.rolling().corr(pairwise=True)` (GH4950)
- Removal of `expanding_corr_pairwise` in favor of `.expanding().corr(pairwise=True)` (GH4950)
- Removal of `DataMatrix` module. This was not imported into the pandas namespace in any event (GH12111)
- Removal of `cols` keyword in favor of `subset` in `DataFrame.duplicated()` and `DataFrame.drop_duplicates()` (GH6680)
- Removal of the `read_frame` and `frame_query` (both aliases for `pd.read_sql`) and `write_frame` (alias of `to_sql`) functions in the `pd.io.sql` namespace, deprecated since 0.14.0 (GH6292).
- Removal of the `order` keyword from `.factorize()` (GH6930)

1.13.3 Performance Improvements

- Improved performance of `andrews_curves` (GH11534)
- Improved huge `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex`'s ops performance including `NaT` (GH10277)
- Improved performance of `pandas.concat` (GH11958)
- Improved performance of `StataReader` (GH11591)
- Improved performance in construction of `Categoricals` with `Series` of datetimes containing `NaT` (GH12077)
- Improved performance of ISO 8601 date parsing for dates without separators (GH11899), leading zeros (GH11871) and with whitespace preceding the time zone (GH9714)

1.13.4 Bug Fixes

- Bug in `GroupBy.size` when data-frame is empty. (GH11699)
- Bug in `Period.end_time` when a multiple of time period is requested (GH11738)
- Regression in `.clip` with tz-aware datetimes (GH11838)
- Bug in `date_range` when the boundaries fell on the frequency (GH11804, GH12409)
- Bug in consistency of passing nested dicts to `.groupby(...)`.agg(...) (GH9052)
- Accept unicode in `Timedelta` constructor (GH11995)
• Bug in value label reading for StataReader when reading incrementally (GH12014)
• Bug in vectorized DateOffset when n parameter is 0 (GH11370)
• Compats for numpy 1.11 w.r.t. NaT comparison changes (GH12049)
• Bug in read_csv when reading from a StringIO in threads (GH11790)
• Bug in not treating NaT as a missing value in datetimelikes when factorizing & with Categoricals (GH12077)
• Bug in getitem when the values of a Series were tz-aware (GH12089)
• Bug in Series.str.get_dummies when one of the variables was ‘name’ (GH12180)
• Bug in pd.concat while concatenating tz-aware NaT series. (GH11693, GH11755, GH12217)
• Bug in pd.read_stata with version <= 108 (GH12232)
• Bug in Series.resample using a frequency of Nano when the index is a DatetimeIndex and contains non-zero nanosecond parts (GH12037)
• Bug in resampling with .nunique and a sparse index (GH12352)
• Removed some compiler warnings (GH12471)
• Work around compat issues with boto in python 3.5 (GH11915)
• Bug in NaT subtraction from Timestamp or DatetimeIndex with timezones (GH11718)
• Bug in subtraction of Series of a single tz-aware Timestamp (GH12290)
• Use compat iterators in PY2 to support .next() (GH12299)
• Bug in Timedelta.round with negative values (GH11690)
• Bug in .loc against CategoricalIndex may result in normal Index (GH11586)
• Bug in DataFrame.info when duplicated column names exist (GH11761)
• Bug in .copy of datetime tz-aware objects (GH11794)
• Bug in Series.apply and Series.map where timedelta64 was not boxed (GH11349)
• Bug in DataFrame.set_index() with tz-aware Series (GH12358)
• Bug in subclasses of DataFrame where AttributeError did not propagate (GH11808)
• Bug groupby on tz-aware data where selection not returning Timestamp (GH11616)
• Bug in pd.read_clipboard and pd.to_clipboard functions not supporting Unicode; upgrade included pyperclip to v1.5.15 (GH9263)
• Bug in DataFrame.query containing an assignment (GH8664)
• Bug in from_msgpack where __contains__() fails for columns of the unpacked DataFrame, if the DataFrame has object columns. (GH11880)
• Bug in .resample on categorical data with TimedeltaIndex (GH12169)
• Bug in timezone info lost when broadcasting scalar datetime to DataFrame (GH11682)
• Bug in Index creation from Timestamp with mixed tz coerces to UTC (GH11488)
• Bug in to_numeric where it does not raise if input is more than one dimension (GH11776)
• Bug in parsing timezone offset strings with non-zero minutes (GH11708)
• Bug in df.plot using incorrect colors for bar plots under matplotlib 1.5+ (GH11614)
• Bug in the `groupbyplot` method when using keyword arguments (GH11805).
• Bug in `DataFrame.duplicated` and `drop_duplicates` causing spurious matches when setting `keep=False` (GH11864)
• Bug in `.loc` result with duplicated key may have `Index` with incorrect dtype (GH11497)
• Bug in `pd.rolling_median` where memory allocation failed even with sufficient memory (GH11697)
• Bug in `DataFrame.style` with spurious zeros (GH12134)
• Bug in `DataFrame.style` with integer columns not starting at 0 (GH12125)
• Bug in `.style.bar` may not rendered properly using specific browser (GH11678)
• Bug in rich comparison of `Timedelta` with a `numpy.array` of `Timedelta` that caused an infinite recursion (GH11835)
• Bug in `DataFrame.round` dropping column index name (GH11986)
• Bug in `df.replace` while replacing value in mixed dtype DataFrame (GH11698)
• Bug in `Index` prevents copying name of passed `Index`, when a new name is not provided (GH1193)
• Bug in `read_excel` failing to read any non-empty sheets when empty sheets exist and `sheetname=None` (GH11711)
• Bug in `read_excel` failing to raise `NotImplemented` error when keywords `parse_dates` and `date_parser` are provided (GH11544)
• Bug in `read_sql` with `pymysql` connections failing to return chunked data (GH11522)
• Bug in `.to_csv` ignoring formatting parameters `decimal`, `na_rep`, `float_format` for float indexes (GH11553)
• Bug in `Int64Index` and `Float64Index` preventing the use of the modulo operator (GH9244)
• Bug in `MultiIndex.drop` for not lexsorted multi-indexes (GH12078)
• Bug in `DataFrame` when masking an empty DataFrame (GH11859)
• Bug in `.plot` potentially modifying the `colors` input when the number of columns didn’t match the number of series provided (GH12039).
• Bug in `Series.plot` failing when index has a `CustomBusinessDay` frequency (GH7222).
• Bug in `.to_sql` for `datetime.time` values with sqlite fallback (GH8341)
• Bug in `read_excel` failing to read data with one column when `squeeze=True` (GH12157)
• Bug in `read_excel` failing to read one empty column (GH12292, GH9002)
• Bug in `.groupby` where a `KeyError` was not raised for a wrong column if there was only one row in the dataframe (GH11741)
• Bug in `.read_csv` with `dtype` specified on empty data producing an error (GH12048)
• Bug in `.read_csv` where strings like `’2E’` are treated as valid floats (GH1237)
• Bug in building `pandas` with debugging symbols (GH12123)
• Removed millisecond property of `DatetimeIndex`. This would always raise a `ValueError` (GH12019).
• Bug in `Series` constructor with read-only data (GH11502)
• Removed `pandas.util.testing.choice()`. Should use `np.random.choice()`, instead. (GH12386)
• Bug in `.loc` setitem indexer preventing the use of a TZ-aware DatetimeIndex (GH12050)
• Bug in `.style` indexes and multi-indexes not appearing (GH11655)
• Bug in `to_msgpack` and `from_msgpack` which did not correctly serialize or deserialize NaT (GH12307).
• Bug in `.skew` and `.kurt` due to roundoff error for highly similar values (GH11974)
• Bug in Timestamp constructor where microsecond resolution was lost if HHMMSS were not separated with ‘:’ (GH10041)
• Bug in `buffer_rd_bytes` src->buffer could be freed more than once if reading failed, causing a segfault (GH12098)
• Bug in `crosstab` where arguments with non-overlapping indexes would return a `KeyError` (GH10291)
• Bug in `DataFrame.apply` in which reduction was not being prevented for cases in which `dtype` was not a numpy dtype (GH12244)
• Bug when initializing categorical series with a scalar value. (GH12336)
• Bug when specifying a UTC DatetimeIndex by setting `utc=True` in `.to_datetime` (GH11934)
• Bug when increasing the buffer size of CSV reader in `read_csv` (GH12494)
• Bug when setting columns of a DataFrame with duplicate column names (GH12344)

1.14 v0.17.1 (November 21, 2015)

Note: We are proud to announce that pandas has become a sponsored project of the (NumFOCUS organization). This will help ensure the success of development of pandas as a world-class open-source project.

This is a minor bug-fix release from 0.17.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

• Support for Conditional HTML Formatting, see here
• Releasing the GIL on the csv reader & other ops, see here
• Fixed regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)

What’s new in v0.17.1

• New features
  – Conditional HTML Formatting
• Enhancements
• API changes
  – Deprecations
• Performance Improvements
• Bug Fixes
1.14.1 New features

1.14.1.1 Conditional HTML Formatting

**Warning:** This is a new feature and is under active development. We’ll be adding features an possibly making breaking changes in future releases. Feedback is welcome.

We’ve added *experimental* support for conditional HTML formatting: the visual styling of a DataFrame based on the data. The styling is accomplished with HTML and CSS. Aceses the styler class with the `pandas.DataFrame.style`, attribute, an instance of `Styler` with your data attached.

Here’s a quick example:

```
In [1]: np.random.seed(123)
In [2]: df = DataFrame(np.random.randn(10, 5), columns=list('abcde'))
In [3]: html = df.style.background_gradient(cmap='viridis', low=.5)
```

We can render the HTML to get the following table.

Styler interacts nicely with the Jupyter Notebook. See the documentation for more.

1.14.2 Enhancements

- DatetimeIndex now supports conversion to strings with `astype(str)` (GH10442)
- Support for compression (gzip/bz2) in `pandas.DataFrame.to_csv()` (GH7615)
- `pd.read_*` functions can now also accept `pathlib.Path`, or `py._path.local.LocalPath` objects for the `filepath_or_buffer` argument. (GH11033) - The DataFrame and Series functions `.to_csv()`, `.to_html()` and `.to_latex()` can now handle paths beginning with tildes (e.g. `/~/Documents/(GH11438)
- DataFrame now uses the fields of a `namedtuple` as columns, if columns are not supplied (GH11181)
- DataFrame.itertuples() now returns `namedtuple` objects, when possible. (GH11269, GH11625)
- Added `axvlines_kwds` to parallel coordinates plot (GH10709)
- Option to `.info()` and `.memory_usage()` to provide for deep introspection of memory consumption. Note that this can be expensive to compute and therefore is an optional parameter. (GH11595)

```
In [4]: df = DataFrame({'A': ['foo']*1000})
In [5]: df['B'] = df['A'].astype('category')
# shows the '+' as we have object dtypes
In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
A 1000 non-null object
B 1000 non-null category
dtypes: category(1), object(1)
memory usage: 9.0+ KB
```
# we have an accurate memory assessment (but can be expensive to compute this)

```python
In [7]: df.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
A 1000 non-null object
B 1000 non-null category
dtypes: category(1), object(1)
memory usage: 75.4 KB
```

• Index now has a `fillna` method (GH10089)

```python
In [8]: pd.Index([1, np.nan, 3]).fillna(2)
```

```
Float64Index([1.0, 2.0, 3.0], dtype='float64')
```

• Series of type `category` now make `.str.<...>` and `.dt.<...>` accessor methods / properties available, if the categories are of that type. (GH10661)

```python
In [9]: s = pd.Series(list('aabb')).astype('category')
```

```
0 a
1 a
2 b
3 b
dtype: category
Categories (2, object): [a, b]
```

```python
In [11]: s.str.contains("a")
```

```
0 True
1 True
2 False
3 False
dtype: bool
```

```python
In [12]: date = pd.Series(pd.date_range('1/1/2015', periods=5)).astype('category')
```

```
0 2015-01-01
1 2015-01-02
2 2015-01-03
3 2015-01-04
4 2015-01-05
dtype: category
```

```python
In [14]: date.dt.day
```

```
```
• pivot_table now has a margins_name argument so you can use something other than the default of ‘All’ (GH3335)

• Implement export of datetime64[ns, tz] dtypes with a fixed HDF5 store (GH11411)

• Pretty printing sets (e.g. in DataFrame cells) now uses set literal syntax ({x, y}) instead of Legacy Python syntax (set([x, y])) (GH11215)

• Improve the error message in pandas.io.gbq.to_gbq() when a streaming insert fails (GH11285) and when the DataFrame does not match the schema of the destination table (GH11359)

1.14.3 API changes

• raise NotImplementedError in Index.shift for non-supported index types (GH8038)

• min and max reductions on datetime64 and timedelta64 dtyped series now result in NaT and not nan (GH11245).

• Indexing with a null key will raise a TypeError, instead of a ValueError (GH11356)

• Series.ptp will now ignore missing values by default (GH11163)

1.14.3.1 Deprecations

• The pandas.io.ga module which implements google-analytics support is deprecated and will be removed in a future version (GH11308)

• Deprecate the engine keyword in .to_csv(), which will be removed in a future version (GH11274)

1.14.4 Performance Improvements

• Checking monotonic-ness before sorting on an index (GH11080)

• Series.dropna performance improvement when its dtype can’t contain NaN (GH11159)

• Release the GIL on most datetime field operations (e.g. DatetimeIndex.year, Series.dt.year), normalization, and conversion to and from Period, DatetimeIndex.to_period and PeriodIndex.to_timestamp (GH11263)

• Release the GIL on some rolling algos: rolling_median, rolling_mean, rolling_max, rolling_min, rolling_var, rolling_kurt, rolling_skew (GH11450)

• Release the GIL when reading and parsing text files in read_csv, read_table (GH11272)

• Improved performance of rolling_median (GH11450)

• Improved performance of to_excel (GH11352)

• Performance bug in repr of Categorical categories, which was rendering the strings before chopping them for display (GH11305)
• Performance improvement in `Categorical.remove_unused_categories`, (GH11643).
• Improved performance of `Series` constructor with no data and `DatetimeIndex` (GH11433)
• Improved performance of `shift`, `cumprod`, and `cumsum` with groupby (GH4095)

1.14.5 Bug Fixes

• `SparseArray.__iter__()` now does not cause `PendingDeprecationWarning` in Python 3.5 (GH11622)
• Regression from 0.16.2 for output formatting of long floats/nan, restored in (GH11302)
• `Series.sort_index()` now correctly handles the `inplace` option (GH11402)
• Incorrectly distributed .c file in the build on PyPi when reading a csv of floats and passing `na_values=<a scalar>` would show an exception (GH11374)
• Bug in `.to_latex()` output broken when the index has a name (GH10660)
• Bug in HDFStore.append with strings whose encoded length exceeded the max unencoded length (GH11234)
• Bug in merging `datetime64[ns, tz]` dtypes (GH11405)
• Bug in HDFStore.select when comparing with a numpy scalar in a where clause (GH11283)
• Bug in using `DataFrame.ix` with a multi-index indexer (GH11372)
• Bug in `date_range` with ambiguous endpoints (GH11626)
• Prevent adding new attributes to the accessors `.str`, `.dt` and `.cat`. Retrieving such a value was not possible, so error out on setting it. (GH10673)
• Bug in tz-conversions with an ambiguous time and `.dt` accessors (GH11295)
• Bug in output formatting when using an index of ambiguous times (GH11619)
• Bug in comparisons of `Series` vs list-likes (GH11339)
• Bug in `DataFrame.replace` with a `datetime64[ns, tz]` and a non-compat `to_replace` (GH11326, GH11153)
• Bug in `isnull` where `numpy.datetime64('NaT')` in a `numpy.array` was not determined to be `null` (GH11206)
• Bug in list-like indexing with a mixed-integer Index (GH11320)
• Bug in `pivot_table` with margins=True when indexes are of `Categorical` dtype (GH10993)
• Bug in `DataFrame.plot` cannot use hex strings colors (GH10299)
• Regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)
• Bug in `pd.eval` where unary ops in a list error (GH11235)
• Bug in `squeeze()` with zero length arrays (GH11230, GH8999)
• Bug in `describe()` dropping column names for hierarchical indexes (GH11517)
• Bug in `DataFrame.pct_change()` not propagating axis keyword on `.fillna` method (GH11150)
• Bug in `.to_csv()` when a mix of integer and string column names are passed as the `columns` parameter (GH11637)
• Bug in indexing with a range, (GH11652)
- Bug in inference of numpy scalars and preserving dtype when setting columns (GH11638)
- Bug in to_sql using unicode column names giving UnicodeEncodeError with (GH11431).
- Fix regression in setting of xticks in plot (GH11529).
- Bug in holiday.dates where observance rules could not be applied to holiday and doc enhancement (GH11477, GH11533)
- Fix plotting issues when having plain Axes instances instead of SubplotAxes (GH11520, GH11556).
- Bug in DataFrame.to_latex() produces an extra rule when header=False (GH7124)
- Bug in df.groupby(...).apply(func) when a func returns a Series containing a new datetimelike column (GH11324)
- Bug in pandas.json when file to load is big (GH11344)
- Bugs in to_excel with duplicate columns (GH11007, GH10982, GH10970)
- Fixed a bug that prevented the construction of an empty series of dtype datetime64[ns, tz] (GH11245).
- Bug in read_excel with multi-index containing integers (GH11317)
- Bug in to_excel with openpyxl 2.2+ and merging (GH11408)
- Bug in DataFrame.to_dict() produces a np.datetetme64 object instead of Timestamp when only datetime is present in data (GH11327)
- Bug in DataFrame.corr() raises exception when computes Kendall correlation for DataFrames with boolean and not boolean columns (GH11560)
- Bug in the link-time error caused by C inline functions on FreeBSD 10+ (with clang) (GH10510)
- Bug in DataFrame.to_csv in passing through arguments for formatting MultiIndexes, including date_format (GH7791)
- Bug in DataFrame.join() with how='right' producing a TypeError (GH11519)
- Bug in Series.quantile with empty list results has Index with object dtype (GH11588)
- Bug in pd.merge results in empty Int64Index rather than Index(dtype=object) when the merge result is empty (GH11588)
- Bug in Categorical.remove_unused_categories when having NaN values (GH11599)
- Bug in DataFrame.to_sparse() loses column names for MultiIndexes (GH11600)
- Bug in DataFrame.round() with non-unique column index producing a Fatal Python error (GH11611)
- Bug in DataFrame.round() with decimals being a non-unique indexed Series producing extra columns (GH11618)

1.15 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)
- Development support for benchmarking with the Air Speed Velocity library (GH8361)
- Support for reading SAS xport files, see here
- Documentation comparing SAS to pandas, see here
- Removal of the automatic TimeSeries broadcasting, deprecated since 0.8.0, see here
- Display format with plain text can optionally align with Unicode East Asian Width, see here
- Compatibility with Python 3.5 (GH11097)
- Compatibility with matplotlib 1.5.0 (GH11111)

Check the API Changes and deprecations before updating.

What’s new in v0.17.0

- New features
  - Datetime with TZ
  - Releasing the GIL
  - Plot submethods
  - Additional methods for `dt` accessor
    - `strftime`
1.15.1 New features

1.15.1.1 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 of 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]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2013-01-01 00:00:00-05:00</td>
<td>2013-01-01 00:00:00+01:00</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2013-01-02 00:00:00-05:00</td>
<td>2013-01-02 00:00:00+01:00</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2013-01-03 00:00:00-05:00</td>
<td>2013-01-03 00:00:00+01:00</td>
<td></td>
</tr>
</tbody>
</table>

In [3]: df.dtypes

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>B</td>
<td>datetime64[ns, US/Eastern]</td>
</tr>
<tr>
<td>C</td>
<td>datetime64[ns, CET]</td>
</tr>
</tbody>
</table>

dtype: object

In [4]: df.B

Out[4]:

<table>
<thead>
<tr>
<th></th>
<th>2013-01-01 00:00:00-05:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

Name: B, dtype: datetime64[ns, US/Eastern]

In [5]: df.B.dt.tz_localize(None)

<table>
<thead>
<tr>
<th></th>
<th>2013-01-01</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

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.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
dtype('<M8[ns]>')

**New Behavior:**

In [8]: pd.date_range('20130101', periods=3, tz='US/Eastern')

(continues on next page)
1.15.1.2 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.

1.15.1.3 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.

### 1.15.1.4 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:

```
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')
```

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# 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    60.0
   1  86460.0
   2  172860.0
   3  259260.0
dtype: float64
1.15.1.5 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.

```python
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.

```python
In [28]: idx = pd.period_range('2015-08-01', periods=4, freq='2D')

In [29]: idx
Out[29]: PeriodIndex(['2015-08-01', '2015-08-03', '2015-08-05', '2015-08-07'], dtype='period[2D]', freq='2D')

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

1.15.1.6 Support for SAS XPORT files

`read_sas()` provides support for reading SAS XPORT format files. (GH4052).

```python
df = pd.read_sas('sas_xport.xpt')
```

It is also possible to obtain an iterator and read an XPORT file incrementally.

```python
for df in pd.read_sas('sas_xport.xpt', chunksize=10000)
do_something(df)
```

See the docs for more details.
1.15.1.7 Support for Math Functions in .eval()

eval() now supports calling math functions (GH4893)

```python
import pandas as pd
df = pd.DataFrame({'a': np.random.randn(10)})
df.eval("b = sin(a)")
```

The support math functions are \( \sin, \cos, \exp, \log, \expm1, \log1p, \sqrt, \sinh, \cosh, \tanh, \arcsin, \arccos, \arctan, \arccosh, \arcsinh, \arctanh, \text{abs} \) and \( \arctan2 \).

These functions map to the intrinsics for the NumExpr engine. For the Python engine, they are mapped to NumPy calls.

1.15.1.8 Changes to Excel with MultiIndex

In version 0.16.2 a DataFrame with MultiIndex columns could not be written to Excel via to_excel. That functionality has been added (GH10564), along with updating read_excel so that the data can be read back with, no loss of information, by specifying which columns/rows make up the MultiIndex in the header and index_col parameters (GH4679)

See the documentation for more details.

```python
In [31]: df = pd.DataFrame([[1,2,3,4], [5,6,7,8]],
                   columns = pd.MultiIndex.from_product([['foo','bar'], ['a','b']]),
                   index = pd.MultiIndex.from_product([['j'], ['l','k']]),
                   names = ['col1', 'col2', 'i1', 'i2'])
In [32]: df
Out[32]:
           col1  foo  bar
       col2   a   b   a   b
      1  1  2  3  4
     j  5  6  7  8
    k      
In [33]: df.to_excel('test.xlsx')
In [34]: df = pd.read_excel('test.xlsx', header=[0,1], index_col=[0,1])
In [35]: df
Out[35]:
           col1  foo  bar
       col2   a   b   a   b
      1  1  2  3  4
     j  5  6  7  8
    k      
```

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
New

1.15.1.9 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).
1.15.1.10 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;
```

```
      0  1
0  Alice  UK
1  しのぶ  日本
```

```
In [38]: pd.set_option('display.unicode.east_asian_width', True)
In [39]: df;
```

```
      0 1
0  Alice  UK
1  しのぶ 日本
```

For further details, see here

1.15.1.11 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']})
```

(continues on next page)
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>0</td>
<td>a</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>b</td>
<td>2.0</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>NaN</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>NaN</td>
<td>2.0</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]:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>

New Behavior:

In [46]: pd.concat([foo, bar, baz, 1])

Out[46]:

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>foo</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

- `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]:

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NaN</td>
</tr>
<tr>
<td>5.0</td>
</tr>
<tr>
<td>5.0</td>
</tr>
<tr>
<td>7.0</td>
</tr>
<tr>
<td>NaN</td>
</tr>
<tr>
<td>11.0</td>
</tr>
<tr>
<td>13.0</td>
</tr>
<tr>
<td>dtype: float64</td>
</tr>
</tbody>
</table>
- 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 0.342764 0.304121 0.417022
second 0.681301 0.875457 0.510422
third 0.669314 0.585937 0.624904

In [51]: df.round(2)
   A   B   C
first 0.34 0.30 0.42
second 0.68 0.88 0.51
third 0.67 0.59 0.62

In [52]: df.round({'A': 0, 'C': 2})
   A       B       C
first 0.0 0.304121 0.42
second 1.0 0.875457 0.51
third 1.0 0.585937 0.62
```

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

```
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]:
0  C
2  A
4  B
5  D
dtype: object

In [56]: s.drop_duplicates(keep=False)
   0  A
   1  B
   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]:
   x     t
0  0.1  0.0 2000-01-01
1  1.9  2.0 2000-01-03
2  3.5  NaN  NaT

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).

1.15.2 Backwards incompatible API changes

1.15.2.1 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:
To sort by the **index**:

<table>
<thead>
<tr>
<th>Previous</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>*Series.sort_index()</td>
<td>Series.sort_index()</td>
</tr>
<tr>
<td>Series.sortlevel(level=...)</td>
<td>Series.sort_index(level=...)</td>
</tr>
<tr>
<td>DataFrame.sort_index()</td>
<td>DataFrame.sort_index()</td>
</tr>
<tr>
<td>DataFrame.sortlevel(level=...)</td>
<td>DataFrame.sort_index(level=...)</td>
</tr>
<tr>
<td>*DataFrame.sort()</td>
<td>DataFrame.sort_index()</td>
</tr>
</tbody>
</table>

We have also deprecated and changed similar methods in two Series-like classes, *Index* and *Categorical*.

<table>
<thead>
<tr>
<th>Previous</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>*Index.order()</td>
<td>Index.sort_values()</td>
</tr>
<tr>
<td>*Categorical.order()</td>
<td>Categorical.sort_values()</td>
</tr>
</tbody>
</table>

1.15.2.2 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:

```python
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:

```python
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.

```python
In [66]: import pandas.tseries.offsets as offsets
In [67]: Timestamp.now()
Out[67]: Timestamp('2018-06-12 14:08:09.185331')
In [68]: Timestamp.now() + offsets.DateOffset(years=1)
Out[68]: Timestamp('2019-06-12 14:08:09.186613')
```

1.15.2.3 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

1.15.2.4 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   0.0
         1  NaN
         2   2.0
       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]:
(continues on next page)
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
```

### 1.15.2.5 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   0.000000  1.000000
1   NaN        NaN
2   2.000000  NaN
```

```
In [27]:
df_with_missing.to_hdf('file.h5',
                         'df_with_missing',
                         format='table',
                         mode='w')
In [28]: pd.read_hdf('file.h5', 'df_with_missing')
Out [28]:
          col1    col2
0   0.000000  1.000000
1   NaN        NaN
2   2.000000  NaN
```
New Behavior:

```python
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  0.0  1.0
1  NaN  NaN
2  2.0  NaN
```

See the docs for more details.

### 1.15.2.6 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`.

```python
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.

```python
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.

### 1.15.2.7 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]
```

### 1.15.2.8 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
```

### 1.15.2.9 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 NotImplementedException (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>

### 1.15.2.10 Deprecations

• For Series the following indexing functions are deprecated (GH10177).

<table>
<thead>
<tr>
<th>Deprecated Function</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>.irow(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
<tr>
<td>.iget(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
<tr>
<td>.iget_value(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
</tbody>
</table>

• For DataFrame the following indexing functions are deprecated (GH10177).

<table>
<thead>
<tr>
<th>Deprecated Function</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>.irow(i)</td>
<td>.iloc[i]</td>
</tr>
<tr>
<td>.iget_value(i, j)</td>
<td>.iloc[i, j] or .iat[i, j]</td>
</tr>
<tr>
<td>.icol(j)</td>
<td>.iloc[: , j]</td>
</tr>
</tbody>
</table>

**Note:** These indexing function have been deprecated in the documentation since 0.11.0.

• Categorical.name was deprecated to make Categorical more numpy.ndarray like. Use Series(cat, name="whatever") instead (GH10482).

• Setting missing values (NaN) in a Categorical's categories will issue a warning (GH10748). You can still have missing values in the values.

• drop_duplicates and duplicated's take_last keyword was deprecated in favor of keep. (GH6511, GH8505)

• Series.nsmallest and nlargest's take_last keyword was deprecated in favor of keep. (GH10792)

• DataFrame.combineAdd and DataFrame.combineMult are deprecated. They can easily be replaced by using the add and mul methods: DataFrame.add(other, fill_value=0) and DataFrame.mul(other, fill_value=1.) (GH10735).
• **TimeSeries** deprecated in favor of **Series** (note that this has been an alias since 0.13.0), (GH10890)
• **SparsePanel** deprecated and will be removed in a future version (GH11157).
• **Series.is_time_series** deprecated in favor of **Series.index.is_all_dates** (GH11135)
• Legacy offsets (like 'A@JAN') are deprecated (note that this has been alias since 0.8.0) (GH10878)
• **WidePanel** deprecated in favor of Panel, LongPanel in favor of DataFrame (note these have been aliases since < 0.11.0), (GH10892)
• **DataFrame.convert_objects** has been deprecated in favor of type-specific functions pd. to_datetime, pd.to_timestamp and pd.to_numeric (new in 0.17.0) (GH11133).

### 1.15.2.11 Removal of prior version deprecations/changes

• Removal of **na_last** parameters from **Series.order()** and **Series.sort()**, in favor of **na_position**. (GH5231)
• Remove of **percentile_width** from .describe(), in favor of **percentiles**. (GH7088)
• Removal of **colSpace** parameter from DataFrame.to_string(), in favor of **col_space**, circa 0.8.0 version.
• Removal of automatic time-series broadcasting (GH2304)

```python
In [90]: np.random.seed(1234)
In [91]: df = 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 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03  1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989
```
```
Current
```
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)

1.15.3 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)
1.15.4 Bug Fixes

- Bug in incorrect computation of mean() on timedelta64[ns] because of overflow (GH9442)
- Bug in .isin on older numpies (GH11232)
- Bug in DataFrame.to_html(index=False) renders unnecessary name row (GH10344)
- Bug in DataFrame.to_latex() the column_format argument could not be passed (GH9402)
- Bug in DatetimeIndex when localizing with NaT (GH10477)
- Bug in Series.dt ops in preserving meta-data (GH10477)
- Bug in preserving NaT when passed in an otherwise invalid to_datetime construction (GH10477)
- Bug in DataFrame.apply when function returns categorical series. (GH9573)
- Bug in to_datetime with invalid dates and formats supplied (GH10154)
- Bug in Index.drop_duplicates dropping name(s) (GH10115)
- Bug in Series.quantile dropping name (GH10881)
- Bug in pd.Series when setting a value on an empty Series whose index has a frequency. (GH10193)
- Bug in pd.Series.interpolate with invalid order keyword values. (GH10633)
- Bug in DataFrame.plot raises ValueError when color name is specified by multiple characters (GH10387)
- Bug in Index construction with a mixed list of tuples (GH10697)
- Bug in DataFrame.reset_index when index contains NaT. (GH10388)
- Bug in ExcelReader when worksheet is empty (GH6403)
- Bug in BinGrouper.group_info where returned values are not compatible with base class (GH10914)
- Bug in clearing the cache on DataFrame.pop and a subsequent inplace op (GH10912)
- Bug in indexing with a mixed-integer Index causing an ImportError (GH10610)
- Bug in Series.count when index has nulls (GH10946)
- Bug in 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 (GH11016)

Bug that caused segfault when resampling an empty Series (GH10228)

Bug in DatetimeIndex and PeriodIndex.value_counts resets name from its result, but retains in result's Index. (GH10150)

Bug in pd.eval using numexpr engine coerces 1 element numpy array to scalar (GH10546)

Bug in pd.concat with axis=0 when column is of dtype category (GH10177)

Bug in read_msgpack where input type is not always checked (GH10369, GH10630)

Bug in pd.read_csv with kwargs 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 NotImplemetedError when operator functions (e.g. .add) of Panel are not implemented (GH7692)

Bug in line and kde plot cannot accept multiple colors when subplots=True (GH9894)
• Bug in `DataFrame.plot` raises `ValueError` when color name is specified by multiple characters (GH10387)
• Bug in left and right align of `Series` with `MultiIndex` may be inverted (GH10665)
• Bug in left and right join of with `MultiIndex` may be inverted (GH10741)
• Bug in `read_stata` when reading a file with a different order set in columns (GH10757)
• Bug in `Categorical` may not representing properly when category contains tz or `Period` (GH10713)
• Bug in `Categorical.__iter__` may not returning correct `datetime` and `Period` (GH10713)
• Bug in indexing with a `PeriodIndex` on an object with a `PeriodIndex` (GH4125)
• Bug in `read_csv` with engine='c': EOF preceded by a comment, blank line, etc. was not handled correctly (GH10728, GH10548)
• Reading “famafrench” data via `DataReader` results in HTTP 404 error because of the website url is changed (GH10591).
• Bug in `read_msgpack` where DataFrame to decode has duplicate column names (GH9618)
• Bug in `io.common.get_filepath_or_buffer` which caused reading of valid S3 files to fail if the bucket also contained keys for which the user does not have read permission (GH10604)
• Bug in vectorised setting of timestamp columns with python `datetime.date` and numpy `datetime64` (GH10408, GH10412)
• Bug in `Index.take` may add unnecessary freq attribute (GH10791)
• Bug in `merge` with empty `DataFrame` may raise `IndexError` (GH10824)
• Bug in `to_latex` where unexpected keyword argument for some documented arguments (GH10888)
• Bug in indexing of large `DataFrame` where `IndexError` is uncaught (GH10645 and GH10692)
• Bug in `read_csv` when using the `nrows` or `chunksize` parameters if file contains only a header line (GH9535)
• Bug in serialization of category types in HDF5 in presence of alternate encodings. (GH10366)
• Bug in `pd.DataFrame` when constructing an empty `DataFrame` with a string dttype (GH9428)
• Bug in `pd.DataFrame.diff` when `DataFrame` is not consolidated (GH10907)
• Bug in `pd.unique` for arrays with the `datetime64` or `timedelta64` dttype that meant an array with object dttype was returned instead the original dttype (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)
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- 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)

1.16 v0.16.2 (June 12, 2015)

This is a minor bug-fix release from 0.16.1 and includes a large number of bug fixes along some new features (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
1.16.1 New features

1.16.1.1 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.ols takes (formula, data)
In [3]: (bb.query('h > 0')
    ...: .assign(ln_h = lambda df: np.log(df.h))
    ...: .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
    ...: .fit()
    ...: .summary()
    ...: )
Out[3]:
<class 'statsmodels.iolib.summary.Summary'>
```

(continues on next page)
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)

1.16.1.2 Other Enhancements

- Added rsplit to Index/Series StringMethods (GH10303)

- Removed the hard-coded size limits on the DataFrame HTML representation in the IPython notebook, and leave this to IPython itself (only for IPython v3.0 or greater). This eliminates the duplicate scroll bars that appeared in the notebook with large frames (GH10231).

  Note that the notebook has a toggle output scrolling feature to limit the display of very large frames (by clicking left of the output). You can also configure the way DataFrames are displayed using the pandas options, see here.

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

1.16.2 API Changes

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

1.16.3 Performance Improvements

- Improved Series.resample performance with dtype= Datetime64[ns] (GH7754)

- Increase performance of str.split when expand=True (GH10081)
1.16.4 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-like. (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.plot` where type promotion is applied to the entire block (GH10289)
- 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 DataFrames, now results in a DataFrame that `.equals` an empty DataFrame (GH10181).
• Bug in `to_hdf` and HDFStore which did not check that complib choices were valid (GH4582, GH8874).

1.17 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`
1.17.1 Enhancements

1.17.1.1 CategoricalIndex

We introduce a CategoricalIndex, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a Categorical (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a DataFrame/Series with a category dtype would convert this to regular object-based Index.

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

In [2]: df
Out[2]:
       A   B
0      0   a
1      1   a
2      2   b
3      3   b
4      4   c
5      5   a

In [3]: df.dtypes
Out[3]:
A    int64
B  category
dtype: object

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

setting the index, will create a CategoricalIndex

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

In [6]: df2.index
Out[6]: 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.
and preserves the `CategoricalIndex`

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

sorting will order by the order of the categories

```python
In [9]: df2.sort_index()
Out[9]:
   A  B
   c 4
   a 0
   a 1
   a 5
   b 2
   b 3
```

groupby operations on the index will preserve the index nature as well

```python
In [10]: df2.groupby(level=0).sum()
Out[10]:
   A  B
   c 4
   a 6
   b 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]:
   B
   a 0.0
   a 1.0
   a 5.0
e NaN
```

(continues on next page)
In [14]: df2.reindex(pd.Categorical(['a','e'], categories=list('abcde')))
Out[14]:
   A  B
0  a  0.0
1  a  1.0
2  a  5.0
3  e  NaN

In [15]: df2.reindex(pd.Categorical(['a','e'], categories=list('abcde'))).index
Out[15]: CategoricalIndex(['a', 'a', 'a', 'e'], categories=['a', 'b', 'c', 'd', 'e'], ordered=False, name='B', dtype='category')

See the documentation for more. (GH7629, GH10038, GH10039)

1.17.1.2 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)

In [1]: example_series = Series([0,1,2,3,4,5])
# When no arguments are passed, returns 1
In [2]: example_series.sample()
Out[2]:
   3 3
   dtype: int64
# One may specify either a number of rows:
In [3]: example_series.sample(n=3)
   5 5
   1 1
   4 4
   dtype: int64
# Or a fraction of the rows:
In [4]: example_series.sample(frac=0.5)
   4 4
   1 1
   0 0
   dtype: int64
# weights are accepted.
In [5]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]
In [6]: example_series.sample(n=3, weights=example_weights)
Out[6]:
   2 2
   3 3
   5 5

(continues on next page)
When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

```
In [9]: df = DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})
In [10]: df.sample(n=3, weights='weight_column')
Out[10]:
    col1  weight_column
   0     9           0.5
   1     8           0.4
   2     7           0.1
```

### 1.17.1.3 String Methods Enhancements

*Continuing from v0.16.0,* the following enhancements make string operations easier and more consistent with standard Python string operations.

- **Added** `StringMethods (.str accessor)` to `Index` (GH9068)  
  
  The `.str accessor is now available for both Series and Index.

```
In [11]: idx = Index([' jack', 'jill ', ' jesse ', 'frank'])
In [12]: idx.str.strip()
Out[12]: Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')
```

One special case for the `.str accessor on Index is that if a string method returns `bool`, the `.str accessor will return `np.array` instead of a boolean `Index` (GH8875). This enables the following expression to work naturally:

```
In [13]: idx = Index(['a1', 'a2', 'b1', 'b2'])
In [14]: s = Series(range(4), index=idx)
In [15]: s
Out[15]:
   a1  0
   a2  1
   b1  2
   b2  3
   dtype: int64
In [16]: idx.str.startswith('a')
Out[16]: array([ True, True, False, False], dtype=bool)
```

(continues on next page)
In [17]: s[s.index.str.startswith('a')]
\n\n\n→
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>
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<tr>
<td>partition()</td>
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<tr>
<td>rpartition()</td>
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<tr>
<td>index()</td>
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<tr>
<td>rindex()</td>
</tr>
<tr>
<td>translate()</td>
</tr>
</tbody>
</table>

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

In [18]: s = Series(['a,b', 'a,c', 'b,c'])

# return Series
In [19]: s.str.split(',')
Out[19]:
\n\n\n0    ['a', 'b']
1    ['a', 'c']
2    ['b', 'c']
dtype: object

# return DataFrame
In [20]: s.str.split(',', expand=True)
\n\n\nOut[20]:
\n\n\n0  1
\n\n\n0  a  b
1  a  c
2  b  c

In [21]: idx = Index(['a,b', 'a,c', 'b,c'])

# return Index
In [22]: idx.str.split(',')
Out[22]:
\n\n\n\n\n\n\nMultiIndex(levels=[[a', b'], [b', c']], labels=[[0, 0, 1], [0, 1, 1]])

• Improved extract and get_dummies methods for Index.str (GH9980)

1.17.1.4 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 [24]: from pandas.tseries.offsets import BusinessHour

In [25]: Timestamp('2014-08-01 09:00') + BusinessHour()
   Out[25]: Timestamp('2014-08-01 10:00:00')

In [26]: Timestamp('2014-08-01 07:00') + BusinessHour()
   Out[26]: Timestamp('2014-08-01 10:00:00')

In [27]: Timestamp('2014-08-01 16:30') + BusinessHour()
   Out[27]: 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 [28]: df = DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])

In [29]: df.drop(['A', 'X'], axis=1, errors='ignore')
   Out[29]:
    B   C
    0 1.058969 -0.397840
    1 1.047579  1.045938
    2-0.122092  0.124713

- 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)
1.17.2 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)

1.17.2.1 Deprecations

• Series.str.split’s return_type keyword was removed in favor of expand (GH9847)

1.17.3 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, ...], dtype='int64')

In [4]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[4]: <class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-01-04 00:00:00-05:00]
Length: 4, Freq: D, Timezone: US/Eastern

In [5]: pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[5]: <class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-04-14 00:00:00-04:00]
Length: 104, Freq: D, Timezone: US/Eastern
```

New Behavior

```
In [30]: pd.set_option('display.width', 80)

In [31]: pd.Index(range(4), name='foo')
Out[31]: RangeIndex(start=0, stop=4, step=1, name='foo')
```
In [32]: pd.Index(range(30), name='foo')
Out[32]: RangeIndex(start=0, stop=30, step=1, name='foo')

In [33]: pd.Index(range(104), name='foo')
Out[33]: RangeIndex(start=0, stop=104, step=1, name='foo')

In [34]: pd.CategoricalIndex(['a','bb','ccc','dddd'], ordered=True, name='foobar')
Out[34]: CategoricalIndex(['a', 'bb', 'ccc', 'dddd'], categories=['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobar', dtype='category')

In [35]: pd.CategoricalIndex(['a','bb','ccc','dddd']*10, ordered=True, name='foobar')
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1.17.4 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)

1.17.5 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_formatted_index` with not applying `max_colwidth` to the `DataFrame` index (GH7856)
- Bug in `.loc` with a read-only ndarray data source (GH10043)
- Bug in `groupby.apply()` that would raise if a passed user defined function either returned only None (for all input). (GH9685)
- Always use temporary files in pytables tests (GH9992)
- Bug in plotting continuously using secondary_y may not show legend properly. (GH9610, GH9779)
- Bug in DataFrame.plot(kind="hist") results in TypeError when DataFrame contains non-numeric columns (GH9853)
- Bug where repeated plotting of DataFrame with a DatetimeIndex may raise TypeError (GH9852)
- Bug in setup.py that would allow an incompat cython version to build (GH9827)
- Bug in plotting secondary_y incorrectly attaches right_ax property to secondary axes specifying itself recursively. (GH9861)
- Bug in Series.quantile on empty Series of type Datetime or Timedelta (GH9675)
- Bug in where causing incorrect results when upcasting was required (GH9731)
- Bug in FloatArrayFormatter where decision boundary for displaying "small" floats in decimal format is off by one order of magnitude for a given display.precision (GH9764)
- Fixed bug where DataFrame.plot() raised an error when both color and style keywords were passed and there was no color symbol in the style strings (GH9671)
- Not showing a DeprecationWarning on combining list-likes with an Index (GH10083)
- Bug in read_csv and read_table when using skip_rows parameter if blank lines are present. (GH9832)
- Bug in read_csv() interprets index_col=True as 1 (GH9798)
- Bug in index equality comparisons using == failing on Index/MultiIndex type incompatibility (GH9785)
- Bug in which SparseDataFrame could not take nan as a column name (GH8822)
- Bug in to_msgpack and read_msgpack zlib and blosc compression support (GH9783)
- Bug GroupBy.size doesn’t attach index name properly if grouped by TimeGrouper (GH9925)
- Bug causing an exception in slice assignments because length_of_indexer returns wrong results (GH9995)
- Bug in csv parser causing lines with initial 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 .iloc and .loc behavior is not consistent on empty dataframes (GH9964)
- Bug in invalid attribute access on a TimedeltaIndex incorrectly raised ValueError instead of AttributeError (GH9680)
- Bug in unequal comparisons between categorical data and a scalar, which was not in the categories (e.g. Series(Categorical(list("abc"), ordered=True)) > "d". This returned False for all elements, but now raises a TypeError. Equality comparisons also now return False for == and True for !=. (GH9848)
- Bug in DataFrame __setitem__ when right hand side is a dictionary (GH9874)
- Bug in where when dtype is datetime64/timedelta64, but dtype of other is not (GH9804)
- Bug in MultiIndex.sortlevel() results in unicode level name breaks (GH9856)
- Bug in which groupby.transform incorrectly enforced output dtypes to match input dtypes. (GH9807)
- Bug in DataFrame constructor when columns parameter is set, and data is an empty list (GH9939)
• Bug in bar plot with log=True raises TypeError if all values are less than 1 (GH9905)
• Bug in horizontal bar plot ignores log=True (GH9905)
• Bug in PyTables queries that did not return proper results using the index (GH8265, GH9676)
• Bug where dividing a dataframe containing values of type Decimal by another Decimal would raise. (GH9787)
• Bug where using DataFrames asfreq would remove the name of the index. (GH9885)
• Bug causing extra index point when resample BM/BQ (GH9756)
• Changed caching in AbstractHolidayCalendar to be at the instance level rather than at the class level as the latter can result in unexpected behaviour. (GH9552)
• Fixed latex output for 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)

### 1.18 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](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.DataFrame.assign.html)
- Series.to_coo/from_coo methods to interact with scipy.sparse, see [here](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.Series.to_coo.html)
- Backwards incompatible change to Timedelta to conform the .seconds attribute with datetime. timedelta, see [here](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.tseries.offsets.Timedelta.html)
- Changes to the .loc slicing API to conform with the behavior of .ix see [here](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.DataFrame.loc.html)
- Changes to the default for ordering in the Categorical constructor, see [here](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.Categorical.html)
- Enhancement to the .str accessor to make string operations easier, see [here](https://pandas.pydata.org/pandas-docs/version/0.16.0/generated/pandas.Series.str.html)
- 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](https://pandas.pydata.org/pandas-docs/version/0.16.0/)

Check the API Changes and deprecations before updating.
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**

### 1.18.1 New features

#### 1.18.1.1 DataFrame Assign

Inspired by dplyr’s `mutate` verb, DataFrame has a new `assign()` method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the DataFrame. The new values are inserted, and the entire DataFrame (with all original and new columns) is returned.

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

In [2]: iris.head()
Out[2]:
   SepalLength  SepalWidth  PetalLength  PetalWidth     Name
0          5.1         3.5          1.4        0.2  Iris-setosa
1          4.9         3.0          1.4        0.2  Iris-setosa
2          4.7         3.2          1.3        0.2  Iris-setosa
3          4.6         3.1          1.5        0.2  Iris-setosa
4          5.0         3.6          1.4        0.2  Iris-setosa

In [3]: iris.assign(sepal_ratio=iris['SepalWidth'] / iris['SepalLength']).head()
\n\n   SepalLength  SepalWidth  PetalLength  PetalWidth  Name  sepal_ratio
0          5.1         3.5          1.4        0.2  Iris-setosa  0.686275
1          4.9         3.0          1.4        0.2  Iris-setosa  0.612245
2          4.7         3.2          1.3        0.2  Iris-setosa  0.680851
3          4.6         3.1          1.5        0.2  Iris-setosa  0.673913
4          5.0         3.6          1.4        0.2  Iris-setosa  0.720000
```

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()
```

```
<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>
```

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'))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c437e2940>
```

See the documentation for more. (GH9229)

1.18.1.2 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),
   ...: ],
   ...: names=['row', 'col', 'label', 'level'])
```

(continues on next page)
...:
(2, 1, 'b', 1],
...:
names=['A', 'B', 'C', 'D'])

In [9]: s
Out[9]:
A  B  C  D
1  2  a  0  3.0
   1  NaN
1  b  0  1.0
   1  3.0
2  1  b  0  NaN
   1  NaN
dtype: float64

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

In [11]: ss
Out[11]:
A  B  C  D
1  2  a  0  3.0
   1  NaN
1  b  0  1.0
   1  3.0
2  1  b  0  NaN
   1  NaN
dtype: float64
BlockIndex
Block locations: array([0, 2], dtype=int32)
Block lengths: array([1, 2], dtype=int32)

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 '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [14]: A.todense()

→
matrix([[ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  1.,  3.],
        [ 0.,  0.,  0.,  0.]])

In [15]: rows
→[(1, 2), (1, 1), (2, 1)]

In [16]: columns
→[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
The `from_coo` method is a convenience method for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`:

```python
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 '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format

In [20]: A.todense()

→ 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 1.0
3 2.0
1 0 3.0
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([3], dtype=int32)
```

### 1.18.1.3 String Methods Enhancements

- Following new methods are accessible via `.str` accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. (GH9282, GH9352, GH9386, GH9387, GH9439)

<table>
<thead>
<tr>
<th>Methods</th>
<th>isalnum()</th>
<th>isalpha()</th>
<th>isdigit()</th>
<th>isdigit()</th>
<th>isspace()</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<tr>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

```python
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
```

(continues on next page)
1 -1
2 -1
dtype: int64

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

```python
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 Not Implemented Error (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
```python
In [30]: s.str.slice_replace(0, 1)
```
```
0 BCD
1 FGH
2 JK
dtype: object
```

1.18.1.4 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).

1.18.2 Backwards incompatible API changes

1.18.2.1 Changes in Timedelta

In v0.15.0 a new scalar type Timedelta was introduced, that is a sub-class of datetime.timedelta. Mentioned here was a notice of an API change w.r.t. the .seconds accessor. The intent was to provide a user-friendly set of accessors that give the ‘natural’ value for that unit, e.g. if you had a Timedelta('1 day, 10:11:12'), then .seconds would return 12. However, this is at odds with the definition of datetime.timedelta, which defines .seconds as \(10 \times 3600 + 11 \times 60 + 12 = 36672\).

So in v0.16.0, we are restoring the API to match that of datetime.timedelta. Further, the component values are still available through the .components accessor. This affects the .seconds and .microseconds accessors, and removes the .hours, .minutes, .milliseconds accessors. These changes affect TimedeltaIndex and the Series .dt accessor as well. (GH9185, GH9139)

Previous Behavior

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')
In [3]: t.days
```

Out[3]: 1  

(continues on next page)
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]: 1

In [35]: t.seconds
Out[35]: 36672

In [36]: t.microseconds
Out[36]: 100123

Using .components allows the full component access

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

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

1.18.2.2 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.

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 -0.322795  0.841675  2.390961  0.076200
2013-01-02 -0.566446  0.036142 -2.074978  0.247792
2013-01-03 -0.897157 -0.136795  0.018289  0.755414
2013-01-04  0.215269  0.841009 -1.445810 -1.401973
2013-01-05  0.100918 -0.548242 -0.144620  0.354020

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

In [42]: s
Out[42]:
-2  0
-1  1
 1  2
 2  3
 3  4
dtype: int64

Previous Behavior

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

In [43]: df.loc['2013-01-02':'2013-01-10']
Out[43]:
     A    B    C    D
2013-01-02 -0.566446 0.036142 -2.074978 0.247792
2013-01-03 -0.897157 -0.136795  0.018289  0.755414
2013-01-04  0.215269  0.841009 -1.445810 -1.401973
2013-01-05 -0.100918 -0.548242 -0.144620  0.354020

In [44]: s.loc[-10:3]

Previous Behavior

In [8]: s.ix[-1.0:2]
TypeError: the slice start value [-1.0] is not a proper indexer for this index

New Behavior

In [2]: s.ix[-1.0:2]
Out[2]:
-2  0
-1  1
 1  2
 2  3
dtype: int64

• Allow slicing with float-like values on an integer index for .ix. Previously this was only enabled for .loc:

Previous Behavior

In [4]: s.ix[-1.0:2]
TypeError: the slice start value [-1.0] is not a proper indexer for this index

New Behavior

In [2]: s.ix[-1.0:2]
Out[2]:
-2  0
-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'> keys

1.18.2.3 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
1 1
2 2
dtype: category
Categories (3, int64): [0 < 1 < 2]
In [5]: s.cat.ordered
Out[5]: True
In [6]: s.cat.ordered = False
In [7]: s
Out[7]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0, 1, 2]

New Behavior

In [45]: s = Series([0,1,2], dtype='category')
In [46]: s
Out[46]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0, 1, 2]
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 [54]: s = Series(["a","b","c","a"]).astype('category', ordered=True)

In [55]: s
Out[55]:
0  a
1  b
2  c
3  a
dtype: category
Categories (3, object): [a < b < c]
```

```
In [56]: s = Series(["a","b","c","a"]).astype('category', categories=list('abcdef'), 
                      ordered=False)

In [57]: s
Out[57]:
0  a
1  b
2  c
```
1.18.2.4 Other API Changes

- `Index.duplicated` now returns `np.array(dtype=bool)` rather than `Index(dtype=object)` containing bool values. (GH8875)

- `DataFrame.to_json` now returns accurate type serialisation for each column for frames of mixed dtype (GH9037)

  Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

  ```python
  In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
  Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1.0,"1":2.0}}'
  ```

  Now each column is serialised using its correct dtype:

  ```python
  In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
  Out[2]: '{"f":3.0,"i":1}''
  ```

- `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
  ```
During division involving a Series or DataFrame, 0/0 and 0//0 now give np.nan instead of np.inf. (GH9144, GH8445)

Previous Behavior

```
In [2]: p = pd.Series([0, 1])
In [3]: p / 0
Out[3]:
0  inf
1  inf
dtype: float64
In [4]: p // 0
Out[4]:
0  inf
1  inf
dtype: float64
```

New Behavior

```
In [54]: p = pd.Series([0, 1])
In [55]: p / 0
Out[55]:
0  NaN
1  inf
dtype: float64
In [56]: p // 0
Out[56]:
0  NaN
1  inf
dtype: float64
```

- Series.values_counts and Series.describe for categorical data will now put NaN entries at the end. (GH9443)
- Series.describe for categorical data will now give counts and frequencies of 0, not NaN, for unused categories (GH9443)
- Due to a bug fix, looking up a partial string label with DatetimeIndex.asof now includes values that match the string, even if they are after the start of the partial string label (GH9258).

Old behavior:

```
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 [57]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[57]: 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).

### 1.18.2.5 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 subtraction yielding a `TimeDeltaIndex` in a future version. `.difference()` should be used for the differencing set operation (GH9094).

### 1.18.2.6 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).

### 1.18.3 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)

1.18.4 Bug Fixes

• Changed .to_html to remove leading/trailing spaces in table body (GH9487)
• 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 (GH9493)
• 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 (GH9879)
• Bug inDataFrame.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.

```python
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']
```

### 1.19 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**
1.19.1 API changes

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

```python
def = pd.DataFrame({'jim': [0, 0, 1, 1],
                   'joe': ['x', 'x', 'z', 'y'],
                   'jolie': np.random.rand(4)}).set_index(['jim', 'joe'])
def
Out[2]:
            jolie
      jim  joe
0    x  0.123943
     x  0.119381
1    z  0.738523
     y  0.587304

def.index.lexsort_depth
In [3]:
Out[3]:
   → 1

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning

def.loc[(1, 'z')]
Out[4]:
            jolie
      jim  joe
0    x  0.123943
     x  0.119381
1    z  0.738523

In [5]: df2 = df.sort_index()
df2
Out[6]:
            jolie
      jim  joe
0    x  0.123943
     x  0.119381
1    y  0.587304
     z  0.738523

def2.index.lexsort_depth
In [7]:
Out[7]:
   → 2

In [8]: df2.loc[(1, 'z')]
Out[8]:
            jolie
      jim  joe
0    x  0.123943
     x  0.119381
1    y  0.587304
     z  0.738523
```

- 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 inNDFrame: 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])

- 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: int64
```

### 1.19.2 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:
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 1
  0  True  True
  1  True  True
  2  False False
  3  True  True
```

• Added support for `utcfromtimestamp()`, `fromtimestamp()`, and `combine()` on `Timestamp` class (GH5351).

• Added Google Analytics (`pandas.io.ga`) basic documentation (GH8835). See here.

• Timedelta arithmetic returns `NotImplemented` in unknown cases, allowing extensions by custom classes (GH8813).

• Timedelta now supports arithmetic with `numpy.ndarray` objects of the appropriate dtype (numpy 1.8 or newer only) (GH8884).

• Added `Timedelta.to_timedelta64()` method to the public API (GH8884).

• Added `gbq.generate_bq_schema()` function to the `gbq` module (GH8325).

• Series now works with map objects the same way as generators (GH8909).

• Added context manager to `HDFStore` for automatic closing (GH8791).

• `to_datetime` gains an `exact` keyword to allow for a format to not require an exact match for a provided format string (if its `False`). `exact` defaults to `True` (meaning that exact matching is still the default) (GH8904)

• Added `axvlines` boolean option to `parallel_coordinates` plot function, determines whether vertical lines will be printed, default is `True`

• Added ability to read table footers to `read_html` (GH8552)

• `to_sql` now infers datatypes of non-NA values for columns that contain NA values and have `dtype object` (GH8778).

1.19.3 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)

### 1.19.4 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 parameters are passed in a groupby (GH8015)
- Bug in packaging pandas with `py2app/cx_Freeze` (GH8602, GH8831)
- Bug in `groupby` signatures that didn’t include `*args` or `**kwargs` (GH8733)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Unclear error message in csv parsing when passing dtype and names and the parsed data is a different data type (GH8833)
- Bug in slicing a 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 outputting a Multindex with `to_html`, `index=False` which would add an extra column (GH8452)
- Imported categorical variables from Stata files retain the ordinal information in the underlying data (GH8836).
- Defined `.size` attribute across `NDFrame` objects to provide compat with numpy >= 1.9.1; buggy with `np.array_split` (GH8846)
• Skip testing of histogram plots for matplotlib <= 1.2 (GH8648).
• Bug where get_data_google returned object dtypes (GH3995)
• Bug in DataFrame.stack(..., dropna=False) when the DataFrame’s columns is a MultiIndex whose labels do not reference all its levels. (GH8844)
• Bug in that Option context applied on __enter__ (GH8514)
• Bug in resample that causes a ValueError when resampling across multiple days and the last offset is not calculated from the start of the range (GH8683)
• Bug where DataFrame.plot(kind='scatter') fails when checking if an np.array is in the DataFrame (GH8852)
• Bug in pd.infer_freq/DataFrame.inferred_freq that prevented proper sub-daily frequency inference when the index contained DST days (GH8772).
• Bug where index name was still used when plotting a series with use_index=False (GH8558).
• Bugs when trying to stack multiple columns, when some (or all) of the level names are numbers (GH8584).
• Bug in MultiIndex where __contains__ returns wrong result if index is not lexically sorted or unique (GH7724)
• BUG CSV: fix problem with trailing whitespace in skipped rows, (GH8679), (GH8661), (GH8983)
• Regression in Timestamp does not parse ‘Z’ zone designator for UTC (GH8771)
• Bug in StataWriter the produces writes strings with 244 characters irrespective of actual size (GH8969)
• Fixed ValueError raised by cummin/cummax when datetime64 Series contains NaT. (GH8965)
• Bug in Datareader returns object dtype if there are missing values (GH8980)
• Bug in plotting if sharex was enabled and index was a timeseries, would show labels on multiple axes (GH3964).
• Bug where passing a unit to the TimedeltaIndex constructor applied the to nano-second conversion twice. (GH9011).
• Bug in plotting of a period-like array (GH9012)

1.20 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.

• Enhancements
• API Changes
• Bug Fixes

1.20.1 API changes

• s.dt.hour and other .dt accessors will now return np.nan for missing values (rather than previously -1), (GH8689)
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  NaN
3  2013-01-04
4  2013-01-05
dtype: datetime64[ns]

previous behavior:

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

current behavior:

In [4]: s.dt.hour
Out[4]:
0   0.0
1   0.0
2   NaN
3   0.0
4   0.0
dtype: float64

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

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 conflicts with the grouper name (GH8112):

In [10]: df = pd.DataFrame({'jim': range(5), 'joe': range(5, 10)})

In [11]: df
Out[11]:
    jim  joe
0     0    5
1     1    6
2     2    7
3     3    8
4     4    9

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

previous behavior (excludes 1st column from output):

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

current behavior:

In [13]: gr.apply(sum)
Out[13]:
    jim  joe
    jim
    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  
1    d  

dtype: object

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 undeprécated 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>
<th>Last</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00080000</td>
<td>29.05</td>
</tr>
<tr>
<td>84</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00084000</td>
<td>24.80</td>
</tr>
<tr>
<td>85</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00085000</td>
<td>24.05</td>
</tr>
<tr>
<td>86</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00086000</td>
<td>22.76</td>
</tr>
<tr>
<td>87</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00087000</td>
<td>21.74</td>
</tr>
</tbody>
</table>

In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2014, 11, 14),
```
datetime.date(2014, 11, 22),
datetime.date(2014, 11, 28),
datetime.date(2014, 12, 5),
datetime.date(2014, 12, 12),
datetime.date(2014, 12, 20),
datetime.date(2015, 1, 17),
datetime.date(2015, 2, 20),
datetime.date(2015, 4, 17),
datetime.date(2015, 7, 17),
datetime.date(2016, 1, 15),
datetime.date(2017, 1, 20)]

In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5,0:1]
Out[21]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
<th>Last</th>
</tr>
</thead>
<tbody>
<tr>
<td>109</td>
<td>2014-11-22</td>
<td>call</td>
<td>AAPL141122C00109000</td>
<td>1.48</td>
</tr>
<tr>
<td>110</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C00110000</td>
<td>0.55</td>
</tr>
</tbody>
</table>

• pandas now also registers the `datetime64` dtype in matplotlib's units registry to plot such values as datetimes. This is activated once pandas is imported. In previous versions, plotting an array of `datetime64` values will have resulted in plotted integer values. To keep the previous behaviour, you can do `del matplotlib.units.registry[np.datetime64]` (GH8614).

1.20.2 Enhancements

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

```python
In [17]: from collections import deque
In [18]: df1 = pd.DataFrame([1, 2, 3])
In [19]: 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 [20]: pd.concat(deque((df1, df2)))
Out[20]:
   0  1
  0  1
  1  2
  2  3
  0  4
  1  5
  2  6
```
• 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)

```python
In [21]: dfi = DataFrame(1, index=pd.MultiIndex.from_product([['a'], range(1000)]),
→columns=['A'])
```

previous behavior:

```python
# 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:

```python
In [22]: dfi.memory_usage(index=True)
Out[22]:
Index   52080
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)

### 1.20.3 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 (GH8703)
• 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).

1.21 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
pandas: powerful Python data analysis toolkit, Release 0.23.1

- New datetimelike properties accessor `.dt` for Series, see Datetimelike Properties
- New DataFrame default display for `df.info()` to include memory usage, see Memory Usage
- `read_csv` will now by default ignore blank lines when parsing, see here
- API change in using Indexes in set operations, see here
- Enhancements in the handling of timezones, see here
- A lot of improvements to the rolling and expanding moment functions, see here
- Internal refactoring of the Index class to no longer sub-class ndarray, see Internal Refactoring
- dropping support for PyTables less than version 3.0.0, and numexpr less than version 2.1 (GH7990)
- Split indexing documentation into Indexing and Selecting Data and MultiIndex / Advanced Indexing
- A lot of improvements to the rolling and expanding moment functions, see here
- Internal refactoring of the Index class to no longer sub-class ndarray, see Internal Refactoring

• Check the API Changes and deprecations before updating

• Other Enhancements

• Performance Improvements

• Bug Fixes

Warning: In 0.15.0 Index has internally been refactored to no longer sub-class ndarray but instead subclass PandasObject, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the Internal Refactoring)

Warning: The refactorings in Categorical changed the two argument constructor from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use Categorical directly, please audit your code before updating to this pandas version and change it to use the `from_codes()` constructor. See more on Categorical here

1.21.1 New features

1.21.1.1 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, GH5318, 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
```

(continues on next page)
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_values("grade")

Out[7]:
   id raw_grade   grade
   5    6      e  very bad
   1    2      b      good
   2    3      b      good
   0    1      a  very good
   3    4      a  very good
   4    5      a  very good

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`.
1.21.1.2 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 whatsnew 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')
Timedelta('0 days 00:00:00.000015')

In [11]: Timedelta('1 hour 15.5us')
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')
Timedelta('-1 days +23:59:59.999999')
```

(continues on next page)
Access fields for a `Timedelta`

```python
In [14]: td = Timedelta('1 hour 3m 15.5us')
In [15]: td.seconds
Out[15]: 3780
In [16]: td.microseconds
Out[16]: 16
In [17]: td.nanoseconds
Out[17]: 500
```

Construct a `TimedeltaIndex`

```python
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

```python
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')
```

```python
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

```python
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: int64
```

You can select with partial string selections

```python
In [23]: s['1 day 00:00:02']
Out[23]: 2

In [24]: s['1 day':'1 day 00:00:02']
Out[24]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
Freq: S, dtype: int64
```

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()  # prior to v0.15.0
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()  # prior to v0.15.0
Out[28]: [Timestamp('2013-01-01 00:00:00', freq='D'),
          Timestamp('2013-01-02 00:00:00', freq='D'),
          Timestamp('2013-01-03 00:00:00', freq='D')]

In [29]: (dti + tdi).tolist()  # prior to v0.15.0
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()  # prior to v0.15.0
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`.

### 1.21.1.3 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'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
int64 5000 non-null int64
float64 5000 non-null float64
datetime64[ns] 5000 non-null datetime64[ns]
timedelta64[ns] 5000 non-null timedelta64[ns]
complex128 5000 non-null complex128
object 5000 non-null object
bool 5000 non-null bool
categorical 5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),
˓→object(1), timedelta64[ns](1)
memory usage: 289.1+ KB

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

```python
In [37]: df.memory_usage(index=True)
Out[37]:
Index     80
int64    40000
float64  40000
datetime64[ns]  40000
timedelta64[ns]  40000
complex128  80000
object     40000
bool       5000
categorical 10920
dtype: int64
```

### 1.21.1.4 .dt accessor

Series has gained an accessor to succinctly return datetime like properties for the values of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the [docs](#).

```python
# datetime
In [38]: s = Series(date_range('20130101 09:10:12', periods=4))
```

(continues on next page)
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]: 'D'

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

(continues on next page)
You can also chain these types of operations:

```python
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.

```python
# 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
1  2013
2  2013
3  2013
dtype: int64
In [52]: s.dt.day
Out[52]:
0  1
1  2
2  3
3  4
dtype: int64
```

```python
# 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
```

(continues on next page)
1.21.1.5 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)

```python
In [58]: ts = Timestamp('2014-08-01 09:00', tz='US/Eastern')

In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-04:00', tz='US/Eastern')

In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = 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)

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)

1.21.1.6 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 [4]: pd.rolling_min(s, window=10, min_periods=5)
Out [4]:
0   NaN
1   NaN
2   NaN
3   NaN
dtype: float64

• rolling_max(), rolling_min(), rolling_sum(), rolling_mean(), rolling_median(), rolling_std(), rolling_var(), rolling_skew(), rolling_kurt(), rolling_quantile(), rolling_cov(), rolling_corr(), rolling_corr_pairwise(), rolling_window(), and rolling_apply() with center=True previously would return a result of the same structure as the input arg with NaN in the final (window-1)/2 entries.

Now the final (window-1)/2 entries of the result are calculated as if the input arg were followed by (window-1)/2 NaN values (or with shrinking windows, in the case of rolling_apply()). (GH7925, GH8269)
Prior behavior (note final value is NaN):

```
In [7]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0   1
1   3
2   6
3  NaN
```

New behavior (note final value is $5 = \sum([2, 3, NaN])$):

```
In [7]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0   1
1   3
2   6
3   5
```

- `rolling_window()` now normalizes the weights properly in rolling mean mode (mean=True) so that the calculated weighted means (e.g. `triang`, `gaussian`) are distributed about the same means as those calculated without weighting (i.e. ‘boxcar’). See the note on normalization for further details. (GH7618)

```
In [65]: s = Series([10.5, 8.8, 11.4, 9.7, 9.3])
Behavior prior to 0.15.0:
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
```

New behavior

```
In [10]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[10]:
0   NaN
1  9.875
2 10.325
3 10.025
4   NaN
```

- 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 [66]: s = Series([1, None, None, None, 2, 3])
In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0    NaN
1    NaN
2  1.000000
3  1.000000
4  1.571429
5  2.189189
dtype: float64
```

New behavior (note values start at index 4, the location of the 2nd (since `min_periods=2`) non-empty value):

```
In [2]: pd.ewma(s, com=3., min_periods=2)
Out[2]:
0    NaN
1    NaN
2    NaN
3    NaN
4  1.759644
5  2.383784
dtype: float64
```

• `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `adjust` argument, just like `ewma()` does, affecting how the weights are calculated. The default value of `adjust` is `True`, which is backwards-compatible. See Exponentially weighted moment functions for details. (GH7911)

• `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `ignore_na` argument. When `ignore_na=False` (the default), missing values are taken into account in the weights calculation. When `ignore_na=True` (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. (GH7543)

```
In [7]: pd.ewma(Series([None, 1., 8.]), com=2.)
Out[7]:
0   NaN
1   NaN
2   NaN
3   NaN
4  1.75964
5  2.38378
dtype: float64

In [8]: pd.ewma(Series([1., None, 8.]), com=2., ignore_na=True) # pre-0.15.0 → behavior
Out[8]:
0   1.0
1   1.0
2   5.2
dtype: float64

In [9]: pd.ewma(Series([1., None, 8.]), com=2., ignore_na=False) # new default
```
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 [67]: 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):
In [14]: pd.ewmvar(s, com=2., bias=False)
Out[14]:
   0    NaN
   1 0.500000
   2 1.210526
   3 4.089069
dtype: float64

In [15]: pd.ewmvar(s, com=2., bias=False) / pd.ewmvar(s, com=2., bias=True)
Out[15]:
   0   NaN
   1 2.083333
   2 1.583333
   3 1.425439
dtype: float64

See *Exponentially weighted moment functions* for details. (GH7912)

### 1.21.1.7 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
def.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).

### 1.21.2 Backwards incompatible API changes

#### 1.21.2.1 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 prior versions there was a difference in these two constructs:

- df.loc[[3]] would return a frame reindexed by 3 (with all np.nan values)
- df.loc[[3],:] would raise KeyError.

Both will now raise a KeyError. The rule is that at least 1 indexer must be found when using a list-like and .loc (GH7999)

Furthermore in prior versions these were also different:

- df.loc[[1,3]] would return a frame reindexed by [1,3]
- df.loc[[1,3],:] would raise KeyError.

Both will now return a frame reindex by [1,3]. E.g.

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

In [4]: df.loc[[1,3],:]
Out[4]:
  0  
  1  a  
  3  NaN

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

In [70]: 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'])

(continues on next page)
In [71]: p
Out[71]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemB
Major_axis axis: 1 to 3
Minor_axis axis: A to D

The following would raise KeyError prior to 0.15.0:

In [5]:
Out[5]:
    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:

In [72]: s = Series(np.arange(3), dtype='int64'),
       index=MultiIndex.from_product([['A'], ['foo', 'bar', 'baz']],
                                   names=['one', 'two']).sort_index()

In [73]: s
Out[73]:
   one   two
  A  bar  1
     baz  2
     foo  0
dtype: int64

In [74]: try:
   ....:     s.loc[['D']]
   ....: except KeyError as e:
   ....:     print("KeyError: " + str(e))
   ....:  
KeyError: "['D'] not in index"

- Assigning values to None now considers the dtype when choosing an 'empty' value (GH7941).

Previously, assigning to None in numeric containers changed the dtype to object (or errored, depending on the call). It now uses NaN:

In [75]: s = Series([1, 2, 3])

In [76]: s.loc[0] = None

In [77]: s
Out[77]:
   0   NaN
   1   2.0
   2   3.0
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 [78]: s = Series(["a", "b", "c"])
In [79]: s.loc[0] = None

In [80]: s
Out[80]:
     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 [81]: s = Series([1, 2, 3])
In [82]: s2 = s
In [83]: 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 [84]: s
Out[84]:
     0  2.5
     1  3.5
     2  4.5
dtype: float64

# a reference to the original object
In [85]: s2
Out[85]:
     0  2.5
```

(continues on next page)
- 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 [86]: i = date_range('1/1/2011', periods=3, freq='10s', tz = 'US/Eastern')
In [87]: i
Out[87]: DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00', '2011-01-01 00:00:20-05:00'], dtype='datetime64[ns, US/Eastern]', freq='10S')
In [88]: df = DataFrame( {'a' : i } )
In [89]: df
Out[89]:
   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
In [90]: df.dtypes
Out[90]:
   a  datetime64[ns, US/Eastern]
dtype: object
```

Previously this would have yielded a column of `datetime64` dtype, but without timezone info.

The behaviour of assigning a column to an existing datafarme 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)
In [3]: df.iloc[0:5]['group'] = 'a'
/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 caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy

- merge, DataFrame.merge, and ordered_merge now return the same type as the left argument (GH7737).
- Previously an enlargement with a mixed-dtype frame would act unlike .append which will preserve dtypes (related GH2578, GH8176):

  ```python
  In [91]: df = DataFrame([[True, 1],[False, 2]],
   ...:                        columns=['female','fitness'])
   ...

  In [92]: df
  Out[92]:
  female  fitness
  0    True     1
  1   False     2

  In [93]: df.dtypes
  Out[93]:
  female  bool
  fitness  int64
dtype: object
  # dtypes are now preserved


  In [95]: df
  Out[95]:
  female  fitness
  0    True     1
  1   False     2
  2   False     2

  In [96]: df.dtypes
  Out[96]:
  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)

1.21.2.2 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.

1.21.2.3 Deprecations

- The attributes Categorical labels and levels attributes are deprecated and renamed to codes and categories.
- The outtype argument to pd.DataFrame.to_dict has been deprecated in favor of orient. (GH7840)
- The convert_dummies method has been deprecated in favor of get_dummies (GH8140)
- The infer_dst argument in tz_localize will be deprecated in favor of ambiguous to allow for more flexibility in dealing with DST transitions. Replace infer_dst=True with ambiguous='infer' for the same behavior (GH7943). See the docs for more details.
- The top-level pd.value_range has been deprecated and can be replaced by .describe() (GH8481)
- The Index set operations + and - were deprecated in order to provide these for numeric type operations on certain index types. + can be replaced by .union() or |, and - by .difference(). Further the method name Index.diff() is deprecated and can be replaced by Index.difference() (GH8226)

```python
# +
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).

1.21.2.4 Removal of prior version deprecations/changes

- Remove DataFrame.delevel method in favor of DataFrame.reset_index
1.21.3 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 option, 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 [97]: df = DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
                   'catB': ['a', 'b', 'c', 'd'] * 6,
                   'numC': np.arange(24),
                   'numD': np.arange(24.) + .5})

In [98]: df.describe(include=['object'])
Out[98]:
          catA  catB
count    24    24
unique   2     4
top      foo   a
freq     16     6

In [99]: df.describe(include=['number', 'object'], exclude=['float'])
           catA  catB  numC
count      24    24   24.000000
unique     2     4     NaN
top         foo   a     NaN
freq       16     6     NaN
```

(continues on next page)
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 [100]: df.describe(include='all')
Out[100]:
     catA  catB  numC  numD
  count  24    24  24.0000  24.0000
  unique  2    4    NaN    NaN
   top    foo    a    NaN    NaN
   freq   16    6    NaN    NaN
  mean  NaN  NaN  11.5000  12.0000
 std  NaN  NaN  7.071068  7.071068
min  NaN  NaN  0.000000  0.500000
25% NaN  NaN  5.750000  6.250000
50% NaN  NaN  11.500000  12.000000
75% NaN  NaN  17.250000  17.750000
 max NaN  NaN  23.000000  23.500000
```

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.

```python
In [101]: df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
                      'C': [1, 2, 3]})

In [102]: pd.get_dummies(df)
Out[102]:
     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)

```python
In [103]: business_dates = date_range(start='4/1/2014', end='6/30/2014', freq='B')
In [104]: df = DataFrame(1, index=business_dates, columns=['a', 'b'])
```
# get the first, 4th, and last date index for each month
In [105]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
Out[105]:
\begin{verbatim}
a b
2014 4 1 1
  1 1
  1 1
  1 1
  1 1
  1 1
  1 1
  1 1
  1 1
  1 1
\end{verbatim}

- *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 [106]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')
In [107]: idx
Out[107]:
\begin{verbatim}
PeriodIndex([\textquoteleft2014-07-01 09:00\textquoteright, \textquoteleft2014-07-01 10:00\textquoteright, \textquoteleft2014-07-01 11:00\textquoteright, \textquoteleft2014-07-01 12:00\textquoteright, \textquoteleft2014-07-01 13:00\textquoteright],
dtype='period[H]', freq='H')
\end{verbatim}

In [108]: idx + pd.offsets.Hour(2)

\begin{verbatim}
PeriodIndex([\textquoteleft2014-07-01 11:00\textquoteright, \textquoteleft2014-07-01 12:00\textquoteright, \textquoteleft2014-07-01 13:00\textquoteright, \textquoteleft2014-07-01 14:00\textquoteright, \textquoteleft2014-07-01 15:00\textquoteright],
dtype='period[H]', freq='H')
\end{verbatim}

In [109]: idx + Timedelta('120m')

\begin{verbatim}
PeriodIndex([\textquoteleft2014-07-01 11:00\textquoteright, \textquoteleft2014-07-01 12:00\textquoteright, \textquoteleft2014-07-01 13:00\textquoteright, \textquoteleft2014-07-01 14:00\textquoteright, \textquoteleft2014-07-01 15:00\textquoteright],
dtype='period[H]', freq='H')
\end{verbatim}

In [110]: idx = pd.period_range('2014-07', periods=5, freq='M')
In [111]: idx
Out[111]:
\begin{verbatim}
PeriodIndex([\textquoteleft2014-07\textquoteright, \textquoteleft2014-08\textquoteright, \textquoteleft2014-09\textquoteright, \textquoteleft2014-10\textquoteright, \textquoteleft2014-11\textquoteright],
    dtype='period[M]', freq='M')
\end{verbatim}

In [112]: idx + pd.offsets.MonthEnd(3)

\begin{verbatim}
PeriodIndex([\textquoteleft2014-10\textquoteright, \textquoteleft2014-12\textquoteright, \textquoteleft2015-01\textquoteright, \textquoteleft2015-02\textquoteright], dtype=
    \textquoteleft period[M]\textquoteright, freq='M')
\end{verbatim}

- 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 [113]: idx = MultiIndex.from_product((["a"], range(3), list("pqr")), names=[
           'foo', 'bar', 'baz'])

In [114]: idx.set_names('qux', level=0)
Out[114]: MultiIndex(levels=[['a'], [0, 1, 2], ['p', 'q', 'r']],
                        labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2]],
                        names=['qux', 'bar', 'baz'])

In [115]: idx.set_names(['qux', 'corge'], level=[0,1])
   MultiIndex(levels=[['a'], [0, 1, 2], ['p', 'q', 'r']],
              labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2]],
              names=['qux', 'corge', 'baz'])

In [116]: idx.set_levels(['a','b','c'], level='bar')
   MultiIndex(levels=[['a'], ['a', 'b', 'c'], ['p', 'q', 'r']],
              labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2]],
              names=['foo', 'bar', 'baz'])

In [117]: idx.set_levels([["a","b","c"],[1,2,3]], level=[1,2])
   MultiIndex(levels=[['a'], ['a', 'b', 'c'], [1, 2, 3]],
              labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2]],
              names=['foo', 'bar', 'baz'])
```

• **Index.isin** now supports a level argument to specify which index level to use for membership tests (GH7892, GH7890)

```
In [1]: idx = MultiIndex.from_product(([0, 1], ["a", "b", "c"]))

In [2]: idx.values
Out[2]: array([(0, 'a'), (0, 'b'), (0, 'c'), (1, 'a'), (1, 'b'), (1, 'c')],
             dtype=object)

In [3]: idx.isin(['a', 'c', 'e'], level=1)
Out[3]: array([ True, False, True, True, False, True],
             dtype=bool)
```

• **Index** now supports **duplicated** and **drop_duplicates**. (GH4060)

```
In [118]: idx = Index([1, 2, 3, 4, 1, 2])
```

(continues on next page)
In [119]: idx
Out[119]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')

In [120]: idx.duplicated()
\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\\→\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\\→ false, false, false, True, True], dtype=bool)

In [121]: idx.drop_duplicates()
\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\:\\→ Int64Index([1, 2, 3, 4], dtype='int64')

• 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)

1.21.4 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)

1.21.5 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 (GH801)
• 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 (GH8780).
• 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.

1.22 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

1.22.1 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, (regression from 0.12) (GH5521)

• Raise a TypeError on inplace-setting with a .where and a non np.nan value as this is inconsistent with a set-item expression like df[mask] = None (GH7656)

### 1.22.2 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)
pandas: powerful Python data analysis toolkit, Release 0.23.1

- 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)

1.22.3 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)

1.22.4 Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a multi-indexed `DataFrame` (GH5602)
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google `bq.py` command line client. This submodule now uses `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).
1.22.5 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 datetime-like 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 (GH7306)
• Bug where nanops._maybe_null_out doesn’t work with complex numbers (GH7353)
• Bug in several nanops functions when axis==0 for 1-dimensional nan arrays (GH7354)
• Bug where nanops.nanmedian doesn’t work when axis==None (GH7352)
• Bug where nanops._has_infs doesn’t work with many dtypes (GH7357)
• Bug in StataReader.data where reading a 0-observation dta failed (GH7369)
• Bug in StataReader when reading Stata 13 (117) files containing fixed width strings (GH7360)
• Bug in StataWriter where encoding was ignored (GH7286)
• Bug in DatetimeIndex comparison doesn’t handle NaT properly (GH7529)
• Bug in passing input with tzinfo to some offsets apply, rollforward or rollback resets tzinfo or raises ValueError (GH7465)
• Bug in DatetimeIndex.to_period, PeriodIndex.asobject, PeriodIndex.to_timestamp doesn’t preserve name (GH7485)
• Bug in DatetimeIndex.to_period and PeriodIndex.to_timestamp handle NaT incorrectly (GH7228)
• Bug in offsets.apply, rollforward and rollback may return normal datetime (GH7502)
• Bug in resample raises ValueError when target contains NaT (GH7227)
• Bug in Timestamp.tz_localize resets nanosecond info (GH7534)
• Bug in DatetimeIndex.asobject raises ValueError when it contains NaT (GH7539)
• Bug in Timestamp.__new__ doesn’t preserve nanosecond properly (GH7610)
• Bug in Index.astype(float) where it would return an object dtype Index (GH7464).
• Bug in DataFrame.reset_index loses tz (GH3950)
• Bug in DatetimeIndex.freqstr raises AttributeError when freq is None (GH7606)
• Bug in GroupBy.size created by TimeGrouper raises AttributeError (GH7453)
• Bug in single column bar plot is misaligned (GH7498).
• Bug in area plot with tz-aware time series raises ValueError (GH7471)
• Bug in non-monotonic Index.union may preserve name incorrectly (GH7458)
• Bug in DatetimeIndex.intersection doesn’t preserve timezone (GH4690)
• Bug in rolling_var where a window larger than the array would raise an error(GH7297)
• Bug with last plotted timeseries dictating xlim (GH2960)
• Bug with secondary_y axis not being considered for timeseries xlim (GH3490)
• Bug in Float64Index assignment with a non scalar indexer (GH7586)
• Bug in pandas.core.strings.str_contains does not properly match in a case insensitive fashion
  when regex=False and case=False (GH7505)
• Bug in expanding_cov, expanding_corr, rolling_cov, and rolling_corr for two arguments
  with mismatched index (GH7512)
• Bug in to_sql taking the boolean column as text column (GH7678)
• Bug in grouped hist doesn’t handle rot kw and sharex kw properly (GH7234)
• Bug in .loc performing fallback integer indexing with object dtype indices (GH7496)
• Bug (regression) in PeriodIndex constructor when passed Series objects (GH7701).

1.23 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
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)

1.23.1 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)

In [1]: dfl = DataFrame(np.random.randn(5,2),columns=list('AB'))

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

In [4]: dfl.iloc[:,1:3]

   B
0 -0.438313
1 -0.780572
2  0.542241
3 -0.251642
4  1.666563

(continues on next page)
These are out-of-bounds selections

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

```python
dfl.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

- Slicing with negative start, stop & step values handles corner cases better (GH6531):
  - `df.iloc[::len(df)]` is now empty
  - `df.iloc[len(df)::1]` 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 internall share more common operations, e.g. `factorize()`, `nunique()`, `value_counts()` are now supported on `Index` types as well. The `Series.weekday` property from is removed from `Series` for API consistency. Using a `DateTimeIndex/PeriodIndex` method on a `Series` will now raise a `TypeError`. (GH4551, GH4056, GH5519, GH6380, GH7206).
- Add `is_month_start`, `is_month_end`, `is_quarter_start`, `is_quarter_end`, `is_year_start`, `is_year_end` accessors for `DateTimeIndex / Timestamp` which return a boolean array of whether the timestamp(s) are at the start/end of the month/quarter/year defined by the frequency of the `DateTimeIndex / Timestamp` (GH4565, GH6998)
- Local variable usage has changed in `pandas.eval()`/`DataFrame.eval()`/`DataFrame.query()` (GH5987). For the `DataFrame` methods, two things have changed
  - Column names are now given precedence over locals
  - Local variables must be referred to explicitly. This means that even if you have a local variable that is not a column you must still refer to it with the '@' prefix.
  - You can have an expression like `df.query('@a < a')` with no complaints from `pandas` about ambiguity of the name `a`.
  - The top-level `pandas.eval()` function does not allow you use the '@' prefix and provides you with an error message telling you so.
  - `NameResolutionError` was removed because it isn’t necessary anymore.
- Define and document the order of column vs index names in `query/eval` (GH6676)
- `concat` will now concatenate mixed `Series` and `DataFrames` using the `Series` name or numbering columns as needed (GH2385). See the docs
- Slicing and advanced/boolean indexing operations on `Index` classes as well as `Index.delete()` and `index.drop()` methods will no longer change the type of the resulting index (GH6440, GH7040)
In [6]: i = pd.Index([1, 2, 3, 'a', 'b', 'c'])

In [7]: i[[0,1,2]]
Out[7]: Index([1, 2, 3], dtype='object')

In [8]: i.drop(['a', 'b', 'c'])
Out[8]: Index([1, 2, 3], dtype='object')

Previously, the above operation would return Int64Index. If you’d like to do this manually, use Index.astype()

In [9]: i[[0,1,2]].astype(np.int_)
Out[9]: Int64Index([1, 2, 3], dtype='int64')

• set_index no longer converts MultiIndexes to an Index of tuples. For example, the old behavior returned an Index in this case (GH6459):

    # Old behavior, casted MultiIndex to an Index
    In [10]: tuple_ind
    Out[10]: Index([('a', 'c'), ('a', 'd'), ('b', 'c'), ('b', '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=[['a', 'b'], ['c', '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

(continues on next page)
# 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`, `ewm cov`, `ewmcorr`, `expanding_cov`, `expanding_corr` to allow the calculation of moving window covariance and correlation matrices (GH4950). See *Computing rolling pairwise covariances and correlations* in the docs.

```
In [1]: df = DataFrame(np.random.randn(10,4), columns=list('ABCD'))
In [4]: covs = pd.rolling_cov(df[['A','B','C']], df[['B','C','D']], 5, pairwise=True)
In [5]: covs[df.index[-1]]
Out[5]:
        B     C     D
   A  0.035310  0.326593 -0.505430
   B  0.137748 -0.006888 -0.005383
   C -0.006888  0.861040  0.020762
```

- `Series.iteritems()` is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added `nunique` and `value_counts` functions to `Index` for counting unique elements. (GH6734)
- `stack` and `unstack` now raise a `ValueError` when the `level` keyword refers to a non-unique item in the `Index` (previously raised a `KeyError`). (GH6738)
- Drop unused `order` argument from `Series.sort`; `args` now are in the same order as `Series.order`; add `na_position` arg to conform to `Series.order` (GH6847)
- Default sorting algorithm for `Series.order` is now quicksort, to conform with `Series.sort` (and `numpy` defaults)
- Add `inplace` keyword to `Series.order/sort` to make them inverses (GH6859)
- `DataFrame.sort` now places Nans at the beginning or end of the sort according to the `na_position` parameter. (GH3917)
- Accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1
- Added `factorize` functions to `Index` and `Series` to get indexer and unique values (GH7090)
- `describe` on a `DataFrame` with a mix of `Timestamp` and string like objects returns a different `Index` (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with only bool dtypes now give a warning indicating that they are evaluated in Python space for `+`, `-`, and `*` operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

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

### 1.23.2 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  6  7  8  9
2001-01-01  0  1  2  3  4  5  6  7  8  9
2001-01-02 10 11 12 13 14 15 16 17 18 19
2001-01-03 20 21 22 23 24 25 26 27 28 29
2001-01-04 30 31 32 33 34 35 36 37 38 39
2001-01-05 40 41 42 43 44 45 46 47 48 49
2001-01-06 50 51 52 53 54 55 56 57 58 59
...       ... ... ... ... ... ... ...
[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  3  4  5  6  7  8  9
2001-01-01  0  1  2  3  4  5  6  7  8  9
2001-01-02 10 11 12 13 14 15 16 17 18 19
2001-01-03 20 21 22 23 24 25 26 27 28 29
2001-01-04 30 31 32 33 34 35 36 37 38 39
...       ... ... ... ... ... ... ...
2001-01-08 70 71 72 73 74 75 76 77 78 79
2001-01-09 80 81 82 83 84 85 86 87 88 89
2001-01-10 90 91 92 93 94 95 96 97 98 99
[10 rows x 10 columns]

• allow option 'truncate' for display.show_dimensions to only show the dimensions if the frame is
truncated (GH6547).

The default for display.show_dimensions will now be truncate. This is consistent with how Series
display length.

In [16]: dfd = pd.DataFrame(np.arange(25).reshape(-1,5), index=[0,1,2,3,4],
˓→columns=[0,1,2,3,4])
# show dimensions since this is truncated
In [17]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
˓→'display.show_dimensions', 'truncate'):
     ....:     print(dfd)
     ....:
(continues on next page)
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)

### 1.23.3 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)

### 1.23.4 Groupby API Changes

More consistent behaviour for some groupby methods:

• `groupby head` and `tail` now act more like `filter` rather than an aggregation:
In [19]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [20]: g = df.groupby('A')

In [21]: g.head(1)  # filters DataFrame
Out[21]:
   A  B
0  1  2
2  5  6

In [22]: g.apply(lambda x: x.head(1))  # used to simply fall-through

In [23]: g[[['B']].head(1)
Out[23]:
   B
0  2
2  6

In [24]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [25]: g = df.groupby('A')

In [26]: g.nth(0)
Out[26]:
   B
0  NaN
5  6.0

• groupby head and tail respect column selection:

In [27]: g.nth(0, dropna='any')

Reducing

In [28]: g.nth(-1, dropna='any')
Filtering

```
In [29]: gf = df.groupby('A', as_index=False)

In [30]: gf.nth(0)
Out[30]:
   A  B
0  1  NaN
2  5  6.0

In [31]: gf.nth(0, dropna='any')
A  B
0  1  4.0
2  5  6.0
```

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

```
In [32]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])

In [33]: g = df.groupby('A')

In [34]: g.count()
Out[34]:
   A  B
0  1  1
1  5  2

In [35]: g.describe()
B    count  mean   std  min  25%  50%  75%  max
A
1   1.0   4.0  NaN   4.0  4.0  4.0  4.0  4.0
5   2.0   7.0  1.414214  6.0  6.5  7.0  7.5  8.0
```

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

```
In [36]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])

In [37]: g = df.groupby('A', as_index=False)

In [38]: g.count()
Out[38]:
   A  B
0  1  1
1  5  2

In [39]: g.describe()
A    count  mean   std  min  25%  50%  75%  max
   count  mean   std  min  25%  50%  75%  max
0    2.0   1.0  0.0   1.0  1.0  1.0  1.0  4.0  NaN
1    4.0   4.0  4.0   4.0  4.0  4.0  4.0  4.0
```

(continues on next page)
• Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See the docs (GH3794)

• Better propagation/preservation of Series names when performing groupby operations:
  – `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result (GH6265).
  – If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` (GH6124). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

### 1.23.5 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 sqlite database:

```python
In [40]: from sqlalchemy import create_engine

    # Create your connection.
In [41]: engine = create_engine('sqlite:///:memory:stä')
```

This engine can then be used to write or read data to/from this database:

```python
In [42]: df = pd.DataFrame({'A': [1,2,3], 'B': ['a', 'b', 'c']})
In [43]: df.to_sql('db_table', engine, index=False)
```

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

```python
In [44]: pd.read_sql_table('db_table', engine)
Out[44]:
   A  B
0  1  a
1  2  b
2  3  c
```

or by specifying a sql query:
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).

#### 1.23.6 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:

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

In [48]: columns = MultiIndex.from_tuples([('a','foo'),('a','bar'),
    ....:     ('b','foo'),('b','bah')],
    ....:     names=['lvl0', 'lvl1'])
    ....:

In [49]: df = DataFrame(np.arange(len(index)*len(columns)).reshape((len(index),
    ....:     len(columns))),
    ....:     index=index,
    ....:     columns=columns).sort_index().sort_index(axis=1)
    ....:

In [50]: df
Out[50]:
lvl0   a  b
lvl1   bar foo bah foo
A0   B0 C0 D0   1  0  3  2
    D1   5  4  7  6
    C1   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
[64 rows x 4 columns]

Basic multi-index slicing using slices, lists, and labels.

In [51]: df.loc[(slice('A1','A3'),slice(None), ['C1','C3'],:),]
Out[51]:
lvl0   a  b
lvl1   bar foo bah foo
A1   B0 C1 D0  73  72  75  74
    D1   77  76  79  78
    C3   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
... ... ... ... ...
(continues on next page)
You can use a `pd.IndexSlice` to shortcut the creation of these slices:

```python
In [52]: idx = pd.IndexSlice

In [53]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out [53]:
    lvl0  a  b
    lvl1 foo foo
   A0   B0  C1  D0  8  10
      D1  12  14
   C3   D0  24  26
      D1  28  30
   B1   C1  D0  40  42
      D1  44  46
   C3   D0  56  58
   ... ... ...
   A3   B0  C1  D1  204 206
      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.

```python
In [54]: df.loc['A1', (slice(None), 'foo')]
Out [54]:
    lvl0  a  b
    lvl1 foo foo
   B0   C0  D0  64  66
      D1  68  70
   C1   D0  72  74
      D1  76  78
   C2   D0  80  82
      D1  84  86
   C3   D0  88  90
   ... ... ...
   B1   C0  D1  100 102
   C1   D0  104 106
      D1  108 110
   C2   D0  112 114
      D1  116 118
   C3   D0  120 122
      D1  124 126
```

(continues on next page)
[16 rows x 2 columns]

In [55]: df.loc[idx[:,:,['C1','C3']],idx[:,,'foo']]

→
   lvl0   a   b
   lvl1   foo  foo
A0  B0  C1  D0  8   10
    D1   12  14
C3  D0  24   26
    D1   28  30
B1  C1  D0  40   42
    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]

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

In [56]: mask = df[('a','foo')]>200

In [57]: df.loc[idx[mask,:,:,['C1','C3']],idx[:,,'foo']]
Out[57]:
   lvl0   a   b
   lvl1   foo  foo
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

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

In [58]: df.loc(axis=0)[:,:,['C1','C3']]
Furthermore you can set the values using these methods

```python
In [59]: df2 = df.copy()
In [60]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10
In [61]: df2
Out[61]:
```

```
```

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

```python
In [62]: df2 = df.copy()
In [63]: df2.loc[idx[:, :, ['C1', 'C3']], :] = df2*1000
In [64]: df2
Out[64]:
```

```
```

... (continues on next page)
1.23.7 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)
• DataFrame.boxplot() now supports layout keyword (GH6769)
• DataFrame.boxplot() has a new keyword argument, return_type. It accepts 'dict', 'axes', or 'both', in which case a named tuple with the matplotlib axes and a dict of matplotlib Lines is returned.

1.23.8 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 function encode in unicode by default (GH2224, GH2225)
• Remove nanRep keyword from DataFrame.to_csv() and DataFrame.to_string() (GH275)
• Remove unique keyword from HDFStore.select_column() (GH3256)
• Remove inferTimeRule keyword from Timestamp.offset() (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)

1.23.9 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 take 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)

```python
# 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 be integers and not floating point
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 and not floating point
Out[2]: 1
```
(continues on next page)
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 and not floating point
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 matpltolib Axes in a future release. You can use the future behavior now by passing return_type='axes' to boxplot.

1.23.10 Known Issues

• OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

1.23.11 Enhancements

• DataFrame and Series will create a MultiIndex object if passed a tuples dict, See the docs (GH3323)
In [65]: Series({('a', 'b'): 1, ('a', 'a'): 0,  
.....: ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
.....:
Out[65]:
a b 1
   a 0
c 2
b a 3
   b 4
dtype: int64

In [66]: DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},  
.....: ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},  
.....: ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},  
.....: ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},  
.....: ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})

Out[66]:
a b
A B 1.0 4.0 5.0 8.0 10.0
   C 2.0 3.0 6.0 7.0 NaN
   D NaN NaN NaN NaN 9.0

• 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]: portfolio
Out[70]:

<table>
<thead>
<tr>
<th>household_id</th>
<th>asset_id</th>
<th>name</th>
<th>share</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>n10000301109</td>
<td>ABN Amro</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>n10000289783</td>
<td>Robeco</td>
<td>0.40</td>
</tr>
<tr>
<td>3</td>
<td>gb00b03mlx29</td>
<td>Royal Dutch Shell</td>
<td>0.60</td>
</tr>
<tr>
<td>4</td>
<td>gb00b03mlx29</td>
<td>Royal Dutch Shell</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>lu0197800237</td>
<td>AAB Eastern Europe Equity Fund</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>n10000289965</td>
<td>Postbank BioTech Fonds</td>
<td>0.25</td>
</tr>
</tbody>
</table>

In [71]: household.join(portfolio, how='inner')

<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>1</td>
<td>n10000301109</td>
<td>0</td>
<td>196087.3</td>
<td>ABN Amro</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>n10000289783</td>
<td>1</td>
<td>316478.7</td>
<td>Robeco</td>
<td>0.40</td>
</tr>
<tr>
<td>3</td>
<td>gb00b03mlx29</td>
<td>1</td>
<td>316478.7</td>
<td>Royal Dutch Shell</td>
<td>0.60</td>
</tr>
<tr>
<td>4</td>
<td>gb00b03mlx29</td>
<td>0</td>
<td>294750.0</td>
<td>Royal Dutch Shell</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>lu0197800237</td>
<td>0</td>
<td>294750.0</td>
<td>AAB Eastern Europe Equity Fund</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>n10000289965</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 [72]: import datetime
In [73]: df = DataFrame({
   ....:     'Branch': ['A A A A A B'].split(),
   ....:     'Buyer': ['Carl Mark Carl Carl Joe Joe'].split(),
   ....:     'Quantity': [1, 3, 5, 1, 8, 1],
   ....:     'Date': [datetime.datetime(2013,11,13,1,0),
              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(2013,9,5,20,0),
                datetime.datetime(2013,10,7,20,0),
                datetime.datetime(2013,9,5,10,0)]})

In [74]: df
Out[74]:
   Branch  Buyer  Quantity    Date     PayDay
0       A      Carl       1  2013-11-01 13:00:00 2013-10-04 00:00:00
1       A      Mark       3  2013-09-01 13:05:00 2013-10-15 13:05:00
2       A      Carl       5  2013-10-01 20:00:00 2013-09-05 20:00:00
3       A      Carl       1  2013-10-02 10:00:00 2013-11-02 10:00:00
4       A      Joe        8  2013-11-01 20:00:00 2013-10-07 20:00:00
5       B      Joe        1  2013-10-02 10:00:00 2013-09-05 10:00:00

In [75]: pivot_table(df, index=Grouper(freq='M', key='Date'),
   ....:     columns=Grouper(freq='M', key='PayDay'),
   ....:     values='Quantity', aggfunc=np.sum)

Out[75]:
                 Date
PayDay
2013-09-30    NaN        3.0     NaN
2013-10-31    6.0        NaN     1.0
2013-11-30    NaN        9.0     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 [76]: prng = period_range('2013-01-01 09:00', periods=100, freq='H')
In [77]: ps = Series(np.random.randn(len(prng)), index=prng)
In [78]: ps

(continues on next page)
• 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.rolling_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)
1.23.12 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).

1.23.13 Experimental

There are no experimental changes in 0.14.0

1.23.14 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 version string gen. for dev versions with shallow clones / install from tarball (GH6127)
- Inconsistent tz parsing `Timestamp/to_datetime` for current year (GH5958)
- Indexing bugs with reordered indexes (GH6252, GH6254)
- Bug in `.xs` with a Series multiindex (GH6258, GH5684)
- Bug in conversion of a string types to a `DatetimeIndex` with a specified frequency (GH6273, GH6274)
- Bug in `eval` where type-promotion failed for large expressions (GH6205)
- Bug in interpolate with `inplace=True` (GH6281)
- `HDFStore.remove` now handles start and stop (GH6177)
- `HDFStore.select_as_multiple` handles start and stop the same way as `select` (GH6177)
- `HDFStore.select_as_coordinates` and `select_column` works with a `where` clause that results in filters (GH6177)
• Regression in join of non_unique_indexes (GH6329)
• Issue with groupby agg with a single function and a 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 nosetests -A disabled) (GH6048).
• Bug in DataFrame.replace() when passing a nested dict that contained keys not in the values to be replaced (GH6342)
• str.match ignored the na flag (GH6609).
• Bug in take with duplicate columns that were not consolidated (GH6240)
• Bug in interpolate changing dtypes (GH6290)
• Bug in Series.get was using a buggy access method (GH6383)
• Bug in hdfstore queries of the form where=[('date', '>=', datetime(2013,1,1)), ('date', '<=', datetime(2014,1,1))] (GH6313)
• Bug in DataFrame.dropna with duplicate indices (GH6355)
• Regression in chained getitem indexing with embedded list-like from 0.12 (GH6394)
• Float64Index with nans not comparing correctly (GH6401)
• eval/query expressions with strings containing the @ character will now work (GH6366).
• Bug in Series.reindex when specifying a method with some nan values was inconsistent (noted on a resample) (GH6418)
• Bug in DataFrame.replace() where nested dicts were erroneously depending on the order of dictionary keys and values (GH5338).
• Perf issue in concatting 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)
• Stopped tests from failing if options data isn’t able to be downloaded from Yahoo (GH7034)
• Bug in parallel_coordinates and radviz where reordering of class column caused possible color/class mismatch (GH6956)
• Bug in radviz and andrews_curves where multiple values of ‘color’ were being passed to plotting method (GH6956)
• Bug in Float64Index.isin() where containing nans would make indices claim that they contained all the things (GH7066).
• Bug in DataFrame.boxplot where it failed to use the axis passed as the ax argument (GH3578)
• Bug in the XlsxWriter and XlwtWriter implementations that resulted in datetime columns being formatted without the time (GH7075) were being passed to plotting method
• read_fwf() treats None in colspec like regular python slices. It now reads from the beginning or until the end of the line when colspec contains a None (previously raised a TypeError)
• Bug in cache coherence with chained indexing and slicing; add _is_view property to NDFrame to correctly predict views; mark is_copy on xs only if its an actual copy (and not a view) (GH7084)
• Bug in DatetimeIndex creation from string ndarray with dayfirst=True (GH5917)
• Bug in MultiIndex.from_arrays created from DatetimeIndex doesn’t preserve freq and tz (GH7090)
• Bug in unstack raises ValueError when MultiIndex contains PeriodIndex (GH4342)
• Bug in boxplot and hist draws unnecessary axes (GH6769)
• Regression in groupby.nth() for out-of-bounds indexers (GH6621)
• Bug in quantile with datetime values (GH6965)
• Bug in Dataframe.set_index, reindex and pivot don’t preserve DatetimeIndex and PeriodIndex attributes (GH3950, GH5878, GH6631)
• Bug in MultiIndex.get_level_values doesn’t preserve DatetimeIndex and PeriodIndex attributes (GH7092)
• Bug in Groupby doesn’t preserve tz (GH3950)
• Bug in PeriodIndex partial string slicing (GH6716)
• Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the large_repr set to ‘info’ (GH7105)
• Bug in DatetimeIndex specifying freq raises ValueError when passed value is too short (GH7098)
• Fixed a bug with the info repr not honoring the display.max_info_columns setting (GH6939)
• Bug PeriodIndex string slicing with out of bounds values (GH5407)
• Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables (GH7157)
• Bug in isnull when applied to 0-dimensional object arrays (GH7176)
• Bug in `query/eval` where global constants were not looked up correctly (GH7178)
• Bug in recognizing out-of-bounds positional list indexers with `iloc` and a multi-axis tuple indexer (GH7189)
• Bug in `setitem` with a single value, 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)

1.24 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:
1.24.1 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)

```
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'>
RangeIndex: 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'>
RangeIndex: 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.
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
1 3 4
2 rows x 2 columns

- The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array (GH3401)

  Previously output might look like:

<table>
<thead>
<tr>
<th>age</th>
<th>today</th>
<th>diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001-01-01</td>
<td>2013-04-19</td>
<td>4491 days</td>
</tr>
<tr>
<td>2004-06-01</td>
<td>2013-04-19</td>
<td>3244 days</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>2001-01-01</td>
<td>2013-04-19</td>
<td>4491 days</td>
</tr>
<tr>
<td>2004-06-01</td>
<td>2013-04-19</td>
<td>3244 days</td>
</tr>
</tbody>
</table>
2 rows x 3 columns

1.24.2 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'])

(continues on next page)
In [24]: s.str.get_dummies(sep='|')
Out[24]:
   a b c
0  1 0 0
1  1 1 0
2  0 0 0
3  1 0 1
[4 rows x 3 columns]

• 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_index())
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]))
---------------------------------------------------------------------------
AttributeError Traceback (most recent call last)
<ipython-input-30-18a036193b45> in
----> 3 com.array_equivalent(np.array([0, np.nan]), np.array([0, np.nan]))
AttributeError: module 'pandas.core.common' has no attribute 'array_equivalent'
In [31]: np.array_equal(np.array([0, np.nan]), np.array([0, np.nan]))

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([], Length: 0, dtype: float64)
Out[34]:
a  NaN
Now, when `apply` is called on an empty DataFrame: if the `reduce` argument is `True` a Series will returned, if it is `False` a DataFrame will be returned, and if it is `None` (the default) the function being applied will be called with an empty series to try and guess the return type.

```
In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a  NaN
b  NaN
Length: 2, dtype: float64

In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []
[0 rows x 2 columns]
```

### 1.24.3 Prior Version Deprecations/Changes

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

### 1.24.4 Deprecations

There are no deprecations of prior behavior in 0.13.1

### 1.24.5 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.

```
# 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 [32]: shades = ['light', 'dark']
In [33]: colors = ['red', 'green', 'blue']
```

(continues on next page)
In [34]: MultiIndex.from_product([shades, colors], names=['shade', 'color'])
Out[34]:
MultiIndex(levels=[['dark', 'light'], ['blue', 'green', '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 [35]: import pandas.util.testing as tm
In [36]: panel = tm.makePanel(5)
In [37]: panel
Out[37]:
<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 [38]: panel['ItemA']

A B C D
2000-01-03 0.694103 1.893534 -1.735349 -0.850346
2000-01-04 0.678630 0.639633 1.210384 1.176812
2000-01-05 0.239556 -0.962029 0.797435 -0.524336
2000-01-06 0.151227 -2.085266 -0.379811 0.700908
2000-01-07 0.816127 1.930247 0.702562 0.984188
[5 rows x 4 columns]

Specifying an apply that operates on a Series (to return a single element)

In [39]: panel.apply(lambda x: x.dtype, axis='items')
Out[39]:
A B C D
2000-01-03 float64 float64 float64 float64
2000-01-04 float64 float64 float64 float64
2000-01-05 float64 float64 float64 float64
2000-01-06 float64 float64 float64 float64
2000-01-07 float64 float64 float64 float64
[5 rows x 4 columns]

A similar reduction type operation

In [40]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[40]:
ItemA ItemB ItemC
A 2.579643 3.062757 0.379252
B 1.416120 -1.960855 0.923558
C 0.595222 -1.079772 -3.118269
D 1.487226 -0.734611 -1.979310
[4 rows x 3 columns]
This is equivalent to

In [41]: panel.sum('major_axis')
Out[41]:
   ItemA  ItemB  ItemC
A  2.579643  3.062757  0.379252
B  1.416120 -1.960855  0.923558
C  0.595222 -1.079772 -3.118269
D  1.487226 -0.734611 -1.979310

[4 rows x 3 columns]

A transformation operation that returns a Panel, but is computing the z-score across the major_axis

In [42]: result = panel.apply(
    ....:     lambda x: (x-x.mean())/x.std(),
    ....:     axis='major_axis')

In [43]: result
Out[43]:
<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 [44]: result['ItemA']

<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>0.595800</td>
<td>0.907552</td>
<td>-1.556260</td>
<td>-1.244875</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.544058</td>
<td>0.200868</td>
<td>0.915883</td>
<td>0.953747</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-0.924165</td>
<td>-0.701810</td>
<td>0.569325</td>
<td>-0.891290</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-1.219530</td>
<td>-1.334852</td>
<td>-0.418654</td>
<td>0.437589</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.003837</td>
<td>0.928242</td>
<td>0.489705</td>
<td>0.744830</td>
</tr>
</tbody>
</table>

[5 rows x 4 columns]

• Panel apply() operating on cross-sectional slabs. (GH1148)

In [45]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T

In [46]: result = panel.apply(f, axis = ['items','major_axis'])

In [47]: result
Out[47]:
<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 [48]: result.loc[:,:,'ItemA']

<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>0.331409</td>
<td>1.071034</td>
<td>-0.914540</td>
<td>-0.510587</td>
</tr>
</tbody>
</table>

(continues on next page)
This is equivalent to the following

```python
In [49]: result = Panel(dict([ (ax,f(panel.loc[:,ax]))
           ....: for ax in panel.minor_axis ]))
    ....:

In [50]: result
```

```python
Out[50]:
<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
```

```python
In [51]: result.loc[:,,'ItemA']
```

```
                              A       B       C       D
2000-01-03          0.331409  1.071034 -0.914540 -0.510587
2000-01-04         -0.741017 -0.118794  0.383277  0.537212
2000-01-05          0.065042 -0.767353  0.655436  0.069467
2000-01-06          0.027932 -0.569477  0.908202  0.610585
2000-01-07          1.116434  1.133591  0.871287  1.004064
```

1.24.6 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)
1.24.7 Experimental

There are no experimental changes in 0.13.1

1.24.8 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.

1.25 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

There 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

1.25.1 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

```python
In [7]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[7]:
0 0.200000
1 0.666667
2 1.500000
```

(continues on next page)
• 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()

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

In [4]: DataFrame([[False]]).bool()

• 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)

### 1.25.2 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 than `None`. This activates truncated display (“...”) of long sequences in various places. (GH3391)

### 1.25.3 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`.

### 1.25.4 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
Length: 3, dtype: int64


In [13]: s
Out[13]:
0  1.0
1  2.0
2  3.0
5  5.0
Length: 4, 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
1  2  3  2
2  4  5  4
3  5  5  5

(continues on next page)
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.index)

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']

→
          Item1  Item2
2001-01-12    30.0  32.0
2001-01-13    30.0  32.0
2001-01-14    30.0  32.0
2001-01-15    30.0  32.0
[4 rows x 2 columns]
```

### 1.25.5 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)

In [28]: s

```

(continues on next page)
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

In [30]: s.loc[3]
Out [30]: 2
```

The only positional indexing is via iloc

```
In [31]: s.iloc[3]
Out [31]: 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 [32]: s[2:4]
Out [32]:
2.0 1
3.0 2
Length: 2, dtype: int64

In [33]: s.loc[2:4]
Out [33]:
2.0 1
3.0 2
Length: 2, dtype: int64

In [34]: s.iloc[2:4]
...
3.0 2
4.5 3
Length: 2, dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [35]: s[2.1:4.6]
Out [35]:
3.0 2
4.5 3
Length: 2, dtype: int64

In [36]: s.loc[2.1:4.6]
Out [36]:
3.0 2
```
4.5 3
Length: 2, dtype: int64

• Indexing on other index types are preserved (and positional fallback for [], ix), with the exception, that floating point slicing on indexes on non Float64Index will now raise a TypeError.

In [1]: Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type
    →(Int64Index)

In [1]: 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]: Series(range(5))[3.0]
Out[3]: 3

1.25.6 HDFStore API Changes

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

In [37]: path = 'test.h5'
In [38]: dfq = DataFrame(randn(10,4),
          ....:     columns=list('ABCD'),
          ....:     index=date_range('20130101',periods=10))
          ....:
In [39]: dfq.to_hdf(path,'dfq',format='table',data_columns=True)
Use boolean expressions, with in-line function evaluation.

In [40]: read_hdf(path,'dfq',
          ....:      where="index>Timestamp('20130104') & columns=['A', 'B']")
          ....:
Out[40]:
     A     B
2013-01-05  1.057633 -0.791489
2013-01-06  1.910759  0.787965
2013-01-07  1.043945  2.107785
2013-01-08  0.749185  0.675521
2013-01-09 -0.276646  1.924533
2013-01-10  0.226363 -2.078618
[6 rows x 2 columns]

Use an inline column reference

In [41]: read_hdf(path,'dfq',
          ....:      where="A>0 or C>0")
          ....:
Out[41]:
     A     B     C     D

<table>
<thead>
<tr>
<th>Date</th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>-0.414505</td>
<td>-1.425795</td>
<td>0.209395</td>
<td>-0.592886</td>
</tr>
<tr>
<td>2013-01-02</td>
<td>-1.473116</td>
<td>-0.896581</td>
<td>1.104352</td>
<td>-0.431550</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>-0.161137</td>
<td>0.889157</td>
<td>0.288377</td>
<td>-1.051539</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>-0.319561</td>
<td>-0.619993</td>
<td>0.156998</td>
<td>-0.571455</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>1.057633</td>
<td>-0.791489</td>
<td>-0.524627</td>
<td>0.071878</td>
</tr>
<tr>
<td>2013-01-06</td>
<td>1.910759</td>
<td>0.787965</td>
<td>0.513082</td>
<td>-0.546416</td>
</tr>
<tr>
<td>2013-01-07</td>
<td>1.043945</td>
<td>2.107785</td>
<td>1.459927</td>
<td>1.015405</td>
</tr>
<tr>
<td>2013-01-08</td>
<td>0.749185</td>
<td>-0.675521</td>
<td>0.440266</td>
<td>0.688972</td>
</tr>
<tr>
<td>2013-01-09</td>
<td>-0.276646</td>
<td>1.924533</td>
<td>0.411204</td>
<td>0.890765</td>
</tr>
<tr>
<td>2013-01-10</td>
<td>0.226363</td>
<td>-2.078618</td>
<td>-0.387886</td>
<td>-0.087107</td>
</tr>
</tbody>
</table>

- the **format** keyword now replaces the **table** keyword; allowed values are **fixed(f)** or **table(t)**; the same defaults as prior < 0.13.0 remain, e.g. put implies fixed format and append implies table format. This default format can be set as an option by setting `io.hdf.default_format`. 

```python
In [42]: path = 'test.h5'

In [43]: df = pd.DataFrame(np.random.randn(10,2))

In [44]: df.to_hdf(path,'df_table',format='table')

In [45]: df.to_hdf(path,'df_table2',append=True)

In [46]: df.to_hdf(path,'df_fixed')

In [47]: with pd.HDFStore(path) as store:
....:     print(store)
....:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
```

- Significant table writing performance improvements
- handle a passed **Series** in table format (GH4330)
- can now serialize a **timedelta64[ns]** dtype in a table (GH3577), See the docs.
- added an **is_open** property to indicate if the underlying file handle is_open; a closed store will now report ‘CLOSED’ when viewing the store (rather than raising an error) (GH4409)
- a close of a HDFStore now will close that instance of the HDFStore but will only close the actual file if the ref count (by PyTables) w.r.t. all of the open handles are 0. Essentially you have a local instance of HDFStore referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise ClosedFileError

```python
In [48]: path = 'test.h5'

In [49]: df = DataFrame(randn(10,2))

In [50]: store1 = HDFStore(path)

In [51]: store2 = HDFStore(path)

In [52]: store1.append('df',df)
```

(continues on next page)
In [53]: store2.append('df2', df)

In [54]: store1
Out[54]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [55]: store2
Out[55]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [56]: store1.close()

In [57]: store2
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [58]: store2.close()

In [59]: store2
Out[59]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

• removed the _quiet attribute, replace by a DuplicateWarning if retrieving duplicate rows from a table (GH4367)
• removed the warn argument from open. Instead a PossibleDataLossError exception will be raised if you try to use mode='w' with an OPEN file handle (GH4367)
• allow a passed locations array or mask as a where condition (GH4467). See the docs for an example.
• add the keyword dropna=True to append to change whether ALL nan rows are not written to the store (default is True, ALL nan rows are NOT written), also settable via the option io.hdf.dropna_table (GH4625)
• pass thru store creation arguments; can be used to support in-memory stores

1.25.7 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')`.

### 1.25.8 Enhancements

- `df.to_clipboard()` learned a new `excel` keyword that let’s you paste df data directly into excel (enabled by default). (GH5070).
- `read_html` now raises a `URLError` instead of catching and raising a `ValueError` (GH4303, GH4305)
- Added a test for `read_clipboard()` and `to_clipboard()` (GH4282)
- Clipboard functionality now works with PySide (GH4282)
- Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
- `to_dict` now takes `records` as a possible outtype. Returns an array of column-keyed dictionaries. (GH4936)
- `NaN` handing in `get_dummies` (GH4446) with `dummy_na`

```python
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
In [60]: get_dummies([1, 2, np.nan])
Out[60]:
          1.0  2.0
     0  1  0
     1  0  1
     2  0  0

[3 rows x 2 columns]

# unless requested
In [61]: get_dummies([1, 2, np.nan], dummy_na=True)
Out[61]:
          1.0  2.0    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 [62]: to_timedelta('1 days 06:05:01.00003')
Out[62]: Timedelta('1 days 06:05:01.000030')

In [63]: to_timedelta('15.5us')
Out[63]: Timedelta('0 days 00:00:00.000015')

In [64]: to_timedelta(['1 days 06:05:01.00003','15.5us','nan'])
Out[64]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta64[ns]', freq=None)

In [65]: to_timedelta(np.arange(5),unit='s')
Out[65]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelta64[ns]', freq=None)

In [66]: to_timedelta(np.arange(5),unit='d')
Out[66]: 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 [67]: from datetime import timedelta

In [68]: td = Series(date_range('20130101',periods=4))-Series(date_range('20121201',periods=4))

In [69]: td[2] += timedelta(minutes=5,seconds=3)

In [70]: td[3] = np.nan

In [71]: td
Out[71]:
0  31 days 00:00:00
1  31 days 00:00:00
2  31 days 00:05:03
3  NaT
Length: 4, dtype: timedelta64[ns]

# to days
In [72]: td / np.timedelta64(1,'D')
Out[72]:
0  31.000000
1  31.000000
2  31.003507
3  NaN
Length: 4, dtype: float64
```

(continues on next page)
In [73]: td.astype('timedelta64[D]')

    0  31.0
    1  31.0
    2  31.0
    3  NaN
Length: 4, dtype: float64

# to seconds
In [74]: td / np.timedelta64(1,'s')

    0  2678400.0
    1  2678400.0
    2  2678703.0
    3  NaN
Length: 4, dtype: float64

In [75]: td.astype('timedelta64[s]')

    0  2678400.0
    1  2678400.0
    2  2678703.0
    3  NaN
Length: 4, dtype: float64

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

In [76]: td * -1
Out[76]:
    0   -31 days +00:00:00
    1   -31 days +00:00:00
    2   -32 days +23:54:57
    3     NaN
Length: 4, dtype: timedelta64[ns]

In [77]: td * Series([1,2,3,4])

    0  31 days 00:00:00
    1  62 days 00:00:00
    2  93 days 00:15:09
    3     NaN
Length: 4, dtype: timedelta64[ns]

Absolute DateOffset objects can act equivalently to timedelta

In [78]: from pandas import offsets

In [79]: td + offsets.Minute(5) + offsets.Milli(5)
Out[79]:
    0  31 days 00:05:00.005000
    1  31 days 00:05:00.005000
    2  31 days 00:10:03.005000

(continues on next page)
Fillna is now supported for timedeltas

```python
In [80]: td.fillna(0)
Out[80]:
0 31 days 00:00:00
1 31 days 00:00:00
2 31 days 00:05:03
3 0 days 00:00:00
Length: 4, dtype: timedelta64[ns]
```

```python
In [81]: td.fillna(timedelta(days=1,seconds=5))
```

You can do numeric reduction operations on timedeltas.

```python
In [82]: td.mean()
Out[82]: Timedelta('31 days 00:01:41')
```

```python
In [83]: td.quantile(.1)
```

• `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to `scipy.stats.gaussian_kde()` (for scipy >= 0.11.0) to set the bandwidth, and to `gkde.evaluate()` to specify the indices at which it is evaluated, respectively. See scipy docs. (GH4298)

• DataFrame constructor now accepts a numpy masked record array (GH3478)

• The new vectorized string method `extract` return regular expression matches more conveniently.

```python
In [84]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
```

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 [85]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
```
Elements that do not match return a row of NaN. Thus, a Series of messy strings can be converted into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating get() to access tuples or re.match objects.

Named groups like

```
In [86]: Series(['a1', 'b2', 'c3']).str.extract(  
    .....:    '(?P<letter>[ab])(?P<digit>\d)')  
    .....:
Out[86]:
   letter digit
0   a    1
1   b    2
2   NaN  NaN
```

and optional groups can also be used.

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

- read_stata now accepts Stata 13 format (GH4291)
- read_fwf now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function (GH4488).
- support for nanosecond times as an offset

**Warning:** These operations require numpy >= 1.7

Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [88]: date_range('2013-01-01', periods=5, freq='5N')
Out[88]:
DatetimeIndex(['2013-01-01 00:00:00',  
              '2013-01-01 00:00:00.000000005',  
              '2013-01-01 00:00:00.000000010',  
              '2013-01-01 00:00:00.000000015',  
              '2013-01-01 00:00:00.000000020'],  
              dtype='datetime64[ns]', freq='5N')
```
In [89]: date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[89]:
DatetimeIndex(['2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
              dtype='datetime64[ns]', freq='5N')

Timestamps can be modified in the nanosecond range

In [90]: t = Timestamp('20130101 09:01:02')
In [91]: t + pd.tseries.offsets.Nano(123)
Out[91]: 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 [92]: dfi = DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})
In [93]: dfi
Out[93]:
   A B
0 1 a
1 2 b
2 3 f
3 4 n

[4 rows x 2 columns]

In [94]: other = DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})
In [95]: mask = dfi.isin(other)
In [96]: mask
Out[96]:
   A   B
0   True  False
1    False  False
2     True   True
3     False  False

[4 rows x 2 columns]

In [97]: dfi[mask.any(1)]

→
   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

```python
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- `tz_localize` can infer a fall daylight savings transition based on the structure of the unlocalized data (GH4230), see the docs
- `DatetimeIndex` is now in the API documentation, see the docs
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. See the docs (GH1067)
- Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
- Python csv parser now supports usecols (GH4335)
- Frequencies gained several new offsets:
  - `LastWeekOfMonth` (GH4637)
  - `FY5253` and `FY5253Quarter` (GH4511)
- DataFrame has a new `interpolate` method, similar to Series (GH4434, GH1892)

```python
In [98]: 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 [99]: df.interpolate()
```

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:

```python
In [100]: ser = Series([1, 3, np.nan, np.nan, np.nan, 11])

In [101]: ser.interpolate(limit=2)
```

1.25. v0.13.0 (January 3, 2014)
• Added `wide_to_long` panel data convenience function. See the docs.

```python
In [102]: np.random.seed(123)

In [103]: 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 [104]: df["id"] = df.index

In [105]: df
Out[105]:
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 [106]: wide_to_long(df, ["A", "B"], i="id", j="year")

id  year   X  A  B
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
[6 rows x 3 columns]
```

• `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)

### 1.25.9 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,
# eval with NumExpr backend

```python
In [109]: %timeit pd.eval('df1 + df2 + df3 + df4')
7.95 ms ± 525 us per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

# pure Python evaluation

```python
In [110]: %timeit df1 + df2 + df3 + df4
10.9 ms ± 722 us per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

For more details, see the [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 [111]: df = DataFrame(randn(10, 2), columns=['a', 'b'])

In [112]: df.eval('a + b')
Out[112]:
    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
Length: 10, 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 [113]: n = 20

In [114]: df = DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b', 'c'])

In [115]: df.query('a < b < c')
Out[115]:
    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](https://pandas.pydata.org/pandas-docs/stable/).

- `pd.read_msgpack()` and `pd.to_msgpack()` are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See [the docs](https://pandas.pydata.org/pandas-docs/stable/).

**Warning:** Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.
In [117]: df.to_msgpack('foo.msg')

In [118]: pd.read_msgpack('foo.msg')
Out[118]:
   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

[5 rows x 2 columns]

In [119]: s = Series(np.random.rand(5),index=date_range('20130101',periods=5))

In [120]: pd.to_msgpack('foo.msg', df, s)

In [121]: pd.read_msgpack('foo.msg')
Out[121]:
[  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

[5 rows x 2 columns], 2013-01-01 0.022321
2013-01-02 0.227025
2013-01-03 0.383282
2013-01-04 0.193225
2013-01-05 0.110977
Freq: D, Length: 5, dtype: float64]

You can pass `iterator=True` to iterator over the unpacked results

In [122]: for o in pd.read_msgpack('foo.msg', iterator=True):
      ....:     print(o)
      ....:
          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

[5 rows x 2 columns]
2013-01-01 0.022321
2013-01-02 0.227025
2013-01-03 0.383282
2013-01-04 0.193225
2013-01-05 0.110977
Freq: D, Length: 5, dtype: float64

- 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
from pandas.io import gbq

# A query to select the average monthly temperatures in the
# in the year 2000 across the USA. The dataset,
# publicdata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA good data.

query = """SELECT station_number as STATION,
    month as MONTH, AVG(mean_temp) as MEAN_TEMP
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC""

# Fetch the result set for this query
# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://console.developers.google.com/iam-admin/projects?authuser=0
# projectid = xxxxxxxxxxx;

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 Tem', 'Mean Temp', 'Max Temp'])

The resulting DataFrame is:

<table>
<thead>
<tr>
<th>MONTH</th>
<th>Min Tem</th>
<th>Mean Temp</th>
<th>Max Temp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-53.33667</td>
<td>39.827892</td>
<td>89.770968</td>
</tr>
<tr>
<td>2</td>
<td>-49.83750</td>
<td>43.685219</td>
<td>93.437932</td>
</tr>
<tr>
<td>3</td>
<td>-77.92608</td>
<td>48.708355</td>
<td>96.099998</td>
</tr>
<tr>
<td>4</td>
<td>-82.89286</td>
<td>55.070087</td>
<td>97.317240</td>
</tr>
<tr>
<td>5</td>
<td>-92.37826</td>
<td>61.428117</td>
<td>102.042856</td>
</tr>
<tr>
<td>6</td>
<td>-77.70334</td>
<td>65.858888</td>
<td>102.900000</td>
</tr>
<tr>
<td>7</td>
<td>-87.82143</td>
<td>68.169663</td>
<td>106.510714</td>
</tr>
<tr>
<td>8</td>
<td>-89.43199</td>
<td>68.614215</td>
<td>105.500000</td>
</tr>
<tr>
<td>9</td>
<td>-86.61112</td>
<td>63.436935</td>
<td>107.142856</td>
</tr>
<tr>
<td>10</td>
<td>-78.20968</td>
<td>56.880838</td>
<td>92.103333</td>
</tr>
<tr>
<td>11</td>
<td>-50.12500</td>
<td>48.861228</td>
<td>94.996428</td>
</tr>
<tr>
<td>12</td>
<td>-50.33225</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.
1.25.10 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.

```
In [123]: s = Series([1,2,3,4])
```

Numpy Usage

```
In [124]: np.ones_like(s)
Out[124]: array([1, 1, 1, 1])

In [125]: np.diff(s)
Out[125]: array([1, 1, 1])

In [126]: np.where(s>1,s,np.nan)
Out[126]: array([ nan, 2., 3., 4.])
```

Pandonic Usage

```
In [127]: Series(1,index=s.index)
Out[127]:
   0  1
   1  1
   2  1
   3  1
Length: 4, dtype: int64

In [128]: s.diff()
Out[128]:
   0  NaN
   1  1.0
   2  1.0
   3  1.0
Length: 4, dtype: float64

In [129]: s.where(s>1)
Out[129]:
   0  NaN
   1  2.0
   2  3.0
   3  4.0
Length: 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)

```
In [130]: s = Series([1,2,3],index=list('abc'))
In [131]: s.b
Out[131]: 2
In [132]: s.a = 5
In [133]: s
Out[133]:
a    5
b    2
c    3
Length: 3, dtype: int64
```

1.25.11 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.

1.26 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.

1.26.1 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
- 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

In [4]: p / p
```
In [5]: p / 0

→ first second
0  inf  NaN
1  inf  NaN
2  inf  inf

[3 rows x 2 columns]

- 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, Length: 4, dtype: float64

# no squeezing (the default, and behavior in 0.10.1)
In [9]: df2.groupby("val1").apply(func)

Out[9]:
     val2
val1
1    0.5
2   -0.5
3    7.5
4  -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 plenty 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
# this is what you should use
In [13]: df.loc[mask]

\[\text{→ a A 0 C 2 E 4}\]
[3 rows x 1 columns]

# this will work as well
In [14]: df.iloc[mask.values]

\[\text{→ a A 0 C 2 E 4}\]
[3 rows x 1 columns]

df.iloc[mask] will raise a ValueError

- The raise_on_error argument to plotting functions is removed. Instead, plotting functions raise a 
  TypeError when the dtype of the object is object to remind you to avoid object arrays whenever 
  possible and thus you should cast to an appropriate numeric dtype if you need to plot something.

- Add colormap keyword to DataFrame plotting methods. Accepts either a matplotlib colormap object (ie, 
  matplotlib.cm.jet) or a string name of such an object (ie, ‘jet’). The colormap is sampled to select the color for 
  each column. Please see Colormaps for more information. (GH3860)

- DataFrame.interpolate() is now deprecated. Please use DataFrame.fillna() and 
  DataFrame.replace() instead. (GH3582, GH3675, GH3676)

- the method and axis arguments of DataFrame.replace() are deprecated

- DataFrame.replace’s infer_types parameter is removed and now performs conversion by default. 
  (GH3907)

- Add the keyword allow_duplicates to DataFrame.insert to allow a duplicate column to be inserted 
  if True, default is False (same as prior to 0.12) (GH3679)

- Implement __nonzero__ for NDFrame objects (GH3691, GH3696)

- IO api
  - added top-level function read_excel to replace the following. The original API is deprecated and will 
    be removed in a future version

```python
from pandas.io.parsers import ExcelFile
xls = ExcelFile('path_to_file.xls')
xls.parse('Sheet1', index_col=None, na_values=["NA"])
```
With

```python
import pandas as pd
pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

- added top-level function `read_sql` that is equivalent to the following

```python
from pandas.io.sql import read_frame
read_frame(....)
```

- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument (GH3702)
- Do not allow astypes on `datetime64[ns]` except to `object`, and `timedelta64[ns]` to `object/int` (GH3425)
- The behavior of `datetime64` dtypes has changed with respect to certain so-called reduction operations (GH3726). The following operations now raise a `TypeError` when performed on a `Series` and return an `empty` Series when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of slice objects:
  - sum, prod, mean, std, var, skew, kurt, corr, and cov
- `read_html` now defaults to None when reading, and falls back on bs4 + html5lib when lxml fails to parse. a list of parsers to try until success is also valid
- The internal pandas class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the base class for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). (GH4090, GH4092)
- New `StringMixin` that, given a _unicode_ method, gets python 2 and python 3 compatible string methods (_str_, _bytes_, and _repr_). Plus string safety throughout. Now employed in many places throughout the pandas library. (GH4090, GH4092)

### 1.26.2 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

```python
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 0 a
1 1 b
2 2 c
```

(continues on next page)
Note that alist here is a Python list so pd.read_html() and DataFrame.to_html() are not inverses.

- pd.read_html() no longer performs hard conversion of date strings (GH3656).

**Warning:** You may have to install an older version of BeautifulSoup4, See the installation docs

- Added module for reading and writing Stata files: pandas.io.stata (GH1512) accessible via read_stata top-level function for reading, and to_stata DataFrame method for writing, See the docs
- Added module for reading and writing json format files: pandas.io.json accessible via read_json top-level function for reading, and to_json DataFrame method for writing, See the docs various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
- MultiIndex column support for reading and writing csv format files
  - The header option in read_csv now accepts a list of the rows from which to read the index.
  - The option, tupleize_cols can now be specified in both to_csv and read_csv, to provide compatibility for the pre 0.12 behavior of writing and reading MultiIndex columns via a list of tuples. The default in 0.12 is to write lists of tuples and not interpret list of tuples as a MultiIndex column.
  
  Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default to write and read MultiIndex columns will be in the new format. (GH3571, GH1651, GH3141)
  - If an index_col is not specified (e.g. you don’t have an index, or wrote it with df.to_csv(..., index=False), then any names on the columns index will be lost.

```python
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')
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_l0_g1,R0C0,R0C1,R0C2
R_l0_g1,R_l1_g0,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])
```

(continues on next page)
• 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

```python
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
    .... 0 1
    3 -0.626968 -0.875772
    4 -0.930687 -0.218983
    5 0.949965 -0.442354
    .... 0 1
    6 -0.402985 1.113358
    7 -0.241527 -0.670477
    8 0.049355 0.632633
    .... 0 1
    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

### 1.26.3 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  1.0
1   b  2.0
```
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]:
      0  1
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:

```python
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.

```python
In [33]: sf = Series([1, 1, 2, 3, 3, 3])
In [34]: sf.groupby(sf).filter(lambda x: x.sum() > 2)  
Out[34]:
      3
0  3
1  3
```

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('aabbbbc')})

In [36]:
dff.groupby('B').filter(lambda x: len(x) > 2)

Out[36]:
   A  B
0  2  b
1  3  b
2  4  b
3  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  2.0 b
3  3.0 b
4  4.0 b
5  5.0 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)

1.26.4 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

```python
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, Length: 5, dtype: object
```

### 1.26.5 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 yields a `Series` with either a single character at each index of the original `Series` or `NaN`. For example,

```python
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
Length: 4, dtype: object
0  o
dtype: object
0  o
1  o
2  o
3  l
Length: 4, dtype: object
0  NaN
1  w
```

(continues on next page)
The last element yielded by the iterator will be a `Series` containing the last element of the longest string in the `Series` with all other elements being `NaN`. Here since 'slow' is the longest string and there are no other strings with the same length 'w' is the only non-null string in the yielded `Series`.

- **HDFStore**
  - will retain index attributes (freq,tz,name) on recreation (GH3499)
  - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as data_columns (GH2852)

- **Non-unique index support clarified** (GH3468).
  - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
  - Fix construction of a DataFrame with a duplicate index
  - ref_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) (GH2194)
  - `applymap` on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
  - 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.

1.27 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*

### 1.27.1 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*.

### 1.27.2 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.
1.27.3 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.

```python
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 -1.203569
[8 rows x 1 columns]
In [3]: df1.dtypes
Out[3]:
       A
dtype: float32
Length: 1, 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  1
6  0.580566  1.378512  1
7 -0.965820  0.292502 255
[8 rows x 3 columns]
In [6]: df2.dtypes
Out[6]:
       A    B    C
dtype: float16    float64    uint8
Length: 3, dtype: object
# here you get some upcasting
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2
```

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In [8]: df3
Out[8]:
   A        B        C
0  1.984462 -0.038605  0.0
1  0.717812 -0.460478  1.0
2 -0.903737 -0.310458  0.0
3 -1.063011  0.866493 254.0
4 -0.495465  0.245972  0.0
5 -1.427497  0.319442  1.0
6  2.650092  1.378512  1.0
7 -2.169390  0.292502 255.0
[8 rows x 3 columns]

In [9]: df3.dtypes

... ...

Out[9]:
<class 'pandas.core.common.PandasObject'>

A float32
B float64
C float64

Length: 3, dtype: object

1.27.4 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  float32
B  float32
C  float32

Length: 3, 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  float32
B  float64
C  float64
D  float64
E  int64

Length: 5, 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
Length: 5, 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 NaT
2 NaT
3 NaT
4 2001-01-04
5 2001-01-05
Length: 6, dtype: datetime64[ns]

### 1.27.5 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([1,2],columns=['a']).dtypes
Out[21]:
a   int64
Length: 1, dtype: object

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

In [23]: DataFrame({'a' : 1 }, index=range(2)).dtypes
Out[23]:
a   int64
Length: 1, dtype: object
Keep in mind that `DataFrame(np.array([1,2]))` **WILL** result in `int32` on 32-bit platforms!

**Upcasting Gotchas**

Performing indexing operations on integer type data can easily upcast the data. The `dtype` of the input data will be preserved in cases where `nans` are not introduced.

```python
In [24]: dfi = df3.astype('int32')
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  1  1  1
2  0  0  0  1  1
3 -1  0  254 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
Length: 5, dtype: object
In [28]: casted = dfi[dfi>0]
In [29]: casted
Out[29]:
   A  B  C  D  E
0  1.0 NaN NaN 1  1
1 NaN  NaN  1.0 1  1
2 NaN  NaN  NaN 1  1
3 NaN NaN  254.0 1  1
4 NaN NaN  NaN 1  1
5 NaN NaN  1.0 1  1
6  2.0 1.0  1.0 1  1
7 NaN NaN  255.0 1  1
[8 rows x 5 columns]
In [30]: casted.dtypes
Out[30]:
A  float64
B  float64
C  float64
D  int64
E  int32
```

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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

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

In [35]: casted

Out[35]:
   A      B      C      D      E
0  1.98  NaN   NaN   1.0   1.0
1  0.72  NaN   NaN   1.0   1.0
2  NaN   NaN   NaN   1.0   1.0
3  NaN  0.87  254.0  1.0   1.0
4  NaN  0.25  NaN   1.0   1.0
5  NaN  0.32  1.0   1.0   1.0
6  2.65  1.38  255.0  1.0   1.0
7  NaN  0.29  NaN   1.0   1.0

[8 rows x 5 columns]

In [36]: casted.dtypes

A float32
B float64
C float64
D float16
E int32

1.27.6 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

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```python
Out[39]:
   A    B      timestamp
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
```python
In [40]: df.get_dtype_counts()

float64    2
datetime64[ns]    1
Length: 2, dtype: int64
```

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

```python
In [42]: df
Out[42]:
   A    B      timestamp
2001-01-02 1.023958  0.660103 2001-01-03
2001-01-03 1.236475 -2.170629 2001-01-03
2001-01-04 NaN   -1.685677 NaT
2001-01-05 NaN   -0.115070 NaT
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]
```

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

```python
In [43]: import datetime
```

```python
In [44]: s = Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])
```

```python
In [45]: s.dtype
Out[45]: dtype('<M8[ns]>
```

```python
In [46]: s[1] = np.nan
```

```python
In [47]: s
Out[47]:
0  2001-01-02
1  NaT
2  2001-01-02
Length: 3, dtype: datetime64[ns]
```

```python
In [48]: s.dtype
Out[48]: dtype('<M8[ns]>
```

```python
In [49]: s = s.astype('O')
```

(continues on next page)
1.27.7 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

1.27.8 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=lrange(5), B=lrange(5)))
In [53]: df.to_hdf('store.h5','table',append=True)
In [54]: read_hdf('store.h5', 'table', where = ['index>2'])
```

- provide dotted attribute access to get from stores, e.g. store.df == store['df']
- new keywords iterator=boolean, and chunksize=number in a chunk are provided to support iteration on select and select_as_multiple (GH3076)

- You can now select timestamps from an unordered timeseries similarly to an ordered timeseries (GH2437)
- You can now select with a string from a DataFrame with a datelike index, in a similar way to a Series (GH3070)
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
Freq: M, Length: 3, 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()

2001-01-02 0.425882
2001-01-03 -0.969649
2001-01-04 -0.218549
2001-01-05 0.907213
Freq: D, Name: B, Length: 4, dtype: float64

• `pd.io.data.Options`,

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Fix bug when trying to fetch data for the current month when already past expiry.

Now using lxml to scrape html instead of Beautiful Soup (lxml was faster).

New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply calls and puts. Also works for future expiry months and save the instance variable as callsMMYY or putsMMYY, where MMYY are, respectively, the month and year of the option’s expiry.

Options.get_near_stock_price now allows the user to specify the month for which to get relevant options data.

Options.get_forward_data now has optional kwargs near and above_below. This allows the user to specify if they would like to only return forward looking data for options near the current stock price. This just obtains the data from Options.get_near_stock_price instead of Options.get_xxx_data() (GH2758).

Cursor coordinate information is now displayed in time-series plots.

Added option display.max_seq_items to control the number of elements printed per sequence pprinting it. (GH2979)

Added option display.chop_threshold to control display of small numerical values. (GH2739)

Added option display.max_info_rows to prevent verbose_info from being calculated for frames above 1M rows (configurable). (GH2807, GH2918)

value_counts() now accepts a “normalize” argument, for normalized histograms. (GH2710).

DataFrame.from_records now accepts not only dicts but any instance of the collections.Mapping ABC.

Added option display.mpl_style providing a sleeker visual style for plots. Based on https://gist.github.com/huyng/816622 (GH3075).

Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)

to_html() now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes &, in addition to < and >. (GH2919)

See the full release notes or issue tracker on GitHub for a complete list.

1.28 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.

1.28.1 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
1.28.2 New features

- MySQL support for database (contribution from Dan Allan)

1.28.3 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.loc[df.index[4:6], 'string'] = np.nan
In [5]: df.loc[df.index[7:9], 'string'] = 'bar'
In [6]: df['string2'] = 'cool'
In [7]: df
Out[7]:
   A      B      C  string  string2
0  1.885  1.451  2.551   foo      cool
1  0.181 -1.117  0.061    nan      cool
2 -0.294 -0.591 -0.877    foo      cool
3  3.127  1.451  0.045    foo      cool
4 -0.243  1.196  1.533   NaN    NaN
5  0.820 -0.281  1.652   NaN    NaN
6  0.034  0.252 -0.499    foo      cool
7 -2.290 -1.601 -0.257   bar      cool
```

# on-disk operations
```
In [8]: store.append('df', df, data_columns=['B','C','string','string2'])
In [9]: store.select('df', "B>0 and string=='foo'")
Out[9]:
   A      B      C  string  string2
0  1.885  1.451  2.551   foo      cool
1  0.181 -1.117  0.061    nan      cool
```

# this is in-memory version of this type of selection
```
In [10]: df[(df.B > 0) & (df.string == 'foo')]
```

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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.loc[df_mixed.index[3:4], ['A','B']] = np.nan
In [14]: store.append('df_mixed', df_mixed)
In [15]: df_mixed1 = store.select('df_mixed')
In [16]: df_mixed1

Out[16]:
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   2001-01-02
4 2000-01-05 -0.242846 1.195819 1.533294    NaN      cool   2001-01-02
5 2000-01-06 0.820521 -0.281201 1.651561    NaN      cool   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()

float64   3
Object     2
datetime64[ns]  1
Length: 3, 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 NaN       NaN
4 2000-01-05 -0.242846 1.195819
5 2000-01-06 0.820521 -0.281201
6 2000-01-07 -0.034086 0.252394
7 2000-01-08 -2.290958 -1.601262

(continues on next page)
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]],
                 names=['foo', 'bar'])

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
two -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
two -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]

(continues on next page)
In [24]: store.select('mi', "foo='bar'")

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>bar</td>
<td>0.152288</td>
<td>-0.862613</td>
</tr>
<tr>
<td>two</td>
<td>-0.859278</td>
<td>1.498195</td>
</tr>
</tbody>
</table>

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['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

# individual tables were created
In [29]: store.select('df1_mt')

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.586924</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-0.102206</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.249874</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.616293</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.431163</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.800353</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.239198</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>-0.040863</td>
</tr>
</tbody>
</table>

In [30]: store.select('df2_mt')

<table>
<thead>
<tr>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>foo</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>-1.573998</td>
<td>0.630925</td>
<td>-0.071659</td>
<td>-1.277640</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>1.275280</td>
<td>-1.199212</td>
<td>1.060780</td>
<td>1.673018</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.710542</td>
<td>0.825392</td>
<td>1.557329</td>
<td>1.993441</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.132104</td>
<td>0.580923</td>
<td>-0.128750</td>
<td>1.445964</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.904578</td>
<td>-1.645852</td>
<td>-0.688741</td>
<td>0.228006</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.831767</td>
<td>0.228760</td>
<td>0.932498</td>
<td>-2.200069</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.540770</td>
<td>-0.370038</td>
<td>1.298390</td>
<td>1.662964</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>-0.096145</td>
<td>1.717830</td>
<td>-0.462446</td>
<td>-0.112019</td>
</tr>
</tbody>
</table>
[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]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>foo</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.249874</td>
<td>1.458210</td>
<td>-0.710542</td>
<td>1.557329</td>
<td>1.993441</td>
<td>bar</td>
<td></td>
</tr>
<tr>
<td>2000-01-03</td>
<td>2000-01-07</td>
<td>1.239198</td>
<td>0.185437</td>
<td>-0.540770</td>
<td>-0.370038</td>
<td>1.298390</td>
</tr>
</tbody>
</table>

[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 automagically create indicies 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 expect. 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.

1.29 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.

1.29.1 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
1.29.2 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
In [4]: df - df[0]
```

Change your code to

```
In [5]: df.sub(df[0], axis=0)  # align on axis 0 (rows)
```

(continues on next page)
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 `nfrequencies` are unaffected. The prior defaults were causing a great deal of confusion for users, especially resampling data to daily frequency (which labeled the aggregated group with the end of the interval: the next day).

```
In [1]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')
In [2]: series = Series(np.arange(len(dates)), index=dates)
In [3]: series
Out[3]:
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
2000-01-02 00:00:00    5
2000-01-02 04:00:00    6
2000-01-02 08:00:00    7
2000-01-02 12:00:00    8
2000-01-02 16:00:00    9
2000-01-03 00:00:00   10
2000-01-03 04:00:00   11
2000-01-03 08:00:00   12
2000-01-03 12:00:00   13
2000-01-03 16:00:00   14
2000-01-04 00:00:00   15
2000-01-04 04:00:00   16
2000-01-04 08:00:00   17
2000-01-04 12:00:00   18
2000-01-04 16:00:00   19
2000-01-05 00:00:00   20
Freq: 4H, dtype: int64

In [4]: series.resample('D', how='sum')
Out[4]:
2000-01-01     15
2000-01-02     51
2000-01-03     87
2000-01-04   123
2000-01-05     24
Freq: D, dtype: int64
```

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

```
In [6]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])
In [7]: pd.isnull(s)
Out[7]:
0   False
1   False
2   False
3   False
Length: 4, dtype: bool
In [8]: s.fillna(0)
Out[8]:
  0   1.500000
   1   inf
   2   3.400000
   3  -inf
Length: 4, dtype: float64
In [9]: pd.set_option('use_inf_as_null', True)
In [10]: pd.isnull(s)
Out[10]:
0   False
1   True
2   False
3   True
Length: 4, dtype: bool
In [11]: s.fillna(0)
Out[11]:
  0   1.5
   1   0.0
   2   3.4
   3   0.0
Length: 4, dtype: float64
In [12]: pd.reset_option('use_inf_as_null')
```

• Methods with the inplace option now all return None instead of the calling object. E.g. code written like df = df.fillna(0, inplace=True) may stop working. To fix, simply delete the unnecessary variable assignment.

• pandas.merge no longer sorts the group keys (sort=False) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnec-
• 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 \(X0, X1, \ldots\)) can be reproduced by specifying \(prefix = 'X'\):

```python
In [6]: data = 'a,b,c
1,Yes,2
3,No,4

In [7]: print(data)
a,b,c
1,Yes,2
3,No,4

In [8]: pd.read_csv(StringIO(data), header=None)
Out[8]:
   0  1  2
  0 a  b  c
  1  1  Yes  2
  2  3  No   4
[3 rows x 3 columns]

In [9]: pd.read_csv(StringIO(data), header=None, prefix='X')
Out[9]:
   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:

```python
In [10]: print(data)
a,b,c
1,Yes,2
3,No,4

In [11]: pd.read_csv(StringIO(data))
Out[11]:
   a  b  c
  0  1  Yes  2
  1  3   No  4
[2 rows x 3 columns]

In [12]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[12]:
   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.

1.29. v0.10.0 (December 17, 2012)
• Calling `fillna` on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

```
In [13]: s = Series([np.nan, 1., 2., np.nan, 4])
In [14]: s
Out[14]:
   0   NaN
   1   1.0
   2   2.0
   3   NaN
   4   4.0
Length: 5, dtype: float64
```

```
In [15]: s.fillna(0)
Out[15]:
   0   0.0
   1   1.0
   2   2.0
   3   0.0
   4   4.0
Length: 5, dtype: float64
```

```
In [16]: s.fillna(method='pad')
Out[16]:
   0   NaN
   1   1.0
   2   2.0
   3   2.0
   4   4.0
Length: 5, dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [17]: s.ffill()
Out[17]:
   0   NaN
   1   1.0
   2   2.0
   3   2.0
   4   4.0
Length: 5, 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 [18]: def f(x):
    ....:     return Series([ x, x**2 ], index = ['x', 'x^2'])
    ....:

In [19]: s = Series(np.random.rand(5))
In [20]: s
Out[20]:
   0  0.717478
   1  0.815199
```

(continues on next page)
In [21]: s.apply(f)

    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 [22]: get_option("display.max_rows")
Out[22]: 15

• to_string() methods now always return unicode strings (GH2224).

1.29.3 New features

1.29.4 Wide DataFrame Printing

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

In [23]: wide_frame = DataFrame(randn(5, 16))

In [24]: wide_frame

Out[24]:
     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  1.209871 -0.941235  0.863067 -0.336232 -0.976847  0.033862             ...
2  1.570114 -0.360875 -0.880096  0.235532             ... -1.
3  1.014601 -0.475108 -0.358944  1.262942             ... -1.
4  0.246392  0.965887  0.246354 -0.727728 -0.094414 -0.276854  0.158399 ...

(continues on next page)
The old behavior of printing out summary information can be achieved via the 'expand_frame_repr' print option:

```
In [25]: pd.set_option('expand_frame_repr', False)
In [26]: wide_frame
```

```
Out[26]:
        0       1       2       3       4       5       6       7
---     ---     ---     ---     ---     ---     ---     ---
     8  0.191356 -0.834179  0.703043  0.166568 -0.583599 -1.201796 -1.
242811 -0.941235  0.863067 -0.336232 -0.976847  0.033862
     1  0.441522 -0.316864 -0.017062  1.570114 -0.360875 -0.880096  0.235532  0.207232 -1.
    983857 -1.702547 -1.621234 -0.906840  1.014601 -0.475108 -0.358944  1.262942
     2 -0.412451 -0.462580  0.288403 -0.487393 -0.777639  0.055865  1.383381  0.
    085638  0.246392  0.965887  0.246354 -0.727728 -0.094414 -0.276854  0.158399
     3 -0.277255  1.331263  0.585174 -0.568825 -0.719412  1.191340 -0.456362  0.089931  0.
   776079  0.752889 -1.195795 -1.425911 -0.548829  0.774225  0.740501  1.510263
     4 -1.642511  0.432560  1.218080 -0.564705 -0.581790  0.286071  0.048725  1.002440  1.
  276582  0.054399  0.241963 -0.471786  0.314510 -0.094414 -0.276854  0.158399
```

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

```
In [27]: pd.set_option('line_width', 40)
```

```
OptionError: "No such keys(s): 'line_width'"
```
1.29.5 Updated PyTables Support

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

```
In [29]: store = HDFStore('store.h5')

In [30]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
                    columns=['A', 'B', 'C'])

In [31]: df
Out[31]:
          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  0.008380 -0.955697
2000-01-08 -0.898872 -0.725411  0.059904

[8 rows x 3 columns]
```

# appending data frames
```
In [32]: df1 = df[0:4]

In [33]: df2 = df[4:]

In [34]: store.append('df', df1)

In [35]: store.append('df', df2)

In [36]: store
Out[36]: <class 'pandas.io.pytables.HDFStore'>
```
File path: store.h5

# selecting the entire store
In [37]: store.select('df')

Out[37]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.369325</td>
<td>-1.502617</td>
<td>-0.376280</td>
</tr>
<tr>
<td>2</td>
<td>0.511936</td>
<td>-0.116412</td>
<td>-0.625256</td>
</tr>
<tr>
<td>3</td>
<td>-0.550627</td>
<td>1.261433</td>
<td>-0.552429</td>
</tr>
<tr>
<td>4</td>
<td>1.695803</td>
<td>-1.025917</td>
<td>-0.910942</td>
</tr>
<tr>
<td>5</td>
<td>0.426805</td>
<td>-0.131749</td>
<td>0.432600</td>
</tr>
<tr>
<td>6</td>
<td>0.044671</td>
<td>-0.341265</td>
<td>1.844536</td>
</tr>
<tr>
<td>7</td>
<td>-2.036047</td>
<td>0.000830</td>
<td>-0.955697</td>
</tr>
<tr>
<td>8</td>
<td>-0.898872</td>
<td>-0.725411</td>
<td>0.059904</td>
</tr>
</tbody>
</table>

[8 rows x 3 columns]

In [38]: 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 [39]: wp

Out[39]:
<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 [40]: store.append('wp', wp)

# selecting via A QUERY
In [41]: store.select('wp', "major_axis>20000102 and minor_axis=['A','B']")

Out[41]:
<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 [42]: store.remove('wp', "major_axis>20000103")

Out[42]:
8

In [43]: store.select('wp')

Out[43]:
<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 [44]: del store['df']

In [45]: store
Out[45]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

Enhancements

• added ability to hierarchical keys

In [46]: store.put('foo/bar/bah', df)

In [47]: store.append('food/orange', df)

In [48]: store.append('food/apple', df)

In [49]: store
Out[49]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# remove all nodes under this level
In [50]: store.remove('food')

In [51]: store
Out[51]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

• added mixed-dtype support!

In [52]: df['string'] = 'string'

In [53]: df['int'] = 1

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

In [55]: df1 = store.select('df')

In [56]: df1
Out[56]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>string</th>
<th>int</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>-0.369325</td>
<td>-1.502617</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.511936</td>
<td>-0.116412</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.550627</td>
<td>1.261433</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.695803</td>
<td>-1.025917</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.426805</td>
<td>-0.131749</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.044671</td>
<td>-0.341265</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-2.036047</td>
<td>0.000830</td>
<td>string</td>
<td>1</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>-0.898872</td>
<td>-0.725411</td>
<td>string</td>
<td>1</td>
</tr>
</tbody>
</table>

[8 rows x 5 columns]

In [57]: df1.get_dtypes_counts()
• performance improvements on table writing
• support for arbitrarily indexed dimensions
• SparseSeries now has a density property (GH2384)
• enable Series.str.strip/lstrip/rstrip methods to take an input argument to strip arbitrary characters (GH2411)
• implement value_vars in melt to limit values to certain columns and add melt to pandas namespace (GH2412)

Bug Fixes
• added Term method of specifying where conditions (GH1996).
• del store['df'] now call store.remove('df') for store deletion
• deleting of consecutive rows is much faster than before
• min_itemsize parameter can be specified in table creation to force a minimum size for indexing columns
  (the previous implementation would set the column size based on the first append)
• indexing support via create_table_index (requires PyTables >= 2.3) (GH698).
• appending on a store would fail if the table was not first created via put
• fixed issue with missing attributes after loading a pickled dataframe (GH2431)
• minor change to select and remove: require a table ONLY if where is also provided (and not None)

Compatibility
0.10 of HDFStore is backwards compatible for reading tables created in a prior version of pandas, however, query terms using the prior (undocumented) methodology are unsupported. You must read in the entire file and write it out using the new format to take advantage of the updates.

1.29.6 N Dimensional Panels (Experimental)

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

```
In [58]: 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'])
         ....:
In [59]: p4d
Out[59]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
```

(continues on next page)
See the full release notes or issue tracker on GitHub for a complete list.

1.30 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.

1.30.1 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)

```
In [2]: df = DataFrame(np.random.randint(0, 2, (6, 3)), columns=['A', 'B', 'C'])
In [3]: df.sort(['A', 'B'], ascending=[1, 0])
```

```
Out[3]:
    A   B   C
0  1   0   0
1  0   1   1
2  0   0   1
3  1   0   0
4  1   0   0
5  1   0   0
```

- **DataFrame.rank** now supports additional argument values for the na_option parameter so missing values can be assigned either the largest or the smallest rank (GH1508, GH2159)

```
In [1]: df = DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])
In [3]: df.rank()
```

```
Out[3]:
    A   B   C
0  3.0  1.0  3.0
1  1.0  3.0  2.0
2 NaN NaN NaN
3 NaN NaN NaN
4 NaN NaN NaN
5  2.0  2.0  1.0
```

```
In [4]: df.rank(na_option='top')
```

```
Out[4]:
    A   B   C
0  6.0  4.0  6.0
```
1 4.0 6.0 5.0  
2 2.0 2.0 2.0  
3 2.0 2.0 2.0  
4 2.0 2.0 2.0  
5 5.0 5.0 4.0  

[6 rows x 3 columns] 

In [5]: df.rank(na_option='bottom')

\[\begin{array}{ccc} 
A & B & C \\
0 & 3.0 & 1.0 & 3.0 \\
1 & 1.0 & 3.0 & 2.0 \\
2 & 5.0 & 5.0 & 5.0 \\
3 & 5.0 & 5.0 & 5.0 \\
4 & 5.0 & 5.0 & 5.0 \\
5 & 2.0 & 2.0 & 1.0 \\
\end{array}\] 

[6 rows x 3 columns] 

• DataFrame has new \texttt{where} and \texttt{mask} methods to select values according to a given boolean mask (GH2109, GH2151) 

DataFrame currently supports slicing via a boolean vector the same length as the DataFrame (inside the \texttt{[]}). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

In [6]: df = DataFrame(np.random.randn(5, 3), columns = ['A','B','C'])

In [7]: df

Out[7]: 
\begin{array}{ccc} 
A & B & C \\
0 & -1.101581 & -1.187831 & 0.630693 \\
1 & 2.369983 & 0.333769 & -0.870464 \\
2 & 1.118760 & -0.224382 & 0.642489 \\
3 & 0.961751 & -1.848369 & 0.440883 \\
4 & 1.235390 & 1.615529 & -0.303272 \\
\end{array} 

[5 rows x 3 columns] 

In [8]: df[df['A'] > 0]

\[\begin{array}{ccc} 
A & B & C \\
1 & 2.369983 & 0.333769 & -0.870464 \\
2 & 1.118760 & -0.224382 & 0.642489 \\
3 & 0.961751 & -1.848369 & 0.440883 \\
4 & 1.235390 & 1.615529 & -0.303272 \\
\end{array}\] 

[4 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 \texttt{NaN}. This is accomplished via the new method \texttt{DataFrame.where}. In addition, \texttt{where} takes an optional \texttt{other} argument for replacement.
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)

DataFrame.mask is the inverse boolean operation of where.
• Enable referencing of Excel columns by their column names (GH1936)

```
In [16]: xl = ExcelFile('data/test.xls')
In [17]: xl.parse('Sheet1', index_col=0, parse_dates=True, parse_cols='A:D')
```

```
Out[17]:
        A          B          C          D
2000-01-03  0.980269    3.685731    -0.364217   -1.159738
2000-01-04  1.047916    -0.041232   -0.161812     0.212549
2000-01-05  0.498581    0.731168    -0.537677     1.346270
2000-01-06  1.120202    1.567621     0.003641     1.675253
2000-01-07  0.487094    0.571455    -1.611639     0.103469
2000-01-11  0.157161    1.340307     1.195778    -1.097007
```

[7 rows x 4 columns]

• Added option to disable pandas-style tick locators and formatters using `series.plot(x_compat=True) or pandas.plot_params['x_compat'] = True` (GH2205)

• Existing TimeSeries methods `at_time` and `between_time` were added to DataFrame (GH2149)

• DataFrame.dot can now accept ndarrays (GH2042)

• DataFrame.drop now supports non-unique indexes (GH2101)

• Panel.shift now supports negative periods (GH2164)

• DataFrame now support unary ~ operator (GH2110)

### 1.30.2 API changes

• Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [1]: prng = period_range('2012Q1', periods=2, freq='Q')
In [2]: s = Series(np.random.randn(len(prng)), prng)
In [4]: s.resample('M')
```

```
Out[4]:
2012-01  -1.471992
2012-02 NaN
2012-03  NaN
2012-04  0.493593
```

(continues on next page)
• Period.end_time now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```python
In [18]: p = Period('2012')
In [19]: p.end_time
Out[19]: Timestamp('2012-12-31 23:59:59.999999999')
```

• File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

```python
In [20]: data = 'A,B,C
   :00001,001,5
   :00002,002,6'
In [21]: read_csv(StringIO(data), converters={'A': lambda x: x.strip()})
Out[21]:
   A  B  C
0  1  5
1  2  6
```

See the full release notes or issue tracker on GitHub for a complete list.

### 1.31 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.

#### 1.31.1 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)
1.31.2 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
Length: 3, dtype: int64
In [6]: s2 = Series(s1, index=['foo', 'bar', 'baz'])
In [7]: s2
Out[7]:
   foo  NaN
   bar  NaN
   baz  NaN
Length: 3, dtype: float64
```

- Deprecated day_of_year API removed from PeriodIndex, use dayofyear (GH1723)
- Don’t modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by HDFStore (GH1834, GH1824)
- Legacy cruft removed: pandas.stats.misc.quantileTS
- Use ISO8601 format for Period repr: monthly, daily, and on down (GH1776)
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) (GH1783)
- Setting parts of DataFrame/Panel using ix now aligns input Series/DataFrame (GH1630)
- first and last methods in GroupBy no longer drop non-numeric columns (GH1809)
• Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type `dict` no longer override default NAs unless `keep_default_na` is set to `false` explicitly (GH1657)

• `DataFrame.dot` will not do data alignment, and also work with `Series` (GH1915)

See the full release notes or issue tracker on GitHub for a complete list.

1.32 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.

1.32.1 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)

1.32.2 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

1.33 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.
1.33.1 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)

1.33.2 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.

1.33.3 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 scikit.timeseries matplotlib-based plotting code
- New `date_range`, `bdate_range`, and `period_range` factory functions
- Robust `freq`ency 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`

### 1.33.4 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 `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

### 1.33.5 New plotting methods

Series.plot now supports a `secondary_y` option:

```python
In [1]: plt.figure()
Out[1]: <Figure size 640x480 with 0 Axes>

In [2]: fx['FR'].plot(style='g')
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0x1c30ffb6a0>

In [3]: fx['IT'].plot(style='k--', secondary_y=True)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x1c30b2a710>
```

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, 'kde' is a new option:

```python
In [4]: s = Series(np.concatenate((np.random.randn(1000),
                          ...: np.random.randn(1000) * 0.5 + 3)))

In [5]: plt.figure()
Out[5]: <Figure size 640x480 with 0 Axes>

In [6]: s.hist(normed=True, alpha=0.2)
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2fb86780>

In [7]: s.plot(kind='kde')
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2fb86780>
```

See the plotting page for much more.

### 1.33.6 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.

### 1.33.7 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', freq='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 `astype(object)` method of `DatetimeIndex` produces an array of `Timestamp` objects:

```python
In [15]: stamp_array = rng.astype(object)
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')
In [17]: stamp_array[5]
----> Timestamp('2000-01-06 00:00:00', freq='D')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```python
In [18]: dt_array = rng.to_pydatetime()
In [19]: dt_array
Out[19]:
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),
```

(continues on next page)
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(['2000-01-01T00:00:00.000000000', '2000-01-02T00:00:00.000000000',
       '2000-01-03T00:00:00.000000000', '2000-01-04T00:00:00.000000000',
       '2000-01-05T00:00:00.000000000', '2000-01-06T00:00:00.000000000',
       '2000-01-07T00:00:00.000000000', '2000-01-08T00:00:00.000000000',
       '2000-01-09T00:00:00.000000000', '2000-01-10T00:00:00.000000000'], dtype='datetime64[ns]')
In [24]: converted = np.asarray(rng, dtype=object)
In [25]: converted[5]
Out[25]: 947116800000000000

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.

1.34 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.
1.34.1 New features

- New *fixed width file reader*, `read_fwf`
- New `scatter_matrix` function for making a scatter plot matrix

```python
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)
```

- Add `stacked` argument to Series and DataFrame's `plot` method for *stacked bar plots*.

```python
df.plot(kind='bar', 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

### 1.34.2 NA Boolean Comparison API Change

Reverted some changes to how NA values (represented typically as NaN or None) are handled in non-numeric Series:

```python
In [1]: series = Series(['Steve', np.nan, 'Joe'])

In [2]: series == 'Steve'
Out[2]:
0   True
1  False
```

(continues on next page)
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()]
Out[5]:
0   Steve
Length: 1, dtype: object
```

While propagating NA in comparisons may seem like the right behavior to some users (and you could argue on purely technical grounds that this is the right thing to do), the evaluation was made that propagating NA everywhere, including in numerical arrays, would cause a large amount of problems for users. Thus, a “practicality beats purity” approach was taken. This issue may be revisited at some point in the future.

### 1.34.3 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:

```
In [6]: df = DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
                   ...
                   'foo', 'bar', 'foo', 'foo'],
                   ...
                   'B' : ['one', 'one', 'two', 'three',
                   ...
                   'two', 'two', 'one', 'three'],
                   ...
                   'C' : np.random.randn(8), 'D' : np.random.randn(8))
...
In [7]: df
Out[7]:
     A      B            C            D
    0 foo    one -0.841015  0.459840
    1 bar    one  0.114219 -0.253040
    2 foo    two -0.405617 -0.261128
    3 bar    three 1.240678  0.406604
    4 foo    two -0.122828 -1.022256
    5 bar    two  1.525196 -0.882785
    6 foo    one  0.520047  1.793331
    7 foo    three 0.163834 -0.429688
[8 rows x 4 columns]
In [8]: grouped = df.groupby('A')['C']
In [9]: grouped.describe()
```

(continues on next page)
Out[9]:

<table>
<thead>
<tr>
<th></th>
<th>count</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3.0</td>
<td>0.960031</td>
<td>0.746181</td>
<td>0.114219</td>
<td>0.677448</td>
<td>1.240678</td>
<td>1.382937</td>
<td>1.525196</td>
</tr>
<tr>
<td>foo</td>
<td>5.0</td>
<td>-0.137116</td>
<td>0.522064</td>
<td>-0.841015</td>
<td>-0.405617</td>
<td>-0.122828</td>
<td>0.163834</td>
<td>0.520047</td>
</tr>
</tbody>
</table>

[2 rows x 8 columns]

In[10]: grouped.apply(lambda x: x.sort_values()[-2:]) # top 2 values

<table>
<thead>
<tr>
<th></th>
<th>count</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3</td>
<td>1.240678</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>foo</td>
<td>7</td>
<td>0.163834</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Name: C, Length: 4, dtype: float64

1.35 v.0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

1.35.1 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)

1.35.2 Performance improvements

- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Intercept __builtin__.sum in groupby (GH885)

1.36 v.0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.
1.36.1 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

1.36.2 Performance improvements

- Improve performance and memory usage of fillna on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame (GH87)

1.37 v.0.7.0 (February 9, 2012)

1.37.1 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  0.424980  0.115056  0.452000 -0.103829
std   0.898046  0.712034  0.867316  0.830197
min  -1.337024 -0.779344 -1.206466 -1.022360
25%  -0.000996 -0.344789 -0.120217 -0.744313
50%   0.860419  0.098422  0.540168 -0.387554
75%   1.094236  0.375137  1.076331  0.674952
max   1.207725  1.601703  1.663859  1.096187
```

(continues on next page)
• 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 MaskedArray to Series constructor (GH563)
• Add Panel item access via attributes and IPython completion (GH554)
• Implement DataFrame.lookup, fancy-indexing analogue for retrieving values given a sequence of row and column labels (GH338)
• Can pass a list of functions to aggregate with groupby on a DataFrame, yielding an aggregated result with hierarchical columns (GH166)
• Can call cummin and cummax on Series and DataFrame to get cumulative minimum and maximum, respectively (GH647)
• value_range added as utility function to get min and max of a dataframe (GH288)
• Added encoding argument to read_csv, read_table, to_csv and from_csv for non-ascii text (GH717)
• Added abs method to pandas objects
• Added crosstab function for easily computing frequency tables
• Added isin method to index objects
• Added level argument to xs method of DataFrame.

1.37.2 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    0.446246
   2   -0.500268
   4     0.814725
   6    -0.312744
   8    1.098892
  10    1.306330
  12   -0.366970
  14   -0.030890
  16    1.608095
  18   -0.023287
Length: 10, dtype: float64

In [5]: s[0]
Out[5]: 0.44624598505731339

In [6]: s[2]
Out[6]: -0.500268093241102

In [7]: s[4]
Out[7]: 0.8147247587659604

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
   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:
### Method Description

<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>

#### 1.37.3 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:

```
In [1]: s = Series(randn(6), index=list('gmkaec'))
In [2]: s
Out[2]:
g -1.182230
m -0.276183
k -0.243550
a 1.628992
e 0.073308
c -0.539890
dtype: float64
```

Then this is OK:

```
In [3]: s.ix['k':'e']
Out[3]:
k -0.243550
   a 1.628992
e 0.073308
dtype: float64
```

But this is not:

```
In [12]: s.ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the “range selection” would have been possible:

```
In [4]: s2 = s.sort_index()
In [5]: s2
Out[5]:
a 1.628992
c -0.539890
e 0.073308
g -1.182230
k -0.243550
m -0.276183
dtype: float64
In [6]: s2.ix['b':'h']
Out[6]:
c -0.539890
```

(continues on next page)
As as notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via [] (i.e. the __getitem__ and __setitem__ methods). The behavior will be the same as passing similar input to ix except in the case of integer indexing:

```
In [8]: s = Series(randn(6), index=list('acegkm'))

In [9]: s
Out[9]:
         a   -0.800734
          c   -0.229737
          e   -0.781940
         g    0.756053
         k    2.613373
         m   -0.159310
Length: 6, dtype: float64

In [10]: s[['m', 'a', 'c', 'e']]
         m   -0.159310
          a   -0.800734
          c   -0.229737
          e   -0.781940
Length: 4, dtype: float64

In [11]: s['b':'l']
         c   -0.229737
          e   -0.781940
         g    0.756053
         k    2.613373
Length: 4, dtype: float64

In [12]: s['c':'k']
         c   -0.229737
          e   -0.781940
         g    0.756053
         k    2.613373
Length: 4, dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing ndarray):

```
In [13]: s = Series(randn(6), index=range(0, 12, 2))

In [14]: s[[4, 0, 2]]
```

(continues on next page)
If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

### 1.37.5 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)

### 1.37.6 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)

### 1.38 v.0.6.1 (December 13, 2011)

#### 1.38.1 New features

• Can `append` single rows (as Series) to a DataFrame
• Add Spearman and Kendall rank `correlation` options to Series.corr and DataFrame.corr (GH428)
• `Added` `get_value` and `set_value` methods to Series, DataFrame, and Panel for very low-overhead access (>2x faster in many cases) to scalar elements (GH437, GH438). `set_value` is capable of producing an enlarged object.
• Add PyQt table widget to sandbox (GH435)
• DataFrame.align can `accept` `Series` arguments and an `axis` option (GH461)
• Implement new `SparseArray` and `SparseList` data structures. SparseSeries now derives from SparseArray (GH463)
• Better console printing options (GH453)
• Implement fast `data ranking` for Series and DataFrame, fast versions of scipy.stats.rankdata (GH428)
• Implement `DataFrame.from_items` alternate constructor (GH444)
• DataFrame.convert_objects method for inferring better dtypes for object columns (GH302)
• Add `rolling_corr_pairwise` function for computing Panel of correlation matrices (GH189)
• Add `margins` option to `pivot_table` for computing subgroup aggregates (GH114)
• Add `Series.from_csv` function (GH482)
• `Can pass` DataFrame/DataFrame and DataFrame/Series to `rolling_corr/rolling_cov` (GH #462)
• MultiIndex.get_level_values can `accept the level name`

#### 1.38.2 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)

### 1.39 v.0.6.0 (November 25, 2011)

#### 1.39.1 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)
1.39.2 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** Add `raw` option to `DataFrame.apply` for getting better performance when
- **VBENCH** Faster cythonized count by level in `Series` and `DataFrame` (GH341)
- **VBENCH**? Significant `GroupBy` performance enhancement with multiple keys with many “empty” combinations
- **VBENCH** New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by (GH355)
- **VBENCH** Significantly improved performance of `Series.order`, which also makes `np.unique` called on a `Series` faster (GH327)
- **VBENCH** Vastly improved performance of `GroupBy` on axes with a `MultiIndex` (GH299)

1.40 v.0.5.0 (October 24, 2011)

1.40.1 New Features

- **Added** `DataFrame.align` method with standard join options
- **Added** `parse_dates` option to `read_csv` and `read_table` methods to optionally try to parse dates in the index columns
- **Added** `nrows`, `chunksize`, and `iterator` arguments to `read_csv` and `read_table`. The last two return a new `TextParser` class capable of lazily iterating through chunks of a flat file (GH242)
- **Added** ability to join on multiple columns in `DataFrame.join` (GH214)
- **Added** private `_get_duplicates` function to `Index` for identifying duplicate values more easily (ENH5c)
- **Added** column attribute access to `DataFrame`
- **Added** Python tab completion hook for `DataFrame` columns. (GH233, GH230)
- **Implemented** `Series.describe` for `Series` containing objects (GH241)
- **Added** inner join option to `DataFrame.join` when joining on key(s) (GH248)
- **Implemented** selecting `DataFrame` columns by passing a list to `__getitem__` (GH253)
- **Implemented** `&` and `|` to intersect / union `Index` objects, respectively (GH261)
- **Added** `pivot_table` convenience function to pandas namespace (GH234)
- **Implemented** `Panel.rename_axis` function (GH243)
- `DataFrame` will show index level names in console output (GH334)
- **Implemented** `Panel.take`
- **Added** `set_eng_float_format` for alternate `DataFrame` floating point string formatting (ENH61)
• **Added** convenience `set_index` function for creating a DataFrame index from its existing columns

• **Implemented** `groupby` hierarchical index level name (GH223)

• **Added** support for different delimiters in `DataFrame.to_csv` (GH244)

• TODO: DOCS ABOUT TAKE METHODS

### 1.40.2 Performance Enhancements

• VBENCH Major performance improvements in file parsing functions `read_csv` and `read_table`

• VBENCH Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations

• VBENCH Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)

• VBENCH Improved speed of `DataFrame.xs` on mixed-type DataFrame objects by about 5x, regression from 0.3.0 (GH215)

• VBENCH With new `DataFrame.align` method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.

• VBENCH Significantly sped up conversion of nested dict into DataFrame (GH212)

• VBENCH Significantly speed up DataFrame `__repr__` and `count` on large mixed-type DataFrame objects

### 1.41 v.0.4.3 through v0.4.1 (September 25 - October 9, 2011)

#### 1.41.1 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)
1.41.2 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
CHAPTER TWO

INSTALLATION

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

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

2.1 Plan for dropping Python 2.7

The Python core team plans to stop supporting Python 2.7 on January 1st, 2020. In line with NumPy’s plans, all pandas releases through December 31, 2018 will support Python 2.

The final release before December 31, 2018 will be the last release to support Python 2. The released package will continue to be available on PyPI and through conda.

Starting January 1, 2019, all releases will be Python 3 only.

If there are people interested in continued support for Python 2.7 past December 31, 2018 (either backporting bugfixes or funding) please reach out to the maintainers on the issue tracker.

For more information, see the Python 3 statement and the Porting to Python 3 guide.

2.2 Python version support

Officially Python 2.7, 3.5, and 3.6.

2.3 Installing pandas

2.3.1 Installing with Anaconda

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

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

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

Installation instructions for Anaconda can be found here.
A full list of the packages available as part of the Anaconda distribution can be found here.

Another advantage to installing Anaconda is that you don’t need admin rights to install it. Anaconda can install in the user’s home directory, which makes it trivial to delete Anaconda if you decide (just delete that folder).

### 2.3.2 Installing with Miniconda

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

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

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

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

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

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

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

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

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

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

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.20.3
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full Anaconda distribution:

```
conda install anaconda
```

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

```
pip install django
```
2.3.3 Installing from PyPI

pandas can be installed via pip from PyPI.

```
pip install pandas
```

2.3.4 Installing with ActivePython

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

2.3.5 Installing using your Linux distribution’s package manager.

The commands in this table will install pandas for Python 3 from your distribution. To install pandas for Python 2, you may need to use the `python-pandas` package.

<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 python3-pandas</code></td>
</tr>
<tr>
<td>Debian &amp; Ubuntu</td>
<td>unstable</td>
<td>NeuroDebian</td>
<td><code>sudo apt-get install python3-pandas</code></td>
</tr>
<tr>
<td>Ubuntu</td>
<td>stable</td>
<td>official Ubuntu repository</td>
<td><code>sudo apt-get install python3-pandas</code></td>
</tr>
<tr>
<td>OpenSuse</td>
<td>stable</td>
<td>OpenSuse Repository</td>
<td><code>zypper in python3-pandas</code></td>
</tr>
<tr>
<td>Fedora</td>
<td>stable</td>
<td>official Fedora repository</td>
<td><code>dnf install python3-pandas</code></td>
</tr>
<tr>
<td>Centos/RHEL</td>
<td>stable</td>
<td>EPEL repository</td>
<td><code>yum install python3-pandas</code></td>
</tr>
</tbody>
</table>

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

2.3.6 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.

2.4 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 that you have all of the dependencies, soft and hard, installed), make sure you have `pytest` and run:

```
>>> import pandas as pd
>>> pd.test()
running: pytest --skip-slow --skip-network C:\Users\TP\Anaconda3\envs\py36\lib\site-packages\pandas
============================================================================= test session starts ===============... (continues on next page)
2.5 Dependencies

- setuptools: 24.2.0 or higher
- NumPy: 1.9.0 or higher
- python-dateutil: 2.5.0 or higher
- pytz

2.5.1 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 2.4.6 or higher.
- bottleneck: for accelerating certain types of nan evaluations. bottleneck uses specialized cython routines to achieve large speedups. If installed, must be Version 1.0.0 or higher.

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

2.5.2 Optional Dependencies

- Cython: Only necessary to build development version. Version 0.24 or higher.
- SciPy: miscellaneous statistical functions, Version 0.14.0 or higher
- xarray: pandas like handling for > 2 dims, needed for converting Panels to xarray objects. Version 0.7.0 or higher is recommended.
- PyTables: necessary for HDF5-based storage. Version 3.0.0 or higher required, Version 3.2.1 or higher highly recommended.
- Feather Format: necessary for feather-based storage, version 0.3.1 or higher.
- Apache Parquet, either pyarrow (>= 0.4.1) or fastparquet (>= 0.0.6) for parquet-based storage. The snappy and brotli are available for compression support.
- SQLAlchemy: for SQL database support. Version 0.8.1 or higher recommended. Besides SQLAlchemy, you also need a database specific driver. You can find an overview of supported drivers for each SQL dialect in the SQLAlchemy docs. Some common drivers are:
  - pycopg2: for PostgreSQL
- **pymysql**: for MySQL.
- **SQLite**: for SQLite, this is included in Python’s standard library by default.
- **matplotlib**: for plotting, Version 1.4.3 or higher.
- **For Excel I/O:**
  - `xlrd/xlwt`: Excel reading (`xlrd`) and writing (`xlwt`)
  - `openpyxl`: `openpyxl` version 2.4.0 for writing `.xlsx` files (`xlrd` >= 0.9.0)
  - `XlsxWriter`: Alternative Excel writer
- **Jinja2**: Template engine for conditional HTML formatting.
- **s3fs**: necessary for Amazon S3 access (`s3fs` >= 0.0.7).
- **blosc**: for msgpack compression using `blosc`
- One of `qtpy` (requires PyQt or PySide), `PyQt5`, `PyQt4`, `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.
- **pandas-gbq**: for Google BigQuery I/O.
- **Backports.lzma**: Only for Python 2, for writing to and/or reading from an xz compressed DataFrame in CSV; Python 3 support is built into the standard library.
- One of the following combinations of libraries is needed to use the top-level `read_html()` function:
  
  Changed in version 0.23.0.

**Note:** If using BeautifulSoup4 a minimum version of 4.2.1 is required

- **BeautifulSoup4 and html5lib** (Any recent version of `html5lib` is okay.)
- **BeautifulSoup4 and lxml**
- **BeautifulSoup4 and html5lib and lxml**
- Only `lxml`, although see `HTML Table Parsing` for reasons as to why you should probably **not** take this approach.

**Warning:**

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

**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 Anaconda, ActivePython (version 2.7 or 3.5), or Enthought Canopy may be worth considering.
CHAPTER
THREE

CONTRIBUTING TO PANDAS

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    * C (cpplint)
    * Python (PEP8)
    * Backwards Compatibility
  - Testing With Continuous Integration
  - Test-driven development/code writing
    * Writing tests
3.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements, and ideas are welcome.

If you are brand new to pandas or open-source development, we recommend going through the GitHub “issues” tab to find issues that interest you. There are a number of issues listed under Docs and good first issue where you could start out. Once you’ve found an interesting issue, you can return here to get your development environment setup.

Feel free to ask questions on the mailing list or on Gitter.

3.2 Bug reports and enhancement requests

Bug reports are an important part of making pandas more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. See this stackoverflow article and this blogpost for tips on writing a good bug report.

Trying the bug-producing code out on the master branch is often a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can format the code nicely by using GitHub Flavored Markdown:

```python
```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...
```

2. Include the full version string of pandas and its dependencies. You can use the built in function:
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 help keep the process straightforward and mostly trouble free. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on GitHub. To contribute you will need to sign up for a free GitHub account. We use Git for version control to allow many people to work together on the project.

Some great resources for learning Git:

- the GitHub help pages.
- the NumPy’s documentation.
- Matthew Brett’s Pydagogue.

#### 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 you can work seamlessly between 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 https://github.com/your-user-name/pandas.git pandas-yourname
$ cd pandas-yourname
$ git remote add upstream https://github.com/pandas-dev/pandas.git
```

This creates the directory pandas-yourname and connects your repository to the upstream (main project) pandas repository.

#### 3.3.4 Creating a development environment

To test out code changes, you’ll need to build pandas from source, which requires a C compiler and Python environment. If you’re making documentation changes, you can skip to Contributing to the documentation but you won’t be able to build the documentation locally before pushing your changes.
3.3.4.1 Installing a C Compiler

Pandas uses C extensions (mostly written using Cython) to speed up certain operations. To install pandas from source, you need to compile these C extensions, which means you need a C compiler. This process depends on which platform you’re using. Follow the CPython contributing guidelines for getting a compiler installed. You don’t need to do any of the ./configure or make steps; you only need to install the compiler.

For Windows developers, the following links may be helpful.

- https://cowboyprogrammer.org/building-python-wheels-for-windows/
- https://blog.ionelmc.ro/2014/12/21/compiling-python-extensions-on-windows/

Let us know if you have any difficulties by opening an issue or reaching out on Gitter.

3.3.4.2 Creating a Python Environment

Now that you have a C compiler, create an isolated pandas development environment:

- Install either Anaconda or miniconda
- Make sure your conda is up to date (conda update conda)
- Make sure that you have cloned the repository
- cd to the pandas source directory

We’ll now kick off a three-step process:

1. Install the build dependencies
2. Build and install pandas
3. Install the optional dependencies

```
# Create and activate the build environment
conda env create -f ci/environment-dev.yaml
conda activate pandas-dev

# or with older versions of Anaconda:
source activate pandas-dev

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e .

# Install the rest of the optional dependencies
conda install -c defaults -c conda-forge --file=ci/requirements-optional-conda.txt
```

At this point you should be able to import pandas from your locally built version:

```
$ python  # start an interpreter
>>> import pandas
>>> print(pandas.__version__)
0.22.0.dev0+29.g4ad6d4d74
```
This will create the new environment, and not touch any of your existing environments, nor any existing Python installation.

To view your environments:

```bash
conda info -e
```

To return to your root environment:

```bash
conda deactivate
```

See the full conda docs here.

### 3.3.4.3 Creating a Python Environment (pip)

If you aren’t using conda for you development environment, follow these instructions. You’ll need to have at least python3.5 installed on your system.

```bash
# Create a virtual environment
# Use an ENV_DIR of your choice. We’ll use ~/virtualenvs/pandas-dev
# Any parent directories should already exist
python3 -m venv ~/virtualenvs/pandas-dev
# Activate the virtualenv
. ~/virtualenvs/pandas-dev/bin/activate

# Install the build dependencies
python -m pip install -r ci/requirements_dev.txt
# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e .

# Install additional dependencies
python -m pip install -r ci/requirements-optional-pip.txt
```

### 3.3.5 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:

```bash
git branch shiny-new-feature
git checkout shiny-new-feature
```

The above can be simplified to:

```bash
git checkout -b shiny-new-feature
```

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to pandas. You can have many shiny-new-features and switch in between them using the git checkout command.

When creating this branch, make sure your master branch is up to date with the latest upstream master version. To update your local master branch, you can do:

```bash
git checkout master
git pull upstream master --ff-only
```
When you want to update the feature branch with changes in master after you created the branch, check the section on updating a PR.

## 3.4 Contributing to the documentation

Contributing to the documentation benefits everyone who uses pandas. We encourage you to help us improve the documentation, and you don’t have to be an expert on pandas to do so! In fact, there are sections of the docs that are worse off after being written by experts. If something in the docs doesn’t make sense to you, updating the relevant section after you figure it out is a great way to ensure it will help the next person.

### Documentation:

- About the pandas documentation
- How to build the pandas documentation
  - Requirements
  - Building the documentation
  - Building master branch documentation

### 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 a pandas convention, based on the Numpy Docstring Standard. Follow the pandas docstring guide for detailed instructions on how to write a correct docstring.

#### 3.4.1.1 pandas docstring guide

Note: Video tutorial: Pandas docstring guide by Frank Akogun.

### About docstrings and standards

A Python docstring is a string used to document a Python module, class, function or method, so programmers can understand what it does without having to read the details of the implementation.

Also, it is a common practice to generate online (html) documentation automatically from docstrings. Sphinx serves this purpose.
Next example gives an idea on how a docstring looks like:

```python
def add(num1, num2):
    """
    Add up two integer numbers.

    This function simply wraps the `+` operator, and does not
    do anything interesting, except for illustrating what is
    the docstring of a very simple function.

    Parameters
    ----------
    num1 : int
        First number to add
    num2 : int
        Second number to add

    Returns
    -------
    int
        The sum of `num1` and `num2`

    See Also
    --------
    subtract : Subtract one integer from another

    Examples
    --------
    >>> add(2, 2)
    4
    >>> add(25, 0)
    25
    >>> add(10, -10)
    0
    """
    return num1 + num2
```

Some standards exist about docstrings, so they are easier to read, and they can be exported to other formats such as html or pdf.

The first conventions every Python docstring should follow are defined in PEP-257.

As PEP-257 is quite open, and some other standards exist on top of it. In the case of pandas, the numpy docstring convention is followed. The conventions is explained in this document:

- numpydoc docstring guide (which is based in the original Guide to NumPy/SciPy documentation)

numpydoc is a Sphinx extension to support the numpy docstring convention.

The standard uses reStructuredText (reST). reStructuredText is a markup language that allows encoding styles in plain text files. Documentation about reStructuredText can be found in:

- Sphinx reStructuredText primer
- Quick reStructuredText reference
- Full reStructuredText specification

Pandas has some helpers for sharing docstrings between related classes, see Sharing Docstrings.

The rest of this document will summarize all the above guides, and will provide additional convention specific to the pandas project.
Writing a docstring

General rules

Docstrings must be defined with three double-quotes. No blank lines should be left before or after the docstring. The text starts in the next line after the opening quotes. The closing quotes have their own line (meaning that they are not at the end of the last sentence).

In rare occasions reST styles like bold text or italics will be used in docstrings, but it is common to have inline code, which is presented between backticks. It is considered inline code:

- The name of a parameter
- Python code, a module, function, built-in, type, literal... (e.g. os, list, numpy.abs, datetime.date, True)
- A pandas class (in the form :class:`pandas.Series`)
- A pandas method (in the form :meth:`pandas.Series.sum`)
- A pandas function (in the form :func:`pandas.to_datetime`)

Note: To display only the last component of the linked class, method or function, prefix it with ~. For example, :class:`~pandas.Series` will link to pandas.Series but only display the last part, Series as the link text. See Sphinx cross-referencing syntax for details.

Good:

```python
def add_values(arr):
    
    Add the values in `arr`.

    This is equivalent to Python `sum` of :meth:`pandas.Series.sum`.

    Some sections are omitted here for simplicity.

    return sum(arr)
```

Bad:

```python
def func():
    
    """Some function.

    With several mistakes in the docstring.

    It has a blank line after the signature `def func():`.

    The text 'Some function' should go in the line after the opening quotes of the docstring, not in the same line.

    There is a blank line between the docstring and the first line of code `foo = 1`.

    The closing quotes should be in the next line, not in this one.""

    foo = 1
```

(continues on next page)
Section 1: Short summary

The short summary is a single sentence that expresses what the function does in a concise way.

The short summary must start with a capital letter, end with a dot, and fit in a single line. It needs to express what the object does without providing details. For functions and methods, the short summary must start with an infinitive verb.

Good:

```python
def astype(dtype):
    """
    Cast Series type.
    
    This section will provide further details.
    """
    pass
```

Bad:

```python
def astype(dtype):
    """
    Casts Series type.
    
    Verb in third-person of the present simple, should be infinitive.
    """
    pass

def astype(dtype):
    """
    Method to cast Series type.
    
    Does not start with verb.
    """
    pass

def astype(dtype):
    """
    Cast Series type
    
    Missing dot at the end.
    """
    pass

def astype(dtype):
    """
    Cast Series type from its current type to the new type defined in the parameter dtype.
    
    Summary is too verbose and doesn't fit in a single line.
    """
    pass
```
Section 2: Extended summary

The extended summary provides details on what the function does. It should not go into the details of the parameters, or discuss implementation notes, which go in other sections.

A blank line is left between the short summary and the extended summary. And every paragraph in the extended summary is finished by a dot.

The extended summary should provide details on why the function is useful and their use cases, if it is not too generic.

```python
def unstack():
    """
    Pivot a row index to columns.
    
    When using a multi-index, a level can be pivoted so each value in
    the index becomes a column. This is especially useful when a subindex
    is repeated for the main index, and data is easier to visualize as a
    pivot table.
    
    The index level will be automatically removed from the index when added
    as columns.
    """
    pass
```

Section 3: Parameters

The details of the parameters will be added in this section. This section has the title “Parameters”, followed by a line with a hyphen under each letter of the word “Parameters”. A blank line is left before the section title, but not after, and not between the line with the word “Parameters” and the one with the hyphens.

After the title, each parameter in the signature must be documented, including *args and **kwargs, but not self.

The parameters are defined by their name, followed by a space, a colon, another space, and the type (or types). Note that the space between the name and the colon is important. Types are not defined for *args and **kwargs, but must be defined for all other parameters. After the parameter definition, it is required to have a line with the parameter description, which is indented, and can have multiple lines. The description must start with a capital letter, and finish with a dot.

For keyword arguments with a default value, the default will be listed after a comma at the end of the type. The exact form of the type in this case will be “int, default 0”. In some cases it may be useful to explain what the default argument means, which can be added after a comma “int, default -1, meaning all cpus”.

In cases where the default value is None, meaning that the value will not be used. Instead of “str, default None”, it is preferred to write “str, optional”. When None is a value being used, we will keep the form “str, default None”. For example, in df.to_csv(compression=None), None is not a value being used, but means that compression is optional, and no compression is being used if not provided. In this case we will use str, optional. Only in cases like func(value=None) and None is being used in the same way as 0 or foo would be used, then we will specify “str, int or None, default None”.

Good:

```python
class Series:
    def plot(self, kind, color='blue', **kwargs):
        """
        Generate a plot.
        """
```

(continues on next page)
Render the data in the Series as a matplotlib plot of the specified kind.

Parameters
----------
kind : str
    Kind of matplotlib plot.
color : str, default 'blue'
    Color name or rgb code.
**kwargs
    These parameters will be passed to the matplotlib plotting function.

Bad:

class Series:
    def plot(self, kind, **kwargs):
        """
        Generate a plot.
        Render the data in the Series as a matplotlib plot of the specified kind.
        Note the blank line between the parameters title and the first parameter. Also, note that after the name of the parameter `kind` and before the colon, a space is missing.
        Also, note that the parameter descriptions do not start with a capital letter, and do not finish with a dot.
        Finally, the `**kwargs` parameter is missing.
        Parameters
        ----------
        kind : str
            kind of matplotlib plot
        """
        pass

Parameter types

When specifying the parameter types, Python built-in data types can be used directly (the Python type is preferred to the more verbose string, integer, boolean, etc):

- int
- float
- str
- bool

For complex types, define the subtypes. For dict and tuple, as more than one type is present, we use the brackets to help read the type (curly brackets for dict and normal brackets for tuple):
- list of int
- dict of {str : int}
- tuple of (str, int, int)
- tuple of (str,)
- set of str

In case where there are just a set of values allowed, list them in curly brackets and separated by commas (followed by a space). If the values are ordinal and they have an order, list them in this order. Otherwise, list the default value first, if there is one:
- {0, 10, 25}
- {'simple', 'advanced'}
- {'low', 'medium', 'high'}
- {'cat', 'dog', 'bird'}

If the type is defined in a Python module, the module must be specified:
- datetime.date
- datetime.datetime
- decimal.Decimal

If the type is in a package, the module must be also specified:
- numpy.ndarray
- scipy.sparse.coo_matrix

If the type is a pandas type, also specify pandas except for Series and DataFrame:
- Series
- DataFrame
- pandas.Index
- pandas.Categorical
- pandas.SparseArray

If the exact type is not relevant, but must be compatible with a numpy array, array-like can be specified. If Any type that can be iterated is accepted, iterable can be used:
- array-like
- iterable

If more than one type is accepted, separate them by commas, except the last two types, that need to be separated by the word ‘or’:
- int or float
- float, decimal.Decimal or None
- str or list of str

If None is one of the accepted values, it always needs to be the last in the list.

For axis, the convention is to use something like:
- axis : {0 or 'index', 1 or 'columns', None}, default None
Section 4: Returns or Yields

If the method returns a value, it will be documented in this section. Also if the method yields its output.

The title of the section will be defined in the same way as the “Parameters”. With the names “Returns” or “Yields” followed by a line with as many hyphens as the letters in the preceding word.

The documentation of the return is also similar to the parameters. But in this case, no name will be provided, unless the method returns or yields more than one value (a tuple of values).

The types for “Returns” and “Yields” are the same as the ones for the “Parameters”. Also, the description must finish with a dot.

For example, with a single value:

```python
def sample():
    """
    Generate and return a random number.

    The value is sampled from a continuous uniform distribution between 0 and 1.
    
    Returns
    -------
    float
    Random number generated.
    """
    return random.random()
```

With more than one value:

```python
def random_letters():
    """
    Generate and return a sequence of random letters.

    The length of the returned string is also random, and is also returned.

    Returns
    -------
    length : int
        Length of the returned string.
    letters : str
        String of random letters.
    """
    length = random.randint(1, 10)
    letters = ''.join(random.choice(string.ascii_lowercase) 
                    for i in range(length))
    return length, letters
```

If the method yields its value:

```python
def sample_values():
    """
    Generate an infinite sequence of random numbers.

    The values are sampled from a continuous uniform distribution between 0 and 1.
    """
    for value in random_values():
        yield value
```

(continues on next page)
Section 5: See Also

This section is used to let users know about pandas functionality related to the one being documented. In rare cases, if no related methods or functions can be found at all, this section can be skipped.

An obvious example would be the `head()` and `tail()` methods. As `tail()` does the equivalent as `head()` but at the end of the `Series` or `DataFrame` instead of at the beginning, it is good to let the users know about it.

To give an intuition on what can be considered related, here there are some examples:

- `loc` and `iloc`, as they do the same, but in one case providing indices and in the other positions
- `max` and `min`, as they do the opposite
- `iterrows`, `itertuples` and `iteritems`, as it is easy that a user looking for the method to iterate over columns ends up in the method to iterate over rows, and vice-versa
- `fillna` and `dropna`, as both methods are used to handle missing values
- `read_csv` and `to_csv`, as they are complementary
- `merge` and `join`, as one is a generalization of the other
- `astype` and `pandas.to_datetime`, as users may be reading the documentation of `astype` to know how to cast as a date, and the way to do it is with `pandas.to_datetime`
- `where` is related to `numpy.where`, as its functionality is based on it

When deciding what is related, you should mainly use your common sense and think about what can be useful for the users reading the documentation, especially the less experienced ones.

When relating to other libraries (mainly `numpy`), use the name of the module first (not an alias like `np`). If the function is in a module which is not the main one, like `scipy.sparse`, list the full module (e.g. `scipy.sparse.coo_matrix`).

This section, as the previous, also has a header, “See Also” (note the capital S and A). Also followed by the line with hyphens, and preceded by a blank line.

After the header, we will add a line for each related method or function, followed by a space, a colon, another space, and a short description that illustrated what this method or function does, why is it relevant in this context, and what are the key differences between the documented function and the one referencing. The description must also finish with a dot.

Note that in “Returns” and “Yields”, the description is located in the following line than the type. But in this section it is located in the same line, with a colon in between. If the description does not fit in the same line, it can continue in the next ones, but it has to be indented in them.

For example:
Section 6: Notes

This is an optional section used for notes about the implementation of the algorithm. Or to document technical aspects of the function behavior.

Feel free to skip it, unless you are familiar with the implementation of the algorithm, or you discover some counter-intuitive behavior while writing the examples for the function.

This section follows the same format as the extended summary section.

Section 7: Examples

This is one of the most important sections of a docstring, even if it is placed in the last position. As often, people understand concepts better with examples, than with accurate explanations.

Examples in docstrings, besides illustrating the usage of the function or method, must be valid Python code, that in a deterministic way returns the presented output, and that can be copied and run by users.

They are presented as a session in the Python terminal. >>> is used to present code. ... is used for code continuing from the previous line. Output is presented immediately after the last line of code generating the output (no blank lines in between). Comments describing the examples can be added with blank lines before and after them.

The way to present examples is as follows:

1. Import required libraries (except numpy and pandas)
2. Create the data required for the example
3. Show a very basic example that gives an idea of the most common use case
4. Add examples with explanations that illustrate how the parameters can be used for extended functionality

A simple example could be:
class Series:
    def head(self, n=5):
        """
        Return the first elements of the Series.
        This function is mainly useful to preview the values of the
        Series without displaying the whole of it.
        Parameters
        ----------
        n : int
            Number of values to return.
        Return
        ------
        pandas.Series
            Subset of the original series with the n first values.
        See Also
        --------
        tail : Return the last n elements of the Series.
        Examples
        --------
        >>> s = pd.Series(['Ant', 'Bear', 'Cow', 'Dog', 'Falcon',
        ...                     'Lion', 'Monkey', 'Rabbit', 'Zebra'])
        >>> s.head()
        0   Ant
        1   Bear
        2    Cow
        3    Dog
        4  Falcon
dtype: object
        
        With the `n` parameter, we can change the number of returned rows:
        
        >>> s.head(n=3)
        0   Ant
        1   Bear
        2    Cow
dtype: object
        """
        return self.iloc[:n]

The examples should be as concise as possible. In cases where the complexity of the function requires long
examples, is recommended to use blocks with headers in bold. Use double star ** to make a text bold, like in
**this example**.

**Conventions for the examples**

Code in examples is assumed to always start with these two lines which are not shown:

```python
import numpy as np
import pandas as pd
```

Any other module used in the examples must be explicitly imported, one per line (as recommended in PEP-8)
and avoiding aliases. Avoid excessive imports, but if needed, imports from the standard library go first, followed by third-party libraries (like matplotlib).

When illustrating examples with a single Series use the name s, and if illustrating with a single DataFrame use the name df. For indices, idx is the preferred name. If a set of homogeneous Series or DataFrame is used, name them s1, s2, s3... or df1, df2, df3... If the data is not homogeneous, and more than one structure is needed, name them with something meaningful, for example df_main and df_to_join.

Data used in the example should be as compact as possible. The number of rows is recommended to be around 4, but make it a number that makes sense for the specific example. For example in the head method, it requires to be higher than 5, to show the example with the default values. If doing the mean, we could use something like [1, 2, 3], so it is easy to see that the value returned is the mean.

For more complex examples (grouping for example), avoid using data without interpretation, like a matrix of random numbers with columns A, B, C, D... And instead use a meaningful example, which makes it easier to understand the concept. Unless required by the example, use names of animals, to keep examples consistent. And numerical properties of them.

When calling the method, keywords arguments head(n=3) are preferred to positional arguments head(3).

Good:

```python
class Series:
    def mean(self):
        ""
        Compute the mean of the input.
        Examples
        --------
        >>> s = pd.Series([1, 2, 3])
        >>> s.mean()
        2
        ""
        pass

    deffillna(self, value):
        ""
        Replace missing values by 'value'.
        Examples
        --------
        >>> s = pd.Series([1, np.nan, 3])
        >>> s.fillna(0)
        [1, 0, 3]
        ""
        pass

    def groupby_mean(self):
        ""
        Group by index and return mean.
        Examples
        --------
        >>> s = pd.Series([380., 370., 24., 26],
        ... name='max_speed',
        ... index=['falcon', 'falcon', 'parrot', 'parrot'])
        >>> s.groupby_mean()
        index
```

(continues on next page)
falcon 375.0
parrot  25.0
Name: max_speed, dtype: float64


def contains(self, pattern, case_sensitive=True, na=numpy.nan):
    ""
    Return whether each value contains `pattern`.
    
    In this case, we are illustrating how to use sections, even if the example is simple enough and does not require them.
    
    Examples
    --------
    >>> s = pd.Series('Antelope', 'Lion', 'Zebra', numpy.nan)
    >>> s.contains(pattern='a')
    0   False
    1   False
    2    True
    3    NaN
    dtype: bool
    
    **Case sensitivity**
    
    With `case_sensitive` set to `False` we can match `a` with both `a` and `A`:
    
    >>> s.contains(pattern='a', case_sensitive=False)
    0    True
    1   False
    2    True
    3    NaN
    dtype: bool
    
    **Missing values**
    
    We can fill missing values in the output using the `na` parameter:
    
    >>> s.contains(pattern='a', na=False)
    0   False
    1   False
    2    True
    3    False
    dtype: bool
    ""
    pass

Bad:

def method(foo=None, bar=None):
    ""
    A sample DataFrame method.
    
    Do not import numpy and pandas.
    
    Try to use meaningful data, when it makes the example easier
to understand.

Try to avoid positional arguments like in `df.method(1)`. They can be all right if previously defined with a meaningful name, like in `present_value(interest_rate)`, but avoid them otherwise.

When presenting the behavior with different parameters, do not place all the calls one next to the other. Instead, add a short sentence explaining what the example shows.

Examples
--------

```python
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(numpy.random.randn(3, 3),
...                    columns=('a', 'b', 'c'))
>>> df.method(1)
21
>>> df.method(bar=14)
123
```  

pass

**Tips for getting your examples pass the doctests**

Getting the examples pass the doctests in the validation script can sometimes be tricky. Here are some attention points:

- Import all needed libraries (except for pandas and numpy, those are already imported as `import pandas as pd` and `import numpy as np`) and define all variables you use in the example.

- Try to avoid using random data. However random data might be OK in some cases, like if the function you are documenting deals with probability distributions, or if the amount of data needed to make the function result meaningful is too much, such that creating it manually is very cumbersome. In those cases, always use a fixed random seed to make the generated examples predictable. Example:

```python
>>> np.random.seed(42)
>>> df = pd.DataFrame({'normal': np.random.normal(100, 5, 20)})
```  

- If you have a code snippet that wraps multiple lines, you need to use ‘...’ on the continued lines:

```python
>>> df = pd.DataFrame(
...                   [[1, 2, 3], [4, 5, 6]],
...                   index=['a', 'b', 'c'],
...                   columns=['A', 'B'])
```  

- If you want to show a case where an exception is raised, you can do:

```python
>>> pd.to_datetime(['712-01-01'])
Traceback (most recent call last):
  OutOfBoundsDatetimError: Out of bounds nanosecond timestamp: 712-01-01 00:00:00
```

It is essential to include the “Traceback (most recent call last):”, but for the actual error only the error name is sufficient.

- If there is a small part of the result that can vary (e.g. a hash in an object representation), you can use ... to represent this part.
If you want to show that `s.plot()` returns a matplotlib AxesSubplot object, this will fail the doctest

```python
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at 0x7efd0c0b0690>
```

However, you can do (notice the comment that needs to be added)

```python
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at ...>
```

### Plots in examples

There are some methods in pandas returning plots. To render the plots generated by the examples in the documentation, the `.. plot::` directive exists.

To use it, place the next code after the “Examples” header as shown below. The plot will be generated automatically when building the documentation.

```python
class Series:
    def plot(self):
        """
        Generate a plot with the `Series` data.
        
        Examples
        --------
        
        .. plot::
            :context: close-figs
            >>> s = pd.Series([1, 2, 3])
            >>> s.plot()
        """
        pass
```

### Sharing Docstrings

Pandas has a system for sharing docstrings, with slight variations, between classes. This helps us keep docstrings consistent, while keeping things clear for the user reading. It comes at the cost of some complexity when writing.

Each shared docstring will have a base template with variables, like `%{klass}s`. The variables filled in later on using the `Substitution` decorator. Finally, docstrings can be appended to with the `Appender` decorator.

In this example, we’ll create a parent docstring normally (this is like `pandas.core.generic.NDFrame`). Then we’ll have two children (like `pandas.core.series.Series` and `pandas.core.frame.DataFrame`). We’ll substitute the children’s class names in this docstring.

```python
class Parent:
    def my_function(self):
        """Apply my function to %{klass}s."""
        ...

class ChildA(Parent):
    @Substitution(klass="ChildA")
    @Appender(Parent.my_function.__doc__)
    def my_function(self):
```

(continues on next page)
... 

```python
class ChildB(Parent):
    @Substitution(klass="ChildB")
    @Appender(Parent.my_function.__doc__)
    def my_function(self):
        ...
```

The resulting docstrings are

```python
>>> print(Parent.my_function.__doc__)
Apply my function to %klass%s.
>>> print(ChildA.my_function.__doc__)
Apply my function to ChildA.
>>> print(ChildB.my_function.__doc__)
Apply my function to ChildB.
```

Notice two things:

1. We “append” the parent docstring to the children docstrings, which are initially empty.
2. Python decorators are applied inside out. So the order is Append then Substitution, even though Substitution comes first in the file.

Our files will often contain a module-level `_shared_doc_kwargs` with some common substitution values (things like klass, axes, etc).

You can substitute and append in one shot with something like

```python
@Appender(template % _shared_doc_kwargs)
def my_function(self):
    ...
```

where `template` may come from a module-level `_shared_docs` dictionary mapping function names to docstrings. Wherever possible, we prefer using Appender and Substitution, since the docstring-writing processes is slightly closer to normal.

See `pandas.core.generic.NDFrame.fillna` for an example template, and `pandas.core.series.Series.fillna` and `pandas.core.generic.frame.fillna` for the filled versions.

- The tutorials make heavy use of the ipython directive sphinx extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

```python
.. ipython:: python
   :metadata:

   x = 2
   x**3
```

will be rendered as:

```
In [1]: x = 2
In [2]: x**3
Out[2]: 8
```

Almost all code examples in the docs are run (and the output saved) during the doc build. This approach means that code examples will always be up to date, but it does make the doc building a bit more complex.

3.4. Contributing to the documentation
Our API documentation in doc/source/api.rst houses the auto-generated documentation from the docstrings. For classes, there are a few subtleties around controlling which methods and attributes have pages auto-generated.

We have two autosummary templates for classes.

1. _templates/autosummary/class.rst. Use this when you want to automatically generate a page for every public method and attribute on the class. The Attributes and Methods sections will be automatically added to the class’ rendered documentation by numpydoc. See DataFrame for an example.

2. _templates/autosummary/class_without_autosummary. Use this when you want to pick a subset of methods / attributes to auto-generate pages for. When using this template, you should include an Attributes and Methods section in the class docstring. See CategoricalIndex for an example.

Every method should be included in a toctree in api.rst, else Sphinx will emit a warning.

**Note:** The .rst files are used to automatically generate Markdown and HTML versions of the docs. For this reason, please do not edit CONTRIBUTING.md directly, but instead make any changes to doc/source/contributing.rst. Then, to generate CONTRIBUTING.md, use pandoc with the following command:

```
pandoc doc/source/contributing.rst -t markdown_github > CONTRIBUTING.md
```

The utility script scripts/validate_docstrings.py can be used to get a csv summary of the API documentation. And also validate common errors in the docstring of a specific class, function or method. The summary also compares the list of methods documented in doc/source/api.rst (which is used to generate the API Reference page) and the actual public methods. This 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

#### 3.4.2.1 Requirements

First, you need to have a development environment to be able to build pandas (see the docs on creating a development environment above).

#### 3.4.2.2 Building the documentation

So how do you build the docs? Navigate to your local pandas/doc/ directory in the console and run:

```
python make.py html
```

Then you can find the HTML output in the folder pandas/doc/build/html/.

The first time you build the docs, it will take quite a while because it has to run all the code examples and build all the generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean
python make.py html
```

You can tell make.py to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes.
For comparison, a full documentation build may take 15 minutes, but a single section may take 15 seconds. Subsequent builds, which only process portions you have changed, will be faster.

You can also specify to use multiple cores to speed up the documentation build:

```
python make.py html --num-jobs 4
```

Open the following file in a web browser to see the full documentation you just built:

```
pandas/docs/build/html/index.html
```

And you’ll have the satisfaction of seeing your new and improved documentation!

### 3.4.2.3 Building master branch documentation

When pull requests are merged into the pandas master branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted here, see also the Continuous Integration section.

### 3.5 Contributing to the code base

**Code Base:**

- Code standards
  - C (cpplint)
  - Python (PEP8)
  - Backwards Compatibility
- Testing With Continuous Integration
- Test-driven development/code writing
  - Writing tests
  - Transitioning to pytest
  - Using pytest
- Running the test suite
- Running the performance test suite
3.5.1 Code standards

Writing good code is not just about what you write. It is also about how you write it. During Continuous Integration testing, several tools will be run to check your code for stylistic errors. Generating any warnings will cause the test to fail. Thus, good style is a requirement for submitting code to pandas.

In addition, because a lot of people use our library, it is important that we do not make sudden changes to the code that could have the potential to break a lot of user code as a result, that is, we need it to be as backwards compatible as possible to avoid mass breakages.

Additional standards are outlined on the code style wiki page.

3.5.1.1 C (cpplint)

pandas uses the Google standard. Google provides an open source style checker called cpplint, but we use a fork of it that can be found here. Here are some of the more common cpplint issues:

- we restrict line-length to 80 characters to promote readability
- every header file must include a header guard to avoid name collisions if re-included

Continuous Integration will run the cpplint tool and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```
 cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
          --build/include_subdir modified-c-file
```

You can also run this command on an entire directory if necessary:

```
 cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
          --build/include_subdir --recursive modified-c-directory
```

To make your commits compliant with this standard, you can install the ClangFormat tool, which can be downloaded here. To configure, in your home directory, run the following command:

```
 clang-format style=google -dump-config > .clang-format
```

Then modify the file to ensure that any indentation width parameters are at least four. Once configured, you can run the tool as follows:

```
 clang-format modified-c-file
```

This will output what your file will look like if the changes are made, and to apply them, run the following command:

```
 clang-format -i modified-c-file
```

To run the tool on an entire directory, you can run the following analogous commands:

```
 clang-format modified-c-directory/*.c modified-c-directory/*.h
 clang-format -i modified-c-directory/*.c modified-c-directory/*.h
```

Do note that this tool is best-effort, meaning that it will try to correct as many errors as possible, but it may not correct all of them. Thus, it is recommended that you run cpplint to double check and make any other style fixes manually.
3.5.1.2 Python (PEP8)

*pandas* uses the PEP8 standard. There are several tools to ensure you abide by this standard. Here are some of the more common PEP8 issues:

- we restrict line-length to 79 characters to promote readability
- passing arguments should have spaces after commas, e.g. `foo(arg1, arg2, kw1='bar')`

Continuous Integration will run the flake8 tool and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself on the diff:

```bash
git diff master -u -- "*.py" | flake8 --diff
```

This command will catch any stylistic errors in your changes specifically, but be beware it may not catch all of them. For example, if you delete the only usage of an imported function, it is stylistically incorrect to import an unused function. However, style-checking the diff will not catch this because the actual import is not part of the diff. Thus, for completeness, you should run this command, though it will take longer:

```bash
git diff master --name-only -- "*.py" | grep "pandas/" | xargs -r flake8
```

Note that on OSX, the `-r` flag is not available, so you have to omit it and run this slightly modified command:

```bash
git diff master --name-only -- "*.py" | grep "pandas/" | xargs flake8
```

Note that on Windows, these commands are unfortunately not possible because commands like `grep` and `xargs` are not available natively. To imitate the behavior with the commands above, you should run:

```bash
git diff master --name-only -- "*.py"
```

This will list all of the Python files that have been modified. The only ones that matter during linting are any whose directory filepath begins with “pandas.” For each filepath, copy and paste it after the flake8 command as shown below:

```
flake8 <python-filepath>
```

Alternatively, you can install the `grep` and `xargs` commands via the MinGW toolchain, and it will allow you to run the commands above.

3.5.1.3 Backwards Compatibility

Please try to maintain backward compatibility. *pandas* has lots of users with lots of existing code, so don’t break it if at all possible. If you think breakage is required, clearly state why as part of the pull request. Also, be careful when changing method signatures and add deprecation warnings where needed. Also, add the deprecated sphinx directive to the deprecated functions or methods.

If a function with the same arguments as the one being deprecated exist, you can use the `pandas.util._decorators.deprecate`:

```python
from pandas.util._decorators import deprecate
deprecate('old_func', 'new_func', '0.21.0')
```

Otherwise, you need to do it manually:

---

3.5. Contributing to the code base
```python
def old_func():
    """Summary of the function.

    .. deprecated:: 0.21.0
        Use new_func instead.
    """
    warnings.warn('Use new_func instead.', FutureWarning, stacklevel=2)
    new_func()
```

3.5.2 Testing With Continuous Integration

The **pandas** test suite will run automatically on **Travis-CI**, **Appveyor**, and **Circle CI** continuous integration services, once your pull request is submitted. However, if you wish to run the test suite on a branch prior to submitting the pull request, then the continuous integration services need to be hooked to your GitHub repository. Instructions are here for **Travis-CI**, **Appveyor**, and **CircleCI**.

A pull-request will be considered for merging when you have an all ‘green’ build. If any tests are failing, then you will get a red ‘X’, where you can click through to see the individual failed tests. This is an example of a green build.

Note: Each time you push to your fork, a new run of the tests will be triggered on the CI. Appveyor will auto-cancel any non-currently-running tests for that same pull-request. You can enable the auto-cancel feature for **Travis-CI** here and for **CircleCI** here.

3.5.3 Test-driven development/code writing

**pandas** is serious about testing and strongly encourages contributors to embrace **test-driven development (TDD)**. This development process “relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount
of code to pass that test.” So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to pandas. Therefore, it is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, pandas uses pytest and the convenient extensions in numpy.testing.

**Note:** The earliest supported pytest version is 3.1.0.

### 3.5.3.1 Writing tests

All tests should go into the tests subdirectory of the specific package. This folder contains many current examples of tests, and we suggest looking to these for inspiration. If your test requires working with files or network connectivity, there is more information on the testing page of the wiki.

The pandas.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)
```

### 3.5.3.2 Transitioning to pytest

pandas existing test structure is mostly classed based, meaning that you will typically find tests wrapped in a class.

```python
class TestReallyCoolFeature(object):
   ....
```

Going forward, we are moving to a more functional style using the pytest framework, which offers a richer testing framework that will facilitate testing and developing. Thus, instead of writing test classes, we will write test functions like this:

```python
def test_really_cool_feature():
   ....
```

---

**3.5. Contributing to the code base**
3.5.3.3 Using pytest

Here is an example of a self-contained set of tests that illustrate multiple features that we like to use.

• functional style: tests are like test_* and only take arguments that are either fixtures or parameters
• pytest.mark can be used to set metadata on test functions, e.g. skip or xfail.
• using parametrize: allow testing of multiple cases
• to set a mark on a parameter, pytest.param(..., marks=...) syntax should be used
• fixture, code for object construction, on a per-test basis
• using bare assert for scalars and truth-testing
• tm.assert_series_equal (and its counter part tm.assert_frame_equal), for pandas object comparisons.
• the typical pattern of constructing an expected and comparing versus the result

We would name this file test_cool_feature.py and put in an appropriate place in the pandas/tests/structure.

```python
import pytest
import numpy as np
import pandas as pd
from pandas.util import testing as tm

@ pytest.mark.parametrize('dtype', ['int8', 'int16', 'int32', 'int64'])
def test_dtypes(dtype):
    assert str(np.dtype(dtype)) == dtype

@ pytest.mark.parametrize('dtype', ['float32',
    pytest.param('int16', marks=pytest.mark.skip),
    pytest.param('int32',
        marks=pytest.mark.xfail(reason='to show how it works'))])
def test_mark(dtype):
    assert str(np.dtype(dtype)) == 'float32'

@ pytest.fixture
def series():
    return pd.Series([1, 2, 3])

@ pytest.fixture(params=['int8', 'int16', 'int32', 'int64'])
def dtype(request):
    return request.param

def test_series(series, dtype):
    result = series.astype(dtype)
    assert result.dtype == dtype
    expected = pd.Series([1, 2, 3], dtype=dtype)
    tm.assert_series_equal(result, expected)

A test run of this yields

((pandas) bash-3.2$ pytest test_cool_feature.py -v
================================== test session starts =================================
platform darwin -- Python 3.6.2, pytest-3.2.1, py-1.4.31, pluggy-0.4.0
collected 11 items
```

(continues on next page)
Tests that we have parametrized are now accessible via the test name, for example we could run these with `\(-k \text{int8}\)` to sub-select only those tests which match `\text{int8}`.

```bash
((pandas) bash-3.2$ pytest  test_cool_feature.py  -v  -k  int8
=========================== test session starts ===========================
platform darwin -- Python 3.6.2, pytest-3.2.1, py-1.4.31, pluggy-0.4.0
collected 11 items
test_cool_feature.py::test_dtypes[int8] PASSED
test_cool_feature.py::test_series[int8] PASSED
```

### 3.5.4 Running the test suite

The tests can then be run directly inside your Git clone (without having to install `pandas`) by typing:

```
pytest pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite.

The easiest way to do this is with:

```
pytest pandas/path/to/test.py  -k  regex_matching_test_name
```

Or with one of the following constructs:

```
pytest pandas/tests/[test-module].py
pytest pandas/tests/[test-module].py::[TestClass]
pytest pandas/tests/[test-module].py::[TestClass]::[test_method]
```

Using `pytest-xdist`, one can speed up local testing on multicore machines. To use this feature, you will need to install `pytest-xdist` via:

```
pip install pytest-xdist
```

Two scripts are provided to assist with this. These scripts distribute testing across 4 threads.

On Unix variants, one can type:

```
test_fast.sh
```

On Windows, one can type:

```
test_fast.bat
```
test_fast.bat

This can significantly reduce the time it takes to locally run tests before submitting a pull request.
For more, see the pytest documentation.

New in version 0.20.0.

Furthermore one can run

```python
pd.test()
```

with an imported pandas to run tests similarly.

### 3.5.5 Running the performance test suite

Performance matters and it is worth considering whether your code has introduced performance regressions. pandas is in the process of migrating to asv benchmarks to enable easy monitoring of the performance of critical pandas operations. These benchmarks are all found in the pandas/asv_bench directory. asv supports both python2 and python3.

To use all features of asv, you will need either conda or virtualenv. For more details please check the asv installation webpage.

To install asv:

```bash
pip install git+https://github.com/spacetelescope/asv
```

If you need to run a benchmark, change your directory to asv_bench/ and run:

```bash
asv continuous -f 1.1 upstream/master HEAD
```

You can replace HEAD with the name of the branch you are working on, and report benchmarks that changed by more than 10%. The command uses conda by default for creating the benchmark environments. If you want to use virtualenv instead, write:

```bash
asv continuous -f 1.1 -E virtualenv upstream/master HEAD
```

The `-E virtualenv` option should be added to all asv commands that run benchmarks. The default value is defined in asv.conf.json.

Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to paste only a subset of the results into the pull request to show that the committed changes do not cause unexpected performance regressions. You can run specific benchmarks using the `-b` flag, which takes a regular expression. For example, this will only run tests from a pandas/asv_bench/benchmarks/groupby.py file:

```bash
asv continuous -f 1.1 upstream/master HEAD -b ^groupby
```

If you want to only run a specific group of tests from a file, you can do it using . as a separator. For example:

```bash
asv continuous -f 1.1 upstream/master HEAD -b groupby.GroupByMethods
```

will only run the GroupByMethods benchmark defined in groupby.py.

You can also run the benchmark suite using the version of pandas already installed in your current Python environment. This can be useful if you do not have virtualenv or conda, or are using the setup.py develop approach discussed above; for the in-place build you need to set PYTHONPATH, e.g. `PYTHONPATH=$PWD/../` asv [remaining arguments]. You can run benchmarks using an existing Python environment by:
asv run -e -E existing

or, to use a specific Python interpreter:

asv run -e -E existing:python3.5

This will display stderr from the benchmarks, and use your local python that comes from your $PATH.

Information on how to write a benchmark and how to use asv can be found in the asv documentation.

3.5.6 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 :issue:`1234` where 1234 is the issue/pull request number).

If your code is an enhancement, it is most likely necessary to add usage examples to the existing documentation. This can be done following the section regarding documentation above. Further, to let users know when this feature was added, the versionadded directive is used. The sphinx syntax for that is:

.. versionadded:: 0.21.0

This will put the text New in version 0.21.0 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 pull request more readable.

Once you’ve made changes, you can see them by typing:

```
  git status
```

If you have created a new file, it is not being tracked by git. Add it by typing:

```
  git add path/to/file-to-be-added.py
```

Doing 'git status' again should give something like:

```
  # 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
The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using GH1234 or #1234. Either style is fine, but the former is generally preferred:

- a subject line with < 80 chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

### 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:

```
git push origin shiny-new-feature
```

Here `origin` is the default name given to your remote repository on GitHub. You can see the remote repositories:

```
git remote -v
```

If you added the upstream repository as described above you will see something like:

```
origin git@github.com:yourname/pandas.git (fetch)
origin git@github.com:yourname/pandas.git (push)
upstream git://github.com/pandas-dev/pandas.git (fetch)
upstream git://github.com/pandas-dev/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the `pandas` project. For that to happen, a pull request needs to be submitted on GitHub.

### 3.6.3 Review your code

When you’re ready to ask for a code review, file a pull request. Before you do, once again make sure that you have followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based on:

1. Navigate to your repository on GitHub – https://github.com/your-user-name/pandas
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 goes to the repository maintainers, and they will review the code.

3.6.5 Updating your pull request

Based on the review you get on your pull request, you will probably need to make some changes to the code. In that case, you can make them in your branch, add a new commit to that branch, push it to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push origin shiny-new-feature
```

This will automatically update your pull request with the latest code and restart the Continuous Integration tests.

Another reason you might need to update your pull request is to solve conflicts with changes that have been merged into the master branch since you opened your pull request.

To do this, you need to “merge upstream master” in your branch:

```
git checkout shiny-new-feature
git fetch upstream
git merge upstream/master
```

If there are no conflicts (or they could be fixed automatically), a file with a default commit message will open, and you can simply save and quit this file.

If there are merge conflicts, you need to solve those conflicts. See for example at https://help.github.com/articles/resolving-a-merge-conflict-using-the-command-line/ for an explanation on how to do this. Once the conflicts are merged and the files where the conflicts were solved are added, you can run git commit to save those fixes.

If you have uncommitted changes at the moment you want to update the branch with master, you will need to stash them prior to updating (see the stash docs). This will effectively store your changes and they can be reapplied after updating.

After the feature branch has been update locally, you can now update your pull request by pushing to the branch on GitHub:

```
git push origin shiny-new-feature
```

3.6.6 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 checkout master
```
git fetch upstream
git checkout master
git merge upstream/master

Then you can do:

```shell
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:

```shell
git push origin --delete shiny-new-feature
```
**pandas** is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the **Python** programming language.

**pandas** consists of the following elements:

- 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.).

### 4.1 Data Structures

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

**4.1.1 Why more than one data structure?**

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

Also, we would like sensible default behaviors for the common API functions which take into account the typical orientation of time series and cross-sectional data sets. When using ndarrays to store 2- and 3-dimensional data, a burden is placed on the user to consider the orientation of the data set when writing functions; axes are considered more or less equivalent (except when C- or Fortran-contiguousness matters for performance). In **pandas**, the axes are intended to lend more semantic meaning to the data; i.e., for a particular data set there is likely to be a “right” way to orient the data. The goal, then, is to reduce the amount of mental effort required to code up data transformations in downstream functions.
For example, with tabular data (DataFrame) it is more semantically helpful to think of the index (the rows) and the columns rather than axis 0 and axis 1. Iterating through the columns of the DataFrame thus results in more readable code:

```python
for col in df.columns:
    series = df[col]
    # do something with series
```

### 4.2 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 we like to favor immutability where sensible.

### 4.3 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.

### 4.4 Community

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

If you’re interested in contributing, please visit Contributing to pandas webpage.

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

### 4.5 Project Governance

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

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

### 4.6 Development Team

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

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

4.8 License

BSD 3-Clause License

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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:

```python
In [1]: import pandas as pd
In [2]: import numpy as np
In [3]: import matplotlib.pyplot as plt
```

### 5.1 Object Creation

See the *Data Structure Intro section*.

Creating a `Series` by passing a list of values, letting pandas create a default integer index:

```python
In [4]: s = pd.Series([1,3,5,np.nan,6,8])
In [5]: s
Out[5]:
   0  1.0
   1  3.0
   2  5.0
   3  NaN
   4  6.0
   5  8.0
dtypes: float64
```

Creating a `DataFrame` by passing a NumPy array, with a datetime index and labeled columns:

```python
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]:
```

(continues on next page)
Creating a DataFrame by passing a dict of objects that can be converted to series-like.

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'} )

In [11]: df2
Out[11]:
A    B       C     D    E      F
0  1.0 2013-01-02 1.0 3  test  foo
1  1.0 2013-01-02 1.0 3  train foo
2  1.0 2013-01-02 1.0 3  test  foo
3  1.0 2013-01-02 1.0 3  train foo

The columns of the resulting DataFrame have different dtypes.

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:

In [13]: df2.<TAB>
df2.A    df2.bool
df2.abs  df2.boxplot
df2.add  df2.C
df2.add_prefix  df2.clip
df2.add_suffix  df2.clip_lower
df2.align  df2.clip_upper
df2.all   df2.columns
df2.any   df2.combine
df2.append  df2.combine_first
df2.apply  df2.compound
df2.applymap  df2.consolidate
df2.D

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.
5.2 Viewing Data

See the Basics section.

Here is how to view the top and bottom rows of the frame:

```
In [14]: df.head()
Out[14]:
   A    B     C     D
2013-01-01 0.469112 -0.282863 -1.509059 -1.135632
2013-01-02 1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
```

```
In [15]: df.tail(3)
Out[15]:
   A    B     C     D
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
```

Display the index, columns, and the underlying NumPy data:

```
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')
```

```
In [17]: df.columns
Out[17]:
Index(['A', 'B', 'C', 'D'], dtype='object')
```

```
In [18]: df.values
Out[18]:
array([[ 0.469112, -0.282863, -1.509059, -1.135632],
       [ 1.212112, -0.173215,  0.119209, -1.044236],
       [-0.861849, -2.104569, -0.494929,  1.071804],
       [ 0.721555, -0.706771, -1.039575,  0.271860],
       [-0.424972,  0.567020,  0.276232, -1.087401],
       [-0.673690,  0.113648, -1.478427,  0.524988]])
```

`describe()` shows a quick statistic summary of your data:

```
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 -1.039696  0.271919
75%   0.658444  0.041933 -0.034326  0.461706
max   1.212112  0.567020  0.276232  1.071804
```
5.3 Selection

Note: While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, .at, .iat, .loc and .iloc.

See the indexing documentation Indexing and Selecting Data and MultiIndex / Advanced Indexing.

5.3.1 Getting

Selecting a single column, which yields a Series, equivalent to df.A:

In [23]: df['A']
Out[23]:
A  0.469112      1.212112      0.721555      -0.424972      -0.673690
B -0.282863     -0.173215     -2.104569     -0.706771       0.567020       0.113648
C -1.509059     0.119209     -0.494929     -1.039575       0.276232      -1.478427
D -1.135632    -1.044236      1.071804      0.271860      -1.087401       0.524988
(continues on next page)
Selecting via [], which slices the rows.

```python
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
```

### 5.3.2 Selection by Label

See more in Selection by Label.

For getting a cross section using a label:

```python
In [26]: df.loc[dates[0]]
Out[26]:
   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  0.567020   0.113648
2013-01-06  0.113648   0.567020
```

Selecting on a multi-axis by label:

```python
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  0.567020   0.113648
2013-01-06  0.113648   0.567020
```

Showing label slicing, both endpoints are included:

```python
In [28]: df.loc['20130102':'20130104',['A','B']]
Out[28]:
    A         B
2013-01-02  1.212112  -0.173215
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    B
2013-01-02  1.212112 -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 (equivalent to the prior method):

```
In [31]: df.at[dates[0], 'A']
Out[31]: 0.46911229990718628
```

### 5.3.3 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    B    C    D
2013-01-04  0.721555 -0.706771 -1.039575  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 -0.173215  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 (equivalent to the prior method):

```
In [38]: df.iat[1,1]
Out[38]:
-0.17321464905330858
```

### 5.3.4 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
2013-01-04  0.721555   -0.706771   -1.039575    0.271860
```

Selecting values from a DataFrame where a boolean condition is met.

```
In [40]: df[df > 0]
Out[40]:
   A          B          C          D
2013-01-01  0.469112         NaN         NaN         NaN
2013-01-02  1.212112         NaN    0.119209         NaN
2013-01-03         NaN         NaN    1.071804         NaN
2013-01-04  0.721555         NaN         NaN    0.271860
2013-01-05         NaN    0.567020    0.276232         NaN
2013-01-06         NaN    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
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 0.23.1

(continued from previous page)

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 -0.673690 0.113648 -1.478427 0.524988 three

In [44]: df2[df2['E'].isin(['two','four'])]

<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>0</td>
<td>2013-01-03</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
<td>1.071804</td>
</tr>
<tr>
<td>1</td>
<td>2013-01-05</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.276232</td>
<td>-1.087401</td>
</tr>
</tbody>
</table>

5.3.5 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]:
2013-01-02  1
2013-01-03  2
2013-01-04  3
2013-01-05  4
2013-01-06  5
2013-01-07  6
Freq: D, dtype: int64

In [47]: df['F'] = s1

Setting values by label:

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]:
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2013-01-01</td>
<td>0.000000</td>
<td>0.000000</td>
<td>-1.509059</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>2013-01-02</td>
<td>1.212112</td>
<td>-0.173215</td>
<td>0.119209</td>
<td>5.0</td>
</tr>
<tr>
<td>2</td>
<td>2013-01-03</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
<td>5.0</td>
</tr>
<tr>
<td>3</td>
<td>2013-01-04</td>
<td>0.721555</td>
<td>-0.706771</td>
<td>-1.039575</td>
<td>5.0</td>
</tr>
<tr>
<td>4</td>
<td>2013-01-05</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.276232</td>
<td>5.0</td>
</tr>
<tr>
<td>5</td>
<td>2013-01-06</td>
<td>-0.673690</td>
<td>0.113648</td>
<td>-1.478427</td>
<td>5.0</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]:
    A      B       C       D       F
--- --- -------- -------- --------
2013-01-01  0.000000  0.000000 -1.509059 -5  NaN
2013-01-02 -1.212112 -0.173215 -0.119209 -5 -1.0
2013-01-03 -0.861849 -2.104569 -0.494929 -5 -2.0
2013-01-04 -0.721555 -0.706771 -1.039575 -5 -3.0
2013-01-05 -0.424972 -0.567020 -0.276232 -5 -4.0
2013-01-06 -0.673690 -0.113648 -1.478427 -5 -5.0

5.4 Missing Data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the Missing Data section.

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])

In [56]: df1.loc[dates[0]:dates[1],'E'] = 1

In [57]: df1
Out [57]:
    A      B       C       D       F   E
--- --- -------- -------- -------- ---
2013-01-01  0.000000  0.000000 -1.509059  5  NaN  1.0
2013-01-02  1.212112 -0.173215  0.119209  5  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5  2.0  NaN
2013-01-04 -0.721555 -0.706771 -1.039575  5  3.0  NaN

To drop any rows that have missing data.

In [58]: df1.dropna(how='any')
Out [58]:
    A      B       C       D       F
--- --- -------- -------- -------- ---
2013-01-02  1.212112 -0.173215  0.119209  5  1.0  1.0

Filling missing data.

In [59]: df1.fillna(value=5)
Out [59]:
    A      B       C       D       F   E
--- --- -------- -------- -------- ---
2013-01-01  0.000000  0.000000 -1.509059  5  5.0  1.0
2013-01-02  1.212112 -0.173215  0.119209  5  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5  2.0  5.0
2013-01-04 -0.721555 -0.706771 -1.039575  5  3.0  5.0

To get the boolean mask where values are `nan`.

In [60]: pd.isna(df1)
Out [60]:
    A      B       C       D       F
--- --- -------- -------- -------- ---
(continues on next page)
5.5 Operations

See the Basic section on Binary Ops.

5.5.1 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   1.0
2013-01-04   3.0
2013-01-05   5.0
2013-01-06  NaN
Freq: D, dtype: float64
```

```
In [65]: df.sub(s, axis='index')
```

\(\text{(continues on next page)}\)
5.5.2 Apply

Applying functions to the data:

```
In [66]: df.apply(np.cumsum)
Out[66]:
     A       B       C       D   F
2013-01-01 0.000000 0.000000 -1.509059 5.0 NaN
2013-01-02 1.212112 -0.173215 -1.389850 10.0 1.0
2013-01-03 0.350263 -2.277784 -1.884779 15.0 3.0
2013-01-04 1.071818 -2.984555 -2.924354 20.0 6.0
2013-01-05 0.646846 -2.417535 -2.648122 25.0 10.0
2013-01-06 -0.026844 -2.303886 -4.126549 30.0 15.0
```

```
In [67]: df.apply(lambda x: x.max() - x.min())
    ...:
        A  2.073961
        B  2.671590
        C  1.785291
        D  0.000000
        F  4.000000

dtype: float64
```

5.5.3 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: int64
```

```
in [70]: s.value_counts()
```

(continues on next page)
5.5.4 String Methods

Series is equipped with a set of string processing methods in the \texttt{str} attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in \texttt{str} generally uses regular expressions by default (and in some cases always uses them). See more at \texttt{Vectorized String Methods}.

\begin{Verbatim}
\texttt{In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])}
\texttt{In [72]: s.str.lower()}
\texttt{Out[72]:}
\begin{verbatim}
 0    a
 1    b
 2    c
 3  aaba
 4  baca
 5   NaN
 6   caba
 7    dog
 8    cat
dtype: object
\end{verbatim}
\end{Verbatim}

5.6 Merge

5.6.1 Concat

\texttt{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 \texttt{Merging section}.

Concatenating \texttt{pandas} objects together with \texttt{concat()}:

\begin{Verbatim}
\texttt{In [73]: df = pd.DataFrame(np.random.randn(10, 4))}
\texttt{In [74]: df}
\texttt{Out[74]:}
\begin{verbatim}
   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
\end{verbatim}
\end{Verbatim}
# 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 0.254161 -1.143704 0.215897
8  1.193555 -0.077118 -0.408530 -0.862495
```

## 5.6.2 Join

SQL style merges. See the Database style joining section.

```
In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})
```

```
In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})
```

```
In [79]: left
Out[79]:
 key  lval
0  foo  1
1  foo  2
```

```
In [80]: right
                 
 key  rval
0  foo  4
1  foo  5
```

```
In [81]: pd.merge(left, right, on='key')
                 
 key  lval  rval
0  foo  1    4
1  foo  1    5
2  foo  2    4
3  foo  2    5
```

Another example that can be given is:

```
In [82]: left = pd.DataFrame({'key': ['foo', 'bar'], 'lval': [1, 2]})
```

```
In [83]: right = pd.DataFrame({'key': ['foo', 'bar'], 'rval': [4, 5]})
```

(continues on next page)
In [84]: left
Out[84]:
   key  lval
0  foo    1
1  bar    2

In [85]: right
   key  rval
0  foo    4
1  bar    5

In [86]: pd.merge(left, right, on='key')
   key  lval  rval
0  foo    1    4
1  bar    2    5

5.6.3 Append

Append rows to a dataframe. See the Appending section.

In [87]: df = pd.DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])

In [88]: df
Out[88]:
   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 [89]: s = df.iloc[3]

In [90]: df.append(s, ignore_index=True)
Out[90]:
   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  1.453749  1.208843 -0.080952 -0.264610
5.7 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.

```
In [91]: 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 [92]: df
Out[92]:
      A    B     C     D
0  foo  one  -1.2  -0.055
1  bar  one  -1.8  2.396
2  foo  two   1.0  1.553
3  bar  three -0.6  0.167
4  foo  two   1.4  0.048
5  bar  two  -0.4  -0.136
6  foo  one   0.0  -0.562
7  foo  three  1.9  -1.623
```

Grouping and then applying the `sum()` function to the resulting groups.

```
In [93]: df.groupby('A').sum()
Out[93]:
      C     D
A
bar  -2.8  2.426
foo   3.1  -0.639
```

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum` function.

```
In [94]: df.groupby(['A', 'B']).sum()
Out[94]:
      C     D
A B
bar one  -1.8  2.396
   three -0.6  0.167
   two  -0.4  -0.136
foo one  1.9  -1.623
   three  1.9  -1.623
   two   2.4  1.604
```

5.8 Reshaping

See the sections on **Hierarchical Indexing** and **Reshaping**.

5.7. Grouping
5.8.1 Stack

```
In [95]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
                           ....:            'foo', 'foo', 'qux', 'qux'],
                           ....:            ['one', 'two', 'one', 'two',
                           ....:            'one', 'two', 'one', 'two']]))

In [96]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [97]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [98]: df2 = df[:4]

In [99]: df2
Out[99]:
   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 [100]: stacked = df2.stack()

In [101]: stacked
Out[101]:
   first second
   bar  one  A   0.029399
           B  -0.542108
           two  A   0.282696
                   B  -0.087302
   baz  one  A  -1.575170
           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 [102]: stacked.unstack()
Out[102]:
   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

In [103]: stacked.unstack(1)
   → second  one  two
   → first
```

(continues on next page)
bar  A  0.029399  0.282696  
   B -0.542108 -0.087302  
baz  A -1.575170  0.816482  
   B  1.771208  1.100230  

In [104]: stacked.unstack(0)

\[
\begin{array}{ccc}
\text{first} & \text{bar} & \text{baz} \\
\text{second} & & \\
\text{one} & A & 0.029399 -1.575170 \\
& B & -0.542108  1.771208  \\
\text{two} & A & 0.282696  0.816482  \\
& B & -0.087302  1.100230  \\
\end{array}
\]

5.8.2 Pivot Tables

See the section on *Pivot Tables*.

In [105]: 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 [106]: df

Out[106]:

<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>0</td>
<td>one</td>
<td>A</td>
<td>foo</td>
<td>1.418757</td>
<td>-0.179666</td>
</tr>
<tr>
<td>1</td>
<td>one</td>
<td>B</td>
<td>foo</td>
<td>-1.879024</td>
<td>1.291836</td>
</tr>
<tr>
<td>2</td>
<td>two</td>
<td>C</td>
<td>foo</td>
<td>0.536826</td>
<td>-0.009614</td>
</tr>
<tr>
<td>3</td>
<td>three</td>
<td>A</td>
<td>bar</td>
<td>1.006160</td>
<td>0.392149</td>
</tr>
<tr>
<td>4</td>
<td>one</td>
<td>B</td>
<td>bar</td>
<td>-0.029716</td>
<td>0.264599</td>
</tr>
<tr>
<td>5</td>
<td>one</td>
<td>C</td>
<td>bar</td>
<td>-1.146178</td>
<td>-0.057409</td>
</tr>
<tr>
<td>6</td>
<td>two</td>
<td>A</td>
<td>foo</td>
<td>0.100900</td>
<td>-1.425638</td>
</tr>
<tr>
<td>7</td>
<td>three</td>
<td>B</td>
<td>foo</td>
<td>-1.035018</td>
<td>1.024098</td>
</tr>
<tr>
<td>8</td>
<td>one</td>
<td>C</td>
<td>foo</td>
<td>0.314665</td>
<td>-0.106062</td>
</tr>
<tr>
<td>9</td>
<td>one</td>
<td>A</td>
<td>bar</td>
<td>-0.773723</td>
<td>1.824375</td>
</tr>
<tr>
<td>10</td>
<td>two</td>
<td>B</td>
<td>bar</td>
<td>-1.170653</td>
<td>0.595974</td>
</tr>
<tr>
<td>11</td>
<td>three</td>
<td>C</td>
<td>bar</td>
<td>0.648740</td>
<td>1.167115</td>
</tr>
</tbody>
</table>

We can produce pivot tables from this data very easily:

In [107]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])

Out[107]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>foo</th>
<th>bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>A</td>
<td>-0.773723</td>
<td>1.418757</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>-0.029716</td>
<td>-1.879024</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>-1.146178</td>
<td>0.314665</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td>three</td>
<td>A</td>
<td>1.006160</td>
<td>NaN</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>NaN</td>
<td>-1.035018</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.648740</td>
<td>NaN</td>
<td>NaN</td>
<td></td>
</tr>
<tr>
<td>two</td>
<td>A</td>
<td>NaN</td>
<td>NaN</td>
<td>0.100900</td>
<td></td>
</tr>
</tbody>
</table>

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5.9 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 [108]: rng = pd.date_range('1/1/2012', periods=100, freq='S')

In [109]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [110]: ts.resample('5Min').sum()
Out[110]:
2012-01-01  25083
Freq: 5T, dtype: int64

Time zone representation:

In [111]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')

In [112]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [113]: ts
Out[113]:
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 [114]: ts_utc = ts.tz_localize('UTC')

In [115]: ts_utc
Out[115]:
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 to another time zone:

In [116]: ts_utc.tz_convert('US/Eastern')
Out[116]:
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:

```
In [117]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
In [118]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
In [119]: ts
Out[119]:
2012-01-31 -1.134623
2012-02-29 -1.561819
2012-03-31 -0.260838
2012-04-30  0.281957
2012-05-31  1.523962
Freq: M, dtype: float64
In [120]: ps = ts.to_period()
In [121]: ps
Out[121]:
2012-01 -1.134623
2012-02 -1.561819
2012-03 -0.260838
2012-04  0.281957
2012-05  1.523962
Freq: M, dtype: float64
In [122]: ps.to_timestamp()
Out[122]:
2012-01-01 -1.134623
2012-02-01 -1.561819
2012-03-01 -0.260838
2012-04-01  0.281957
2012-05-01  1.523962
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 [123]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
In [124]: ts = pd.Series(np.random.randn(len(prng)), prng)
In [125]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
In [126]: ts.head()
Out[126]:
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
```
5.10 Categoricals

pandas can include categorical data in a DataFrame. For full docs, see the categorical introduction and the API documentation.

In [127]: 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 [128]: df["grade"] = df["raw_grade"].astype("category")

In [129]: df["grade"]
Out[129]:
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 [130]: 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 by default).

In [131]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"])  

In [132]: df["grade"]
Out[132]:
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 [133]: df.sort_values(by="grade")
Out[133]:
   id  raw_grade grade
5   6    e    very bad
1   2     b      good
2   3     b      good
0   1    a    very good
3   4    a    very good
4   5    a    very good

Grouping by a categorical column also shows empty categories.
5.11 Plotting

See the Plotting docs.

```python
In [135]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
In [136]: ts = ts.cumsum()
In [137]: ts.plot()
Out[137]: <matplotlib.axes._subplots.AxesSubplot at 0x115bf6668>
```

On a DataFrame, the `plot()` method is a convenience to plot all of the columns with labels:
5.12 Getting Data In/Out

5.12.1 CSV

Writing to a csv file.

In [141]: df.to_csv('foo.csv')

Reading from a csv file.

In [142]: pd.read_csv('foo.csv')
Out[142]:
   Unnamed: 0   A   B   C   D
0          0 -18 -20 -20 -20
5.12.2 HDF5

Reading and writing to *HDFStores*.

Writing to a HDF5 Store.

\textbf{In [143]:} df.to_hdf('foo.h5', 'df')

Reading from a HDF5 Store.

\textbf{In [144]:} pd.read_hdf('foo.h5', 'df')

\textbf{Out [144]:}

\begin{tabular}{cccc}
  A & B & C & D \\
  0.266457 & -0.399641 & -0.219582 & 1.186860 \\
  -1.170732 & -0.345873 & 1.653061 & -0.282953 \\
  -1.734933 & 0.530468 & 2.060811 & -0.515536 \\
  -1.555121 & 1.452620 & 0.239859 & -1.156896 \\
  0.578117 & 0.511371 & 0.103552 & -2.428202 \\
  0.478344 & 0.449933 & -0.741620 & -1.962409 \\
  1.235339 & -0.091757 & -1.543861 & -1.084753 \\
  ... & ... & ... & ... \\
  -10.390377 & -8.727491 & -6.399645 & 30.914107 \\
  -8.985362 & -8.485624 & -4.669462 & 31.367740 \\
  -10.216020 & -9.480682 & -3.933802 & 29.758560 \\
  -11.856774 & -10.671012 & -3.216025 & 29.369368 \\
\end{tabular}

\textbf{[1000 rows x 4 columns]}

5.12.3 Excel

Reading and writing to *MS Excel*.

Writing to an excel file.
In [145]: df.to_excel('foo.xlsx', sheet_name='Sheet1')

Reading from an excel file.

In [146]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
Out[146]:
     A      B      C      D
2000-01-01  0.266457 -0.399641 -0.219582  1.186860
2000-01-02  1.170732  0.345873  1.653061 -0.282953
2000-01-03  1.734933  0.530468  2.060811 -0.515536
2000-01-04  1.555121  1.452620  0.239859 -1.156896
2000-01-05  0.578117  0.511371  0.103552 -2.428202
2000-01-06  0.478344  0.449933 -0.741620 -1.962409
2000-01-07  1.235339 -0.091757 -1.543861 -1.084753
     ...    ...    ...    ...
2002-09-21 -10.390377 -8.727491 -6.399645  30.914107
2002-09-22 -8.985362  8.485624 -4.669462  31.367740
2002-09-23  9.558560  8.781216 -4.499815  30.518439
2002-09-25 -10.216020  9.480682 -3.933802  29.758560
2002-09-26  11.856774  10.671012 -3.216025  29.369368
[1000 rows x 4 columns]

5.13 Gotchas

If you are attempting to perform an operation you might see an exception like:

>>> 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.

6.1 Internal Guides

pandas’ own 10 Minutes to pandas.
More complex recipes are in the Cookbook.
A handy pandas cheat sheet.

6.2 pandas Cookbook

The goal of this 2015 cookbook (by Julia Evans) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that entails.

Here are links to the v0.2 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.
• Chapter 9: Reading data from SQL databases.
6.3 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

6.4 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

6.5 Exercises for new users

Practice your skills with real data sets and exercises. For more resources, please visit the main repository.

• 01 - Getting & Knowing Your Data
• 02 - Filtering & Sorting
• 03 - Grouping
• 04 - Apply
• 05 - Merge
• 06 - Stats
• 07 - Visualization
• 08 - Creating Series and DataFrames
6.6 Modern pandas

Tutorial series written in 2016 by Tom Augspurger. The source may be found in the GitHub repository TomAugspurger/effective-pandas.

- Modern Pandas
- Method Chaining
- Indexes
- Performance
- Tidy Data
- Visualization
- Timeseries

6.7 Excel charts with pandas, vincent and xlsxwriter

- Using Pandas and XlsxWriter to create Excel charts

6.8 Video Tutorials

- Pandas: .head() to .tail() (2016) (1:26) GitHub repo

6.9 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
- Pandas DataFrames Tutorial, by Karlijn Willems
- A concise tutorial with real life examples
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 Stack Overflow and GitHub links. Many of the links contain expanded information, above what the in-line examples offer.

Pandas (pd) and Numpy (np) are the only two abbreviated imported modules. The rest are kept explicitly imported for newer users.

These examples are written for Python 3. Minor tweaks might be necessary for earlier python versions.

### 7.1 Idioms

These are some neat pandas idioms

if-then/if-then-else on one column, and assignment to another one or more columns:

```python
In [1]: df = pd.DataFrame(
       ...:     {'AAA': [4, 5, 6, 7], 'BBB': [10, 20, 30, 40], 'CCC': [100, 50, -30, -50]}); df
       ...
Out[1]:
       AAA  BBB  CCC
       0     4    10  100
       1     5    20   50
       2     6    30  -30
       3     7    40  -50

7.1.1 if-then...

An if-then on one column

```python
In [2]: df.loc[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:

```python
In [3]: df.loc[df.AAA >= 5, ['BBB', 'CCC']] = [-1, -2]; df
```  

```
Out[3]:
      AAA  BBB  CCC
     0     4    10  100
     1     5    -1   50
     2     6    -1  -30
     3     7    -1  -50
```
In [3]: df.loc[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.loc[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

7.1.2 Splitting

Split a frame with a boolean criterion
7.1.3 Building Criteria

Select with multi-column criteria

```
In [12]: df = pd.DataFrame(
    ....:     {'AAA': [4, 5, 6, 7], 'BBB': [10, 20, 30, 40], 'CCC': [100, 50, -30, -50]}); df
    ....:
Out[12]:
   AAA  BBB  CCC
0   4    10  100
1   5     20   50
2   6    30  -30
3   7    40  -50
```

... and (without assignment returns a Series)

```
In [13]: newseries = df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']; newseries
Out[13]:
0    4
1    5
Name: AAA, dtype: int64
```

... or (without assignment returns a Series)

```
In [14]: newseries = df.loc[(df['BBB'] > 25) | (df['CCC'] >= -40), 'AAA']; newseries;
```

... or (with assignment modifies the DataFrame.)

```
In [15]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA'] = 0.1; df
Out[15]:
   AAA  BBB  CCC
0   0.1   10  100
```

(continues on next page)
Select rows with data closest to certain value using argsort

```python
In [16]: df = pd.DataFrame(
    ....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
    ....:
Out[16]:
     AAA  BBB  CCC
0     4    10  100
1     5    20   50
2     6    30   -30
3     7    40   -50
```

```python
In [17]: aValue = 43.0
```

```python
In [18]: df.loc[(df.CCC-aValue).abs().argsort()]
Out[18]:
     AAA  BBB  CCC
1     5    20   50
0     4    10  100
2     6    30   -30
3     7    40   -50
```

Dynamically reduce a list of criteria using a binary operators

```python
In [19]: df = pd.DataFrame(
    ....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
    ....:
Out[19]:
     AAA  BBB  CCC
0     4    10  100
1     5    20   50
2     6    30   -30
3     7    40   -50
```

```python
In [20]: Crit1 = df.AAA <= 5.5
```

```python
In [21]: Crit2 = df.BBB == 10.0
```

```python
In [22]: Crit3 = df.CCC > -40.0
```

One could hard code:

```python
In [23]: AllCrit = Crit1 & Crit2 & Crit3
```

... Or it can be done with a list of dynamically built criteria

```python
In [24]: CritList = [Crit1,Crit2,Crit3]
```

```python
In [25]: AllCrit = functools.reduce(lambda x,y: x & y, CritList)
```

```python
In [26]: df[AllCrit]
Out[26]:
```

(continues on next page)
7.2 Selection

7.2.1 DataFrames

The indexing docs.

Using both row labels and value conditionals

```python
In [27]: df = pd.DataFrame(
            ....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}); df
            ....:
Out[27]:
    AAA  BBB  CCC
0    4    10  100
1    5    20   50
2    6    30  -30
3    7    40  -50

In [28]: df[(df.AAA <= 6) & (df.index.isin([0,2,4]))]
      \             \         \             
    AAA  BBB  CCC
0    4    10  100
2    6    30  -30

Use loc for label-oriented slicing and iloc positional slicing

```python
In [29]: data = {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}
In [30]: df = pd.DataFrame(data=data,index=['foo','bar','boo','kar']); df
Out[30]:
    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)

```python
In [31]: df.loc['bar':'kar'] #Label
Out[31]:
    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.

Using inverse operator (~) to take the complement of a mask
7.2.2 Panels

Extend a panel frame by transposing, adding a new dimension, and transposing back to the original dimensions

```python
In [39]: rng = pd.date_range('1/1/2013', periods=100, freq='D')

In [40]: data = np.random.randn(100, 4)

In [41]: cols = ['A', 'B', 'C', 'D']

In [42]: df1, df2, df3 = pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols),
   ...: pd.DataFrame(data, rng, cols)

In [43]: pf = pd.Panel({'df1':df1,'df2':df2,'df3':df3});pf
Out[43]:
<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

In [44]: pf.loc[:,:,'F'] = pd.DataFrame(data, rng, cols);pf
...<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 F
```

Mask a panel by using np.where and then reconstructing the panel with the new masked values

7.2.3 New Columns

Efficiently and dynamically creating new columns using applymap

```python
In [45]: df = pd.DataFrame(
   ....:     {'AAA': [1,2,1,3], 'BBB': [1,1,2,2], 'CCC': [2,1,3,1]}); df
....:
Out[45]:
   AAA  BBB  CCC
0  1  1  2
1  2  1  1
2  1  2  3
3  3  2  1

In [46]: source_cols = df.columns # or some subset would work too.

In [47]: new_cols = [str(x) + '_cat' for x in source_cols]

In [48]: categories = {1 : 'Alpha', 2 : 'Beta', 3 : 'Charlie' }

In [49]: df[new_cols] = df[source_cols].applymap(categories.get);df
Out[49]:
   AAA  BBB  CCC  AAA_cat  BBB_cat  CCC_cat
0  1  1  2  Alpha  Alpha  Beta
```

(continues on next page)
Keep other columns when using min() with groupby

```python
In [50]: df = pd.DataFrame(
....:
    {'AAA' : [1,1,1,2,2,3,3], 'BBB' : [2,1,3,4,5,1,2]}); df
....:
Out[50]:
   AAA  BBB
0  1    2
1  1    1
2  1    3
3  2    4
4  2    5
5  2    1
6  3    2
7  3    3
```

Method 1 : idxmin() to get the index of the mins

```python
In [51]: df.loc[df.groupby("AAA")["BBB"].idxmin()]
Out[51]:
   AAA  BBB
1  1    1
5  2    1
6  3    2
```

Method 2 : sort then take first of each

```python
In [52]: df.sort_values(by="BBB").groupby("AAA", as_index=False).first()
Out[52]:
   AAA  BBB
0  1    1
1  2    1
2  3    2
```

Notice the same results, with the exception of the index.

### 7.3 MultIndexing

The `multindexing` docs.

Creating a multi-index from a labeled frame

```python
In [53]: 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]}; df
....:
Out[53]:
   row  One_X  One_Y  Two_X  Two_Y
0   0     1.1    1.2   1.11   1.22
```

(continues on next page)
# As Labelled Index

In [54]: df = df.set_index('row'); df

\[\begin{array}{cccc}
\text{One}_X & \text{One}_Y & \text{Two}_X & \text{Two}_Y \\
\text{row} & & & \\
0 & 1.1 & 1.2 & 1.11 & 1.22 \\
1 & 1.1 & 1.2 & 1.11 & 1.22 \\
2 & 1.1 & 1.2 & 1.11 & 1.22 \\
\end{array}\]

# With Hierarchical Columns

In [55]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_')) for c in df.columns]); df

\[\begin{array}{cc}
\text{One} & \text{Two} \\
\text{X} & \text{Y} \\
\text{Y} & \text{X} \\
\text{row} & & & \\
0 & 1.1 & 1.2 & 1.11 & 1.22 \\
1 & 1.1 & 1.2 & 1.11 & 1.22 \\
2 & 1.1 & 1.2 & 1.11 & 1.22 \\
\end{array}\]

# Now stack & Reset

In [56]: df = df.stack(0).reset_index(1); df

\[\begin{array}{cc}
\text{level}_1 & \text{X} & \text{Y} \\
\text{row} & & & \\
0 & \text{One} & 1.10 & 1.20 \\
0 & \text{Two} & 1.11 & 1.22 \\
1 & \text{One} & 1.10 & 1.20 \\
1 & \text{Two} & 1.11 & 1.22 \\
2 & \text{One} & 1.10 & 1.20 \\
2 & \text{Two} & 1.11 & 1.22 \\
\end{array}\]

# And fix the labels (Notice the label 'level_1' got added automatically)

In [57]: df.columns = ['Sample','All_X','All_Y']; df

\[\begin{array}{ccc}
\text{Sample} & \text{All}_X & \text{All}_Y \\
\text{row} & & & \\
0 & \text{One} & 1.10 & 1.20 \\
0 & \text{Two} & 1.11 & 1.22 \\
1 & \text{One} & 1.10 & 1.20 \\
1 & \text{Two} & 1.11 & 1.22 \\
2 & \text{One} & 1.10 & 1.20 \\
2 & \text{Two} & 1.11 & 1.22 \\
\end{array}\]

### 7.3.1 Arithmetic

Performing arithmetic with a multi-index that needs broadcasting
In [58]: cols = pd.MultiIndex.from_tuples([(x,y) for x in ['A','B','C'] for y in ['O','I']])

In [59]: df = pd.DataFrame(np.random.randn(2,6),index=['n','m'],columns=cols); df
Out[59]:
      A    B    C
    O I   O I   O I
n  1.920906 -0.388231 -2.314394  0.665508  0.402562  0.399562
m -1.765956  0.850423  0.388054  0.992312  0.744086 -0.739776

In [60]: df = df.div(df['C'],level=1); df

    A    B    C
  O I   O I   O I
n  4.771702 -0.971660 -5.749162  1.665625  1.0        1.0
m -2.373321 -1.149568  0.521518 -1.341367  1.0        1.0

7.3.2 Slicing

Slicing a multi-index with xs

In [61]: coords = [('AA','one'), ('AA','six'), ('BB','one'), ('BB','two'), ('BB','six')]
In [62]: index = pd.MultiIndex.from_tuples(coords)
In [63]: df = pd.DataFrame([11,22,33,44,55],index,['MyData']); df
Out[63]:
      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 [64]: df.xs('BB',level=0,axis=0) #Note: level and axis are optional, and default to zero
Out[64]:
      MyData
one  33
two 44
      six  55

...and now the 2nd level of the 1st axis.

In [65]: df.xs('six',level=1,axis=0)
Out[65]:
      MyData
AA  22
BB  55

Slicing a multi-index with xs, method #2
In [66]: index = list(itertools.product(['Ada', 'Quinn', 'Violet'], ['Comp', 'Math', 'Sci']))

In [67]: headr = list(itertools.product(['Exams', 'Labs'], ['I', 'II']))

In [68]: indx = pd.MultiIndex.from_tuples(index, names=['Student', 'Course'])

In [69]: cols = pd.MultiIndex.from_tuples(headr)  # Notice these are un-named

In [70]: data = [[70+x+y+(x*y) % 3 for x in range(4)] for y in range(9)]

In [71]: df = pd.DataFrame(data, indx, cols); df

Out[71]:

<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>Student</td>
<td>Course</td>
</tr>
<tr>
<td>Ada</td>
<td>Comp</td>
</tr>
<tr>
<td></td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>71</td>
</tr>
<tr>
<td>Math</td>
<td></td>
</tr>
<tr>
<td></td>
<td>72</td>
</tr>
<tr>
<td>Sci</td>
<td></td>
</tr>
<tr>
<td></td>
<td>73</td>
</tr>
<tr>
<td>Quinn</td>
<td>Comp</td>
</tr>
<tr>
<td></td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>75</td>
</tr>
<tr>
<td>Math</td>
<td></td>
</tr>
<tr>
<td></td>
<td>76</td>
</tr>
<tr>
<td></td>
<td>77</td>
</tr>
<tr>
<td>Sci</td>
<td></td>
</tr>
<tr>
<td></td>
<td>78</td>
</tr>
</tbody>
</table>

In [72]: All = slice(None)

In [73]: df.loc['Violet']

Out[73]:

<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>Course</td>
<td></td>
</tr>
<tr>
<td>Comp</td>
<td></td>
</tr>
<tr>
<td></td>
<td>76</td>
</tr>
<tr>
<td>Math</td>
<td></td>
</tr>
<tr>
<td></td>
<td>77</td>
</tr>
<tr>
<td>Sci</td>
<td></td>
</tr>
<tr>
<td></td>
<td>78</td>
</tr>
</tbody>
</table>

In [74]: df.loc[(All, 'Math'), All]

<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>Student</td>
<td>Course</td>
</tr>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td></td>
<td>71</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
<tr>
<td></td>
<td>74</td>
</tr>
<tr>
<td>Violet</td>
<td>Math</td>
</tr>
<tr>
<td></td>
<td>77</td>
</tr>
</tbody>
</table>

In [75]: df.loc[(slice('Ada', 'Quinn'), 'Math'), All]

<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>Student</td>
<td>Course</td>
</tr>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td></td>
<td>71</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
<tr>
<td></td>
<td>74</td>
</tr>
</tbody>
</table>

In [76]: df.loc[(All, 'Math'), ('Exams')]

(continues on next page)
Setting portions of a multi-index with xs

### 7.3.3 Sorting

Sort by specific column or an ordered list of columns, with a multi-index

```python
In [78]: df.sort_values(by=('Labs', 'II'), ascending=False)
```

```
Out[78]:
     Exams  Labs
    I  II  I  II
Student Course
Violet Sci  78  81  81  81
    Math  77  79  81  80
    Comp  76  77  78  79
Quinn Sci  75  78  78  78
    Math  74  76  78  77
    Comp  73  74  75  76
Ada Sci  72  75  75  75
    Math  71  73  75  74
    Comp  70  71  72  73
```

Partial Selection, the need for sortedness;

### 7.3.4 Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

### 7.4 Missing Data

The *missing data* docs.

Fill forward a reversed timeseries
In [79]: df = pd.DataFrame(np.random.randn(6,1), index=pd.date_range('2013-08-01', periods=6, freq='B'), columns=list('A'))

In [80]: df.loc[df.index[3], 'A'] = np.nan

In [81]: df
Out[81]:
A
2013-08-01 -1.054874
2013-08-02 -0.179642
2013-08-05 0.639589
2013-08-06 NaN
2013-08-07 1.906684
2013-08-08 0.104050

In [82]: 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

7.4.1 Replace

Using replace with backrefs

7.5 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 [83]: 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[83]:

    animal size  weight  adult
0  cat     S     8    False
1  dog     S    10    False
2  cat     M    11    False
3  fish    M     1    False
4  dog     M    20    False
5  cat     L    12     True
6  cat     L    12     True

(continues on next page)
#List the size of the animals with the highest weight.

In [84]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])

animal
cat   L
dog   M
fish  M
dtype: object

Using `get_group`

In [85]: gb = df.groupby(['animal'])

In [86]: gb.get_group('cat')

Out[86]:
animal size  weight adult
0     cat    S      8  False
2     cat    M     11  False
5     cat    L     12   True
6     cat    L     12   True

Apply to different items in a group

In [87]:
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 [88]: expected_df = gb.apply(GrowUp)

In [89]: expected_df

Out[89]:
size  weight  adult
animal
  cat   L 12.4375   True
  dog   L 20.0000   True
  fish  L  1.2500   True

Expanding Apply

In [90]: S = pd.Series([i / 100.0 for i in range(1,11)])

In [91]:
def CumRet(x,y):
    ...
    return x * (1 + y)
    ...

In [92]:
def Red(x):
    ...
    return functools.reduce(CumRet,x,1.0)
    ...

In [93]: S.expanding().apply(Red, raw=True)

Out[93]:
(continues on next page)
Replacing some values with mean of the rest of a group

```python
In [94]: df = pd.DataFrame({'A' : [1, 1, 2, 2], 'B' : [1, -1, 1, 2]})
In [95]: gb = df.groupby('A')
In [96]: def replace(g):
    ...:     mask = g < 0
    ...:     g.loc[mask] = g[~mask].mean()
    ...:     return g
    ...

In [97]: gb.transform(replace)
Out[97]:
   B
0  1.0
1  1.0
2  1.0
3  2.0
```

Sort groups by aggregated data

```python
In [98]: 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 [99]: code_groups = df.groupby('code')
In [100]: agg_n_sort_order = code_groups[['data']].transform(sum).sort_values(by='data')
In [101]: sorted_df = df.loc[agg_n_sort_order.index]
In [102]: sorted_df
```

Create multiple aggregated columns

```python
7.5. Grouping  537
```
```
In [103]: rng = pd.date_range(start="2014-10-07", periods=10, freq='2min')

In [104]: ts = pd.Series(data = list(range(10)), index = rng)

In [105]: def MyCust(x):
      .....:     if len(x) > 2:
      .....:         return x[1] * 1.234
      .....:     return pd.NaT
      .....:

In [106]: mhc = {'Mean' : np.mean, 'Max' : np.max, 'Custom' : MyCust}

In [107]: ts.resample("5min").apply(mhc)
Out[107]:
          Custom 2014-10-07 00:00:00 1.234
               2014-10-07 00:05:00 NaT
               2014-10-07 00:10:00 7.404
               2014-10-07 00:15:00 NaT
          Max   2014-10-07 00:00:00   2
               2014-10-07 00:05:00   4
               2014-10-07 00:10:00   7
               2014-10-07 00:15:00   9
          Mean  2014-10-07 00:00:00   1
               2014-10-07 00:05:00   3.5
               2014-10-07 00:10:00   6
               2014-10-07 00:15:00   8.5

dtype: object

In [108]: ts

     2014-10-07 00:00:00  0
     2014-10-07 00:02:00  1
     2014-10-07 00:04:00  2
     2014-10-07 00:06:00  3
     2014-10-07 00:08:00  4
     2014-10-07 00:10:00  5
     2014-10-07 00:12:00  6
     2014-10-07 00:14:00  7
     2014-10-07 00:16:00  8
     2014-10-07 00:18:00  9
Freq: 2T, dtype: int64

Create a value counts column and reassign back to the DataFrame
```

```
In [109]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),
                       'Value': [100, 150, 50, 50]}); df

Out[109]:
         Color  Value
0        Red   100
1        Red   150
2        Red    50
3        Blue    50

In [110]: df['Counts'] = df.groupby(['Color']).transform(len)

(continues on next page)
In [111]: df
Out[111]:
   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 [112]: df = pd.DataFrame(
   .....:     {u'line_race': [10, 10, 8, 10, 10, 8],
   .....:        u'beyer': [99, 102, 103, 103, 88, 100],
   .....:        index=[u'Last Gunfighter', u'Last Gunfighter', u'Last Gunfighter',
   .....:                      u'Paynter', u'Paynter', u'Paynter']}; df
   .....:
Out[112]:
                             line_race  beyer
   Last Gunfighter            10    99
   Last Gunfighter            10   102
   Last Gunfighter             8   103
   Paynter                    10   103
   Paynter                     10   88
   Paynter                     8   100

In [113]: df['beyer_shifted'] = df.groupby(level=0)['beyer'].shift(1)
In [114]: df
Out[114]:
     line_race  beyer  beyer_shifted
   Last Gunfighter   10    99          NaN
   Last Gunfighter   10   102          99.0
   Last Gunfighter     8   103       102.0
   Paynter           10   103          NaN
   Paynter           10    88       103.0
   Paynter             8   100        88.0

Select row with maximum value from each group

In [115]: df = pd.DataFrame({'host':[other, other, that, this, this],
   .....: 'service':[mail, web, mail, mail, web],
   .....: 'no':[1, 2, 1, 2, 1]}.set_index(['host', 'service'])
   .....:
In [116]: mask = df.groupby(level=0).agg('idxmax')
In [117]: df_count = df.loc[mask['no']].reset_index()
In [118]: df_count
Out[118]:
     host  service  no
   0    other      web  2
   1    that      mail  1
   2    this      mail  2

Grouping like Python's itertools.groupby
In [119]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])

In [120]: df.A.groupby((df.A != df.A.shift()).cumsum()).groups
Out[120]:
{1: Int64Index([0], dtype='int64'),
  2: Int64Index([1], dtype='int64'),
  3: Int64Index([2], dtype='int64'),
  4: Int64Index([3, 4, 5], dtype='int64'),
  5: Int64Index([6], dtype='int64'),
  6: Int64Index([7, 8], dtype='int64')}

In [121]: df.A.groupby((df.A != df.A.shift()).cumsum()).cumsum()

0 0
1 1
2 0
3 1
4 2
5 3
6 0
7 1
8 2
Name: A, dtype: int64

7.5.1 Expanding Data

Alignment and to-date
Rolling Computation window based on values instead of counts
Rolling Mean by Time Interval

7.5.2 Splitting

Splitting a frame
Create a list of dataframes, split using a delineation based on logic included in rows.

In [122]: df = pd.DataFrame(data={'Case': ['A', 'A', 'A', 'B', 'A', 'A', 'B', 'A', 'A'],
                           'Data' : np.random.randn(9)})

In [123]: dfs = list(zip(*df.groupby((1*(df['Case']=='B')).cumsum().rolling(window=3,
 ˓→min_periods=1).median())))[-1]

In [124]: dfs[0]
Out[124]:
Case  Data
0  A  0.174068
1  A -0.439461
2  A -0.741343
3  B -0.079673

In [125]: dfs[1]
### 7.5.3 Pivot

The *Pivot* docs.

Partial sums and subtotals

```python
In [127]: df = pd.DataFrame(data={'Province': ['ON', 'QC', 'BC', 'AL', 'AL', 'MN', 'ON'],
                            'City': ['Toronto', 'Montreal', 'Vancouver', 'Calgary',
                                     'Edmonton', 'Winnipeg', 'Windsor'],
                            'Sales': [13, 6, 16, 8, 4, 3, 1]})
```

```python
In [128]: table = pd.pivot_table(df, values=['Sales'], index=['Province'], columns=['City'],
                           aggfunc=np.sum, margins=True)
```

```python
In [129]: table.stack('City')
```

```
    Sales
Case City
AL All  12.0
      Calgary  8.0
      Edmonton  4.0
BC All  16.0
      Vancouver  16.0
MN All  3.0
      Winnipeg  3.0
... ...  ...
All Calgary  8.0
           Edmonton  4.0
           Montreal  6.0
           Toronto  13.0
           Vancouver  16.0
           Windsor  1.0
           Winnipeg  3.0
```

```
[20 rows x 1 columns]
```

Frequency table like plyr in R

```python
In [130]: grades = [48, 99, 75, 80, 42, 80, 72, 68, 36, 78]
```

(continues on next page)
In [131]: df = pd.DataFrame({ 'ID': ["x%d" % r for r in range(10)],
          'Gender': ['F', 'M', 'F', 'M', 'F', 'M', 'F', 'M', 'M', 'M'],
                       '2009', '2009', '2009', '2009'],
          'Class': ['algebra', 'stats', 'bio', 'algebra', 'algebra',
                     'stats', 'stats', 'algebra', 'bio', 'bio'],
          'Participated': ['yes', 'yes', 'yes', 'yes', 'no', 'yes', 'yes',
                           'yes', 'yes', 'yes'],
          'Passed': ['yes' if x > 50 else 'no' for x in grades],
          'Employed': [True, True, True, False, False, False, False, True,
                        True, True, False],
          'Grade': grades})

In [132]: 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[132]:

<table>
<thead>
<tr>
<th>ExamYear</th>
<th>Participated</th>
<th>Passed</th>
<th>Employed</th>
<th>Grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>74.000000</td>
</tr>
<tr>
<td>2008</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>68.500000</td>
</tr>
<tr>
<td>2009</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>60.666667</td>
</tr>
</tbody>
</table>

Plot pandas DataFrame with year over year data

To create year and month crosstabulation:

In [133]: df = pd.DataFrame({'value': np.random.randn(36),
                        index=pd.date_range('2011-01-01', freq='M', periods=36))

In [134]: pd.pivot_table(df, index=df.index.month, columns=df.index.year,
                          values='value', aggfunc='sum')

Out[134]:

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.560859</td>
<td>0.120930</td>
<td>0.516870</td>
</tr>
<tr>
<td>2</td>
<td>-0.589005</td>
<td>-0.210518</td>
<td>0.343125</td>
</tr>
<tr>
<td>3</td>
<td>-1.070678</td>
<td>-0.931184</td>
<td>2.137827</td>
</tr>
<tr>
<td>4</td>
<td>-1.681101</td>
<td>0.240647</td>
<td>0.452429</td>
</tr>
<tr>
<td>5</td>
<td>0.403776</td>
<td>-0.027462</td>
<td>0.483103</td>
</tr>
<tr>
<td>6</td>
<td>0.609862</td>
<td>0.033113</td>
<td>0.061495</td>
</tr>
<tr>
<td>7</td>
<td>0.387936</td>
<td>-0.658418</td>
<td>0.240767</td>
</tr>
<tr>
<td>8</td>
<td>1.815066</td>
<td>0.324102</td>
<td>0.782413</td>
</tr>
<tr>
<td>9</td>
<td>0.705200</td>
<td>-1.403048</td>
<td>0.628462</td>
</tr>
<tr>
<td>10</td>
<td>-0.668049</td>
<td>-0.581967</td>
<td>-0.880627</td>
</tr>
<tr>
<td>11</td>
<td>0.242501</td>
<td>-1.233862</td>
<td>0.777575</td>
</tr>
<tr>
<td>12</td>
<td>0.313421</td>
<td>-3.520876</td>
<td>-0.779367</td>
</tr>
</tbody>
</table>
7.5.4 Apply

Rolling Apply to Organize - Turning embedded lists into a multi-index frame

```
In [135]: 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 [136]: def SeriesFromSubList(aList):
    .....:     return pd.Series(aList)
    .....:
```

```
In [137]: 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 [138]: def gm(aDF, Const):
    .....:     v = (((aDF.A+aDF.B)+1).cumprod())-1)*Const
    .....:     return (aDF.index[0], v.iloc[-1])
    .....:
```

```
In [139]: S = pd.Series(dict([( gm(df.iloc[i:min(i+51, len(df)-1)], 5) for i in range(len(df)-50) )]))
```

(continues on next page)
2006-04-28 -0.002682
2006-04-29 -0.002436
2006-04-30 -0.002602
2006-05-01 -0.001785
2006-05-02 -0.001799
2006-05-03 -0.000605
2006-05-04 -0.000541
Length: 1950, 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 [141]: rng = pd.date_range(start = '2014-01-01',periods = 100)
In [142]: 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[142]:
           Open  Close  Volume
2014-01-01   0.01174 -0.653039    1581
2014-01-02   0.214258  1.314205    1707
2014-01-03  -1.046922  -0.341915    1768
2014-01-04  -0.752902  -1.303586     836
2014-01-05  -0.410793   0.396288     694
2014-01-06   0.648401  -0.548006    265
2014-01-07   0.737320   0.481380    265
...         ...       ...     ...
2014-04-04   0.120378  -2.548128    564
2014-04-05   0.231661   0.223346    1908
2014-04-06   0.952664   1.228841    1090
2014-04-07  -0.176090   0.552784    1813
2014-04-08   1.781318  -0.795389    1103
2014-04-09  -0.753493  -0.018815    1456
2014-04-10  -1.047997   1.138197    1193
[100 rows x 3 columns]

In [143]: def vwap(bars):
In [144]: window = 5
In [145]: s = pd.concat([pd.Series(vwap(df.iloc[i:i+window]), index=df.index[i+window])
                      for i in range(len(df)-window)]);
In [146]: s.round(2)
Out[146]:
2014-01-06 -0.03
2014-01-07  0.07
2014-01-08 -0.40
2014-01-09 -0.81
2014-01-10 -0.63
2014-01-11 -0.86
2014-01-12 -0.36
...
### 7.6 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

```python
In [147]: dates = pd.date_range('2000-01-01', periods=5)
In [148]: dates.to_period(freq='M').to_timestamp()
Out[148]:
               '2000-01-01'],
              dtype='datetime64[ns]', freq=None)
```

#### 7.6.1 Resampling

The `Resample` docs.

- Using Grouper instead of TimeGrouper for time grouping of values
- Time grouping with some missing values
- Valid frequency arguments to Grouper
- Grouping using a MultiIndex
- Using TimeGrouper and another grouping to create subgroups, then apply a custom function
- Resampling with custom periods
- Resample intraday frame without adding new days
- Resample minute data
- Resample with groupby
7.7 Merge

The `Concat` docs. The `Join` docs.

Append two dataframes with overlapping index (emulate R `rbind`)

```python
In [149]: rng = pd.date_range('2000-01-01', periods=6)
In [150]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C'])
In [151]: df2 = df1.copy()
```

Depending on df construction, `ignore_index` may be needed

```python
In [152]: df = df1.append(df2,ignore_index=True); df
```

Self Join of a DataFrame

```python
In [153]: 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
```

```python
In [154]: df['Test_1'] = df['Test_0'] - 1
```

```python
In [155]: pd.merge(df, df, left_on=['Bins', 'Area','Test_0'], right_on=['Bins', 'Area', 'Test_1'],suffixes=('L','R'))
```
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

## 7.8 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 [156]: df = pd.DataFrame(
    ......:     {u'stratifying_var': np.random.uniform(0, 100, 20),
    ......:       u'price': np.random.normal(100, 5, 20)})
    ......:

In [157]: df[u'quartiles'] = pd.qcut(
    ......:     df[u'stratifying_var'],
    ......:     4,
    ......:     labels=[u'0-25%', u'25-50%', u'50-75%', u'75-100%'])
    ......:

In [158]: df.boxplot(column=u'price', by=u'quartiles')
Out[158]: <matplotlib.axes._subplots.AxesSubplot at 0x1c28eaad68>
```
7.9 Data In/Out

Performance comparison of SQL vs HDF5

7.9.1 CSV

The CSV docs
read_csv in action
appending to a csv
Reading a csv chunk-by-chunk
Reading only certain rows of a csv chunk-by-chunk
Reading the first few lines of a frame

Reading a file that is compressed but not by gzip/bz2 (the native compressed formats which read_csv understands). This example shows a WinZipped file, but is a general application of opening the file within a context manager and using that handle to read. See here

Inferring dtypes from a file
Dealing with bad lines
Dealing with bad lines II

**Reading CSV with Unix timestamps and converting to local timezone**

**Write a multi-row index CSV without writing duplicates**

### 7.9.1.1 Reading multiple files to create a single DataFrame

The best way to combine multiple files into a single DataFrame is to read the individual frames one by one, put all of the individual frames into a list, and then combine the frames in the list using `pd.concat()`:

```python
In [159]: for i in range(3):
   ....:     data = pd.DataFrame(np.random.randn(10, 4))
   ....:     data.to_csv('file_{}.csv'.format(i))
   ....:

In [160]: files = ['file_0.csv', 'file_1.csv', 'file_2.csv']

In [161]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

You can use the same approach to read all files matching a pattern. Here is an example using `glob`:

```python
In [162]: import glob

In [163]: files = glob.glob('file_*\.csv')

In [164]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

Finally, this strategy will work with the other `pd.read_*(...)` functions described in the `io docs`.

### 7.9.1.2 Parsing date components in multi-columns

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

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 combinging into a string, then parsing
In [34]: ds = df.apply(lambda x: "%04d%02d%02d" % (x['year'], x['month'], x['day']), axis=1)

In [35]: ds.head()
Out[35]:
```

(continues on next page)
7.9.1.3 Skip row between header and data

In [165]: data = """;;;
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: /////
.....: date;Param1;Param2;Param4;Param5
.....: °C;m²;m²;m
.....: 01.01.1990 00:00;1;1;2;3
.....: 01.01.1990 01:00;5;3;4;5
.....: 01.01.1990 02:00;9;5;6;7
.....: 01.01.1990 03:00;13;7;8;9
.....: 01.01.1990 04:00;17;9;10;11
.....: 01.01.1990 05:00;21;11;12;13
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: ''''
.....: """;

Option 1: pass rows explicitly to skiprows

In [166]: pd.read_csv(StringIO(data), sep=';', skiprows=[11,12],
.....: index_col=0, parse_dates=True, header=10)

Out[166]:

<table>
<thead>
<tr>
<th>date</th>
<th>Param1</th>
<th>Param2</th>
<th>Param4</th>
<th>Param5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-01-01 00:00:00</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1990-01-01 01:00:00</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>1990-01-01 02:00:00</td>
<td>9</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>1990-01-01 03:00:00</td>
<td>13</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>1990-01-01 04:00:00</td>
<td>17</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>1990-01-01 05:00:00</td>
<td>21</td>
<td>11</td>
<td>12</td>
<td>13</td>
</tr>
</tbody>
</table>
Option 2: read column names and then data

```
In [167]: pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns
Out[167]: Index(['date', 'Param1', 'Param2', 'Param4', 'Param5'], dtype='object')

In [168]: columns = pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns

In [169]: pd.read_csv(StringIO(data), sep=';', index_col=0,
   ...:        header=12, parse_dates=True, names=columns)
   ...:
Out[169]:
   date         Param1  Param2  Param4  Param5
1990-01-01  00:00:00     1      1     2     3
1990-01-01  01:00:00     5      3     4     5
1990-01-01  02:00:00     9      5     6     7
1990-01-01  03:00:00    13      7     8     9
1990-01-01  04:00:00    17      9    10    11
1990-01-01  05:00:00    21     11    12    13
```

### 7.9.2 SQL

The [SQL](#) docs

Reading from databases with SQL

### 7.9.3 Excel

The [Excel](#) docs

Reading from a filelike handle

Modifying formatting in XlsxWriter output

### 7.9.4 HTML

Reading HTML tables from a server that cannot handle the default request header

### 7.9.5 HDFStore

The [HDFStores](#) docs

Simple Queries with a Timestamp Index

Managing heterogeneous data using a linked multiple table hierarchy

Merging on-disk tables with millions of rows

Avoiding inconsistencies when writing to a store from multiple processes/threads

De-duplicating a large store by chunks, essentially a recursive reduction operation. Shows a function for taking in data from csv file and creating a store by chunks, with date parsing as well. See [here](#)

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

7.9. Data In/Out 551
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 [170]: df = pd.DataFrame(np.random.randn(8,3))
In [171]: store = pd.HDFStore('test.h5')
In [172]: store.put('df',df)
# you can store an arbitrary Python object via pickle
In [173]: store.get_storer('df').attrs.my_attribute = dict(A = 10)
In [174]: store.get_storer('df').attrs.my_attribute
Out[174]: {'A': 10}
```

7.9.6 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,

```
#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;
    }
```

(continues on next page)
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.

## 7.10 Computation

Numerical integration (sample-based) of a time series

### 7.11 Timedeltas

The Timedeltas docs.

Using timedeltas

```python
In [175]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))

In [176]: s - s.max()
Out[176]:
          0 -2 days
         1 -1 days
         2  0 days
dtype: timedelta64[ns]

In [177]: s.max() - s
```

(continues on next page)
Adding and subtracting deltas and dates

```
In [178]: s = datetime.datetime(2011,1,1,3,5)
   ...:
   ...: →
   ...
   ...: 0 364 days 20:55:00
   ...: 1 365 days 20:55:00
   ...: 2 366 days 20:55:00
   ...: dtype: timedelta64[ns]

In [179]: s + datetime.timedelta(minutes=5)
   ...:
   ...: →
   ...
   ...: 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 [180]: datetime.datetime(2011,1,1,3,5) - s
   ...:
   ...: →
   ...
   ...: 0 -365 days +03:05:00
   ...: 1 -366 days +03:05:00
   ...: 2 -367 days +03:05:00
   ...: dtype: timedelta64[ns]

In [181]: datetime.timedelta(minutes=5) + s
   ...:
   ...: →
   ...
   ...: 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 [182]: deltas = pd.Series([datetime.timedelta(days=i) for i in range(3)])

In [183]: df = pd.DataFrame(dict(A = s, B = deltas)); df
   ...: Out[183]:
   ...:   A       B
   ...: 0 2012-01-01 0 days
   ...: 1 2012-01-02 1 days
   ...: 2 2012-01-03 2 days

In [184]: df['New Dates'] = df['A'] + df['B'];

In [185]: df['Delta'] = df['A'] - df['New Dates']; df
   ...: Out[185]:
   ...:   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 [186]: df.dtypes
   ...:
   ...: →
   ...
   ...: A            datetime64[ns]
```

(continues on next page)
Another example

Values can be set to NaT using `np.nan`, similar to `datetime`

```python
In [187]: y = s - s.shift(); y
Out[187]:
0    NaT
1   1 days
2   1 days
dtype: timedelta64[ns]

In [188]: y[1] = np.nan; y
Out[188]:
0    NaT
1    NaT
2   1 days
dtype: timedelta64[ns]
```

### 7.12 Aliasing Axis Names

To globally provide aliases for axis names, one can define these 2 functions:

```python
In [189]: 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 [190]: 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)
    ....:
```

```python
In [191]: set_axis_alias(pd.DataFrame,'columns', 'myaxis2')

In [192]: df2 = pd.DataFrame(np.random.randn(3,2),columns=['c1','c2'],index=['i1','i2 →','i3'])

In [193]: df2.sum(axis='myaxis2')
Out[193]:
   i1   0.745167
   i2  -0.176251
   i3   0.014354
dtype: float64

In [194]: clear_axis_alias(pd.DataFrame,'columns', 'myaxis2')
```
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:

```python
In [195]: def expand_grid(data_dict):
    .....:     rows = itertools.product(*data_dict.values())
    .....:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
    .....:

In [196]: df = expand_grid(
    .....:     {'height': [60, 70],
    .....:     'weight': [100, 140, 180],
    .....:     'sex': ['Male', 'Female']})

In [197]: df
Out[197]:
   height  weight  sex
0      60     100   Male
1      60     100   Female
2      60     140    Male
3      60     140   Female
4      60     180    Male
5      60     180   Female
6      70     100    Male
7      70     100   Female
8      70     140    Male
9      70     140   Female
10     70     180    Male
11     70     180   Female
```
We’ll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import NumPy and load pandas into your namespace:

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

Here is a basic tenet to keep in mind: data alignment is intrinsic. The link between labels and data will not be broken unless done so explicitly by you.

We’ll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

### 8.1 Series

*Series* is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the *index*. The basic method to create a Series is to call:

```python
>>> s = pd.Series(data, index=index)
```

Here, data can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed index is a list of axis labels. Thus, this separates into a few cases depending on what data is:

**From ndarray**

If data is an ndarray, index must be the same length as data. If no index is passed, one will be created having values [0, ..., len(data) - 1].

```python
In [3]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [4]: s
Out[4]:
     a   0.4691
     b  -0.2829
(continues on next page)
```
c -1.5091
d -1.1356
e 1.2121
dtype: float64

In [5]: s.index
Out[5]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [6]: pd.Series(np.random.randn(5))
Out[6]:
   0  -0.1732
   1   0.1192
   2  -1.0442
   3  -0.8618
   4  -2.1046
dtype: float64

Note: pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

From dict

Series can be instantiated from dicts:

In [7]: d = {'b' : 1, 'a' : 0, 'c' : 2}

In [8]: pd.Series(d)
Out[8]:
b 1
a 0
c 2
dtype: int64

Note: When the data is a dict, and an index is not passed, the Series index will be ordered by the dict’s insertion order, if you’re using Python version >= 3.6 and Pandas version >= 0.23.

If you’re using Python < 3.6 or Pandas < 0.23, and an index is not passed, the Series index will be the lexically ordered list of dict keys.

In the example above, if you were on a Python version lower than 3.6 or a Pandas version lower than 0.23, the Series would be ordered by the lexical order of the dict keys (i.e. ['a', 'b', 'c'] rather than ['b', 'a', 'c']).

If an index is passed, the values in data corresponding to the labels in the index will be pulled out.

In [9]: d = {'a' : 0., 'b' : 1., 'c' : 2.}

In [10]: pd.Series(d)
Out[10]:
a  0.0
b  1.0
c  2.0
dtype: float64

In [11]: pd.Series(d, index=['b', 'c', 'd', 'a'])

Out[11]:
b 1.0
c 2.0
d NaN
a 0.0
dtype: float64

Note: NaN (not a number) is the standard missing data marker used in pandas.

From scalar value

If `data` is a scalar value, an index must be provided. The value will be repeated to match the length of `index`.

In [12]: pd.Series(5., index=['a', 'b', 'c', 'd', 'e'])

Out[12]:
a 5.0
b 5.0
c 5.0
d 5.0
e 5.0
dtype: float64

8.1.1 Series is ndarray-like

Series acts very similarly to ndarray, and is a valid argument to most NumPy functions. However, operations such as slicing will also slice the index.

In [13]: s[0]

Out[13]: 0.46911229990718628

In [14]: s[:3]

Out[14]:
a 0.4691
b -0.2829
c -1.5091
dtype: float64

In [15]: s[s > s.median()]

Out[15]:
a 0.4691
e 1.2121
dtype: float64

In [16]: s[[4, 3, 1]]

Out[16]:
e 1.2121
d -1.1356
b -0.2829

(continues on next page)
We will address array-based indexing in a separate section.

### 8.1.2 Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```python
In [18]: s['a']
Out[18]: 0.46911229990718628
In [19]: s['e'] = 12.
In [20]: s
Out[20]:
a    0.4691
b   -0.2829
c   -1.5091
d   -1.1356
e    12.00
dtype: float64
```

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 [23]: s.get('f')
In [24]: s.get('f', np.nan)
Out[24]: nan
```

See also the section on attribute access.
8.1.3 Vectorized operations and label alignment with Series

When working with raw NumPy arrays, looping through value-by-value is usually not necessary. The same is true when working with Series in pandas. Series can also be passed into most NumPy methods expecting an ndarray.

```
In [25]: s + s
Out[25]:
   a    0.9382
   b   -0.5657
   c   -3.0181
   d   -2.2713
   e   24.0000
   dtype: float64

In [26]: s * 2
Out[26]:
   a     0.9382
   b    -0.5657
   c    -3.0181
   d    -2.2713
   e     24.0000
   dtype: float64

In [27]: np.exp(s)
Out[27]:
   a  1.5986
   b  0.7536
   c  0.2211
   d  0.3212
   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 labels.

```
In [28]: s[1:] + s[:-1]
Out[28]:
   a   NaN
   b  -0.5657
   c  -3.0181
   d  -2.2713
   e   NaN
   dtype: float64
```

The result of an operation between unaligned Series will have the **union** of the indexes involved. If a label is not found in one Series or the other, the result will be marked as missing NaN. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

**Note:** In general, we chose to make the default result of operations between differently indexed objects yield the **union** of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with
missing data via the `dropna` function.

### 8.1.4 Name attribute

Series can also have a `name` attribute:

```python
In [29]: s = pd.Series(np.random.rand(5), name='something')
In [30]: s
Out[30]:
0  -0.4949
1   1.0718
2   0.7216
3  -0.7068
4  -1.0396
Name: something, dtype: float64
```

```python
In [31]: s.name
\rightarrow 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

New in version 0.18.0.

You can rename a Series with the `pandas.Series.rename()` method.

```python
In [32]: s2 = s.rename("different")
In [33]: s2.name
Out[33]: 'different'
```

Note that `s` and `s2` refer to different objects.

### 8.2 DataFrame

**DataFrame** is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D `numpy.ndarray`
- Structured or record `ndarray`
- A Series
- Another DataFrame

Along with the data, you can optionally pass `index` (row labels) and `columns` (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.
8.2.1 From dict of Series or dicts

The resulting index will be the union of the indexes of the various Series. If there are any nested dicts, these will first be converted to Series. If no columns are passed, the columns will be the ordered list of dict keys.

```
In [34]: d = {'one' : pd.Series([1., 2., 3.], index=['a', 'b', 'c']),
       'two' : pd.Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}

In [35]: df = pd.DataFrame(d)

In [36]: df
Out[36]:
      one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0

In [37]: pd.DataFrame(d, index=['d', 'b', 'a'])
Out[37]:
      one  two
  d    NaN  4.0
  b  2.0    NaN
  a  1.0    NaN

In [38]: pd.DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
   →
      two  three
  d    4.0    NaN
  b  2.0  NaN
  a  1.0  NaN
```

The row and column labels can be accessed respectively by accessing the `index` and `columns` attributes:

Note: When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

```
In [39]: df.index
Out[39]: Index(['a', 'b', 'c', 'd'], dtype='object')

In [40]: df.columns
Out[40]: Index(['one', 'two'], dtype='object')
```
8.2.2 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.

```python
In [41]: d = {'one' : [1., 2., 3., 4.],
       ....:     'two' : [4., 3., 2., 1.]}

In [42]: pd.DataFrame(d)
Out[42]:
   one  two
0  1.0  4.0
1  2.0  3.0
2  3.0  2.0
3  4.0  1.0

In [43]: pd.DataFrame(d, index=['a', 'b', 'c', 'd'])
   one  two
  a  1.0  4.0
  b  2.0  3.0
  c  3.0  2.0
  d  4.0  1.0
```

8.2.3 From structured or record array

This case is handled identically to a dict of arrays.

```python
In [44]: data = np.zeros((2,), dtype=[('A', 'i4'), ('B', 'f4'), ('C', 'a10')])

In [45]: data[:]= [(1,2.,'Hello'), (2,3.,'World')]

In [46]: pd.DataFrame(data)
Out[46]:
   A     B     C
0  1  2.0 b'Hello'
1  2  3.0 b'World'

In [47]: pd.DataFrame(data, index=['first', 'second'])
   A     B     C
first 1  2.0 b'Hello'
second 2  3.0 b'World'

In [48]: pd.DataFrame(data, columns=['C', 'A', 'B'])
   C     A     B
0 b'Hello' 1  2.0
1 b'World' 2  3.0
```

Note: DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.
8.2.4 From a list of dicts

```py
In [49]: data2 = [{'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20}]
In [50]: pd.DataFrame(data2)
Out[50]:
   a  b  c
0  1  2 NaN
1  5 10 20.0
In [51]: pd.DataFrame(data2, index=['first', 'second'])
   a  b  c
first 1  2 NaN
second 5 10 20.0
In [52]: pd.DataFrame(data2, columns=['a', 'b'])
   a  b
0  1  2
1  5 10
```

8.2.5 From a dict of tuples

You can automatically create a multi-indexed frame by passing a tuples dictionary.

```py
In [53]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
                  ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
                  ('b', 'a'): {('A', 'C'): 5, ('A', 'B'): 6},
                  ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
   a  b
A B 1.0 4.0 5.0 8.0 10.0
C 2.0 3.0 6.0 7.0 NaN
D NaN NaN NaN NaN 9.0
```

8.2.6 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, we use `np.nan` to represent missing values. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

8.2.7 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.

```python
In [54]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]))
Out[54]:
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass orient='index', the keys will be the row labels. In this case, you can also pass the desired column names:

```python
In [55]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]), orient='index', columns=['one', 'two', 'three'])
```

DataFrame.from_records

DataFrame.from_records takes a list of tuples or an ndarray with structured dtype. It works analogously to the normal DataFrame constructor, except that the resulting DataFrame index may be a specific field of the structured dtype. For example:

```python
In [56]: data
Out[56]:
array([(1, 2., b'Hello'), (2, 3., b'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [57]: pd.DataFrame.from_records(data, index='C')
```

8.2.8 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:

```python
In [58]: df['one']
Out[58]:
a  1.0
b  2.0
c  3.0
d  NaN
Name: one, dtype: float64

In [59]: df['three'] = df['one'] * df['two']
```
In [60]: df['flag'] = df['one'] > 2

In [61]: df
Out[61]:
      one   two   three  flag
  a   1.0   1.0   1.0  False
  b   2.0   2.0   4.0  False
  c   3.0   3.0   9.0   True
  d  NaN   4.0  NaN  False

Columns can be deleted or popped like with a dict:

In [62]: del df['two']

In [63]: three = df.pop('three')

In [64]: df
Out[64]:
      one  flag
  a   1.0  False
  b   2.0  False
  c   3.0   True
  d  NaN  False

When inserting a scalar value, it will naturally be propagated to fill the column:

In [65]: df['foo'] = 'bar'

In [66]: df
Out[66]:
      one   flag  foo
  a   1.0  False   bar
  b   2.0  False   bar
  c   3.0   True   bar
  d  NaN  False   bar

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame’s index:

In [67]: df['one_trunc'] = df['one'][:2]

In [68]: df
Out[68]:
      one   flag  foo one_trunc
  a   1.0  False   bar      1.0
  b   2.0  False   bar      2.0
  c   3.0   True   bar     NaN
  d  NaN  False   bar     NaN

You can insert raw ndarrays but their length must match the length of the DataFrame’s index.

By default, columns get inserted at the end. The `insert` function is available to insert at a particular location in the columns:

In [69]: df.insert(1, 'bar', df['one'][:2])

In [70]: df

(continues on next page)
8.2.9 Assigning New Columns in Method Chains

Inspired by dplyr’s `mutate` verb, DataFrame has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [71]: iris = pd.read_csv('data/iris.data')

In [72]: iris.head()
```

```
Out[72]:
    SepalLength  SepalWidth  PetalLength  PetalWidth  Name   sepal_ratio
0        5.1         3.5         1.4         0.2  Iris-setosa  0.6863
1        4.9         3.0         1.4         0.2  Iris-setosa  0.6122
2        4.7         3.2         1.3         0.2  Iris-setosa  0.6809
3        4.6         3.1         1.5         0.2  Iris-setosa  0.6739
4        5.0         3.6         1.4         0.2  Iris-setosa  0.7200
```

In the example above, we inserted a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

```
In [74]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] / x['SepalLength'])).head()
```

```
Out[74]:
    SepalLength  SepalWidth  PetalLength  PetalWidth  Name   sepal_ratio
0        5.1         3.5         1.4         0.2  Iris-setosa  0.6863
1        4.9         3.0         1.4         0.2  Iris-setosa  0.6122
2        4.7         3.2         1.3         0.2  Iris-setosa  0.6809
3        4.6         3.1         1.5         0.2  Iris-setosa  0.6739
4        5.0         3.6         1.4         0.2  Iris-setosa  0.7200
```

`assign` always returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don’t have a reference to the DataFrame at hand. This is common when using `assign` in a chain of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:
Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that’s been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn’t have a reference to the filtered DataFrame available.

The function signature for assign is simply **kwargs. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a Series or NumPy array), or a function of one argument to be called on the DataFrame. A copy of the original DataFrame is returned, with the new values inserted.

Changed in version 0.23.0.

Starting with Python 3.6 the order of **kwargs is preserved. This allows for dependent assignment, where an expression later in **kwargs can refer to a column created earlier in the same assign().
In the second expression, \(x['C']\) will refer to the newly created column, that’s equal to \(dfa['A'] + dfa['B']\).

To write code compatible with all versions of Python, split the assignment in two.

```python
In [78]: dependent = pd.DataFrame({'A': [1, 1, 1]})
In [79]: (dependent.assign(A=lambda x: x['A'] + 1)  
    ....: .assign(B=lambda x: x['A'] + 2))
```

Out[79]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

**Warning:** Dependent assignment maybe subtly change the behavior of your code between Python 3.6 and older versions of Python.

If you wish write code that supports versions of python before and after 3.6, you’ll need to take care when passing `assign` expressions that

- Updating an existing column
- Referring to the newly updated column in the same `assign`

For example, we’ll update column “A” and then refer to it when creating “B”.

```python
>>> dependent = pd.DataFrame({'A': [1, 1, 1]})
>>> dependent.assign(A=lambda x: x['A'] + 1,  
    B=lambda x: x['A'] + 2)
```

For Python 3.5 and earlier the expression creating B refers to the “old” value of A, [1, 1, 1]. The output is then

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

For Python 3.6 and later, the expression creating A refers to the “new” value of A, [2, 2, 2], which results in

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

## 8.2.10 Indexing / Selection

The basics of indexing are as follows:
### Row selection

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```python
In [80]: df.loc['b']
Out[80]:
one  2
bar  2
flag  False
foo  bar
one_trunc  2
Name: b, dtype: object
```

```python
In [81]: df.iloc[2]
Out[81]:
one  3
bar  3
flag  True
foo  bar
one_trunc  NaN
Name: c, dtype: object
```

For a more exhaustive treatment of sophisticated label-based indexing and slicing, see the section on indexing. We will address the fundamentals of reindexing / conforming to new sets of labels in the section on reindexing.

### 8.2.11 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.

```python
In [82]: df = pd.DataFrame(np.random.randn(10, 4), columns=['A', 'B', 'C', 'D'])
In [83]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=['A', 'B', 'C'])
In [84]: df + df2
Out[84]:
   A   B   C   D
0  0.457 -0.014 1.3809  NaN
1 -0.9554 -1.5010  0.0372  NaN
2 -0.6627 1.5348 -0.8597  NaN
3 -2.4529 1.2373 -0.1337  NaN
4  1.4145  1.9517 -2.3204  NaN
5 -0.4949 -1.6497 -1.0846  NaN
6 -1.0476 -0.7486 -0.8055  NaN
7  NaN  NaN  NaN  NaN
8  NaN  NaN  NaN  NaN
9  NaN  NaN  NaN  NaN
```

---

<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>
When doing an operation between DataFrame and Series, the default behavior is to align the Series index on the DataFrame columns, thus broadcasting row-wise. For example:

```
In [85]: df - df.iloc[0]
Out[85]:
     A    B    C    D
0  0.000 0.000 0.000 0.000
1 -1.359 -0.249 -0.453 -1.755
2  0.253 0.829 0.010 -1.991
3 -1.311 0.054 -1.725 -1.620
4  0.573 1.501 -0.676 -2.053
5 -1.742 0.782 -1.246 -2.053
6 -1.240 -0.869 0.000 0.000
7 -0.743 0.411 -0.929 -0.282
8 -1.194 1.320 0.238 -1.483
9  2.294 1.856 0.773 -1.447
```

In the special case of working with time series data, and the DataFrame index also contains dates, the broadcasting will be column-wise:

```
In [86]: index = pd.date_range('1/1/2000', periods=8)

In [87]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=list('ABC'))

In [88]: df
Out[88]:
      A    B    C
2000-01-01 -1.227 0.769 -1.281
2000-01-02 -0.728 -0.121 -0.098
2000-01-03  0.696 0.342  0.934
2000-01-04 -1.110 -0.620  0.149
2000-01-05 -0.732  0.688  0.176
2000-01-06  0.403 -0.155  0.301
2000-01-07 -2.179 -1.369 -0.954
2000-01-08  1.463 -1.743 -0.826

In [89]: type(df['A'])
   → pandas.core.series.Series

In [90]: df - df['A']
```

(continues on next page)
Warning:

```
def - 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 [91]: df * 5 + 2

Out[91]:
   A     B     C
2000-01-01 -4.1341  5.8490 -4.4062
2000-01-02 -1.6385  1.3935  1.5106
2000-01-03  5.4789  3.7087  6.7986
2000-01-04 -3.5517 -1.0999  2.7487
2000-01-05 -1.6617  5.4387  2.8822
2000-01-06  4.0165  1.2252  3.5081
2000-01-07 -8.8993 -4.8492 -2.7710
2000-01-08  9.3135 -6.7158 -2.1330
```

```
In [92]: 1 / df

Out[92]:
   A     B     C
2000-01-01 -0.8151  1.2990 -0.7805
2000-01-02 -1.3742 -8.2436 -10.2163
2000-01-03  1.4372  2.9262  1.0420
2000-01-04 -0.9006 -1.6130  6.6775
2000-01-05 -1.3655  1.4540  5.6675
2000-01-06  2.4795 -6.4537  3.3154
2000-01-07 -0.4587 -0.7300 -1.0480
2000-01-08  0.6837 -0.5737 -1.2098
```

```
In [93]: df ** 4

Out[93]:
   A     B     C
2000-01-01  2.2653  0.3512  2.6948e+00
2000-01-02  0.2804  0.0002  9.1796e-05
2000-01-03  0.2344  0.0136  8.4838e-01
2000-01-04  1.5199  0.1477  5.0286e-04
2000-01-05  0.2876  0.2237  9.6924e-04
2000-01-06  0.0265  0.0006  8.2769e-03
2000-01-07  22.5795  3.5212  8.2903e-01
2000-01-08  4.5774  9.2332  4.6683e-01
```

8.2. DataFrame 573
Boolean operators work as well:

```python
In [94]: df1 = pd.DataFrame({'a' : [1, 0, 1], 'b' : [0, 1, 1] }, dtype=bool)
In [95]: df2 = pd.DataFrame({'a' : [0, 1, 1], 'b' : [1, 1, 0] }, dtype=bool)
In [96]: df1 & df2
Out[96]:
   a  b
0  0  0
1  1  1
2  1  0
In [97]: df1 | df2
Out[97]:
   a  b
0  1  1
1  1  1
2  1  1
In [98]: df1 ^ df2
Out[98]:
   a  b
0  1  1
1  0  0
2  1  1
In [99]: -df1
Out[99]:
   a  b
0  0  1
1  1  0
2  0  0
```

### 8.2.12 Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an ndarray:

```python
# only show the first 5 rows
In [100]: df[:5].T
Out[100]:
A  -1.2268  -0.7277   0.6958  -1.1103  -0.7323
B   0.7698  -0.1213   0.3417  -0.6200   0.6877
C  -1.2812  -0.0979   0.9597   0.1497   0.1764
```

### 8.2.13 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:

```python
In [101]: np.exp(df)
Out[101]:
(continues on next page)
```
A B C
2000-01-01 0.2932 2.1593 0.2777
2000-01-02 0.4830 0.8858 0.9068
2000-01-03 2.0053 1.4074 2.6110
2000-01-04 0.3294 0.5380 1.1615
2000-01-05 0.4808 1.9892 1.1930
2000-01-06 1.4968 0.8565 1.3521
2000-01-07 0.1131 0.2541 0.3851
2000-01-08 4.3176 0.1750 0.4375

In [102]: np.asarray(df)

array([[-1.2268, 0.7698, -1.2812],
       [-0.7277, -0.1213, -0.0979],
       [ 0.6958, 0.3417, 0.9597],
       [-1.1103, -0.62 , 0.1497],
       [-0.7323, 0.6877, 0.1764],
       [ 0.4033, -0.155 , 0.3016],
       [-2.1799, -1.3698, -0.9542],
       [ 1.4627, -1.7432, -0.8266]])

The dot method on DataFrame implements matrix multiplication:

In [103]: df.T.dot(df)

Out[103]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>11.3419</td>
<td>-0.0598</td>
<td>3.0080</td>
</tr>
<tr>
<td>-0.0598</td>
<td>6.5206</td>
<td>2.0833</td>
</tr>
<tr>
<td>3.0080</td>
<td>2.0833</td>
<td>4.3105</td>
</tr>
</tbody>
</table>

Similarly, the dot method on Series implements dot product:

In [104]: s1 = pd.Series(np.arange(5,10))
In [105]: s1.dot(s1)
Out[105]: 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.

### 8.2.14 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 [106]: baseball = pd.read_csv('data/baseball.csv')
In [107]: print (baseball)
In [108]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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
g      100 non-null int64
ab     100 non-null int64
r      100 non-null int64
h      100 non-null int64
X2b    100 non-null int64
X3b    100 non-null int64
hr     100 non-null int64
rbi    100 non-null float64
sb     100 non-null float64
cs     100 non-null float64
bb     100 non-null int64
so     100 non-null float64
hbp    100 non-null float64
sh     100 non-null float64
sf     100 non-null float64
gidp   100 non-null float64
dtypes: float64(9), int64(11), object(3)
memory usage: 18.0+ KB

However, using `to_string` will return a string representation of the DataFrame in tabular form, though it won’t always fit the console width:

<table>
<thead>
<tr>
<th>id</th>
<th>player</th>
<th>year</th>
<th>stint</th>
<th>team</th>
<th>lg</th>
<th>g</th>
<th>ab</th>
<th>r</th>
<th>h</th>
<th>X2b</th>
<th>X3b</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>finest01</td>
<td>2007</td>
<td></td>
<td>COL</td>
<td>NL</td>
<td>43</td>
<td>94</td>
<td>9</td>
<td>17</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>81</td>
<td>embrea01</td>
<td>2007</td>
<td></td>
<td>OAK</td>
<td>AL</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>82</td>
<td>edmonji01</td>
<td>2007</td>
<td></td>
<td>SLN</td>
<td>NL</td>
<td>117</td>
<td>365</td>
<td>39</td>
<td>92</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>83</td>
<td>easleda01</td>
<td>2007</td>
<td></td>
<td>NYN</td>
<td>NL</td>
<td>76</td>
<td>193</td>
<td>24</td>
<td>54</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
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<td>2007</td>
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<td>NL</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Wide DataFrames will be printed across multiple rows by default:

```
In [110]: pd.DataFrame(np.random.randn(3, 12))
Out[110]:
          0   1   2   3   4   5   6   7
   0 -0.345352 1.314232 0.690579 0.995761 2.396780 0.014871 3.357427 -0.317441
   1 -2.182937 0.380396 0.084844 0.432390 1.519970 -0.493662 0.600178 0.274230
   2  0.206053 -0.251905 -2.213588 1.063327 1.266143 0.299368 -0.863838 0.408204
```

You can change how much to print on a single row by setting the `display.width` option:

```
In [111]: pd.set_option('display.width', 40)  # default is 80

In [112]: pd.DataFrame(np.random.randn(3, 12))
Out[112]:
          0   1   2   3   4   5   6   7
   0  1.262731 1.289997 0.082423 -0.055758 0.536580 -0.489682 0.369374 -0.034571
   1  1.126203 -0.977349 1.474071 -0.064034 -1.282782 0.781836 -1.071357 0.441153
   2  0.758527 1.729689 -0.964980 -0.845696 -1.340896 1.846883 -1.328865 1.682706
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.
8.2.15 DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like an attribute:

```
In [118]: df = pd.DataFrame({'foo1': np.random.randn(5),
                         'foo2': np.random.randn(5)})
In [119]: df
Out[119]:
   foo1    foo2
0  1.1712  -0.8584
1  0.5203  0.3069
2 -1.1971  -0.0287
3 -1.0670  0.3843
4 -0.3034  1.5742
```

The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```
In [5]: df.fo<TAB>
   df.foo1   df.foo2
```

8.3 Panel

**Warning:** In 0.20.0, Panel is deprecated and will be removed in a future version. See the section *Deprecate 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:
8.3.1 From 3D ndarray with optional axis labels

```python
In [121]: 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 [122]: wp
Out[122]:
<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
```

8.3.2 From dict of DataFrame objects

```python
In [123]: data = {'Item1' : pd.DataFrame(np.random.randn(4, 3)),
    .....:   'Item2' : pd.DataFrame(np.random.randn(4, 2))}
    .....:
In [124]: pd.Panel(data)
Out[124]:
<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 <code>minor</code> to use DataFrames’ columns as panel items</td>
</tr>
</tbody>
</table>

For example, compare to the construction above:

```python
In [125]: pd.Panel.from_dict(data, orient='minor')
Out[125]:
<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'`:

```python
In [126]: df = pd.DataFrame({'a': ['foo', 'bar', 'baz'],
    .....:   'b': np.random.randn(3)})
```

(continues on next page)
In [127]: df
Out[127]:
   a    b
0  foo -0.308853
1  bar -0.681087
2  baz  0.377953

In [128]: data = {'item1': df, 'item2': df}

In [129]: panel = pd.Panel.from_dict(data, orient='minor')

In [130]: panel['a']
Out[130]:
   item1  item2
0     foo     foo
1     bar     bar
2     baz     baz

In [131]: panel['b']
Out[131]:
   item1  item2
0 -0.308853 -0.308853
1 -0.681087 -0.681087
2  0.377953  0.377953

In [132]: panel['b'].dtypes
Out[132]:
   item1    float64
   item2    float64
   dtype: object

Note: 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.

### 8.3.3 From DataFrame using to_panel method

to_panel converts a DataFrame with a two-level index to a Panel.

In [133]: midx = pd.MultiIndex(levels=[['one', 'two'], ['x','y']], labels=[[1,1,0,0], [1,0,1,0]])

In [134]: df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [5, 6, 7, 8]}, index=midx)

In [135]: df.to_panel()
Out[135]:
<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
8.3.4 Item selection / addition / deletion

Similar to DataFrame functioning as a dict of Series, Panel is like a dict of DataFrames:

```python
In [136]: wp['Item1']
Out[136]:
             A        B         C         D
2000-01-01  1.588931  0.476720  0.473424 -0.242861
2000-01-02 -0.014805 -0.284319  0.650776 -1.461665
2000-01-03 -1.137707 -0.891060 -0.693921  1.613616
2000-01-04  0.464000  0.227371 -0.496922  0.306389
2000-01-05 -2.290613 -1.134623 -1.561819 -0.260838
```

```
In [137]: 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.

8.3.5 Transposing

A Panel can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```python
In [138]: wp.transpose(2, 0, 1)
Out[138]:
<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
```

8.3.6 Indexing / Selection

<table>
<thead>
<tr>
<th>Operation</th>
<th>Syntax</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select item</td>
<td><code>wp[item]</code></td>
<td>DataFrame</td>
</tr>
<tr>
<td>Get slice at major_axis label</td>
<td><code>wp.major_xs(val)</code></td>
<td>DataFrame</td>
</tr>
<tr>
<td>Get slice at minor_axis label</td>
<td><code>wp.minor_xs(val)</code></td>
<td>DataFrame</td>
</tr>
</tbody>
</table>

For example, using the earlier example data, we could do:

```python
In [139]: wp['Item1']
Out[139]:
             A        B         C         D
2000-01-01  1.588931  0.476720  0.473424 -0.242861
2000-01-02 -0.014805 -0.284319  0.650776 -1.461665
2000-01-03 -1.137707 -0.891060 -0.693921  1.613616
2000-01-04  0.464000  0.227371 -0.496922  0.306389
2000-01-05 -2.290613 -1.134623 -1.561819 -0.260838
```

```
In [140]: wp.major_xs(wp.major_axis[2])
```

→ Item1 Item2 Item3

(continues on next page)
8.3.7 Squeezing

Another way to change the dimensionality of an object is to squeeze a 1-len object, similar to `wp['Item1']`.

```
In [143]: wp.reindex(items=['Item1']).squeeze()
Out[143]:
                    A         B         C         D
2000-01-01  1.588931  0.476720  0.473424 -0.242861
2000-01-02 -0.014805 -0.284319  0.650776 -1.461665
2000-01-03 -1.137707 -0.891060 -1.069094  1.613616
2000-01-04  0.464000  0.227371 -0.496922  0.306389
2000-01-05 -2.290613 -1.134623 -1.561819 -0.260838
Freq: D, Name: B, dtype: float64
```

8.3.8 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 [145]: 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 [146]: panel.to_frame()
```

(continues on next page)
8.4 Deprecate Panel

Over the last few years, pandas has increased in both breadth and depth, with new features, datatype support, and manipulation routines. As a result, supporting efficient indexing and functional routines for Series, DataFrame and Panel has contributed to an increasingly fragmented and difficult-to-understand codebase.

The 3-D structure of a Panel is much less common for many types of data analysis, than the 1-D of the Series or the 2-D of the DataFrame. Going forward it makes sense for pandas to focus on these areas exclusively.

Oftentimes, one can simply use a MultiIndex DataFrame for easily working with higher dimensional data.

In addition, the xarray package was built from the ground up, specifically in order to support the multi-dimensional analysis that is one of Panel’s main usecases. Here is a link to the xarray panel-transition documentation.

```
In [147]: p = tm.makePanel()

In [148]: p
Out[148]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 30 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-02-11 00:00:00
Minor_axis axis: A to D
```

Convert to a MultiIndex DataFrame.

```
In [149]: p.to_frame()
Out[149]:
major minor  ItemA  ItemB  ItemC
2000-01-03 A  -0.390201 -1.624062 -0.605044
```

(continues on next page)
<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
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<td>-0.288156</td>
</tr>
<tr>
<td>2000-02-13</td>
<td></td>
<td>1.337122</td>
<td>-0.314399</td>
<td>-1.044208</td>
</tr>
<tr>
<td>2000-02-14</td>
<td></td>
<td>0.249698</td>
<td>0.728197</td>
<td>0.565375</td>
</tr>
<tr>
<td>2000-02-15</td>
<td></td>
<td>-0.741343</td>
<td>1.092633</td>
<td>0.013910</td>
</tr>
<tr>
<td>2000-02-16</td>
<td></td>
<td>-1.157886</td>
<td>0.516870</td>
<td>-1.199945</td>
</tr>
<tr>
<td>2000-02-17</td>
<td></td>
<td>-1.531095</td>
<td>-0.860626</td>
<td>-0.821179</td>
</tr>
<tr>
<td>2000-02-18</td>
<td></td>
<td>1.103949</td>
<td>1.326768</td>
<td>0.068184</td>
</tr>
<tr>
<td>2000-02-19</td>
<td></td>
<td>-0.079673</td>
<td>-1.675194</td>
<td>-0.458272</td>
</tr>
<tr>
<td>2000-02-20</td>
<td></td>
<td>-0.551865</td>
<td>0.343125</td>
<td>-0.072869</td>
</tr>
<tr>
<td>2000-02-21</td>
<td></td>
<td>1.331458</td>
<td>0.370239</td>
<td>-1.914267</td>
</tr>
<tr>
<td>2000-02-22</td>
<td></td>
<td>-1.087532</td>
<td>0.208927</td>
<td>0.788871</td>
</tr>
<tr>
<td>2000-02-23</td>
<td></td>
<td>-0.922875</td>
<td>0.437234</td>
<td>-1.531004</td>
</tr>
<tr>
<td>2000-02-24</td>
<td></td>
<td>1.592673</td>
<td>2.137827</td>
<td>-1.828740</td>
</tr>
<tr>
<td>2000-02-25</td>
<td></td>
<td>-0.571329</td>
<td>-1.761442</td>
<td>-0.826439</td>
</tr>
<tr>
<td>2000-02-26</td>
<td></td>
<td>1.998044</td>
<td>0.292058</td>
<td>-0.280343</td>
</tr>
<tr>
<td>2000-02-27</td>
<td></td>
<td>0.303638</td>
<td>0.388254</td>
<td>-0.500569</td>
</tr>
<tr>
<td>2000-02-28</td>
<td></td>
<td>1.559318</td>
<td>0.452429</td>
<td>-1.716981</td>
</tr>
</tbody>
</table>
Alternatively, one can convert to an xarray DataArray.

```python
In [150]: p.to_xarray()
Out[150]:
xarray.DataArray (items: 3, major_axis: 30, minor_axis: 4)
array([[[-0.390201,  1.562443, -1.085663,  0.136235],
       [ 1.207122,  0.763264, -1.114738,  0.886313],
       ...,
       [ 1.592673, -0.571329,  1.998044,  0.303638],
       [ 1.559318, -0.026671, -0.244548, -0.917368]],
      [[-1.624062,  0.483103,  0.768159, -0.021763],
       [-0.758514,  0.061495,  0.225441, -0.047152],
       ...,
       [ 2.137827, -1.761442,  0.292058,  0.388254],
       [ 0.452429, -0.899454, -2.019610,  0.479630]],
      [[-0.605044,  0.583129, -0.273458, -0.700648],
       [ 0.878404, -0.876690, -0.335117, -1.166607],
       ...,
       [-1.828740, -0.826439, -0.280343, -0.500569],
       [-1.716981,  0.124808,  0.931536,  0.870690]]])
Coordinates:
* items (items) object 'ItemA' 'ItemB' 'ItemC'
* major_axis (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05 ...
* minor_axis (minor_axis) object 'A' 'B' 'C' 'D'
```

You can see the full-documentation for the xarray package.
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]: index = pd.date_range('1/1/2000', periods=8)
In [2]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [3]: df = pd.DataFrame(np.random.randn(8, 3), index=index,
                       columns=['A', 'B', 'C'])
In [4]: 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'])

9.1 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]: long_series = pd.Series(np.random.randn(1000))
In [6]: long_series.head()
Out[6]:
0    0.229453
1    0.304418
2    0.736135
3   -0.859631
4   -0.424100
dtype: float64

In [7]: long_series.tail(3)
Out[7]:
997  -0.351587
998   1.136249
999  -0.448789
dtype: float64
9.2 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!

```python
In [8]: df[:2]
Out[8]:
   A     B     C
2000-01-01 0.048869 -1.360687 -0.47901
2000-01-02 -0.859661 -0.231595 -0.52775

In [9]: df.columns = [x.lower() for x in df.columns]

In [10]: df
Out[10]:
   a     b     c
2000-01-01 0.048869 -1.360687 -0.479010
2000-01-02 -0.859661 -0.231595 -0.527750
2000-01-03 -1.296337  0.150680  0.123836
2000-01-04  0.571764  1.555563  0.203109
2000-01-05 -1.032011  0.969818  0.962723
2000-01-06  1.304124  1.449735  0.669142
2000-01-07  1.382083 -0.938794  0.669142
2000-01-08 -1.032011  0.969818  0.962723
2000-01-09 -0.011124  1.234567  0.789012
2000-01-10  0.111234 -0.234567  0.345678

To get the actual data inside a data structure, one need only access the **values** property:

```python
In [11]: s.values
Out[11]: array([-1.9339, 0.3773, 0.7341, 2.1416, -0.0112])

In [12]: df.values
array([[ 0.0489, -1.3607, -0.479 ],
       [-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],
       [-1.032 ,  0.9698, -0.9627],
       [ 1.3821, -0.9388,  0.6691]])

In [13]: wp.values
array([[-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]])

(continues on next page)
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.

### 9.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have `nans`.

Here is a sample (using 100 column x 100,000 row DataFrames):

<table>
<thead>
<tr>
<th>Operation</th>
<th>0.11.0 (ms)</th>
<th>Prior Version (ms)</th>
<th>Ratio to Prior</th>
</tr>
</thead>
<tbody>
<tr>
<td>df1 &gt; df2</td>
<td>13.32</td>
<td>125.35</td>
<td>0.1063</td>
</tr>
<tr>
<td>df1 * df2</td>
<td>21.71</td>
<td>36.63</td>
<td>0.5928</td>
</tr>
<tr>
<td>df1 + df2</td>
<td>22.04</td>
<td>36.50</td>
<td>0.6039</td>
</tr>
</tbody>
</table>

You are highly encouraged to install both libraries. See the section *Recommended Dependencies* for more installation info.

These are both enabled to be used by default, you can control this by setting the options:

New in version 0.20.0.

```python
pd.set_option('compute.use_bottleneck', False)
pd.set_option('compute.use_numexpr', False)
```

### 9.4 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.
9.4.1 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 [15]: df
Out[15]:
   one     two     three
  a -1.101558  1.124472  NaN
  b -0.177289  2.487104 -0.634293
  c  0.462215 -0.486066  1.931194
  d  NaN      -0.456288 -1.222918

In [16]: row = df.iloc[1]

In [17]: column = df['two']

In [18]: df.sub(row, axis='columns')
Out[18]:
   one     two     three
  a -0.924269 -1.362632  NaN
  b  0.000000  0.000000  0.000000
  c  0.639504 -2.973170  2.565487
  d  NaN      -2.943392 -0.588625

In [19]: df.sub(row, axis=1)
   one     two     three
  a -2.226031  0.0      NaN
  b -2.664393  0.0   -3.121397
  c  0.948280  0.0    2.417260
  d  NaN      0.0     -0.766631

In [20]: df.sub(column, axis='index')
  one     two     three
  a -0.924269 -1.362632  NaN
  b  0.000000  0.000000  0.000000
  c  0.639504 -2.973170  2.565487
  d  NaN      -2.943392 -0.588625

In [21]: df.sub(column, axis=0)
  one     two     three
  a -2.226031  0.0      NaN
  b -2.664393  0.0   -3.121397
```

(continues on next page)
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]:
<table>
<thead>
<tr>
<th>first</th>
<th>second</th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>two</td>
</tr>
<tr>
<td>1 a</td>
<td>-2.226031</td>
</tr>
<tr>
<td>b</td>
<td>-2.664393</td>
</tr>
<tr>
<td>c</td>
<td>0.948280</td>
</tr>
<tr>
<td>2 a</td>
<td>NaN</td>
</tr>
</tbody>
</table>

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]:
<table>
<thead>
<tr>
<th>Item1</th>
<th>Item2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-0.878036</td>
</tr>
<tr>
<td>B</td>
<td>-0.060128</td>
</tr>
<tr>
<td>C</td>
<td>0.099453</td>
</tr>
<tr>
<td>D</td>
<td>0.248599</td>
</tr>
</tbody>
</table>

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...
```python
In [30]: div, rem = divmod(s, 3)

In [31]: div
Out[31]:
0 0
1 0
2 0
3 1
4 1
5 1
6 2
7 2
8 2
9 3
dtype: int64

In [32]: rem
Out[32]:
0 0
1 1
2 2
3 0
4 1
5 2
6 0
7 1
8 2
9 0
dtype: int64

In [33]: idx = pd.Index(np.arange(10))

In [34]: idx
Out[34]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype='int64')

In [35]: div, rem = divmod(idx, 3)

In [36]: div
Out[36]: Int64Index([0, 0, 0, 1, 1, 1, 2, 2, 2, 3], dtype='int64')

In [37]: rem
Out[37]: Int64Index([0, 1, 2, 0, 1, 2, 0, 1, 2, 0], dtype='int64')
```

Chapter 9. Essential Basic Functionality
We can also do elementwise `divmod()`:

```python
In [38]: div, rem = divmod(s, [2, 2, 3, 4, 4, 5, 5, 6, 6])
```

```python
In [39]: div
Out[39]:
0     0
1     0
2     0
3     1
4     1
5     1
6     1
7     1
8     1
9     1
dtype: int64
```

```python
In [40]: rem
Out[40]:
0     0
1     1
2     2
3     1
4     0
5     1
6     1
7     2
8     2
9     3
dtype: int64
```

9.4.2 Missing data / operations with fill values

In Series and DataFrame, the arithmetic functions have the option of inputting a `fill_value`, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using `fillna` if you wish).

```python
In [41]: df
Out[41]:
   one  two  three
a  1.101558  1.124472      NaN
b -0.177289  2.487104 -0.634293
c  0.462215 -0.486066  1.931194
d      NaN -0.456288 -1.222918
```

```python
In [42]: df2
```

(continues on next page)
9.4.3 Flexible Comparisons

Series and DataFrame have the binary comparison methods `eq`, `ne`, `lt`, `gt`, `le`, and `ge` whose behavior is analogous to the binary arithmetic operations described above:

```python
In [45]: df.gt(df2)
Out[45]:
   one   two   three
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False

In [46]: df2.ne(df)
```

These operations produce a pandas object of the same type as the left-hand-side input that is of dtype `bool`. These boolean objects can be used in indexing operations, see the section on `Boolean indexing`.

9.4.4 Boolean Reductions

You can apply the reductions: `empty`, `any()`, `all()`, and `bool()` to provide a way to summarize a boolean result.

```python
In [47]: (df > 0).all()
Out[47]:
   one   two   three
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False
```
You can reduce to a final boolean value.

```
In [49]: (df > 0).any().any()
Out[49]: True
```

You can test if a pandas object is empty, via the `empty` property.

```
In [50]: df.empty
Out[50]: False
In [51]: pd.DataFrame(columns=list('ABC')).empty
Out[51]: True
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

```
In [52]: pd.Series([True]).bool()
Out[52]: True
In [53]: pd.Series([False]).bool()
Out[53]: False
In [54]: pd.DataFrame([[True]]).bool()
Out[54]: True
In [55]: pd.DataFrame([[False]]).bool()
Out[55]: False
```

**Warning:** You might be tempted to do the following:

```python
>>> if df:
...    ...
```

Or

```python
>>> df and df2
```

These will both raise errors, 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.

9.4. Flexible binary operations
9.4.5 Comparing if objects are equivalent

Often you may find that there is more than one way to compute the same result. As a simple example, consider \( df+df \) 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:

```python
In [56]: df+df == df*2
Out[56]:
     one  two  three
   a  True  True  False
   b  True  True  True
   c  True  True  True
   d  False  True  True

In [57]: (df+df == df*2).all()
   one False
two  True
three False
dtype: bool
```

Notice that the boolean DataFrame \( df+df == df*2 \) contains some False values! This is because NaNs do not compare as equals:

```python
In [58]: np.nan == np.nan
Out[58]: False
```

So, NDFrames (such as Series, DataFrames, and Panels) have an \texttt{equals()}\ method for testing equality, with NaNs in corresponding locations treated as equal.

```python
In [59]: (df+df).equals(df*2)
Out[59]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```python
In [60]: df1 = pd.DataFrame({'col':['foo', 0, np.nan]})

In [61]: df2 = pd.DataFrame({'col':[np.nan, 0, 'foo']}, index=[2,1,0])

In [62]: df1.equals(df2)
Out[62]: False

In [63]: df1.equals(df2.sort_index())
Out[63]: True
```

9.4.6 Comparing array-like objects

You can conveniently perform element-wise comparisons when comparing a pandas data structure with a scalar value:

```python
In [64]: pd.Series(['foo', 'bar', 'baz']) == 'foo'
Out[64]:
0   True
1  False
2  False
dtype: bool
```

(continues on next page)
In [65]: pd.Index(['foo', 'bar', 'baz']) == 'foo'
Out[65]: array([ True, False, False], dtype=bool)

Pandas also handles element-wise comparisons between different array-like objects of the same length:

In [66]: pd.Series(['foo', 'bar', 'baz']) == pd.Index(['foo', 'bar', 'qux'])
Out[66]:
0   True
1   True
2  False
dtype: bool

In [67]: pd.Series(['foo', 'bar', 'baz']) == np.array(['foo', 'bar', 'qux'])
Out[67]:
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 [68]: np.array([1, 2, 3]) == np.array([2])
Out[68]: array([False, True, False], dtype=bool)

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

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

9.4.7 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 [70]: df1 = pd.DataFrame({'A': [1., np.nan, 3., 5., np.nan],
                      'B': [np.nan, 2., 3., np.nan, 6.]})

In [71]: df2 = pd.DataFrame({'A': [5., 2., 4., np.nan, 3., 7.],
                      'B': [np.nan, np.nan, 3., 4., 6., 8.]})
9.4.8 General DataFrame Combine

The `combine_first()` method above calls the more general `DataFrame.combine()` method. 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:

```python
In [75]: combiner = lambda x, y: np.where(pd.isna(x), y, x)
In [76]: df1.combine(df2, combiner)
Out[76]:
   A  B
0  1.0 NaN
1  2.0  2.0
2  3.0  3.0
3  5.0  4.0
4  3.0  6.0
5  7.0  8.0
```
9.5 Descriptive statistics

There exists 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:

```python
In [77]: df
Out[77]:
          one      two      three
a -1.101558  1.124472 NaN
b -0.177289  2.487104 -0.634293
c  0.462215 -0.486066  1.931194
d  NaN -0.456288 -1.222918

In [78]: df.mean(0)
Out[78]:
  one     0.272211
  two     0.667306
  three   0.024661

In [79]: df.mean(1)
Out[79]:
  a  0.011457
  b  0.558507
  c  0.635781
  d -0.839603

In [80]: df.sum(0, skipna=False)
Out[80]:
  one  NaN
  two  2.669223
  three NaN

In [81]: df.sum(axis=1, skipna=True)
Out[81]:
  a  0.022914
  b  1.675522
  c  1.907343
  d -1.679206
```

All such methods have a skipna option signaling whether to exclude missing data (True by default):

```python
In [80]: df.sum(0, skipna=False)
Out[80]:
  one  NaN
  two  2.669223
  three NaN

In [81]: df.sum(axis=1, skipna=True)
Out[81]:
  a  0.022914
  b  1.675522
  c  1.907343
  d -1.679206
```
Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

```python
In [82]: ts_stand = (df - df.mean()) / df.std()

In [83]: ts_stand.std()
Out[83]:
   one     two    three
0     1.0      1.0     NaN
1     1.0      1.0     NaN
2     1.0      1.0     NaN
3     1.0      1.0     NaN
dtype: float64
```

```python
In [84]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)

In [85]: xs_stand.std(1)
Out[85]:
a   1.0
b   1.0
c   1.0
d   1.0
dtype: float64
```

Note that methods like `cumsum()` and `cumprod()` preserve the location of NaN values. This is somewhat different from `expanding()` and `rolling()`. For more details please see this note.

```python
In [86]: df.cumsum()
Out[86]:
    one   two   three
a -1.101558 1.124472   NaN
b -1.278848 3.611576 -0.634293
c -0.816633 3.125511  1.296901
d   NaN  2.669223  0.073983
```

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.
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>Number of non-NA observations</td>
</tr>
<tr>
<td>sum</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean</td>
<td>Mean of values</td>
</tr>
<tr>
<td>mad</td>
<td>Mean absolute deviation</td>
</tr>
<tr>
<td>median</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min</td>
<td>Minimum</td>
</tr>
<tr>
<td>max</td>
<td>Maximum</td>
</tr>
<tr>
<td>mode</td>
<td>Mode</td>
</tr>
<tr>
<td>abs</td>
<td>Absolute Value</td>
</tr>
<tr>
<td>prod</td>
<td>Product of values</td>
</tr>
<tr>
<td>std</td>
<td>Bessel-corrected sample standard deviation</td>
</tr>
<tr>
<td>var</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>sem</td>
<td>Standard error of the mean</td>
</tr>
<tr>
<td>skew</td>
<td>Sample skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt</td>
<td>Sample kurtosis (4th moment)</td>
</tr>
<tr>
<td>quantile</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>cumsum</td>
<td>Cumulative sum</td>
</tr>
<tr>
<td>cumprod</td>
<td>Cumulative product</td>
</tr>
<tr>
<td>cummax</td>
<td>Cumulative maximum</td>
</tr>
<tr>
<td>cummin</td>
<td>Cumulative minimum</td>
</tr>
</tbody>
</table>

Note that by chance some NumPy methods, like \texttt{mean}, \texttt{std}, and \texttt{sum}, will exclude NAs on Series input by default:

```python
In [87]: np.mean(df['one'])
Out[87]: -0.27221094480450114
In [88]: np.mean(df['one'].values)
```

\texttt{Series.nunique()} will return the number of unique non-NA values in a Series:

```python
In [89]: series = pd.Series(np.random.randn(500))
In [90]: series[20:500] = np.nan
In [91]: series[10:20] = 5
In [92]: series.nunique()
Out[92]: 11
```

### 9.5.1 Summarizing data: describe

There is a convenient \texttt{describe()} function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```python
In [93]: series = pd.Series(np.random.randn(1000))
In [94]: series[:2] = np.nan
In [95]: series.describe()
Out[95]:
```

(continues on next page)
You can select specific percentiles to include in the output:

```
In [99]: series.describe(percentiles=[.05, .25, .75, .95])
Out[99]:
    count  mean   std     min    25%     50%     75%     95%     max
dtype: float64
          a   b   c    d    e
count  500.000 500.000 500.000 500.000 500.000
mean -0.045109 -0.052045 0.024520 0.006117 0.001141
std  1.029268  1.002320 1.042793 1.040134 1.005207
min -2.915767 -3.294023 -3.610499 -2.907036 -3.010899
25% -1.733545 -0.720389 -0.609600 -0.665896 -0.682900
50% -0.086033 -0.048843  0.006093  0.043191 -0.001651
75%  0.663399  0.620980  0.728382  0.735973  0.656439
max  3.400646  2.925597  3.416896  3.331522  3.007143
```

By default, the median is always included.

For a non-numerical Series object, `describe()` will give a simple summary of the number of unique values and most frequently occurring values:

```
In [100]: s = pd.Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])

In [101]: s.describe()
Out[101]:
    count     unique     top    freq
dtype: object
           9          4         a        5
Note that on a mixed-type DataFrame object, `describe()` will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```python
In [102]: frame = pd.DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})

In [103]: frame.describe()
Out[103]:
   b
count 4.000000
mean  1.500000
std  1.290994
min  0.000000
25%  0.750000
50%  1.500000
75%  2.250000
max  3.000000

This behaviour can be controlled by providing a list of types as `include/exclude` arguments. The special value `all` can also be used:

```python
In [104]: frame.describe(include=['object'])
Out[104]:
   a
count  4
unique  2
top  No
freq   2

In [105]: frame.describe(include=['number'])
Out[105]:
   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 [106]: frame.describe(include='all')
Out[106]:
   →
   a    b
count  4   4.000000
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.

9.5. Descriptive statistics
9.5.2 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:

```python
In [107]: s1 = pd.Series(np.random.randn(5))

In [108]: s1
Out[108]:
0 -1.649461
1  0.169660
2  1.246181
3  0.131682
4 -2.001988
dtype: float64

In [109]: s1.idxmin(), s1.idxmax()

(4, 2)
```

```python
In [110]: df1 = pd.DataFrame(np.random.randn(5,3), columns=['A','B','C'])

In [111]: df1
Out[111]:
    A         B         C
0 -1.273023  0.870502  0.214583
1  0.088452 -0.173364  1.207466
2  0.546121  0.409515 -0.310515
3  0.585014 -0.490528 -0.054639
4 -0.239226  0.701089  0.228656

In [112]: df1.idxmin(axis=0)

     A     B     C
0 -1.273  0.870  0.215
1  0.088 -0.173  1.207
2  0.546  0.409 -0.310
3  0.585 -0.490 -0.055
4 -0.239  0.701  0.229

dtype: int64

In [113]: df1.idxmax(axis=1)

     0   1   2
A  0  3  2
B  1  2  3
C  3  1  0

dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin()` and `idxmax()` return the first matching index:

```python
In [114]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [115]: df3
Out[115]:
     A
e  2.0
```

(continues on next page)
Note: idxmin and idxmax are called argmin and argmax in NumPy.

9.5.3 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 [117]: data = np.random.randint(0, 7, size=50)
In [118]: data
Out[118]: array([3, 3, 0, 2, 1, 0, 5, 5, 3, 6, 1, 5, 6, 2, 0, 0, 6, 3, 3, 5, 0, 4, 3,
                     3, 3, 0, 6, 1, 3, 5, 5, 0, 4, 0, 6, 3, 6, 5, 4, 3, 2, 1, 5, 0, 1, 1,
                     6, 4, 1, 4])
In [119]: s = pd.Series(data)
In [120]: s.value_counts()
Out[120]:
3    11
0     9
5     8
6     7
1     7
4     5
2     3
dtype: int64
```

Similarly, you can get the most frequently occurring value(s) (the mode) of the values in a Series or DataFrame:

```
In [121]: pd.value_counts(data)
Out[121]:
3    11
0     9
5     8
6     7
1     7
4     5
2     3
dtype: int64
```

```
9.5.4 Discretization and quantiling

Continuous values can be discretized using the \texttt{cut()} (bins based on values) and \texttt{qcut()} (bins based on sample quantiles) functions:

\begin{verbatim}
In [126]: arr = np.random.randn(20)
In [127]: factor = pd.cut(arr, 4)

Out[128]:
[(2.611, -1.58], (0.473, 1.499], (-0.554, 0.473], (-2.611, -1.58]
Length: 20
Categories (4, interval[float64]): (-2.611, -1.58] < (-1.58, -0.554] < (-0.554, 0.473] < (0.473, 1.499]

In [129]: factor = pd.cut(arr, [-5, -1, 0, 1, 5])

Out[130]:
[(-5, -1], (0, 1], (-5, -1], (-1, 0], (-1, 0], ..., (1, 5], (1, 5], (-1, 0], (-1, 0],...
Length: 20
Categories (4, interval[int64]): (-5, -1] < (-1, 0] < (0, 1] < (1, 5]
\end{verbatim}

\texttt{qcut()} computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

\begin{verbatim}
In [131]: arr = np.random.randn(30)
In [132]: factor = pd.qcut(arr, [0, .25, .5, .75, 1])

Out[133]:
[(0.544, 1.976], (0.544, 1.976], (-1.255, -0.375], (0.544, 1.976], (-0.103, 0.544],...
Length: 30
\end{verbatim}


We can also pass infinite values to define the bins:

```
In [135]: arr = np.random.randn(20)
In [136]: factor = pd.cut(arr, [-np.inf, 0, np.inf])
In [137]: factor
Out[137]:
[(0.0, inf], (0.0, inf], (0.0, inf], (0.0, inf], (-inf, 0.0], ..., (-inf, 0.0], (-inf, 0.0], (0.0, inf],
Length: 20
Categories (2, interval[float64]): [(-inf, 0.0] < (0.0, inf]]
```

9.6 Function application

To apply your own or another library’s functions to pandas objects, you should be aware of the three methods below. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame or Series, row- or column-wise, or elementwise.

1. **Tablewise Function Application**: `pipe()`
2. **Row or Column-wise Function Application**: `apply()`
3. **Aggregation API**: `agg()` and `transform()`
4. **Applying Elementwise Functions**: `applymap()`

9.6.1 Tablewise Function Application

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

```
# f, g, and h are functions taking and returning `DataFrames`
>>> f(g(h(df), arg1=1), arg2=2, arg3=3)
```

with the equivalent

```
>>> (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)`.

For example, we can fit a regression using statsmodels. Their API expects a formula first and a DataFrame as the second argument, `data`. We pass in the function, keyword pair `(sm.ols, 'data')` to `pipe`:

```python
In [138]: import statsmodels.formula.api as sm
In [139]: bb = pd.read_csv('data/baseball.csv', index_col='id')
In [140]: (bb.query('h > 0')
       ....: .assign(ln_h = lambda df: np.log(df.h))
       ....: .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
       ....: .fit()
       ....: .summary()
       ....: )
```

```
Out[140]:
```

The pipe method is inspired by unix pipes and more recently `dplyr` and `magrittr`, which have introduced the popular `%>%` (read pipe) operator for R. The implementation of `pipe` here is quite clean and feels right at home in python.
We encourage you to view the source code of \textit{pipe()}. 

### 9.6.2 Row or Column-wise Function Application

Arbitrary functions can be applied along the axes of a DataFrame using the \textit{apply()} method, which, like the descriptive statistics methods, takes an optional \texttt{axis} argument:

```python
In [141]: df.apply(np.mean)
Out[141]:
one   -0.272211
two    0.667306
three   0.024661
dtype: float64

In [142]: df.apply(np.mean, axis=1)
Out[142]:
a  0.011457
b  0.558507
c  0.635781
d -0.839603
dtype: float64

In [143]: df.apply(lambda x: x.max() - x.min())
Out[143]:
one   1.563773
two   2.973170
three  3.154112
dtype: float64

In [144]: df.apply(np.cumsum)
Out[144]:
   one   two   three
a -1.101558 1.124472  NaN
b -1.278848 3.611576 -0.634293
c -0.816633 3.125511  1.296901
d  NaN    2.669223 0.073983

In [145]: df.apply(np.exp)
Out[145]:
   one    two    three
a  0.332353 3.078592  NaN
b  0.837537 12.026397 0.53031
  1.587586  0.615041  6.89774
d  NaN 0.633631  0.29437
```

The \textit{apply()} method will also dispatch on a string method name.

```python
In [146]: df.apply('mean')
Out[146]:
one   -0.272211
two    0.667306
three   0.024661
dtype: float64
```

(continues on next page)
In [147]: df.apply('mean', axis=1)
\-----------------------------------\-----------------------------------
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.011457</td>
<td></td>
</tr>
<tr>
<td>b</td>
<td>0.558507</td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.635781</td>
<td></td>
</tr>
<tr>
<td>d</td>
<td>-0.839603</td>
<td></td>
</tr>
</tbody>
</table>
\-----------------------------------\-----------------------------------

The return type of the function passed to `apply()` affects the type of the final output from `DataFrame.apply` for the default behaviour:

- If the applied function returns a `Series`, the final output is a `DataFrame`. The columns match the index of the `Series` returned by the applied function.
- If the applied function returns any other type, the final output is a `Series`.

This default behaviour can be overridden using the `result_type`, which accepts three options: `reduce`, `broadcast`, and `expand`. These will determine how list-likes return values expand (or not) to a `DataFrame`.

`apply()` combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

In [148]: tsdf = pd.DataFrame(np.random.randn(1000, 3), columns=['A', 'B', 'C'], index=pd.date_range('1/1/2000', periods=1000))

In [149]: tsdf.apply(lambda x: x.idxmax())
Out[149]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2001-04-25</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>2002-05-31</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>2002-09-25</td>
<td></td>
</tr>
</tbody>
</table>
\-----------------------------------\-----------------------------------

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:

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:

In [150]: tsdf
Out[150]:
<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>-0.720299</td>
<td>0.546303</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.200295</td>
<td>-0.577554</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.102533</td>
<td>1.653614</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>
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.

### 9.6.3 Aggregation API

New in version 0.20.0.

The aggregation API allows one to express possibly multiple aggregation operations in a single concise way. This API is similar across pandas objects, see groupby API, the window functions API, and the resample API. The entry point for aggregation is `DataFrame.aggregate()`, or the alias `DataFrame.agg()`.

We will use a similar starting frame from above:

```
In [152]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
                  index=pd.date_range('1/1/2000', periods=10))
                  ....:
                  ....:
In [153]: tsdf.iloc[3:7] = np.nan
```

```
In [154]: tsdf
Out[154]:
   A         B         C
2000-01-01  0.170247 -0.916844  0.835024
2000-01-02  1.259919  0.801111  0.445614
2000-01-03  1.453046  2.430373  0.653093
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 -1.874526  0.569822 -0.609644
2000-01-09  0.812462  0.565894 -1.461363
2000-01-10 -0.985475  1.388154 -0.078747
```

Using a single function is equivalent to `apply()`. You can also pass named methods as strings. These will return a Series of the aggregated output:
In [155]: tsdf.agg(np.sum)
Out[155]:
A  0.835673
B  4.838510
C -0.216025
dtype: float64

In [156]: tsdf.agg('sum')
Out[156]:
A  0.835673
B  4.838510
C -0.216025
dtype: float64

# these are equivalent to a `.sum()` because we are aggregating on a single function
In [157]: tsdf.sum()
→
A  0.835673
B  4.838510
C -0.216025
dtype: float64

Single aggregations on a Series this will return a scalar value:

In [158]: tsdf.A.agg('sum')
Out[158]: 0.83567297915820504

### 9.6.3.1 Aggregating with multiple functions

You can pass multiple aggregation arguments as a list. The results of each of the passed functions will be a row in the resulting DataFrame. These are naturally named from the aggregation function.

In [159]: tsdf.agg(['sum'])
Out[159]:
   A   B   C
sum 0.835673 4.838510 -0.216025

Multiple functions yield multiple rows:

In [160]: tsdf.agg(['sum', 'mean'])
Out[160]:
   A   B   C
  sum 0.835673 4.838510 -0.216025
  mean 0.139279 0.806418 -0.036004

On a Series, multiple functions return a Series, indexed by the function names:

In [161]: tsdf.A.agg(['sum', 'mean'])
Out[161]:
   sum 0.835673
   mean 0.139279
Name: A, dtype: float64

Passing a lambda function will yield a `<lambda>` named row:
In [162]: tsdf.A.agg(['sum', lambda x: x.mean()])
Out[162]:
sum 0.835673
<lambda> 0.139279
Name: A, dtype: float64

Passing a named function will yield that name for the row:

In [163]: def mymean(x):
   ....:     return x.mean()
   ....:

In [164]: tsdf.A.agg(['sum', mymean])
Out[164]:
sum 0.835673
mymean 0.139279
Name: A, dtype: float64

### 9.6.3.2 Aggregating with a dict

Passing a dictionary of column names to a scalar or a list of scalars, to `DataFrame.agg` allows you to customize which functions are applied to which columns. Note that the results are not in any particular order, you can use an `OrderedDict` instead to guarantee ordering.

In [165]: tsdf.agg({'A': 'mean', 'B': 'sum'})
Out[165]:
A 0.139279
B 4.838510
dtype: float64

Passing a list-like will generate a `DataFrame` output. You will get a matrix-like output of all of the aggregators. The output will consist of all unique functions. Those that are not noted for a particular column will be NaN:

In [166]: tsdf.agg({'A': ['mean', 'min'], 'B': 'sum'})
Out[166]:
     A     B
mean 0.139279 NaN
min -1.874526 NaN
sum NaN 4.83851

### 9.6.3.3 Mixed Dtypes

When presented with mixed dtypes that cannot aggregate, `.agg` will only take the valid aggregations. This is similar to how `groupby` `.agg` works.

In [167]: mdf = pd.DataFrame({'A': [1, 2, 3],
   ....:     'B': [1., 2., 3.],
   ....:     'C': ['foo', 'bar', 'baz'],
   ....:     'D': pd.date_range('20130101', periods=3)})
In [168]: mdf.dtypes
Out[168]:
A    int64
(continues on next page)
9.6.3.4 Custom describe

With `.agg()` is it possible to easily create a custom describe function, similar to the built in `describe` function.

```python
In [170]: from functools import partial
In [171]: q_25 = partial(pd.Series.quantile, q=0.25)
In [172]: q_25.__name__ = '25%'
In [173]: q_75 = partial(pd.Series.quantile, q=0.75)
In [174]: q_75.__name__ = '75%'
In [175]: tsdf.agg(['count', 'mean', 'std', 'min', q_25, 'median', q_75, 'max'])
```

9.6.4 Transform API

New in version 0.20.0.

The `transform()` method returns an object that is indexed the same (same size) as the original. This API allows you to provide multiple operations at the same time rather than one-by-one. Its API is quite similar to the `.agg` API.

We create a frame similar to the one used in the above sections.

```python
In [176]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
                        index=pd.date_range('1/1/2000', periods=10))
In [177]: tsdf.iloc[3:7] = np.nan
In [178]: tsdf
```
Transform the entire frame. `.transform()` allows input functions as: a NumPy function, a string function name or a user defined function.

```
In [179]: tsdf.transform(np.abs)
Out[179]:
   A    B    C
2000-01-01  0.578465  0.503335  0.987140
2000-01-02  0.767147  0.266046  1.083797
2000-01-03  0.195348  0.722247  0.894537
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  0.556397  0.542165  0.308675
2000-01-09  1.010924  0.672504  1.139222
2000-01-10  0.354653  0.563622  0.365106
```

```
In [180]: tsdf.transform('abs')

In [181]: tsdf.transform(lambda x: x.abs())
```

(continues on next page)
Here \texttt{transform()} received a single function; this is equivalent to a ufunc application.

\begin{verbatim}
In [182]: np.abs(tsdf)
Out[182]:
          A     B     C
2000-01-01 0.578465 0.503335 0.987140
2000-01-02 0.767147 0.266046 1.083797
2000-01-03 0.195348 0.722247 0.894537
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 0.556397 0.542165 0.308675
2000-01-09 1.010924 0.672504 1.139222
2000-01-10 0.354653 0.563622 0.365106
\end{verbatim}

Passing a single function to \texttt{.transform()} with a \texttt{Series} will yield a single \texttt{Series} in return.

\begin{verbatim}
In [183]: tsdf.A.transform(np.abs)
Out[183]:
          absolute   <lambda>
2000-01-01 0.578465 0.421535
2000-01-02 0.767147 0.232853
2000-01-03 0.195348 1.195348
2000-01-04 NaN  NaN
2000-01-05 NaN  NaN
2000-01-06 NaN  NaN
2000-01-07 NaN  NaN
2000-01-08 0.556397 0.542165
2000-01-09 1.010924 0.672504
2000-01-10 0.354653 0.563622
Freq: D, Name: A, dtype: float64
\end{verbatim}

9.6.4.1 Transform with multiple functions

Passing multiple functions will yield a column multi-indexed DataFrame. The first level will be the original frame column names; the second level will be the names of the transforming functions.

\begin{verbatim}
In [184]: tsdf.transform([np.abs, lambda x: x+1])
Out[184]:
          absolute  <lambda> absolute  <lambda> absolute  <lambda>
2000-01-01 0.578465 0.421535 0.503335 0.496665 0.987140 0.012860
2000-01-02 0.767147 0.232853 0.266046 0.733954 1.083797 2.083797
2000-01-03 0.195348 1.195348 0.722247 1.722247 0.894537 0.105463
2000-01-04 NaN  NaN  NaN  NaN  NaN  NaN
2000-01-05 NaN  NaN  NaN  NaN  NaN  NaN
2000-01-06 NaN  NaN  NaN  NaN  NaN  NaN
2000-01-07 NaN  NaN  NaN  NaN  NaN  NaN
2000-01-08 0.556397 0.443603 0.542165 1.542165 0.308675 0.691325
2000-01-09 1.010924 -0.010924 0.672504 0.327496 1.139222 -0.139222
2000-01-10 0.354653 1.354653 0.563622 1.563622 0.365106 0.634894
\end{verbatim}
Passing multiple functions to a Series will yield a DataFrame. The resulting column names will be the transforming functions.

```
In [185]: tsdf.A.transform([np.abs, lambda x: x+1])
Out[185]:
       absolute    <lambda>
2000-01-01  0.578465   0.421535
2000-01-02  0.767147   0.232853
2000-01-03  0.195348  1.195348
2000-01-04   NaN       NaN
2000-01-05   NaN       NaN
2000-01-06   NaN       NaN
2000-01-07   NaN       NaN
2000-01-08  0.556397   0.443603
2000-01-09  1.010924  -0.010924
2000-01-10  0.354653   1.354653
```

9.6.4.2 Transforming with a dict

Passing a dict of functions will allow selective transforming per column.

```
In [186]: tsdf.transform({'A': np.abs, 'B': lambda x: x+1})
Out[186]:
     A  B
2000-01-01  0.578465  0.496665
2000-01-02  0.767147  0.733954
2000-01-03  0.195348  1.722247
2000-01-04   NaN     NaN
2000-01-05   NaN     NaN
2000-01-06   NaN     NaN
2000-01-07   NaN     NaN
2000-01-08  0.556397  1.542165
2000-01-09  1.010924  0.327496
2000-01-10  0.354653  1.563622
```

Passing a dict of lists will generate a multi-indexed DataFrame with these selective transforms.

```
In [187]: tsdf.transform({'A': np.abs, 'B': [lambda x: x+1, 'sqrt']})
Out[187]:
       absolute    <lambda>  sqrt
2000-01-01  0.578465   0.496665  NaN
2000-01-02  0.767147   0.733954  NaN
2000-01-03  0.195348  1.195348  0.849851
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  0.556397  0.542165  0.736318
2000-01-09  1.010924  0.327496   NaN
2000-01-10  0.354653  1.563622  0.750748
```

9.6.5 Applying Elementwise Functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods `applymap()` on DataFrame and analogously `map()` on Series accept any Python function taking a single value and
returning a single value. For example:

```python
In [188]: df4
Out[188]:
   one   two   three
a -1.101558  1.124472    NaN
b -0.177289  2.487104 -0.634293
c  0.462215 -0.486066  1.931194
d    NaN  -0.456288 -1.222918

In [189]: f = lambda x: len(str(x))

In [190]: df4['one'].map(f)
Out[190]:
   a  19
   b  20
   c  18
   d   3
Name: one, dtype: int64

In [191]: df4.applymap(f)
   one   two   three
a  19    18     3
b  20    18    19
c  18    20    18
d   3     19    19

Series.map() has an additional feature; it can be used to easily “link” or “map” values defined by a secondary series. This is closely related to merging/joining functionality:

```python
In [192]: s = pd.Series(['six', 'seven', 'six', 'seven', 'six'],
               index=['a', 'b', 'c', 'd', 'e'])

In [193]: t = pd.Series({'six' : 6., 'seven' : 7.})

In [194]: s
Out[194]:
a   six
b   seven
c   six
d   seven
e   six
dtype: object

In [195]: s.map(t)
   a  6.0
   b  7.0
   c  6.0
   d  7.0
   e  6.0
dtype: float64
9.6.6 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.

In [196]: import pandas.util.testing as tm

In [197]: panel = tm.makePanel(5)

In [198]: panel
Out[198]:
<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 [199]: panel['ItemA']

→
A   B   C   D
2000-01-03 1.092702 0.604244 -2.927808 0.339642
2000-01-04 -1.481449 -0.487265 0.082065 1.499953
2000-01-05  1.781190  1.990533 0.456554 -0.317818
2000-01-06 -0.031543  0.327007 -1.757911  0.447371
2000-01-07  0.480993  1.053639  0.982407 -1.315799

A transformational apply.

In [200]: result = panel.apply(lambda x: x*2, axis='items')

In [201]: result
Out[201]:
<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 [202]: result['ItemA']

→
A   B   C   D
2000-01-03  2.185405  1.208489  -5.855616  0.679285
2000-01-04  -2.962899  -0.974530  0.164130  2.999905
2000-01-05   3.562379   3.981066  0.913107 -0.635635
2000-01-06  -0.063086   0.654013 -3.515821  0.894742
2000-01-07  0.961986   2.107278  1.964815 -2.631598

A reduction operation.

In [203]: panel.apply(lambda x: x.dtype, axis='items')
Out[203]:
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
(continues on next page)
A similar reduction type operation.

```
In [204]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[204]:
           ItemA   ItemB   ItemC
A  1.841893  0.918017 -1.160547
B  3.488158 -2.629773  0.603397
C -3.164692  0.805970  0.806501
D  0.653349 -0.152299  0.252577
```

This last reduction is equivalent to:

```
In [205]: panel.sum('major_axis')
Out[205]:
           ItemA   ItemB   ItemC
A  1.841893  0.918017 -1.160547
B  3.488158 -2.629773  0.603397
C -3.164692  0.805970  0.806501
D  0.653349 -0.152299  0.252577
```

A transformation operation that returns a Panel, but is computing the z-score across the major_axis.

```
In [206]: result = panel.apply(
                      ....:       lambda x: (x-x.mean())/x.std(),
                      ....:       axis='major_axis')

In [207]: result
Out[207]:
<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
```

Apply can also accept multiple axes in the axis argument. This will pass a DataFrame of the cross-section to the applied function.

```
In [209]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T

In [210]: result = panel.apply(f, axis = ['items','major_axis'])

In [211]: result
```
This is equivalent to the following:

```python
In [213]: result = pd.Panel(dict((ax, f(panel.loc[:,:,ax])) for ax in panel.minor_axis))
```

```python
In [214]: result
Out[214]:
<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
```

```python
In [215]: result.loc[:, :, 'ItemA']
```

9.7 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:
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:

You may also use `reindex` with an axis keyword:

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:
c -0.951631
d -0.535459
dtype: float64

In [224]: rs.index is df.index

Out[224]: True

This means that the reindexed Series’s index is the same Python object as the DataFrame’s index.

New in version 0.21.0.

DataFrame.reindex() also supports an “axis-style” calling convention, where you specify a single labels argument and the axis it applies to.

In [225]: df.reindex(['c', 'f', 'b'], axis='index')

Out[225]:
three two one
   c  0.462215 -0.486066 1.931194
   f         NaN         NaN
   b -0.177289  2.487104 -0.634293

In [226]: df.reindex(['three', 'two', 'one'], axis='columns')

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.

9.7.1 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 [227]: df2
Out[227]:
   one   two
   a -1.101558 1.124472
   b -0.177289 2.487104
   c  0.462215 -0.486066

In [228]: df3

Although this method is not yet documented, you can see that it offers a cleaner syntax.
### 9.7.2 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:

```python
In [230]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [231]: s1 = s[:4]
In [232]: s2 = s[1:]
In [233]: s1.align(s2)
Out[233]:
   a    b    c    d    e
--- --- --- --- ---
   a  0.505453
   b  1.788110
   c -0.405908
   d -0.801912
   e  NaN
dtype: float64, a  NaN
   b  1.788110
   c -0.405908
   d -0.801912
   e  0.768460
dtype: float64)
```

```python
In [234]: s1.align(s2, join='inner')
```

(continues on next page)
c -0.405908
d -0.801912
dtype: float64)

In [235]: s1.align(s2, join='left')

→
(a 0.505453
 b 1.788110
c -0.405908
d -0.801912
dtype: float64, a NaN
 b 1.788110
c -0.405908
d -0.801912
dtype: float64)

For DataFrames, the join method will be applied to both the index and the columns by default:

In [236]: df.align(df2, join='inner')

Out[236]:
( one two
 a -1.101558 1.124472
 b -0.177289 2.487104
c 0.462215 -0.486066, one two
 a -1.101558 1.124472
 b -0.177289 2.487104
c 0.462215 -0.486066)

You can also pass an axis option to only align on the specified axis:

In [237]: df.align(df2, join='inner', axis=0)

Out[237]:
( one two three
 a -1.101558 NaN 1.124472
 b -0.177289 -0.634293 2.487104
c 0.462215 1.931194 -0.486066, one two
 a -1.101558 1.124472
 b -0.177289 2.487104
c 0.462215 -0.486066)

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 [238]: df.align(df2.iloc[0], axis=1)

Out[238]:
( one three two
 a -1.101558 NaN 1.124472
 b -0.177289 -0.634293 2.487104
c 0.462215 1.931194 -0.486066, one two
 d NaN -1.222918 -0.456288, one -1.101558
three NaN
two 1.124472
Name: a, dtype: float64)
9.7.3 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 [239]: rng = pd.date_range('1/3/2000', periods=8)
In [240]: ts = pd.Series(np.random.randn(8), index=rng)
In [241]: ts2 = ts[[0, 3, 6]]
In [242]: ts
Out[242]:
2000-01-03  0.466284
2000-01-04 -0.457411
2000-01-05 -0.364060
2000-01-06  0.785367
2000-01-07 -1.463093
2000-01-08  1.187315
2000-01-09 -0.493153
2000-01-10 -1.323445
Freq: D, dtype: float64
```

```
In [243]: ts2
    →
2000-01-03 0.466284
2000-01-06 0.785367
2000-01-09 -0.493153
dtype: float64
```

```
In [244]: ts2.reindex(ts.index)
    →
2000-01-03 0.466284
2000-01-04 NaN
2000-01-05 NaN
2000-01-06 0.785367
2000-01-07 NaN
2000-01-08 NaN
2000-01-09 -0.493153
2000-01-10 NaN
Freq: D, dtype: float64
```

```
In [245]: ts2.reindex(ts.index, method='ffill')
    →
2000-01-03 0.466284
2000-01-04 0.466284
2000-01-05 0.466284
2000-01-06 0.785367
(continues on next page)
```
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 [248]: ts2.reindex(ts.index).fillna(method='ffill')
```

```
Out[248]:
2000-01-03  0.466284
2000-01-04  0.466284
2000-01-05  0.466284
2000-01-06  0.466284
2000-01-07  0.785367
2000-01-08  0.785367
2000-01-09  0.785367
2000-01-10  -0.493153
Freq: D, dtype: float64
```

`reindex()` will raise a `ValueError` if the index is not monotonically increasing or decreasing. `fillna()` and `interpolate()` will not perform any checks on the order of the index.

### 9.7.4 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:
In [249]: ts2.reindex(ts.index, method='ffill', limit=1)
Out[249]:
2000-01-03  0.466284
2000-01-04  0.466284
2000-01-05  NaN
2000-01-06  0.785367
2000-01-07  0.785367
2000-01-08  NaN
2000-01-09 -0.493153
2000-01-10 -0.493153
Freq: D, dtype: float64

In contrast, tolerance specifies the maximum distance between the index and indexer values:

In [250]: ts2.reindex(ts.index, method='ffill', tolerance='1 day')
Out[250]:
2000-01-03  0.466284
2000-01-04  0.466284
2000-01-05  NaN
2000-01-06  0.785367
2000-01-07  0.785367
2000-01-08  NaN
2000-01-09 -0.493153
2000-01-10 -0.493153
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.

9.7.5 Dropping labels from an axis

A method closely related to reindex is the drop() function. It removes a set of labels from an axis:

In [251]: df
Out[251]:
     one    two    three
a -1.101558 1.124472  NaN
b -0.177289 2.487104 -0.634293
c  0.462215 -0.486066  1.931194
d   NaN -0.456288 -1.222918

In [252]: df.drop(['a', 'd'], axis=0)

     one    two    three
b -0.177289 2.487104 -0.634293
c  0.462215 -0.486066  1.931194

In [253]: df.drop(['one'], axis=1)

     two    three
a  1.124472  NaN
b  2.487104 -0.634293
c -0.486066  1.931194
d -0.456288 -1.222918
Note that the following also works, but is a bit less obvious / clean:

```
In [254]: df.reindex(df.index.difference(['a', 'd']))
Out[254]:
     one   two   three
b -0.177289  2.487104 -0.634293
c   0.462215 -0.486066  1.931194
```

### 9.7.6 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 [255]: s
Out[255]:
a   0.505453
b  1.788110
c -0.405908
d -0.801912
e   0.768460
dtype: float64

In [256]: s.rename(str.upper)
Out[256]:
   A  0.505453
   B  1.788110
   C -0.405908
   D -0.801912
   E  0.768460
dtype: float64
```

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). A dict or Series can also be used:

```
In [257]: df.rename(columns={'one': 'foo', 'two': 'bar'},
index={'a': 'apple', 'b': 'banana', 'd': 'durian'})
```

If the mapping doesn’t include a column/index label, it isn’t renamed. Note that extra labels in the mapping don’t throw an error.

New in version 0.21.0.

`DataFrame.rename()` also supports an “axis-style” calling convention, where you specify a single mapper and the axis to apply that mapping to.

```
In [258]: df.rename({'one': 'foo', 'two': 'bar'}, axis='columns')
```

(continues on next page)
The `rename()` method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place.

New in version 0.18.0.

Finally, `rename()` also accepts a scalar or list-like for altering the `Series.name` attribute.

The Panel class has a related `rename_axis()` class which can rename any of its three axes.

### 9.8 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 [261]: df = pd.DataFrame({'col1' : np.random.randn(3), 'col2' : np.random.randn(3)})
       .....:
       .....:
In [262]: 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 namedtuples of the values. This is a lot faster than `iterrows()`, and is in most cases preferable to use to iterate over the values of a DataFrame.

**Warning**: Iterating through pandas objects is generally **slow**. In many cases, iterating manually over the rows is not needed and can be avoided with one of the following approaches:

- Look for a *vectorized* solution: many operations can be performed using built-in methods or NumPy functions, (boolean) indexing,...
- When you have a function that cannot work on the full DataFrame/Series at once, it is better to use `apply()` instead of iterating over the values. See the docs on function application.
- If you need to do iterative manipulations on the values but performance is important, consider writing the inner loop with cython or numba. See the *enhancing performance* section for some examples of this approach.

**Warning**: You should **never modify** something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect!

For example, in the following case setting the value has no effect:

```python
In [263]: df = pd.DataFrame({'a': [1, 2, 3], 'b': ['a', 'b', 'c']})
In [264]: for index, row in df.iterrows():
    ...:    row['a'] = 10
    ...:
In [265]: df
Out[265]:
   a  b
0  1  a
1  2  b
2  3  c
```

### 9.8.1 `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:

```python
In [266]: for item, frame in wp.iteritems():
    ...:    print(item)
    ...:    print(frame)
    ...:
```
9.8.2 `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:

```python
In [267]: for row_index, row in df.iterrows():
    print('%s
%s' % (row_index, row))

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 [268]: df_orig = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])

In [269]: df_orig.dtypes
Out[269]:
int     int64
float  float64
dtype: object

In [270]: row = next(df_orig.iterrows())[1]

In [271]: row
Out[271]:
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:

```
In [272]: row['int'].dtype
Out[272]: dtype('float64')

In [273]: df_orig['int'].dtype
Out[273]: dtype('int64')
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns namedtuples of the values and which is generally much faster than `iterrows()`.

For instance, a contrived way to transpose the DataFrame would be:

```
In [274]: df2 = pd.DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})

In [275]: print(df2)
    x  y
0  1  4
1  2  5
2  3  6

In [276]: print(df2.T)
   0  1  2
  x  y  
0 4  5  6
1 1  2  3

In [277]: df2_t = pd.DataFrame(dict((idx,values) for idx, values in df2.iterrows()))

In [278]: print(df2_t)
   0  1  2
  x  y  
0 4  5  6
1 1  2  3
```

### 9.8.3 `itertuples`

The `itertuples()` method will return an iterator yielding a namedtuple for each row in the DataFrame. The first element of the tuple will be the row’s corresponding index value, while the remaining values are the row values.

For instance:

```
In [279]: for row in df.itertuples():
    .....:   print(row)
    .....:
Pandas(Index=0, a=1, b='a')
Pandas(Index=1, a=2, b='b')
Pandas(Index=2, a=3, b='c')
```

This method does not convert the row to a Series object; it merely returns the values inside a namedtuple. Therefore, `itertuples()` preserves the data type of the values and is generally faster as `iterrows()`.

**Note:** The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. With a large number of columns (>255), regular tuples are returned.
9.9 .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.

```python
# datetime
In [280]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [281]: s
Out[281]:
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 [282]: s.dt.hour
→
0 9
1 9
2 9
3 9
dtype: int64

In [283]: s.dt.second
→
0 12
1 12
2 12
3 12
dtype: int64

In [284]: s.dt.day
→
0 1
1 2
2 3
3 4
dtype: int64
```

This enables nice expressions like this:

```python
In [285]: s[s.dt.day==2]
Out[285]:
1 2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produces tz aware transformations:

```python
In [286]: stz = s.dt.tz_localize('US/Eastern')

In [287]: stz
Out[287]:
0 2013-01-01 09:10:12-05:00
```

(continues on next page)
You can also chain these types of operations:

```python
In [289]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[289]:
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()`.

```python
# DatetimeIndex
In [290]: s = pd.Series(pd.date_range('20130101', periods=4))

In [291]: s
Out[291]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
3 2013-01-04
dtype: datetime64[ns]

In [292]: s.dt.strftime('%Y/%m/%d')
Out[292]:
0 2013/01/01
1 2013/01/02
2 2013/01/03
3 2013/01/04
dtype: object
```

```python
# PeriodIndex
In [293]: s = pd.Series(pd.period_range('20130101', periods=4))

In [294]: s
Out[294]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
3 2013-01-04
dtype: object

In [295]: s.dt.strftime('%Y/%m/%d')
Out[295]:
```

(continues on next page)
The `.dt` accessor works for period and timedelta dtypes.

```python
# period
In [296]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))

In [297]: s
Out[297]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
3  2013-01-04
dtype: object

In [298]: s.dt.year
Out[298]:
0  2013
1  2013
2  2013
3  2013
dtype: int64

In [299]: s.dt.day
Out[299]:
0  1
1  2
2  3
3  4
dtype: int64
```

```python
# timedelta
In [300]: s = pd.Series(pd.timedelta_range('1 days 00:00:05', periods=4, freq='s'))

In [301]: s
Out[301]:
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 [302]: s.dt.days
Out[302]:
0  1
1  1
2  1
3  1
dtype: int64
```
In [303]: s.dt.seconds

   0  5
   1  6
   2  7
   3  8
dtype: int64

In [304]: s.dt.components

<table>
<thead>
<tr>
<th></th>
<th>days</th>
<th>hours</th>
<th>minutes</th>
<th>seconds</th>
<th>milliseconds</th>
<th>microseconds</th>
<th>nanoseconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Series.dt will raise a TypeError if you access with a non-datetime-like values.

9.10 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 [305]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog →', 'cat'])

In [306]: s.str.lower()

Out[306]:
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.
9.11 Sorting

Pandas supports three kinds of sorting: sorting by index labels, sorting by column values, and sorting by a combination of both.

9.11.1 By Index

The `Series.sort_index()` and `DataFrame.sort_index()` methods are used to sort a pandas object by its index levels.

```
In [307]: df = pd.DataFrame({'one' : pd.Series(np.random.randn(3), index=['a', 'b', 'c', 'd']),
                      'two' : pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd']),
                      'three' : pd.Series(np.random.randn(3), index=['b', 'c', 'd']))

In [308]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'], columns=['three', 'two', 'one'])

In [309]: unsorted_df
Out[309]:
   three  two  one
a    NaN  0.708543  0.036274
d -0.540166  0.586626    NaN
c  0.410238  1.121731  1.044630
b -0.282532 -2.038777 -0.490032

# DataFrame
In [310]: unsorted_df.sort_index()
   three  two  one
a    NaN  0.708543  0.036274
d -0.540166  0.586626    NaN
c  0.410238  1.121731  1.044630
b -0.282532 -2.038777 -0.490032

In [311]: unsorted_df.sort_index(ascending=False)
   three  two  one
d -0.540166  0.586626    NaN
c  0.410238  1.121731  1.044630
b -0.282532 -2.038777 -0.490032
a    NaN  0.708543  0.036274

In [312]: unsorted_df.sort_index(axis=1)
   one  three  two
a  0.036274    NaN  0.708543
d    NaN -0.540166  0.586626
c  1.044630  0.410238  1.121731
```

(continues on next page)
### 9.11.2 By Values

The `Series.sort_values()` method is used to sort a `Series` by its values. The `DataFrame.sort_values()` method is used to sort a `DataFrame` by its column or row values. The optional `by` parameter to `DataFrame.sort_values()` may be used to specify one or more columns to use to determine the sorted order.

```python
In [314]: df1 = pd.DataFrame({'one':[2,1,1,1],'two':[1,3,2,4],'three':[5,4,3,2]})
In [315]: df1.sort_values(by='two')
Out[315]:
   one  two  three
0  2.0   1.0   5.0
1  1.0   3.0   4.0
2  1.0   2.0   3.0
3  1.0   4.0   2.0
```

The `by` parameter can take a list of column names, e.g.:

```python
In [316]: df1[['one', 'two', 'three']].sort_values(by=['one','two'])
Out[316]:
   one  two  three
1  1.0   3.0   4.0
2  1.0   2.0   3.0
3  1.0   4.0   2.0
0  2.0   1.0   5.0
```

These methods have special treatment of NA values via the `na_position` argument:

```python
In [317]: s[2] = np.nan
In [318]: s.sort_values()
Out[318]:
   0  A
   3  Aaba
   1  B
   4  Baca
   6  CABA
   8  cat
   7  dog
  2  NaN
  5  NaN
dtype: object
```

(continues on next page)
9.11.3 By Indexes and Values

New in version 0.23.0.

Strings passed as the by parameter to DataFrame.sort_values() may refer to either columns or index level names.

```python
# Build MultiIndex
In [320]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
                                    ('b', 2), ('b', 1), ('b', 1)])

# Build DataFrame
In [321]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
                              index=idx)

In [322]: df_multi
Out[322]:
   A
first second
a  1  6
   2  5
   2  4
b  2  3
   1  2
   1  1

Sort by ‘second’ (index) and ‘A’ (column)

In [323]: df_multi.sort_values(by=['second', 'A'])
Out[323]:
   A
first second
b  1  1
   1  2
a  1  6
b  2  3
a  2  4
   2  5
```
Note: If a string matches both a column name and an index level name then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

9.11.4 searchsorted

Series has the `searchsorted()` method, which works similarly to `numpy.ndarray.searchsorted()`.

```python
In [325]: ser = pd.Series([1, 2, 3])
In [326]: ser.searchsorted([0, 3])
Out[326]: array([0, 2])

In [327]: ser.searchsorted([0, 4])
Out[327]: array([0, 3])

In [328]: ser.searchsorted([1, 3], side='right')
Out[328]: array([1, 3])

In [329]: ser.searchsorted([1, 3], side='left')
Out[329]: array([0, 2])

In [330]: ser = pd.Series([3, 1, 2])
In [331]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[331]: array([0, 2])
```

9.11.5 smallest / largest values

Series has the `nsmallest()` and `nlargest()` methods which return the smallest or largest \( n \) values. For a large Series this can be much faster than sorting the entire Series and calling `head(n)` on the result.

```python
In [332]: s = pd.Series(np.random.permutation(10))
In [333]: s
Out[333]:
     0  8
     1  2
     2  9
     3  5
     4  6
     5  0
     6  1
     7  7
     8  4
     9  3
dtype: int64

In [334]: s.sort_values()
Out[334]:
     5  0
     6  1
```

(continues on next page)
DataFrame also has the nlargest and nsmallest methods.

In [337]: 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 [338]: df.nlargest(3, 'a')
Out[338]:
   a  b  c
0  11 f 3.0
1  10 c 3.2
2   8 e NaN

In [339]: df.nlargest(5, ['a', 'c'])
Out[339]:
   a  b  c
0  11 f 3.0
1  10 c 3.2
2   8 e NaN
3 -1  f 4.0
4 -1  e NaN

In [340]: df.nsmallest(3, 'a')
Out[340]:
   a  b  c
0 -2  a 1.0
1  1 b 2.0
2  6 f 4.0
9.11.6 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.

```python
In [342]: df1.columns = pd.MultiIndex.from_tuples([('a','one'),('a','two'),('b','three'))
In [343]: df1.sort_values(by=('a','two'))
Out[343]:
   a  b  
one  
   two three
0  2  1  5
2  1  2  3
1  1  3  4
3  1  4  2
```

9.12 Copying

The `copy()` method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that it is seldom necessary to copy objects. For example, there are only a handful of ways to alter a DataFrame in-place:

- Inserting, deleting, or modifying a column.
- Assigning to the index or columns attributes.
- For homogeneous data, directly modifying the values via the values attribute or advanced indexing.

To be clear, no pandas method has the side effect of modifying your data; almost every method returns a new object, leaving the original object untouched. If the data is modified, it is because you did so explicitly.

9.13 dtypes

The main types stored in pandas objects are `float`, `int`, `bool`, `datetime64[ns]` and `datetime64[ns, tz]`, `timedelta[ns]`, `category` 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 DataFrame returns a Series with the data type of each column.
In [345]: dft
Out[345]:
     A     B   C       D       E  F   G
0  0.809585  1  foo  2001-01-02  1.0   False  1
1  0.128238  1  foo  2001-01-02  1.0   False  1
2  0.775752  1  foo  2001-01-02  1.0   False  1
In [346]: dft.dtypes
   →
A    float64
B     int64
C       object
D   datetime64[ns]
E      float32
F        bool
G      int8
dtype: object

On a Series object, use the `dtype` attribute.

In [347]: dft['A'].dtype
Out[347]: dtype('float64')

If a pandas object contains data with multiple dtypes in a single column, the dtype of the column will be chosen to accommodate all of the data types (object is the most general).

# these ints are coerced to floats
In [348]: pd.Series([1, 2, 3, 4, 5, 6.])
Out[348]:
     0  1.0
     1  2.0
     2  3.0
     3  4.0
     4  5.0
     5  6.0
dtype: float64

# string data forces an `object` dtype
In [349]: pd.Series([1, 2, 3, 6., 'foo'])
   →
     0  1
     1  2
     2  3
     3  6
     4  foo
dtype: object

The number of columns of each type in a DataFrame can be found by calling `get_dtype_counts()`. 
In [350]: dft.get_dtype_counts()
Out[350]:
float64 1
float32 1
int64 1
int8 1
datetime64[ns] 1
bool 1
object 1
dtype: int64

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will NOT be combined. The following example will give you a taste.

In [351]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [352]: df1
Out[352]:
   A
0  0.890400
1  0.283331
2 -0.303613
3 -1.192210
4  0.065420
5  0.455918
6  2.008328
7  0.188942

In [353]: df1.dtypes

Out[353]:
A float32
dtype: object

In [354]: 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 [355]: df2
Out[355]:
   A     B      C
0 -0.454346 0.200071 255
1 -0.916504 -0.557756 255
2  0.640625 -0.141988   0
3  2.675781 -0.174060   0
4 -0.007866 0.258626   0
5 -0.204224  0.941688   0
6 -0.100098 -1.849045   0
7 -0.402100 -0.949458   0

In [356]: df2.dtypes

Out[356]:
A float16

(continues on next page)
9.13.1 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.

```python
In [357]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[357]:
   a
dtype: int64
```

```python
In [358]: pd.DataFrame({'a': [1, 2]}).dtypes
   a
Out[358]:
   a     int64
          dtype: object
```

```python
In [359]: pd.DataFrame({'a': 1}, index=list(range(2))).dtypes
   a     int64
          dtype: object
```

Note that Numpy will choose platform-dependent types when creating arrays. The following WILL result in `int32` on 32-bit platform.

```python
In [360]: frame = pd.DataFrame(np.array([1, 2]))
```

9.13.2 upcasting

Types can potentially be upcasted when combined with other types, meaning they are promoted from the current type (e.g. `int` to `float`).

```python
In [361]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2
```

```python
In [362]: df3
Out[362]:
   A   B    C
0  0.436054  0.200071  255.0
1  0.633173 -0.557756  255.0
2  0.337012  0.149888  255.0
3  1.483571  0.174060  255.0
4  0.057555  0.258626  255.0
5  2.51695  0.941688  255.0
6  1.908231 -1.849045  255.0
7  0.213158 -0.949458  255.0
```

```python
In [363]: df3.dtypes
```

```python
   → A     float32
          B     float64
          dtype: object
```

(continues on next page)
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 dtyped NumPy array. This can force some *upcasting*.

```python
In [364]: df3.values.dtype
Out[364]: dtype('float64')
```

### 9.13.3 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.

```python
In [365]: df3
Out[365]:
   A    B    C
0  0.436 0.200 255.0
1 -0.633 -0.558 255.0
2  0.337 -0.142  0.0
3  1.484 -0.174  0.0
4  0.058  0.259  0.0
5  0.252  0.942  0.0
6  1.908 -1.849  0.0
7 -0.213 -0.949  0.0

In [366]: df3.dtypes
   →
A  float32
B  float64
C  float64
dtype: object

# conversion of dtypes
In [367]: df3.astype('float32').dtypes
   →
A  float32
B  float32
C  float32
dtype: object
```

Convert a subset of columns to a specified type using `astype()`.

```python
In [368]: dft = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [369]: dft[['a', 'b']] = dft[['a', 'b']].astype(np.uint8)

In [370]: dft
(continues on next page)
Out[370]:
   a  b  c
0 1  4  7
1 2  5  8
2 3  6  9

In [371]: dft.dtypes
Out[371]:
   a   uint8
   b   uint8
   c   int64
   dtype: object

New in version 0.19.0.

Convert certain columns to a specific dtype by passing a dict to \textit{astype()}. \footnote{Note: When trying to convert a subset of columns to a specified type using \textit{astype()} and \textit{loc()}, upcasting occurs. \textit{loc()} tries to fit in what we are assigning to the current dtypes, while [] will overwrite them taking the dtype from the right hand side. Therefore the following piece of code produces the unintended result.}

In [372]: dft1 = pd.DataFrame({'a': [1,0,1], 'b': [4,5,6], 'c': [7, 8, 9]})
In [373]: dft1 = dft1.astype({'a': np.bool, 'c': np.float64})
In [374]: dft1
Out[374]:
   a  b  c
0  True 4 7.0
1 False 5 8.0
2  True 6 9.0
In [375]: dft1.dtypes
Out[375]:
   a   bool
   b   int64
   c   float64
   dtype: object

In [376]: dft = pd.DataFrame({'a': [1,2,3], 'b': [4,5,6], 'c': [7, 8, 9]})
In [377]: dft.loc[:, ['a', 'b']].astype(np.uint8).dtypes
Out[377]:
   a   uint8
   b   uint8
   dtype: object
In [378]: dft.loc[:, ['a', 'b']] = dft.loc[:, ['a', 'b']].astype(np.uint8)
In [379]: dft.dtypes
Out[379]:
   a   int64
   b   int64
   c   int64

(continues on next page)
9.13.4 object conversion

pandas offers various functions to try to force conversion of types from the object dtype to other types. In cases where the data is already of the correct type, but stored in an object array, the DataFrame.infer_objects() and Series.infer_objects() methods can be used to soft convert to the correct type.

```python
In [380]: import datetime
In [381]:
In [381]: df = pd.DataFrame([[1, 2],
                      ['a', 'b'],
                      [datetime.datetime(2016, 3, 2),
                       datetime.datetime(2016, 3, 2)]])
In [382]: df = df.T
In [383]: df
Out[383]:
       0  1         2
0   1 a 2016-03-02 00:00:00
1   2 b 2016-03-02 00:00:00
In [384]: df.dtypes
         0     1         2
dtype: object     object  datetime64[ns]
```

Because the data was transposed the original inference stored all columns as object, which infer_objects will correct.

```python
In [385]: df.infer_objects().dtypes
Out[385]:
         0     1         2
dtype: int64     object  datetime64[ns]
```

The following functions are available for one dimensional object arrays or scalars to perform hard conversion of objects to a specified type:

- `to_numeric()` (conversion to numeric dtypes)

```python
In [386]: m = ['1.1', 2, 3]
In [387]: pd.to_numeric(m)
Out[387]: array([1.1, 2.0, 3.0])
```

- `to_datetime()` (conversion to datetime objects)
to_datetime() (conversion to datetime objects)

To force a conversion, we can pass in an errors argument, which specifies how pandas should deal with elements that cannot be converted to desired dtype or object. By default, errors='raise', meaning that any errors encountered will be raised during the conversion process. However, if errors='coerce', these errors will be ignored and pandas will convert problematic elements to pd.NaT (for datetime and timedelta) or np.nan (for numeric). This might be useful if you are reading in data which is mostly of the desired dtype (e.g. numeric, datetime), but occasionally has non-conforming elements intermixed that you want to represent as missing:

errors parameter has a third option of errors='ignore', which will simply return the passed in data if it encounters any errors with the conversion to a desired data type:
In addition to object conversion, `to_numeric()` provides another argument `downcast`, which gives the option of
downcasting the newly (or already) numeric data to a smaller dtype, which can conserve memory:

```python
In [407]: m = ['1', 2, 3]
In [408]: pd.to_numeric(m, downcast='integer')  # smallest signed int dtype
Out[408]: array([1, 2, 3], dtype=int8)
In [409]: pd.to_numeric(m, downcast='signed')  # same as 'integer'
Out[409]: array([1, 2, 3], dtype=int8)
In [410]: pd.to_numeric(m, downcast='unsigned')  # smallest unsigned int dtype
Out[410]: array([1, 2, 3], dtype=uint8)
In [411]: pd.to_numeric(m, downcast='float')  # smallest float dtype
Out[411]: array([ 1., 2., 3.], dtype=float32)
```

As these methods apply only to one-dimensional arrays, lists or scalars; they cannot be used directly on multi-
dimensional objects such as DataFrames. However, with `apply()`, we can “apply” the function over each column
efficiently:

```python
In [412]: import datetime
In [413]: df = pd.DataFrame([['2016-07-09', datetime.datetime(2016, 3, 2)] * 2,
                       dtype='O')
In [414]: df
Out[414]:
   0     1
0 2016-07-09 2016-03-02
1 2016-07-09 2016-03-02
In [415]: df.apply(pd.to_datetime)
   0     1
0 2016-07-09 2016-03-02
1 2016-07-09 2016-03-02
In [416]: df = pd.DataFrame([['1.1', 2, 3]] * 2, dtype='O')
In [417]: df
Out[417]:
   0  1  2
0   1  2  3
1   1  2  3
In [418]: df.apply(pd.to_numeric)
   0  1  2
0   1.1 2  3
0   1.1 2  3
```

(continues on next page)
1 1.1 2 3

In [419]: df = pd.DataFrame([[5us, pd.Timedelta('1day')]] * 2, dtype='O')

In [420]: df
Out[420]:
     0      1
0  5us 1 days 00:00:00
1  5us 1 days 00:00:00

In [421]: df.apply(pd.to_timedelta)

Out[421]:
     0      1
0  00:00:00.000005 1 days
1  00:00:00.000005 1 days

9.13.5 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. See also Support for integer NA.

In [422]: dfi = df3.astype('int32')
In [423]: dfi['E'] = 1
In [424]: dfi
Out[424]:
     A  B  C  E
0   0  0  255  1
1   1  0  255  1
2   2  0  0  1
3   3  0  0  1
4   4  0  0  1
5   5  0  0  1
6   6 -1  0  1
7   7  0  0  1
In [425]: dfi.dtypes

Out[425]:
     A    int32
     B    int32
     C    int32
     E    int64
dtype: object
In [426]: casted = dfi[dfi>0]
In [427]: casted
Out[427]:
     A  B  C  E
0 NaN NaN 255.0 1
1 NaN NaN 255.0 1
2 NaN NaN NaN 1

(continues on next page)
In [428]: casted.dtypes

→
A    float64
B    float64
C    float64
E    int64
dtype: object

While float dtypes are unchanged.

In [429]: dfa = df3.copy()

In [430]: dfa['A'] = dfa['A'].astype('float32')

In [431]: dfa.dtypes
Out[431]:
A    float32
B    float64
C    float64
dtype: object

In [432]: casted = dfa[df2>0]

In [433]: casted
Out[433]:
   A    B    C
0  NaN 0.200071 255.0
1  NaN    NaN 255.0
2 0.337012   NaN   NaN
3 1.483571   NaN   NaN
4  NaN  0.258626   NaN
5  NaN  0.941688   NaN
6  NaN    NaN   NaN
7  NaN    NaN   NaN

In [434]: casted.dtypes

→
A    float32
B    float64
C    float64
dtype: object

9.14 Selecting columns based on dtype

The `select_dtypes()` method implements subsetting of columns based on their `dtype`. First, let’s create a `DataFrame` with a slew of different dtypes:
In [435]: 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"), dtype='category'))
.....:
In [436]: df['tdeltas'] = df.dates.diff()
In [437]: df['uint64'] = np.arange(3, 6).astype('u8')
In [438]: df['other_dates'] = pd.date_range('20130101', periods=3).values
In [439]: df['tz_aware_dates'] = pd.date_range('20130101', periods=3, tz='US/Eastern')
In [440]: df
Out[440]:
      string  int64  uint8  float64  bool1 ...  category  tdeltas
    0    a       1     3  4.0   True   ...      A       NaT
    1    b       2     4  5.0    False   ...      B        1 days
    2    c       3     5  6.0    True   ...      C        1 days
[3 rows x 12 columns]

And the dtypes:

In [441]: df.dtypes
Out[441]:
string          object
int64           int64
uint8           uint8
float64         float64
bool1           bool
bool2           bool
dates           datetime64[ns]
category        category
tdeltas          timedelta64[ns]
other_dates      datetime64[ns]
tz_aware_dates   datetime64[ns, US/Eastern]
dtype: object

`select_dtypes()` has two parameters `include` and `exclude` that allow you to say “give me the columns with these dtypes” (`include`) and/or “give the columns without these dtypes” (`exclude`).

For example, to select bool columns:

In [442]: df.select_dtypes(include=[bool])
Out[442]:
    bool1  bool2
0    True    False
1 False True
2 True False

You can also pass the name of a dtypes in the NumPy dtype hierarchy:

```python
In [443]: df.select_dtypes(include=['bool'])
Out[443]:
   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:

```python
In [444]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
Out[444]:
     int64  float64   bool1  bool2  tdelta
0      1.0      4.0   True  False  NaT
1      2.0      5.0  False   True  1 days
2      3.0      6.0   True  False  1 days

To select string columns you must use the object dtype:

```python
In [445]: df.select_dtypes(include=['object'])
Out[445]:
          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:

```python
In [446]: def subdtypes(dtype):
    ....:     subs = dtype.__subclasses__()
    ....:     if not subs:
    ....:         return dtype
    ....:     return [dtype, [subdtypes(dt) for dt in subs]]

All NumPy dtypes are subclasses of numpy.generic:

```python
In [447]: subtypes(np.generic)
Out[447]:
[numpy.generic,
 [[numpy.number,
   [[numpy.integer,
     [[numpy.signedinteger,
       [numpy.int8,
       numpy.int16,
       numpy.int32,
       numpy.int64,
     numpy.int64,
     numpy.timedelta64]],
   [numpy.unsignedinteger,
   [numpy.bool]],
   [numpy.object]],
   [numpy.float]],
   [numpy.bool]],
   [numpy.object]]],
   [numpy.object]]
```

(continues on next page)
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.
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 [1]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

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    1.0
1    1.0
2    1.0
3    4.0
4    4.0
5    NaN
6    4.0
7    3.0
```
The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

```python
In [9]: df = pd.DataFrame(randn(3, 2), columns=[' Column A ', ' Column B '],
                  index=range(3))

Out[9]:
        Column A    Column B
0 -1.425575 -1.336299
1  0.740933  1.032121
2 -1.585660  0.913812
```

Since `df.columns` is an Index object, we can use the `.str` accessor

```python
In [10]: df.columns.str.strip()

Out[10]:
Index(['Column A', 'Column B'], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing whitespaces, lowercasing all names, and replacing any remaining whitespaces with underscores:

```python
In [11]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')

Out[11]:
Index(['column_a', 'column_b'], dtype='object')
```

Note: If you have a Series where lots of elements are repeated (i.e. the number of unique elements in the Series is a lot smaller than the length of the Series), it can be faster to convert the original Series to one of type category and then use `.str.<method>` or `.dt.<property>` on that. The performance difference comes from the fact that, for Series of type category, the string operations are done on the `.categories` and not on...
each element of the Series.

Please note that a Series of type category with string .categories has some limitations in comparison of Series of type string (e.g. you can’t add strings to each other: `s + " " + s` won’t work if `s` is a Series of type category). Also, .str methods which operate on elements of type list are not available on such a Series.

### 10.1 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
3    [f, g, h]
dtype: object
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
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('_')[1]
```

It is easy to expand this to return a DataFrame using `expand`.

```
In [19]: s2.str.split('_', expand=True)
Out[19]:
   0  1  2
0  a  b  c
1  c  d  e
2  NaN NaN NaN
3  f  g  h
```

It is also possible to limit the number of splits:

```
In [20]: s2.str.split('_', expand=True, n=1)
Out[20]:
   0  1
0  a  b_c
1  c  d_e
```

(continues on next page)
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  NaN
3   f_g   h
```

replace by default replaces regular expressions:

```python
In [22]: s3 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca',
                   'dog', 'cat'])
In [23]: s3
Out[23]:
0 A
1 B
2 C
3 Aaba
4 Baca
5 dog
6 cat
dtype: object
In [24]: s3.str.replace('^\.|dog', 'XX-XX ', case=False)
```

Some caution must be taken to keep regular expressions in mind! For example, the following code will cause trouble because of the regular expression meaning of $:

```python
# Consider the following badly formatted financial data
In [25]: dollars = pd.Series(['12', '-$10', '$10,000'])
# This does what you'd naively expect:
```

(continues on next page)
New in version 0.23.0.

If you do want literal replacement of a string (equivalent to \texttt{str.replace()}) you can set the optional \texttt{regex} parameter to \texttt{False}, rather than escaping each character. In this case both \texttt{pat} and \texttt{repl} must be strings:

```python
# These lines are equivalent
In [29]: dollars.str.replace(r'\$', '-', regex=False)
Out[29]:
0    12
1    -10
2   $10,000
dtype: object
```

New in version 0.20.0.

The \texttt{replace} method can also take a callable as replacement. It is called on every \texttt{pat} using \texttt{re.sub()}. The callable should expect one positional argument (a regex object) and return a string.

```python
# Reverse every lowercase alphabetic word
In [31]: pat = r'[a-z]+'

In [32]: repl = lambda m: m.group(0)[::-1]

In [33]: pd.Series(['foo 123', 'bar baz', np.nan]).str.replace(pat, repl)
Out[33]:
0    oof 123
```
1 rab zab
2 NaN
dtype: object

# Using regex groups
In [34]: pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"

In [35]: repl = lambda m: m.group('two').swapcase()

In [36]: pd.Series(['Foo Bar Baz', np.nan]).str.replace(pat, repl)
Out[36]:
0 bAR
1 NaN
dtype: object

New in version 0.20.0.
The `replace` method also accepts a compiled regular expression object from `re.compile()` as a pattern. All flags should be included in the compiled regular expression object.

In [37]: import re
In [38]: regex_pat = re.compile(r'^.a|dog', flags=re.IGNORECASE)
In [39]: s3.str.replace(regex_pat, 'XX-XX ')
Out[39]:
0 A
1 B
2 C
3 XX-XX ba
4 XX-XX ca
5 NaN
6 XX-XX BA
7 XX-XX
8 XX-XX
9 XX-XX t
dtype: object

Including a `flags` argument when calling `replace` with a compiled regular expression object will raise a `ValueError`.

In [40]: s3.str.replace(regex_pat, 'XX-XX ', flags=re.IGNORECASE)
---------------------------------------------
ValueError: case and flags cannot be set when pat is a compiled regex

## 10.2 Concatenation

There are several ways to concatenate a `Series` or `Index`, either with itself or others, all based on `cat()`, resp. `Index.str.cat`.

### 10.2.1 Concatenating a single Series into a string

The content of a `Series` (or `Index`) can be concatenated:
In [41]: s = pd.Series(['a', 'b', 'c', 'd'])
In [42]: s.str.cat(sep=',')
Out[42]: 'a,b,c,d'

If not specified, the keyword `sep` for the separator defaults to the empty string, `sep='':`

In [43]: s.str.cat()
Out[43]: 'abcd'

By default, missing values are ignored. Using `na_rep`, they can be given a representation:

In [44]: t = pd.Series(['a', 'b', np.nan, 'd'])
In [45]: t.str.cat(sep=',')
Out[45]: 'a,b,d'
In [46]: t.str.cat(sep=',', na_rep='-')
Out[46]: 'a,b,-,d'

### 10.2.2 Concatenating a Series and something list-like into a Series

The first argument to `cat()` can be a list-like object, provided that it matches the length of the calling `Series` (or `Index`).

In [47]: s.str.cat(['A', 'B', 'C', 'D'])
Out[47]:
   0  aA
   1  bB
   2  cC
   3  dD
   dtype: object

Missing values on either side will result in missing values in the result as well, unless `na_rep` is specified:

In [48]: s.str.cat(t)
Out[48]:
   0  aa
   1  bb
   2  NaN
   3  dd
   dtype: object

In [49]: s.str.cat(t, na_rep='-')
Out[49]:
   0  aa
   1  bb
   2  c-
   3  dd
   dtype: object

### 10.2.3 Concatenating a Series and something array-like into a Series

New in version 0.23.0.
The parameter `others` can also be two-dimensional. In this case, the number or rows must match the lengths of the calling `Series` (or `Index`).

```
In [50]: d = pd.concat([t, s], axis=1)

In [51]: s
Out[51]:
0  a
1  b
2  c
3  d
dtype: object

In [52]: d
Out[52]:
     0  1
0  a  a
1  b  b
2  NaN  c
3  d  d

In [53]: s.str.cat(d, na_rep='--')
Out[53]:
0  aaa
1  bbb
2  c-c
3  ddd
dtype: object
```

### 10.2.4 Concatenating a Series and an indexed object into a Series, with alignment

New in version 0.23.0.

For concatenation with a `Series` or `DataFrame`, it is possible to align the indexes before concatenation by setting the `join`-keyword.

```
In [54]: u = pd.Series(['b', 'd', 'a', 'c'], index=[1, 3, 0, 2])

In [55]: s
Out[55]:
0  a
1  b
2  c
3  d
dtype: object

In [56]: u
Out[56]:
1  b
3  d
0  a
2  c
dtype: object

In [57]: s.str.cat(u)
```

(continues on next page)
0    ab
1    bd
2    ca
3    dc
dtype: object

In [58]: s.str.cat(u, join='left')

→
0    aa
1    bb
2    cc
3    dd
dtype: object

**Warning:** If the `join` keyword is not passed, the method `cat()` will currently fall back to the behavior before version 0.23.0 (i.e. no alignment), but a `FutureWarning` will be raised if any of the involved indexes differ, since this default will change to `join='left'` in a future version.

The usual options are available for `join` (one of 'left', 'outer', 'inner', 'right'). In particular, alignment also means that the different lengths do not need to coincide anymore.

In [59]: v = pd.Series(['z', 'a', 'b', 'd', 'e'], index=[-1, 0, 1, 3, 4])

In [60]: s
Out[60]:
  0    a
  1    b
  2    c
  3    d
dtype: object

In [61]: v
Out[61]:
  -1    z
  0    a
  1    b
  3    d
  4    e
dtype: object

In [62]: s.str.cat(v, join='left', na_rep='-')

→
  0    aa
  1    bb
  2    c-
  3    dd
dtype: object

In [63]: s.str.cat(v, join='outer', na_rep='-')

→
  -1   -z
  0    aa
  1    bb
  2    c-
  3    dd
  3    dd
  4    e

(continues on next page)
The same alignment can be used when `others` is a DataFrame:

```
In [64]: f = d.loc[[3, 2, 1, 0], :]

In [65]: s
Out[65]:
0   a
1   b
2   c
3   d
dtype: object

In [66]: f
Out[66]:
0  NaN  c
1   b   b
2   a   a
dtype: object

In [67]: s.str.cat(f, join='left', na_rep='--')
Out[67]:
0   aaa
1   bbb
2  --c
3  --d
dtype: object
```

### 10.2.5 Concatenating a Series and many objects into a Series

All one-dimensional list-likes can be arbitrarily combined in a list-like container (including iterators, dict-views, etc.):

```
In [68]: s
Out[68]:
0   a
1   b
2   c
3   d
dtype: object

In [69]: u
Out[69]:
1   b
3   d
0   a
2   c
```
All elements must match in length to the calling Series (or Index), except those having an index if join is not None:

```
In [71]: v
Out[71]:
-1  z
 0  a
 1  b
 3  d
 4  e
dtype: object
```

```
In [72]: s.str.cat([u, v, ['A', 'B', 'C', 'D']], join='outer', na_rep='--')
```

```
-1  --z--
 0  a-a
 3  dddD
 4  --e--
dtype: object
```

If using join='right' on a list of others that contains different indexes, the union of these indexes will be used as the basis for the final concatenation:

```
In [73]: u.loc[[3]]
Out[73]:
3  d
dtype: object
```

```
In [74]: v.loc[[-1, 0]]
```

```
-1  --z--
 0  a-a
dtype: object
```

```
In [75]: s.str.cat([u.loc[[3]], v.loc[[-1, 0]]], join='right', na_rep='--')
```
10.3 Indexing with .str

You can use [] notation to directly index by position locations. If you index past the end of the string, the result will be a NaN.

```
In [76]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 
    .....:     'CABA', 'dog', 'cat'])

In [77]: s.str[0]
Out[77]:
0  A
1  B
2  C
3  A
4  B
5  NaN
6  C
7  d
8  c
dtype: object

In [78]: s.str[1]
Out[78]:
 0  NaN
 1  NaN
 2  NaN
 3  a
 4  a
 5  NaN
 6  A
 7  o
 8  a
dtype: object
```

10.4 Extracting Substrings

10.4.1 Extract first match in each subject (extract)

```
Warning: In version 0.18.0, extract gained the expand argument. When expand=False it returns a Series, Index, or DataFrame, depending on the subject and regular expression pattern (same behavior as pre-0.18.0). When expand=True it always returns a DataFrame, which is more consistent and less confusing from the perspective of a user. expand=True is the default since version 0.23.0.
```

The extract method accepts a regular expression with at least one capture group.

Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [79]: pd.Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)', expand=False)
Out[79]:
    0
0  1
```
Elements that do not match return a row filled with NaN. Thus, a Series of messy strings can be “converted” into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating get() to access tuples or re.match objects. The dtype of the result is always object, even if no match is found and the result only contains NaN.

Named groups like

```python
In [80]: pd.Series(['a1', 'b2', 'c3']).str.extract('(?P<letter>[ab])(?P<digit>\d)\d', expand=False)
```

```text
Out[80]:
letter digit
0  a  1
1  b  2
2  NaN  NaN
```

and optional groups like

```python
In [81]: pd.Series(['a1', 'b2', '3']).str.extract('(\?P<as>[ab])?\?P<digit>\d', expand=False)
```

```text
Out[81]:
0  1
1  2
2  3
```

can also be used. Note that any capture group names in the regular expression will be used for column names; otherwise capture group numbers will be used.

Extracting a regular expression with one group returns a DataFrame with one column if expand=True.

```python
In [82]: pd.Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)', expand=True)
```

```text
Out[82]:
0  1
1  2
2  NaN
```

It returns a Series if expand=False.

```python
In [83]: pd.Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)', expand=False)
```

```text
Out[83]:
0  1
1  2
2  NaN
dtype: object
```

Calling on an Index with a regex with exactly one capture group returns a DataFrame with one column if expand=True.

```python
In [84]: s = pd.Series(['a1', 'b2', 'c3'], ['A11', 'B22', 'C33'])
```

```python
In [85]: s
```

```text
Out[85]:
A11 a1
```

(continues on next page)
B22  b2  
C33  c3

dtype: object

In [86]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)

Out[86]:

<table>
<thead>
<tr>
<th>letter</th>
</tr>
</thead>
<tbody>
<tr>
<td>0  A</td>
</tr>
<tr>
<td>1  B</td>
</tr>
<tr>
<td>2  C</td>
</tr>
</tbody>
</table>

It returns an Index if expand=False.

In [87]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)

Out[87]: Index(['A', 'B', 'C'], dtype='object', name='letter')

Calling on an Index with a regex with more than one capture group returns a DataFrame if expand=True.

In [88]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)

Out[88]:

<table>
<thead>
<tr>
<th>letter 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0  A  11</td>
</tr>
<tr>
<td>1  B  22</td>
</tr>
<tr>
<td>2  C  33</td>
</tr>
</tbody>
</table>

It raises ValueError if expand=False.

>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)

ValueError: only one regex group is supported with Index

The table below summarizes the behavior of extract (expand=False) (input subject in first column, number of groups in regex in first row)

<table>
<thead>
<tr>
<th></th>
<th>1 group</th>
<th>&gt;1 group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index</td>
<td>Index</td>
<td>ValueError</td>
</tr>
<tr>
<td>Series</td>
<td>Series</td>
<td>DataFrame</td>
</tr>
</tbody>
</table>

10.4.2 Extract all matches in each subject (extractall)

New in version 0.18.0.

Unlike extract (which returns only the first match),

In [89]: s = pd.Series(['ala2', 'bl1', 'cl1'], index=['A', 'B', 'C'])

In [90]: s

Out[90]:

| A | ala2 |
| B | bl1  |
| C | cl1  |

dtype: object

In [91]: two_groups = '(?P<letter>[a-z])(?P<digit>[0-9])'

(continues on next page)
the `extractall` method returns every match. The result of `extractall` is always a DataFrame with a MultiIndex on its rows. The last level of the MultiIndex is named `match` and indicates the order in the subject.

When each subject string in the Series has exactly one match, `extractall(pat).xs(0, level='match')` gives the same result as `extract(pat).

```python
In [93]: s = pd.Series(['a3', 'b3', 'c2'])
In [95]: s
Out[95]:
0    a3
1    b3
2    c2
dtype: object
```

then `extractall(pat).xs(0, level='match')` gives the same result as `extract(pat).

```python
In [94]: extract_result = s.str.extract(two_groups, expand=True)
In [96]: extract_result
Out[96]:
    letter digit
   0     a 3
   1     b 3
   2     c 2
In [97]: extractall_result = s.str.extractall(two_groups)
In [99]: extractall_result
Out[99]:
   letter digit
   match
  0     a 3
  1     b 3
  2     c 2
In [100]: extractall_result.xs(0, level='match')
```

(continues on next page)
Index also supports `.str.extractall`. It returns a DataFrame which has the same result as a Series.str.extractall with a default index (starts from 0).

New in version 0.19.0.

```
In [101]: pd.Index(["a1a2", "b1", "c1"]).str.extractall(two_groups)
Out[101]:
     letter digit
   match
0      a 1
1      a 2
1.0    b 1
2.0    c 1
```

```
In [102]: pd.Series(["a1a2", "b1", "c1"]).str.extractall(two_groups)
Out[102]:
     letter digit
   match
0      a 1
1      a 2
1.0    b 1
2.0    c 1
```

### 10.5 Testing for Strings that Match or Contain a Pattern

You can check whether elements contain a pattern:

```
In [103]: pattern = r'[0-9][a-z]'
In [104]: pd.Series(['1', '2', '3a', '3b', '03c']).str.contains(pattern)
Out[104]:
0   False
1   False
2   True
3   True
4   True
dtype: bool
```

Or whether elements match a pattern:

```
In [105]: pd.Series(['1', '2', '3a', '3b', '03c']).str.match(pattern)
Out[105]:
0   False
1   False
2   True
3   True
4   False
dtype: bool
```
The distinction between `match` and `contains` is strictness: `match` relies on strict `re.match`, while `contains` relies on `re.search`.

Methods like `match`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```
In [106]: s4 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [107]: s4.str.contains('A', na=False)
Out[107]:
0    True
1   False
2   False
3    True
4   False
5    True
6   False
7   False
8   False
dtype: bool
```

### 10.6 Creating Indicator Variables

You can extract dummy variables from string columns. For example if they are separated by a ' | ':

```
In [108]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'])

In [109]: s.str.get_dummies(sep='|')
Out[109]:
          a  b  c
0       1  0  0
1       1  1  0
2       0  0  0
3       1  0  1
```

String `Index` also supports `get_dummies` which returns a `MultiIndex`.

New in version 0.18.1.

```
In [110]: idx = pd.Index(['a', 'a|b', np.nan, 'a|c'])

In [111]: idx.str.get_dummies(sep='|')
Out[111]:
MultiIndex(levels=[0, 1], codes=[[0, 1, 0, 0], [0, 1, 0, 0], [0, 0, 0, 1]],
           names=['a', 'b', 'c'])
```

See also `get_dummies()`.

### 10.7 Method Summary
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat()</td>
<td>Concatenate strings</td>
</tr>
<tr>
<td>split()</td>
<td>Split strings on delimiter</td>
</tr>
<tr>
<td>rsplit()</td>
<td>Split strings on delimiter working from the end of the string</td>
</tr>
<tr>
<td>get()</td>
<td>Index into each element (retrieve i-th element)</td>
</tr>
<tr>
<td>join()</td>
<td>Join strings in each element of the Series with passed separator</td>
</tr>
<tr>
<td>get_dummies()</td>
<td>Split strings on the delimiter returning DataFrame of dummy variables</td>
</tr>
<tr>
<td>contains()</td>
<td>Return boolean array if each string contains pattern/regex</td>
</tr>
<tr>
<td>replace()</td>
<td>Replace occurrences of pattern/regex/string with some other string or the return value of a callable given the occurrence</td>
</tr>
<tr>
<td>repeat()</td>
<td>Duplicate values (s.str.repeat(3) equivalent to x * 3)</td>
</tr>
<tr>
<td>pad()</td>
<td>Add whitespace to left, right, or both sides of strings</td>
</tr>
<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.search on each element, returning DataFrame with one row for each element and one column for each regex capture group</td>
</tr>
<tr>
<td>extractall()</td>
<td>Call re.findall on each element, returning DataFrame with one row for each match and one column for each regex capture group</td>
</tr>
<tr>
<td>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>
</tbody>
</table>
Table 1 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>isnumeric()</code></td>
<td>Equivalent to <code>str.isnumeric</code></td>
</tr>
<tr>
<td><code>isdecimal()</code></td>
<td>Equivalent to <code>str.isdecimal</code></td>
</tr>
</tbody>
</table>

10.7. Method Summary
11.1 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:

```
In [1]: import pandas as pd
In [2]: pd.options.display.max_rows
Out[2]: 15
In [3]: pd.options.display.max_rows = 999
In [4]: pd.options.display.max_rows
Out[4]: 999
```

The API is composed of 5 relevant functions, available directly from the pandas namespace:

- `get_option()` / `set_option()` - get/set the value of a single option.
- `reset_option()` - reset one or more options to their default value.
- `describe_option()` - print the descriptions of one or more options.
- `option_context()` - execute a codeblock with a set of options that revert to prior settings after execution.

**Note:** Developers can check out `pandas/core/config.py` for more information.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous:

```
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`:

```python
In [10]: try:
    ....:     pd.get_option("column")
    ....:     except KeyError as e:
    ....:         print(e)
    ....:
'Pattern matched multiple keys'
```

**Note:** Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out the descriptions for all available options.

### 11.2 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)`.

```python
In [11]: pd.get_option('mode.sim_interactive')
Out[11]: False

In [12]: pd.set_option('mode.sim_interactive', True)

In [13]: pd.get_option('mode.sim_interactive')
Out[13]: True
```

**Note:** The option `mode.sim_interactive` is mostly used for debugging purposes.

All options also have a default value, and you can use `reset_option` to do just that:

```python
In [14]: pd.get_option("display.max_rows")
Out[14]: 60

In [15]: pd.set_option("display.max_rows",999)

In [16]: pd.get_option("display.max_rows")
Out[16]: 999

In [17]: pd.reset_option("display.max_rows")

In [18]: pd.get_option("display.max_rows")
Out[18]: 60
```

It’s also possible to reset multiple options at once (using a regex):

```python
In [19]: pd.reset_option("^display")
```

`option_context` context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the `with` block:

```python
In [20]: with pd.option_context("display.max_rows",10,"display.max_columns", 5):
    ....:     print(pd.get_option("display.max_rows"))
    ....:     print(pd.get_option("display.max_columns"))
....:
```

(continues on next page)
11.3 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)
```

11.4 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
```

(continues on next page)
display.expand_frame_repr allows for the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

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 [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  7  8  9
0 -1.413681 1.607920 1.024180 0.569605 0.875906 -2.211372 0.974466 -2.006747 -0.
-410001 -0.078638
1  0.545952 -1.219217 -1.226825 0.769804 -1.281247 -0.727707 -0.121306 -0.097883 0.
   695775 0.341734
 ..   ..   ..   ..   ..   ..   ..   ..   ..   ..
8 -2.484478 -0.281461 0.030711 1.126203 -0.977349 1.474071 -0.064034 -1.
   -282782 0.781834
9 -1.071357 0.441153 2.353925 0.583787 0.221471 -0.744471 0.758527 1.729689 -0.
   -964980 -0.845696
[10 rows x 10 columns]
In [39]: df = pd.DataFrame(np.array([['foo', 'bar', 'bim', 'uncomfortably long string
 .....:''],['horse', 'cow', 'banana', 'apple']]))
In [40]: pd.set_option('max_colwidth', 40)

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
    0  foo bar  bim uncomfortably long string
    1   horse  cow  banana    apple

In [46]: pd.set_option('max_colwidth', 6)

In [47]: df
   Out[47]:
     0  1  2  3
    0  foo bar  bim un...
    1   horse  cow ba... apple

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'>
RangeIndex: 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'>
RangeIndex: 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  0.0 1.0 1.0 0.0 1.0 1.0 0.0 NaN 1.0 NaN
1   1.0 NaN 0.0 0.0 1.0 1.0 NaN 1.0 0.0 1.0
2   NaN NaN NaN 1.0 1.0 0.0 NaN 0.0 1.0 NaN
3   0.0 1.0 1.0 NaN 0.0 NaN 1.0 NaN NaN 0.0
4   0.0 1.0 0.0 0.0 1.0 0.0 0.0 NaN 0.0 0.0
5   0.0 NaN 1.0 NaN NaN NaN NaN 0.0 1.0 NaN
6   0.0 1.0 0.0 0.0 NaN 1.0 NaN NaN 0.0 NaN
7   0.0 NaN 1.0 1.0 NaN 1.0 1.0 1.0 1.0 NaN
8   0.0 0.0 NaN 0.0 NaN 1.0 0.0 0.0 NaN NaN
9   NaN NaN 0.0 NaN NaN NaN 0.0 1.0 1.0 NaN

In [57]: pd.set_option('max_info_rows', 11)

In [58]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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 [59]: pd.set_option('max_info_rows', 5)

In [60]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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 -2.049  2.846 -1.208 -0.450  2.424
1  0.121  0.266  0.843 -0.222  2.021
2 -0.717 -2.224 -1.061 -0.233  0.431
3 -0.665  1.830 -1.406  1.078  0.323
4  0.200  0.890  0.194  0.352  0.449

In [65]: pd.set_option('precision',4)

In [66]: df
Out[66]:
   0     1     2     3     4
0 -2.049  2.846 -1.208 -0.450  2.423
1  0.121  0.267  0.844 -0.222  2.022
2 -0.717 -2.224 -1.061 -0.233  0.431
3 -0.665  1.829 -1.406  1.078  0.323
4  0.200  0.890  0.195  0.352  0.449

display.chop_threshold sets at what level pandas rounds to zero when it displays a Series of DataFrame. This setting does not change the precision at which the number is stored.

In [67]: df = pd.DataFrame(np.random.randn(6,6))

In [68]: pd.set_option('chop_threshold', 0)

In [69]: df
Out[69]:
   0     1     2     3     4     5
0 -0.198  0.966 -1.523 -0.117  0.296 -1.048
1  1.641  1.906  2.772  0.089 -1.144 -0.633
2 -0.824 -0.338 -0.928 -0.840  0.249 -0.109
3  0.432 -0.461  0.336 -3.208 -1.535  0.409
4 -0.673 -0.741 -0.111 -2.673  0.865  0.060
5  0.000  0.966 -1.523  0.000  0.000 -1.048

In [70]: pd.set_option('chop_threshold', .5)

In [71]: df
Out[71]:
   0     1     2     3     4     5
0  0.000  0.966 -1.523  0.000  0.000 -1.048
1  1.641  1.906  2.772  0.089 -1.144 -0.633
2  0.925 -0.007 -0.820 -0.601 -1.039  0.824
3 -0.824 -0.338 -0.928 -0.840  0.249 -0.109
4  0.432 -0.461  0.336 -3.208 -1.535  0.409
5 -0.673 -0.741 -0.111 -2.673  0.865  0.060

In [72]: pd.reset_option('chop_threshold')

display.colheader_justify controls the justification of the headers. The options are ‘right’, and ‘left’.

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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]:
   A  B  C
0 0.9331 0.3 0.0
1 0.2888 0.2 0.0
2 1.3250 0.2 0.0
3 0.5892 0.7 0.0
4 0.5314 0.1 0.0
5 -1.1987 0.7 0.0

In [76]: pd.set_option('colheader_justify', 'left')

In [77]: df
Out[77]:
   A  B  C
0 0.9331 0.3 0.0
1 0.2888 0.2 0.0
2 1.3250 0.2 0.0
3 0.5892 0.7 0.0
4 0.5314 0.1 0.0
5 -1.1987 0.7 0.0

In [78]: pd.reset_option('colheader_justify')

11.5 Available Options

<table>
<thead>
<tr>
<th>Option</th>
<th>Default</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>display.chop_threshold</td>
<td>None</td>
<td>If set to a float value, all float values smaller than the given threshold will be displayed as 0</td>
</tr>
<tr>
<td>display.colheader_justify</td>
<td>right</td>
<td>Controls the justification of column headers. Used by DataFrameFormatter.</td>
</tr>
<tr>
<td>display.column_space</td>
<td>12</td>
<td>No description available.</td>
</tr>
<tr>
<td>display.date_dayfirst</td>
<td>False</td>
<td>When True, prints and parses dates with the day first, eg 20/01/2005</td>
</tr>
<tr>
<td>display.date_yearfirst</td>
<td>False</td>
<td>When True, prints and parses dates with the year first, eg 2005/01/20</td>
</tr>
<tr>
<td>display.encoding</td>
<td>UTF-8</td>
<td>Defaults to the detected encoding of the console. Specifies the encoding to be used.</td>
</tr>
<tr>
<td>display.expand_frame_repr</td>
<td>True</td>
<td>Whether to print out the full DataFrame repr for wide DataFrames across multiple columns</td>
</tr>
<tr>
<td>display.float_format</td>
<td>None</td>
<td>The callable should accept a floating point number and return a string with the desired format.</td>
</tr>
<tr>
<td>display.large_repr</td>
<td>truncate</td>
<td>For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show only the first max_rows entries. This function is used to truncate results.</td>
</tr>
<tr>
<td>display.latex.repr</td>
<td>False</td>
<td>Whether to produce a \texttt{latex} DataFrame representation for Jupyter frontends that support it.</td>
</tr>
<tr>
<td>display.latex.escape</td>
<td>True</td>
<td>Escapes special characters in DataFrames, when using the \texttt{to_latex} method.</td>
</tr>
<tr>
<td>display.latex.longtable</td>
<td>False</td>
<td>Specifies if the \texttt{to_latex} method of a DataFrame uses the longtable format.</td>
</tr>
<tr>
<td>display.latex.multicolumn</td>
<td>True</td>
<td>Combines columns when using a MultiIndex</td>
</tr>
<tr>
<td>display.latex.multicolumn_format</td>
<td>'l'</td>
<td>Alignment of multicolumn labels</td>
</tr>
<tr>
<td>display.latex.multirow</td>
<td>False</td>
<td>Combines rows when using a MultiIndex. Centered instead of top-aligned, separated by double lines.</td>
</tr>
<tr>
<td>display.max_columns</td>
<td>0 or 20</td>
<td>max_rows and max_columns are used in \texttt{<strong>repr</strong>}() methods to decide if to_string() should be called.</td>
</tr>
<tr>
<td>display.max_colwidth</td>
<td>50</td>
<td>The maximum width in characters of a column in the repr of a pandas data structure.</td>
</tr>
<tr>
<td>Option</td>
<td>Default</td>
<td>Function</td>
</tr>
<tr>
<td>----------------------</td>
<td>---------</td>
<td>---------------------------------------------------------------------------</td>
</tr>
<tr>
<td>display.max_info_columns</td>
<td>100</td>
<td>max_info_columns is used in DataFrame.info method to decide if per column information will be printed.</td>
</tr>
<tr>
<td>display.max_info_rows</td>
<td>169075</td>
<td>df.info() will usually show null-counts for each column. For large frames this can be quite slow.</td>
</tr>
<tr>
<td>display.max_rows</td>
<td>60</td>
<td>This sets the maximum number of rows pandas should output when printing out.</td>
</tr>
<tr>
<td>display.max_seq_items</td>
<td>100</td>
<td>When pretty-printing a long sequence, no more than max_seq_items will be printed.</td>
</tr>
<tr>
<td>display.memory_usage</td>
<td>True</td>
<td>This specifies if the memory usage of a DataFrame should be displayed when the DataFrame is truncated.</td>
</tr>
<tr>
<td>display.multi_sparse</td>
<td>True</td>
<td>“Sparsify” MultiIndex display (don’t display repeated elements in outer levels when outputting).</td>
</tr>
<tr>
<td>display.notebook_repr_html</td>
<td>True</td>
<td>When True, IPython notebook will use html representation for pandas objects (if available).</td>
</tr>
<tr>
<td>display.pprint_nest_depth</td>
<td>3</td>
<td>Controls the number of nested levels to process when pretty-printing.</td>
</tr>
<tr>
<td>display.precision</td>
<td>6</td>
<td>Floating point output precision in terms of number of places after the decimal.</td>
</tr>
<tr>
<td>display.show_dimensions</td>
<td>truncate</td>
<td>Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out dimensions if the frame is truncated (e.g. not display all rows and/or columns).</td>
</tr>
<tr>
<td>display.width</td>
<td>80</td>
<td>Width of the display in characters. In case python/IPython is running in a terminal, this setting will apply.</td>
</tr>
<tr>
<td>display.html.table_schema</td>
<td>False</td>
<td>Whether to publish a Table Schema representation for frontends that support it.</td>
</tr>
<tr>
<td>display.html.border</td>
<td>1</td>
<td>A border=attribute is inserted in the &lt;table&gt; tag for the DataFrame HTML representation.</td>
</tr>
<tr>
<td>display.html.use_mathjax</td>
<td>True</td>
<td>When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol.</td>
</tr>
<tr>
<td>io.excel.xls.writer</td>
<td>xlwt</td>
<td>The default Excel writer engine for ‘xls’ files.</td>
</tr>
<tr>
<td>io.excel.xlsx.writer</td>
<td>openpyxl</td>
<td>The default Excel writer engine for ‘xlsx’ files.</td>
</tr>
<tr>
<td>io.hdf.default_format</td>
<td>None</td>
<td>default format writing format, if None, then put will default to ‘fixed’ and append to ‘table’.</td>
</tr>
<tr>
<td>io.hdf.dropna_table</td>
<td>None</td>
<td>True drop ALL nan rows when appending to a table.</td>
</tr>
<tr>
<td>mode.chained_assignment</td>
<td>warn</td>
<td>Controls SettingWithCopyWarning: ‘raise’, ‘warn’, or None. Raise an exception, warn, or don’t raise an exception if using chained assignment.</td>
</tr>
<tr>
<td>mode.sim_interactive</td>
<td>False</td>
<td>Whether to simulate interactive mode for purposes of testing.</td>
</tr>
<tr>
<td>mode.use_inf_as_na</td>
<td>False</td>
<td>True means treat None, NaN, -INF, INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way).</td>
</tr>
<tr>
<td>compute.use_bottleneck</td>
<td>True</td>
<td>Use the bottleneck library to accelerate computation if it is installed.</td>
</tr>
<tr>
<td>compute.use_numexpr</td>
<td>True</td>
<td>Use the numexpr library to accelerate computation if it is installed.</td>
</tr>
<tr>
<td>plotting.matplotlib.register_converters</td>
<td>True</td>
<td>Register custom converters with matplotlib. Set to False to de-register.</td>
</tr>
</tbody>
</table>

### 11.6 Number Formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the set_options API.

Use the set_eng_float_format function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```python
In [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
```

(continues on next page)
To round floats on a case-by-case basis, you can also use `round()` and `round()`.

### 11.7 Unicode Formatting

**Warning:** Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters whose width corresponds to two Latin characters. If a DataFrame or Series contains these characters, the default output mode may not align them properly.

**Note:** Screen captures are attached for each output to show the actual results.

```python
In [84]: df = pd.DataFrame({u'': ['UK', u''], u'': ['Alice', u'']})
In [85]: df;
```

Enabling `display.unicode.east_asian_width` allows pandas to check each character’s “East Asian Width” property. These characters can be aligned properly by setting this option to True. However, this will result in longer render times than the standard `len` function.

```python
In [86]: pd.set_option('display.unicode.east_asian_width', True)
In [87]: df;
```

In addition, Unicode characters whose width is “Ambiguous” can either be 1 or 2 characters wide depending on the terminal setting or encoding. The option `display.unicode.ambiguous_as_wide` can be used to handle the ambiguity.
By default, an “Ambiguous” character’s width, such as “¡” (inverted exclamation) in the example below, is taken to be 1.

```python
In [88]: df = pd.DataFrame({
'a': ['xxx', u'¡¡'], 'b': ['yyy', u'¡¡']})
In [89]: df;

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>xxx</td>
<td>yyy</td>
</tr>
<tr>
<td>1</td>
<td>¡¡</td>
<td>¡¡</td>
</tr>
</tbody>
</table>
```

Enabling `display.unicode.ambiguous_as_wide` makes pandas interpret these characters’ widths to be 2. (Note that this option will only be effective when `display.unicode.east_asian_width` is enabled.) However, setting this option incorrectly for your terminal will cause these characters to be aligned incorrectly:

```python
In [90]: pd.set_option('display.unicode.ambiguous_as_wide', True)
In [91]: df;

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>xxx</td>
<td>yyy</td>
</tr>
<tr>
<td>1</td>
<td>¡¡</td>
<td>¡¡</td>
</tr>
</tbody>
</table>
```

### 11.8 Table Schema Display

New in version 0.20.0.

`DataFrame` and `Series` will publish a Table Schema representation by default. False by default, this can be enabled globally with the `display.html.table_schema` option:

```python
In [92]: pd.set_option('display.html.table_schema', True)
```

Only `display.max_rows` are serialized and published.
INDEXING AND SELECTING DATA

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides metadata) using known indicators, important for analysis, visualization, and interactive console display.
- Enables automatic and explicit data alignment.
- Allows intuitive getting and setting of subsets of the data set.

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area.

Note: The Python and NumPy indexing operators [] and attribute operator . provide quick and easy access to pandas data structures across a wide range of use cases. This makes interactive work intuitive, as there’s little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn’t known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called chained assignment and should be avoided. See Returning a View versus Copy.

Warning: Indexing on an integer-based Index with floats has been clarified in 0.18.0, for a summary of the changes, see here.

See the MultiIndex / Advanced Indexing for MultiIndex and more advanced indexing documentation.
See the cookbook for some advanced strategies.

12.1 Different Choices for Indexing

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- .loc is primarily label based, but may also be used with a boolean array. .loc will raise KeyError when the items are not found. Allowed inputs are:
- A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a label of the index. This use is not an integer position along the index).
- A list or array of labels ['a', 'b', 'c'].
- A slice object with labels 'a':'f' (Note that contrary to usual python slices, both the start and the stop are included, when present in the index! See Slicing with labels.).
- A boolean array
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above).

New in version 0.18.1.

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.
  - A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above).

New in version 0.18.1.

See more at Selection by Position, Advanced Indexing and Advanced Hierarchical.

• .loc, .iloc, and also [] indexing can accept a callable as indexer. See more at Selection By Callable.

Getting values from an object with multi-axes selection uses the following notation (using .loc as an example, but the following applies to .iloc as well). Any of the axes accessors may be the null slice :. Axes left out of the specification are assumed to be :. e.g. p.loc['a'] is equivalent to p.iloc['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>

### 12.2 Basics

As mentioned when introducing the data structures in the last section, the primary function of indexing with [] (a.k.a. __getitem__ for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. The following table shows return type values when indexing pandas objects with []:

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Selection</th>
<th>Return Value Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series</td>
<td>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:

```python
In [1]: dates = pd.date_range('1/1/2000', periods=8)

In [2]: df = pd.DataFrame(np.random.randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])

In [3]: df
Out[3]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.469112</td>
<td>-0.282863</td>
<td>-1.509059</td>
<td>-1.135632</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>1.212112</td>
<td>-0.173215</td>
<td>0.119209</td>
<td>-1.044236</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
<td>1.071804</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.721555</td>
<td>-0.706771</td>
<td>-1.039575</td>
<td>0.271860</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.276232</td>
<td>-1.087401</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.673690</td>
<td>0.113648</td>
<td>-1.478427</td>
<td>0.524988</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>0.404705</td>
<td>0.577046</td>
<td>-1.715002</td>
<td>-1.039268</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>-0.370647</td>
<td>-1.157892</td>
<td>-1.344312</td>
<td>0.844885</td>
</tr>
</tbody>
</table>
```

```python
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 []:

```python
In [6]: s = df['A']

In [7]: s[dates[5]]
Out[7]: -0.67368970808837059

In [8]: panel['two']
```

You can pass a list of columns to [] to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```python
In [9]: df
Out[9]:
A B C D
```

(continues on next page)
You may find this useful for applying a transform (in-place) to a subset of the columns.

**Warning:** pandas aligns all AXES when setting `Series` and `DataFrame` from `.loc` and `.iloc`. This will not modify `df` because the column alignment is before value assignment.

```
In [12]: df[['A', 'B']]  
Out[12]:  
   A      B  
2000-01-01 -0.282863  0.469112  
2000-01-02 -0.173215  1.212112  
2000-01-03 -2.104569 -0.861849  
2000-01-04 -0.706771  0.721555  
2000-01-05  0.567020 -0.424972  
2000-01-06  0.113648 -0.673690  
2000-01-07  0.577046  0.404705  
2000-01-08 -1.157892 -0.370647  
```

The correct way to swap column values is by using raw values:
In [15]: df.loc[:, ['B', 'A']] = df[['A', 'B']].values

In [16]: df[['A', 'B']]

Out[16]:
       A         B
2000-01-01  0.469112 -0.282863
2000-01-02  1.212112 -0.173215
2000-01-03 -0.861849 -2.104569
2000-01-04  0.721555 -0.706771
2000-01-05 -0.424972  0.567020
2000-01-06 -0.673690  0.113648
2000-01-07  0.404705  0.577046
2000-01-08 -0.370647 -1.157892

12.3 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 [17]: sa = pd.Series([1, 2, 3], index=list('abc'))

In [18]: dfa = df.copy()

In [19]: sa.b

Out[19]:

In [20]: dfa.A

Out[20]:
       2000-01-01  0.469112
       2000-01-02  1.212112
       2000-01-03 -0.861849
       2000-01-04  0.721555
       2000-01-05 -0.424972
       2000-01-06 -0.673690
       2000-01-07  0.404705
       2000-01-08 -0.370647
Freq: D, Name: A, dtype: float64

In [21]: panel.one

Out[21]:

In [22]: sa.a = 5

In [23]: sa

(continues on next page)
\[ \text{Out}[23]: \]
\[
\begin{align*}
a & \quad 5 \\
b & \quad 2 \\
c & \quad 3 \\
dtype & : \text{int64}
\end{align*}
\]

\[ \text{In}[24]: \text{dfa.A} = \text{list(range(len(dfa.index)))} \quad \# \text{ok if A already exists} \]

\[ \text{In}[25]: \text{dfa} \]
\[ \text{Out}[25]: \]
\[
\begin{array}{cccc}
A & B & C & D \\
\hline
2000-01-01 & 0 & -0.282863 & -1.509059 & -1.135632 \\
2000-01-02 & 1 & -0.173215 & 0.119209 & -1.044236 \\
2000-01-03 & 2 & -2.104569 & 0.494929 & 1.071804 \\
2000-01-04 & 3 & -0.706771 & -1.039575 & 0.271860 \\
2000-01-05 & 4 & 0.567020 & 0.276232 & -1.087401 \\
2000-01-06 & 5 & 0.113648 & 1.478427 & 0.524988 \\
2000-01-07 & 6 & 0.577046 & -1.75002 & -1.039268 \\
2000-01-08 & 7 & -1.157892 & -1.344312 & 0.844885 \\
\end{array}
\]

\[ \text{In}[26]: \text{dfa[} \text{'A'} \text{]} = \text{list(range(len(dfa.index)))} \quad \# \text{use this form to create a new column} \]

\[ \text{In}[27]: \text{dfa} \]
\[ \text{Out}[27]: \]
\[
\begin{array}{cccc}
A & B & C & D \\
\hline
2000-01-01 & 0 & -0.282863 & -1.509059 & -1.135632 \\
2000-01-02 & 1 & -0.173215 & 0.119209 & -1.044236 \\
2000-01-03 & 2 & -2.104569 & 0.494929 & 1.071804 \\
2000-01-04 & 3 & -0.706771 & -1.039575 & 0.271860 \\
2000-01-05 & 4 & 0.567020 & 0.276232 & -1.087401 \\
2000-01-06 & 5 & 0.113648 & 1.478427 & 0.524988 \\
2000-01-07 & 6 & 0.577046 & -1.75002 & -1.039268 \\
2000-01-08 & 7 & -1.157892 & -1.344312 & 0.844885 \\
\end{array}
\]

\textbf{Warning:}

- You can use this access only if the index element is a valid Python identifier, e.g. \text{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. \text{s.min} is not allowed.

- Similarly, the attribute will not be available if it conflicts with any of the following list: \text{index, major_axis, minor_axis, items}.

- In any of these cases, standard indexing will still work, e.g. \text{s['1'], s['min'], and s['index']} will access the corresponding element or column.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a \text{dict} to a row of a \text{DataFrame}:

\[ \text{In}[28]: \text{x = pd.DataFrame({}x': [1, 2, 3], 'y': [3, 4, 5])} \]

\[ \text{In}[29]: \text{x.iloc[1] = dict(x=9, y=99)} \]

(continues on next page)
You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it creates a new attribute rather than a new column. In 0.21.0 and later, this will raise a UserWarning:

```python
In[1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In[2]: df.two = [4, 5, 6]
UserWarning: Pandas doesn't allow Series to be assigned into nonexistent columns -- see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute_access
In[3]: df
Out[3]:
<table>
<thead>
<tr>
<th>one</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
</tr>
<tr>
<td>2.0</td>
</tr>
<tr>
<td>3.0</td>
</tr>
</tbody>
</table>
```

### 12.4 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:

```python
In [31]: s[:5]
Out[31]:
2000-01-01  0.469112
2000-01-02  1.212112
2000-01-03 -0.861849
2000-01-04  0.721555
2000-01-05 -0.424972
Freq: D, Name: A, dtype: float64
```

```python
In [32]: s[::2]
Out[32]:
2000-01-01  0.469112
2000-01-03 -0.861849
2000-01-05 -0.424972
2000-01-07  0.404705
Freq: 2D, Name: A, dtype: float64
```

```python
In [33]: s[::-1]
```

(continues on next page)
Note that setting works as well:

```
In [34]: s2 = s.copy()
In [35]: s2[:5] = 0
In [36]: s2
```

```
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
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 [37]: df[: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
```

```
In [38]: df[::-1]
```

```
          A        B        C        D
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
```

## 12.5 Selection By Label

### Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called chained assignment and should be avoided. See Returning a View versus Copy.
Warning:
.loc is strict when you present slicers that are not compatible (or convertible) with the index type. For example using integers in a DatetimeIndex. These will raise a TypeError.

```
In [39]: df1 = pd.DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=pd.date_range('20130101',periods=5))

In [40]: df1.loc[2:3]
```

```
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these indexers [2] of <type 'int'>
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [41]: df1.loc['20130102':'20130104']
```

```
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
```

Warning: Starting in 0.21.0, pandas will show a FutureWarning if indexing with a list with missing labels. In the future this will raise a KeyError. See list-like Using loc with missing keys in a list is Deprecated.

pandas provides a suite of methods in order to have purely label based indexing. This is a strict inclusion based protocol. Every label asked for must be in the index, or a KeyError will be raised. When slicing, both the start bound AND the stop bound are included, if present in the index. Integers are valid labels, but they refer to the label and not the position.

The .loc attribute is the primary access method. The following are valid inputs:

- A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a label of the index. This use is not an integer position along the index.).
- A list or array of labels ['a', 'b', 'c'].
- A slice object with labels 'a':'f' (Note that contrary to usual python slices, both the start and the stop are included, when present in the index! See Slicing with labels.).
- A boolean array.
- A callable, see Selection By Callable.

```
In [42]: s1 = pd.Series(np.random.randn(6),index=list('abcdef'))

In [43]: s1
Out[43]:
```

```
a   1.431256
```

(continues on next page)
b  1.340309  
c -1.170299  
d -0.226169  
e  0.410835  
f  0.813850  
dtype: float64

In [44]: s1.loc['c':]

Out[44]:
c -1.170299  
d -0.226169  
e  0.410835  
f  0.813850  
dtype: float64

In [45]: s1.loc['b']

Out[45]:
1.3403088497993827

Note that setting works as well:

In [46]: s1.loc['c'] = 0

In [47]: s1

Out[47]:
a  1.431256  
b  1.340309  
c  0.000000  
d  0.000000  
e  0.000000  
f  0.000000  
dtype: float64

With a DataFrame:

In [48]: df1 = pd.DataFrame(np.random.randn(6,4),
                        index=list('abcdef'),
                        columns=list('ABCD'))

In [49]: df1

Out[49]:
   A   B    C   D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
c  1.024180  0.569605  0.875906 -2.211372
d  0.974466 -2.006747 -0.410001 -0.078638
e  0.545952 -1.219217 -1.226825  0.769804
f -1.281247 -0.727707 -0.121306 -0.097883

In [50]: df1.loc[['a', 'b', 'd'], :]

Out[50]:
   A   B    C   D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
Accessing via label slices:

\begin{verbatim}
In [51]: df1.loc['d':, 'A':'C']
Out[51]:
   A    B    C
d 0.974466 -2.006747 -0.410001
e 0.545952 -1.219217 -1.226825
f -1.281247 -0.727707 -0.121306
\end{verbatim}

For getting a cross section using a label (equivalent to df.xs('a')):

\begin{verbatim}
In [52]: df1.loc['a']
Out[52]:
    A    B    C
   a   0.132003 -0.827317 -0.076467
   b -1.187678
Name: a, dtype: float64
\end{verbatim}

For getting values with a boolean array:

\begin{verbatim}
In [53]: df1.loc['a'] > 0
Out[53]:
    A
   a  True
   b False
   c False
   d False
Name: a, dtype: bool
\end{verbatim}

\begin{verbatim}
In [54]: df1.loc[:, df1.loc['a'] > 0]
Out[54]:
    A
   a 0.132003
   b 1.130127
   c 1.024180
   d 0.974466
   e 0.545952
   f -1.281247
\end{verbatim}

For getting a value explicitly (equivalent to deprecated df.get_value('a','A')):

\begin{verbatim}
# this is also equivalent to `df1.at['a','A']`
In [55]: df1.loc['a', 'A']
Out[55]:
    A
   a 0.13200317033032932
\end{verbatim}

12.5.1 Slicing with labels

When using .loc with slices, if both the start and the stop labels are present in the index, then elements located between the two (including them) are returned:

\begin{verbatim}
In [56]: s = pd.Series(list('abcde'), index=[0,3,2,5,4])
In [57]: s.loc[3:5]
\end{verbatim}
If at least one of the two is absent, but the index is sorted, and can be compared against start and stop labels, then slicing will still work as expected, by selecting labels which rank between the two:

```
In [58]: s.sort_index()
Out[58]:
0  a
2  c
3  b
4  e
5  d
dtype: object
```

```
In [59]: s.sort_index().loc[1:6]
```

However, if at least one of the two is absent and the index is not sorted, an error will be raised (since doing otherwise would be computationally expensive, as well as potentially ambiguous for mixed type indexes). For instance, in the above example, `s.loc[1:6]` would raise `KeyError`.

### 12.6 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 an `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. 5.
- A list or array of integers [4, 3, 0].
- A slice object with ints 1:7.
- A boolean array.
- A callable, see *Selection By Callable*.

```
In [60]: sl = pd.Series(np.random.randn(5), index=list(range(0,10,2)))
```

```
In [61]: sl
```

(continues on next page)
Out[61]:
0  0.695775
2  0.341734
4  0.959726
6  1.110336
8 -0.619976
dtype: float64

In [62]: s1.iloc[:3]
Out[62]:
0  0.695775
2  0.341734
4  0.959726
dtype: float64

In [63]: s1.iloc[3]
→ -1.1103361028911669

Note that setting works as well:

In [64]: s1.iloc[:3] = 0

In [65]: s1
Out[65]:
0   0.000000
2   0.000000
4   0.000000
6 -1.110336
8  0.619976
dtype: float64

With a DataFrame:

In [66]: df1 = pd.DataFrame(np.random.randn(6,4),
                    index=list(range(0,12,2)),
                    columns=list(range(0,8,2)))

In [67]: df1
Out[67]:
          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  0.682538  1.933209 0.471276  0.894030
8  0.995761  2.396780 0.014871  3.357427
10 -0.317441 -1.236269 0.896171 -0.487602

Select via integer slicing:

In [68]: df1.iloc[:3]
Out[68]:
          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

(continues on next page)
In [69]: df1.iloc[1:5, 2:4]

Out[69]:

<table>
<thead>
<tr>
<th></th>
<th>2</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.301624</td>
<td>-2.179861</td>
</tr>
<tr>
<td>2</td>
<td>1.462696</td>
<td>-1.743161</td>
</tr>
<tr>
<td>4</td>
<td>1.314232</td>
<td>0.690579</td>
</tr>
<tr>
<td>6</td>
<td>0.014871</td>
<td>3.357427</td>
</tr>
</tbody>
</table>

Select via integer list:

In [70]: df1.iloc[[1, 3, 5], [1, 3]]

Out[70]:

<table>
<thead>
<tr>
<th></th>
<th>2</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.403310</td>
<td>-0.154951</td>
</tr>
<tr>
<td>2</td>
<td>-0.345352</td>
<td>0.690579</td>
</tr>
<tr>
<td>4</td>
<td>-1.369849</td>
<td>-0.345352</td>
</tr>
<tr>
<td>6</td>
<td>1.314232</td>
<td>1.314232</td>
</tr>
<tr>
<td>8</td>
<td>0.014871</td>
<td>3.357427</td>
</tr>
</tbody>
</table>

Out of range slice indexes are handled gracefully just as in Python/Numpy.

For getting a cross section using an integer position (equiv to df.xs(1)):

In [73]: df1.iloc[1]

Out[73]:

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>2</th>
<th>4</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.403310</td>
<td>-0.154951</td>
<td>0.301624</td>
<td>-2.179861</td>
</tr>
<tr>
<td>2</td>
<td>-0.345352</td>
<td>0.690579</td>
<td>1.462696</td>
<td>-1.743161</td>
</tr>
</tbody>
</table>

Out of range slice indexes are handled gracefully just as in Python/Numpy.

In [75]: x = list('abcdef')

(continues on next page)
In [76]: x
Out[76]: ['a', 'b', 'c', 'd', 'e', 'f']

In [77]: x[4:10]
Out[77]: ['e', 'f']

In [78]: x[8:10]
Out[78]: []

In [79]: s = pd.Series(x)

In [80]: s
Out[80]:
    0   a
    1   b
    2   c
    3   d
    4   e
    5   f
dtype: object

In [81]: s.iloc[4:10]
Out[81]:
    4   e
    5   f
dtype: object

In [82]: s.iloc[8:10]
Out[82]:
     Series([], dtype: object)

Note that using slices that go out of bounds can result in an empty axis (e.g. an empty DataFrame being returned).

In [83]: dfl = pd.DataFrame(np.random.randn(5,2), columns=list('AB'))

In [84]: dfl
Out[84]:
    0      1
   ---    ---
   A   B
   0 -0.082240 -2.182937
   1  0.380396  0.084844
   2  0.432390  1.519970
   3 -0.493662  0.600178
   4  0.274230  0.132885

In [85]: dfl.iloc[:, 2:3]
Out[85]:
     Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [86]: dfl.iloc[:, 1:3]
Out[86]:
     B
      0 -2.182937
      1  0.084844
2 1.519970 0.600178 0.132885

In [87]: df.iloc[4:6]

→ A B
   4 0.27423 0.132885

A single indexer that is out of bounds will raise an `IndexError`. A list of indexes where any element is out of bounds will raise an `IndexError`.

```
dfl.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds
dfl.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

### 12.7 Selection By Callable

New in version 0.18.1.

`.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. The `callable` must be a function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing.

```
In [88]: df1 = pd.DataFrame(np.random.randn(6, 4),
                   index=list('abcdef'),
                   columns=list('ABCD'))

In [89]: df1
```

<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>-0.023688</td>
<td>2.410179</td>
<td>1.450520</td>
<td>0.206053</td>
</tr>
<tr>
<td>b</td>
<td>-0.251905</td>
<td>-2.213588</td>
<td>1.063327</td>
<td>1.266143</td>
</tr>
<tr>
<td>c</td>
<td>0.299368</td>
<td>-0.863838</td>
<td>0.408204</td>
<td>-1.048089</td>
</tr>
<tr>
<td>d</td>
<td>-0.025747</td>
<td>-0.988387</td>
<td>0.094055</td>
<td>1.262731</td>
</tr>
<tr>
<td>e</td>
<td>1.289997</td>
<td>0.082423</td>
<td>-0.055758</td>
<td>0.536580</td>
</tr>
<tr>
<td>f</td>
<td>-0.489682</td>
<td>0.369374</td>
<td>-0.034571</td>
<td>-2.484478</td>
</tr>
</tbody>
</table>

```
In [90]: df1.loc[lambda df: df.A > 0, :]
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>0.299368</td>
<td>-0.863838</td>
<td>0.408204</td>
<td>-1.048089</td>
</tr>
<tr>
<td>e</td>
<td>1.289997</td>
<td>0.082423</td>
<td>-0.055758</td>
<td>0.536580</td>
</tr>
</tbody>
</table>

```
In [91]: df1.loc[:, lambda df: ['A', 'B']]
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.023688</td>
<td>2.410179</td>
</tr>
<tr>
<td>b</td>
<td>-0.251905</td>
<td>-2.213588</td>
</tr>
</tbody>
</table>

(continues on next page)
c 0.299368 -0.863838
d -0.025747 -0.988387
e 1.289997 0.082423
f -0.489682 0.369374

In [92]: df1.iloc[:, lambda df: [0, 1]]

\ A B 
| a | -0.023688 2.410179 |
| b | -0.251905 -2.213588 |
| c | 0.299368 -0.863838 |
| d | -0.025747 -0.988387 |
| e | 1.289997 0.082423 |
| f | -0.489682 0.369374 |

In [93]: df1[lambda df: df.columns[0]]

\ A 
| a | -0.023688 |
| b | -0.251905 |
| c | 0.299368 |
| d | -0.025747 |
| e | 1.289997 |
| f | -0.489682 |
Name: A, dtype: float64

You can use callable indexing in Series.

In [94]: df1.A.loc[lambda s: s > 0]
Out[94]:
c 0.299368
e 1.289997
Name: A, dtype: float64

Using these methods / indexers, you can chain data selection operations without using temporary variable.

In [95]: bb = pd.read_csv('data/baseball.csv', index_col='id')
In [96]: (bb.groupby(['year', 'team']).sum()
        .loc[lambda df: df.r > 100])
Out[96]:

| year | team | stint | g  | ab  | r | h  | X2b | X3b | hr  | rbi | sb  | cs  | bb  | so  | ibb | hbp | sh  | sf  | gidp |
|------|------|-------|----|-----|---|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|      |      | 2007  | CIN| 6   | 379| 745| 101 | 203 | 35  | 2   | 36  | 125.0| 10.0| 1.0 | 105 | 127.0| 14.0|
|      |      | 2007  | DET| 5   | 301| 1062| 162 | 283 | 54  | 4   | 37  | 144.0| 24.0| 7.0 | 97  | 176.0| 3.0 |
|      |      | 2007  | HOU| 4   | 311| 926 | 109 | 218 | 47  | 6   | 14  | 77.0 | 10.0| 4.0 | 60  | 212.0| 3.0 |
|      |      | 2007  | LAN| 11  | 413| 1021| 153 | 293 | 61  | 3   | 36  | 154.0| 7.0 | 5.0 | 114 | 141.0| 8.0 |
|      |      | 2007  | NYN| 13  | 622| 1854| 240 | 509 | 101 | 3   | 61  | 243.0| 22.0| 4.0 | 174 | 310.0| 24.0 |
Warning: Starting in 0.20.0, the .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers.

.ix offers a lot of magic on the inference of what the user wants to do. To wit, .ix can decide to index *positionally* OR via *labels* depending on the data type of the index. This has caused quite a bit of user confusion over the years.

The recommended methods of indexing are:

- .loc if you want to *label* index.
- .iloc if you want to *positionally* index.

```
In [97]: df = pd.DataFrame({'A': [1, 2, 3],
            'B': [4, 5, 6]},
            index=list('abc'))

In [98]: df
Out[98]:
    A  B
   a 1  4
   b 2  5
   c 3  6
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: df.ix[[0, 2], 'A']
Out[3]:
   a 1
   c 3
Name: A, dtype: int64
```

Using .loc. Here we will select the appropriate indexes from the index, then use *label* indexing.

```
In [99]: df.loc[df.index[[0, 2]], 'A']
Out[99]:
   a 1
   c 3
Name: A, dtype: int64
```

This can also be expressed using .iloc, by explicitly getting locations on the indexers, and using *positional* indexing to select things.

```
In [100]: df.iloc[[0, 2], df.columns.get_loc('A')]
Out[100]:
   a 1
   c 3
```

(continues on next page)
For getting multiple indexers, using `.get_indexer`:

```python
In [101]: dfd.iloc[[0, 2], dfd.columns.get_indexer(['A', 'B'])]
Out[101]:
   A  B
a  1  4
c  3  6
```

### 12.9 Indexing with list with missing labels is Deprecated

**Warning:** Starting in 0.21.0, using `.loc` or `[]` with a list with one or more missing labels, is deprecated, in favor of `.reindex`.

In prior versions, using `.loc[list-of-labels]` would work as long as at least 1 of the keys was found (otherwise it would raise a `KeyError`). This behavior is deprecated and will show a warning message pointing to this section. The recommended alternative is to use `.reindex()`.

For example.

```python
In [102]: s = pd.Series([1, 2, 3])
In [103]: s
Out[103]:
0    1
1    2
2    3
dtype: int64
```

Selection with all keys found is unchanged.

```python
In [104]: s.loc[[1, 2]]
Out[104]:
  1    2
  2    3
dtype: int64
```

Previous Behavior

```python
In [4]: s.loc[[1, 2, 3]]
Out[4]:
  1  2.0
  2  3.0
  3  NaN
dtype: float64
```

Current Behavior
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc with any non-matching elements will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
˓
→listlike

Out[4]:
1 2.0
2 3.0
3 NaN
dtype: float64

12.9.1 Reindexing

The idiomatic way to achieve selecting potentially not-found elements is via .reindex(). See also the section on reindexing.

In [105]: s.reindex([1, 2, 3])
Out[105]:
1 2.0
2 3.0
3 NaN
dtype: float64

Alternatively, if you want to select only valid keys, the following is idiomatic and efficient; it is guaranteed to preserve the dtype of the selection.

In [106]: labels = [1, 2, 3]
In [107]: s.loc[s.index.intersection(labels)]
Out[107]:
1 2
2 3
dtype: int64

Having a duplicated index will raise for a .reindex():

In [108]: s = pd.Series(np.arange(4), index=['a', 'a', 'b', 'c'])
In [109]: labels = ['c', 'd']

In [17]: s.reindex(labels)
ValueError: cannot reindex from a duplicate axis

Generally, you can intersect the desired labels with the current axis, and then reindex.

In [110]: s.loc[s.index.intersection(labels)].reindex(labels)
Out[110]:
c 3.0
d NaN
dtype: float64

However, this would still raise if your resulting index is duplicated.
In [41]: labels = ['a', 'd']

In [42]: s.loc[s.index.intersection(labels)].reindex(labels)
ValueError: cannot reindex from a duplicate axis

### 12.10 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 [111]: s = pd.Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1 row.
In [112]: s.sample()
Out[112]:
4 4
dtype: int64

# One may specify either a number of rows:
In [113]: s.sample(n=3)

Out[113]:
0 0
4 4
1 1
dtype: int64

# Or a fraction of the rows:
In [114]: s.sample(frac=0.5)

Out[114]:
5 5
3 3
1 1
dtype: int64

By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

In [115]: s = pd.Series([0,1,2,3,4,5])

# Without replacement (default):
In [116]: s.sample(n=6, replace=False)
Out[116]:
0 0
1 1
5 5
3 3
2 2
4 4
dtype: int64

# With replacement:
In [117]: s.sample(n=6, replace=True)

Out[117]:
0 0
4 4

(continues on next page)
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:

```python
In [118]: s = pd.Series([0, 1, 2, 3, 4, 5])
In [119]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]
In [120]: s.sample(n=3, weights=example_weights)
Out[120]:
      5
   3
   4
dtype: int64
# Weights will be re-normalized automatically
In [121]: example_weights2 = [0.5, 0, 0, 0, 0, 0]
In [122]: s.sample(n=1, weights=example_weights2)
Out[122]:
   0
dtype: int64
```

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```python
In [123]: df2 = pd.DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})
In [124]: df2.sample(n=3, weights = 'weight_column')
Out[124]:
        col1  weight_column
   0      8          0.4
   1      9          0.5
   2      7          0.1
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```python
In [125]: df3 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})
In [126]: df3.sample(n=1, axis=1)
Out[126]:
   col
0  1
1  2
2  3
```

Finally, one can also set a seed for `sample`'s random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a NumPy RandomState object.
In [127]: df4 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

# With a given seed, the sample will always draw the same rows.
In [128]: df4.sample(n=2, random_state=2)
Out[128]:
   col1  col2
0     2     3
1     1     2

In [129]: df4.sample(n=2, random_state=2)

In [130]: se = pd.Series([1,2,3])

In [131]: se
Out[131]:
0   1
1   2
2   3
dtype: int64


In [133]: se
Out[133]:
0   1.0
1   2.0
2   3.0
5   5.0
dtype: float64

A DataFrame can be enlarged on either axis via .loc.

In [134]: dfi = pd.DataFrame(np.arange(6).reshape(3,2),
              columns=['A','B'])

In [135]: dfi
Out[135]:
        A  B
0  0.0  1.0
1  2.0  3.0
2  4.0  5.0

In [136]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

12.11 Setting With Enlargement

The .loc[] operations can perform enlargement when setting a non-existent key for that axis.

In the Series case this is effectively an appending operation.

In [137]: se.loc[5] = 5.

In [138]: se
Out[138]:
0   1.0
1   2.0
2   3.0
5   5.0

A DataFrame can be enlarged on either axis via .loc.

In [139]: dfi = pd.DataFrame(np.arange(6).reshape(3,2),
              columns=['A','B'])

In [140]: dfi.loc[:,'C'] = dfi.loc[:,'A']

In [141]: dfi
Out[141]:
         A  B  C
0  0.0  1.0  1.0
1  2.0  3.0  2.0
2  4.0  5.0  4.0

12.11 Setting With Enlargement
In [137]: dfi
Out[137]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4

This is like an append operation on the DataFrame.

In [138]: dfi.loc[3] = 5
In [139]: dfi
Out[139]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5

12.12 Fast scalar value getting and setting

Since indexing with [] must handle a lot of cases (single-label access, slicing, boolean indexing, etc.), it has a bit of overhead in order to figure out what you’re asking for. If you only want to access a scalar value, the fastest way is to use the at and iat methods, which are implemented on all of the data structures.

Similarly to loc, at provides label based scalar lookups, while, iat provides integer based lookups analogously to iloc

In [140]: s.iat[5]
Out[140]: 5

In [141]: df.at[dates[5], 'A']
\Out[141]: -0.67368970808837059

In [142]: df.iat[3, 0]
\Out[142]: 0.72155516224436689

You can also set using these same indexers.

In [143]: df.at[dates[5], 'E'] = 7
In [144]: df.iat[3, 0] = 7

at may enlarge the object in-place as above if the indexer is missing.

In [145]: df.at[dates[-1]+1, 0] = 7
In [146]: df
Out[146]:
   A   B   C   D   E   0
0  2000-01-01  0.469112 -0.282863 -1.509059 -1.135632 NaN NaN
1  2000-01-02  1.212112 -0.173215  0.119209 -1.044236 NaN NaN
2  2000-01-03 -0.861849 -2.104569 -0.494929  1.071804 NaN NaN
3  2000-01-04  7.000000  0.706771 -1.039575  0.271860 NaN NaN
Another common operation is the use of boolean vectors to filter the data. The operators are: \( \text{or} \), \( \& \) for and, and \( \sim \) for not. These must be grouped by using parentheses, since by default Python will evaluate an expression such as \( \text{df.A > 2 & df.B < 3} \) as \( \text{df.A} > (2 \& \text{df.B}) < 3 \), while the desired evaluation order is \( (\text{df.A} > 2) \& (\text{df.B} < 3) \).

Using a boolean vector to index a Series works exactly as in a NumPy ndarray:

```python
In [147]: s = pd.Series(range(-3, 4))

In [148]: s
Out[148]:
0   -3
1   -2
2   -1
3    0
4    1
5    2
6    3
dtype: int64

In [149]: s[s > 0]
Out[149]:
4    1
5    2
6    3
dtype: int64

In [150]: s[(s < -1) | (s > 0.5)]
Out[150]:
    0   -3
   1   -2
   4    1
   5    2
   6    3
 dtype: int64

In [151]: s[~(s < 0)]
Out[151]:
    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):

```python
In [152]: df[df['A'] > 0]
Out[152]:
      A          B         C         D         E
2000-01-01 0.469112 -0.282863 -1.509059 -1.135632 NaN
2000-01-02 1.212112 -0.173215  0.119209 -1.044236 NaN
2000-01-04 7.000000 -0.706771 -1.039575  0.271860 NaN
2000-01-07 0.404705  0.577046 -1.715002 -1.039268 NaN
```

List comprehensions and `map` method of Series can also be used to produce more complex criteria:

```python
In [153]: df2 = pd.DataFrame({'a' : ["one", 'one', 'two', 'three', 'two', 'one', 'six →'],
                          'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
                          'c' : np.random.randn(7)})

# only want 'two' or 'three'
In [154]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [155]: df2[criterion]
Out[155]:
     a   b   c
   2  two  0.041290
   3  three  0.361719
   4  two  -0.238075

# Multiple criteria
In [157]: df2[criterion & (df2['b'] == 'x')]
```

With the choice methods `Selection by Label`, `Selection by Position`, and `Advanced Indexing` you may select along more than one axis using boolean vectors combined with other indexing expressions.

```python
In [158]: df2.loc[criterion & (df2['b'] == 'x'), 'b':'c']
```

### 12.14 Indexing with `isin`

Consider the `isin()` method of Series, which returns a boolean vector that is true wherever the Series elements exist in the passed list. This allows you to select rows where one or more columns have values you want:
In [159]: s = pd.Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')

In [160]: s
Out[160]:
4  0
3  1
2  2
1  3
0  4
dtype: int64

In [161]: s.isin([2, 4, 6])
Out[161]:
4  False
3  False
2  True
1  False
0  True
dtype: bool

In [162]: s[s.isin([2, 4, 6])]
Out[162]:
   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 [163]: s[s.index.isin([2, 4, 6])]
Out[163]:
   2  2
   0  4
dtype: int64

# compare it to the following
In [164]: s.reindex([2, 4, 6])
Out[164]:
2  2.0
4  0.0
6  NaN
dtype: float64

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

In [165]: s_mi = pd.Series(np.arange(6),
                      index=pd.MultiIndex.from_product([[0, 1],
                                                  ['a', 'b', 'c']]))

In [166]: s_mi
Out[166]:
   0  a  0
   b  1
   c  2
   1  a  3

(continues on next page)
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 [169]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
                     ....:                 'ids2': ['a', 'n', 'c', 'n']})
In [170]: values = ['a', 'b', 1, 3]
In [171]: df.isin(values)
Out[171]:
   vals  ids  ids2
0   True  True  True
1   False  True  False
2   True  False  False
3   False  False  False
```

Oftentimes you’ll want to match certain values with certain columns. Just make values a dict where the key is the column, and the value is a list of items you want to check for.

```
In [172]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}
In [173]: df.isin(values)
Out[173]:
   vals  ids  ids2
0   True  True  False
1   False  True  False
2   True  False  False
3   False  False  False
```

Combine DataFrame’s `isin` with the `any()` and `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 [174]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}
```
In [175]: row_mask = df.isin(values).all(1)

In [176]: df[row_mask]
 Out[176]:
vals ids ids2
0 1    a   a

12.15 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in `Series` and `DataFrame`.

To return only the selected rows:

In [177]: s[s > 0]
 Out[177]:
3   1
2   2
1   3
0   4
dtype: int64

To return a Series of the same shape as the original:

In [178]: s.where(s > 0)
 Out[178]:
4   NaN
3    1.0
2    2.0
1    3.0
0    4.0
dtype: float64

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. The code below is equivalent to `df.where(df < 0)`.

In [179]: df[df < 0]
 Out[179]:
          A         B         C         D
2000-01-01 -2.104139 -1.309525   NaN   NaN
2000-01-02 -0.352480  NaN -1.192319   NaN
2000-01-03  NaN -0.864883  NaN -0.227870
2000-01-04  NaN  NaN -1.222082 -1.233203
2000-01-05  NaN -0.605656 -1.169184   NaN
2000-01-06  NaN  NaN  NaN -0.684718
2000-01-07  NaN  NaN -0.048788 -0.808838
2000-01-08  NaN  NaN  NaN -0.808838

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

In [180]: df.where(df < 0, -df)
 Out[180]:
          A         B         C         D
2000-01-01 -2.104139 -1.309525   NaN   NaN
2000-01-02 -0.352480  NaN -1.192319   NaN
2000-01-03  NaN -0.864883  NaN -0.227870
2000-01-04  NaN  NaN -1.222082 -1.233203
2000-01-05  NaN -0.605656 -1.169184   NaN
2000-01-06  NaN  NaN  NaN -0.684718
2000-01-07  NaN  NaN -0.048788 -0.808838
2000-01-08  NaN  NaN  NaN -0.808838

(continues on next page)
You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```python
In [181]: s2 = s.copy()

In [182]: s2[s2 < 0] = 0

In [183]: s2
Out[183]:
   4  0
   3  1
   2  2
   1  3
   0  4
dtype: int64

In [184]: df2 = df.copy()

In [185]: df2[df2 < 0] = 0

In [186]: df2
Out[186]:
     A       B       C       D
   2000-01-01  0.000000  0.000000  0.485855  0.245166
   2000-01-02  0.000000  0.390389  0.000000  1.655824
   2000-01-03  0.000000  0.299674  0.000000  0.281059
   2000-01-04  0.846958  0.000000  0.600705  0.233203
   2000-01-05  0.669692  0.000000  1.169184  0.342416
   2000-01-06  0.868584  0.948458  2.297780  0.684718
   2000-01-07  0.000000  0.000000  0.168904  0.000000
   2000-01-08  0.801196  1.392071  0.048788  0.000000
```

By default, `where` returns a modified copy of the data. There is an optional parameter `inplace` so that the original data can be modified without creating a copy:

```python
In [187]: df_orig = df.copy()

In [188]: df_orig.where(df > 0, -df, inplace=True);

In [189]: df_orig
Out[189]:
     A       B       C       D
   2000-01-01  2.104139  1.309525  0.485855  0.245166
   2000-01-02  0.352480  0.390389  1.92319  1.655824
   2000-01-03  0.864883  0.299674  0.227870  0.281059
   2000-01-04  0.846958  1.222082  0.600705  1.233203
   2000-01-05  0.669692  0.605656  1.169184  0.342416
   2000-01-06  0.868584  0.948458  2.297780  0.684718
```

(continues on next page)
2000-01-07 2.670153 0.114722 0.168904 0.048048
2000-01-08 0.801196 1.392071 0.048788 0.808838

Note: The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2).

```
In [190]: df.where(df < 0, -df) == np.where(df < 0, df, -df)
Out[190]:
     A     B     C     D
2000-01-01 True  True  True  True
2000-01-02 True  True  True  True
2000-01-03 True  True  True  True
2000-01-04 True  True  True  True
2000-01-05 True  True  True  True
2000-01-06 True  True  True  True
2000-01-07 True  True  True  True
2000-01-08 True  True  True  True
```

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.loc` (but on the contents rather than the axis labels).

```
In [191]: df2 = df.copy()
In [192]: df2[df2[1:4] > 0] = 3
In [193]: df2
Out[193]:
     A     B     C     D
2000-01-01 -2.104139 -2.104139 0.485855 0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  3.000000 -1.222082  3.000000 -1.233203
2000-01-05  0.669692 -0.605656  0.669692  0.342416
2000-01-06  0.868584  0.948458  0.868584 -0.684718
2000-01-07  0.670153 -0.114722  0.168904 -0.808838
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

```
In [194]: df2 = df.copy()
In [195]: df2.where(df2>0,df2['A'],axis='index')
Out[195]:
     A     B     C     D
2000-01-01 -2.104139 -2.104139 0.485855 0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  3.000000 -1.222082  3.000000 -1.233203
2000-01-05  0.669692 -0.605656  0.669692  0.342416
2000-01-06  0.868584  0.948458  0.868584 -0.684718
2000-01-07  0.670153 -0.114722  0.168904 -0.808838
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

12.15. The `where()` Method and Masking

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This is equivalent to (but faster than) the following.

```
In [196]: df2 = df.copy()

In [197]: df.apply(lambda x, y: x.where(x>0,y), y=df['A'])
Out[197]:
     A         B         C         D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

New in version 0.18.1.

Where can accept a callable as condition and other arguments. The function must be with one argument (the calling Series or DataFrame) and that returns valid output as condition and other argument.

```
In [198]: df3 = pd.DataFrame({'A': [1, 2, 3],
                      'B': [4, 5, 6],
                      'C': [7, 8, 9]})

In [199]: df3.where(lambda x: x > 4, lambda x: x + 10)
```

```
Out[199]:
    A  B  C
0   11 14  7
1   12  5  8
2   13  6  9
```

### 12.15.1 Mask

*`mask()`* is the inverse boolean operation of *where*.

```
In [200]: s.mask(s >= 0)
```

```
Out[200]:
   4    NaN
   3    NaN
   2    NaN
   1    NaN
   0    NaN
dtype: float64
```

```
In [201]: df.mask(df >= 0)
```

```
Out[201]:
          A         B         C         D
2000-01-01 -2.104139 -1.309525     NaN     NaN
2000-01-02 -0.352480  0.192319     NaN     NaN
2000-01-03 -0.864883  0.227870     NaN     NaN
2000-01-04  0.846958 -1.222082     NaN -1.233203
2000-01-05  0.669692 -1.169184     NaN     NaN
2000-01-06  0.868584 -0.684718     NaN     NaN
2000-01-07 -2.670153 -0.048788  0.048048  0.808838
2000-01-08  0.801196  0.801196  0.801196  0.801196
```
12.16 The query() Method

`DataFrame` objects have a `query()` method that allows selection using an expression.

You can get the value of the frame where column `b` has values between the values of columns `a` and `c`. For example:

```
In [202]: n = 10
In [203]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
In [204]: df
Out[204]:
   a    b    c
0  0.438921  0.118680  0.863670
1  0.138138  0.577363  0.686602
2  0.595307  0.564592  0.520630
3  0.913052  0.926075  0.616184
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
6  0.792342  0.216974  0.564056
7  0.397890  0.454131  0.915716
8  0.074315  0.437913  0.019794
9  0.559209  0.502065  0.026437
```

# pure python
```
In [205]: df[(df.a < df.b) & (df.b < df.c)]
   a    b    c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

# query
```
In [206]: df.query('(a < b) & (b < c)')
   a    b    c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

Do the same thing but fall back on a named index if there is no column with the name `a`.

```
In [207]: df = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))
In [208]: df.index.name = 'a'
In [209]: df
Out[209]:
   b    c
a
0  0  4
1  0  1
2  3  4
```

(continues on next page)
3 4 3
4 1 4
5 0 3
6 0 1
7 3 4
8 2 3
9 1 1

```
In [210]: df.query('a < b and b < c')
```

```
   b  c
a
2 3 4
```

If instead you don’t want to or cannot name your index, you can use the name `index` in your query expression:

```
In [211]: df = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))
In [212]: df
Out[212]:
   b  c
0 3 1
1 3 0
2 5 6
3 5 2
4 7 4
5 0 1
6 2 5
7 0 1
8 6 0
9 7 9
In [213]: df.query('index < b < c')
```

```
   b  c
2 5 6
```

**Note:** If the name of your index overlaps with a column name, the column name is given precedence. For example,

```
In [214]: df = pd.DataFrame({'a': np.random.randint(5, size=5)})
In [215]: df.index.name = 'a'
In [216]: df.query('a > 2')  # uses the column 'a', not the index
Out[216]:
   a
0 1
1 3
2 3
```

You can still use the index in a query expression by using the special identifier ‘index’:

```
In [217]: df.query('index > 2')
```
If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

### 12.16.1 `MultiIndex` `query()` Syntax

You can also use the levels of a `DataFrame` with a `MultiIndex` as if they were columns in the frame:

```
In [218]: n = 10
In [219]: colors = np.random.choice(['red', 'green'], size=n)
In [220]: foods = np.random.choice(['eggs', 'ham'], size=n)
In [221]: colors
Out[221]:
array(['red', 'red', 'red', 'green', 'green', 'green', 'green', 'green', 'green', 'green'],
      dtype='<U5')
In [222]: foods
Out[222]:
array(['ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham', 'ham', 'eggs', 'eggs', 'eggs'],
      dtype='<U4')
In [223]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])
In [224]: df = pd.DataFrame(np.random.randn(n, 2), index=index)
```

```
0 1
color food
red ham 0.194889 -0.381994
  ham 0.318587  2.089075
  eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
  eggs -2.029766  0.792652
  ham  0.461007 -0.542749
  ham -0.305384 -0.479195
  eggs  0.095031 -0.270099
  eggs -0.707140 -0.773882
  eggs  0.229453  0.304418
```

```
In [226]: df.query('color == "red"')
```

(continues on next page)
If the levels of the MultiIndex are unnamed, you can refer to them using special names:

```python
In [227]: df.index.names = [None, None]
```

```python
In [228]: df
```

```python
Out[228]:
   0    1
red 0.194889 -0.381994
ham 0.318587  2.089075
eggs-0.728293 -0.090255
green eggs -0.748199  1.318931
  eggs -2.029766  0.792652
ham 0.461007 -0.542749
eggs -0.305384 -0.270099
eggs  0.229453  0.304418
```

```python
In [229]: df.query('ilevel_0 == "red"')
```

```python
In [230]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
```

The convention is `ilevel_0`, which means “index level 0” for the 0th level of the index.

### 12.16.2 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 [232]: df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)

In [233]: df2
Out[233]:
   a          b          c
0  0.357579  0.229800  0.596001
1  0.309059  0.957923  0.965663
2  0.123102  0.336914  0.318616
3  0.526506  0.323321  0.860813
4  0.518736  0.486514  0.384724
5  0.190804  0.505723  0.614533
6  0.891939  0.623977  0.676639
7  0.480559  0.378528  0.460858
8  0.420223  0.136404  0.141295
9  0.732206  0.419540  0.604675
10 0.604466  0.848974  0.896165
11 0.589168  0.920046  0.732716

In [234]: expr = '0.0 <= a <= c <= 0.5'

In [235]: map(lambda frame: frame.query(expr), [df, df2])
Out[235]: <map at 0x1155dd198>

12.16.3 query() Python versus pandas Syntax Comparison

Full numpy-like syntax:

In [236]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=list('abc'))

In [237]: df
Out[237]:
   a  b  c
0  7  8  9
1  1  0  7
2  2  7  2
3  6  2  2
4  2  6  3
5  3  8  2
6  1  7  2
7  5  1  5
8  9  8  0
9  1  5  0

In [238]: df.query('(a < b) & (b < c)')
   →
   a  b  c
0  7  8  9

In [239]: df[(df.a < df.b) & (df.b < df.c)]
   →
   a  b  c
0  7  8  9
Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than \& and |).

In [240]: df.query('a < b & b < c')
Out[240]:
    a  b  c
0  7  8  9

Use English instead of symbols:

In [241]: df.query('a < b and b < c')
Out[241]:
    a  b  c
0  7  8  9

Pretty close to how you might write it on paper:

In [242]: df.query('a < b < c')
Out[242]:
    a  b  c
0  7  8  9

12.16.4 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 [243]: df = pd.DataFrame({'a': list('aabbccddeeff'), 'b': list('aaaabbbbcccd'),
                       'c': np.random.randint(5, size=12),
                       'd': np.random.randint(9, size=12)})

In [244]: df
Out[244]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2

In [245]: df.query('a in b')

...: a  b  c  d
0 a  a  2  6
1 a  a  4  7
2 b  a  1  6
3 b  a  2  1

(continues on next page)
# How you’d do it in pure Python

In [246]: df[df.a.isin(df.b)]

→

    a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2

In [247]: df.query('a not in b')

→

    a  b  c  d
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2

# pure Python

In [248]: df[~df.a.isin(df.b)]

→

    a  b  c  d
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2

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 [249]: df.query('a in b and c < d')

Out[249]:

    a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
4  c  b  3  6
5  c  b  0  2

# pure Python

In [250]: df[df.b.isin(df.a) & (df.c < df.d)]

→

    a  b  c  d
0  a  a  2  6

(continues on next page)
Note: Note that \texttt{in} and \texttt{not in} are evaluated in Python, since \texttt{numexpr} has no equivalent of this operation. However, only the \texttt{in/not in} expression itself is evaluated in vanilla Python. For example, in the expression
\begin{verbatim}
dl.query('a in b + c + d')
\end{verbatim}
(b + c + d) is evaluated by \texttt{numexpr} and then the \texttt{in} operation is evaluated in plain Python. In general, any operations that can be evaluated using \texttt{numexpr} will be.

\subsection{12.16.5 Special use of the \texttt{==} operator with \texttt{list} objects}

Comparing a list of values to a column using \texttt{==/!=} works similarly to \texttt{in/not in}.

\begin{verbatim}
In [251]: df.query('b == ["a", "b", "c"]')
Out[251]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2
\end{verbatim}

# pure Python

\begin{verbatim}
In [252]: df[df.b.isin(["a", "b", "c"])])
\end{verbatim}

\begin{verbatim}
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2
\end{verbatim}
In [253]: df.query('c == [1, 2]')

    a  b  c  d
0  a  a  2  6
2  b  a  1  6
3  b  a  2  1
7  d  b  2  1
9  e  c  2  0
11 f  c  1  2

In [254]: df.query('c != [1, 2]')

    a  b  c  d
1  a  a  4  7
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
8  e  c  4  3
10 f  c  0  6

# using in/not in
In [255]: df.query('[1, 2] in c')

    a  b  c  d
0  a  a  2  6
2  b  a  1  6
3  b  a  2  1
7  d  b  2  1
9  e  c  2  0
11 f  c  1  2

In [256]: df.query('[1, 2] not in c')

    a  b  c  d
1  a  a  4  7
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
8  e  c  4  3
10 f  c  0  6

# pure Python
In [257]: df[df.c.isin([1, 2])]
12.16.6 Boolean Operators

You can negate boolean expressions with the word **not** or the ~ operator.

```
In [258]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
In [259]: df['bools'] = np.random.rand(len(df)) > 0.5
In [260]: df.query('~bools')
Out[260]:
          a          b          c  bools
2  0.697753  0.212799  0.329209   False
7  0.275396  0.691034  0.826619   False
8  0.190649  0.558748  0.262467   False
In [261]: df.query('not bools')
  
          a          b          c  bools
2  0.697753  0.212799  0.329209   False
7  0.275396  0.691034  0.826619   False
8  0.190649  0.558748  0.262467   False
In [262]: df.query('not bools') == df[~df.bools]
  
          a          b          c  bools
2   True   True   True   True
7   True   True   True   True
8   True   True   True   True
```

Of course, expressions can be arbitrarily complex too:

```
# short query syntax
In [263]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [264]: longer = df[(df.a < df.b) & (df.b < df.c) & (~df.bools) | (df.bools > 2)]

In [265]: shorter
Out[265]:
          a          b          c  bools
7  0.275396  0.691034  0.826619   False

In [266]: longer
Out[266]:
          a          b          c  bools
7  0.275396  0.691034  0.826619   False
In [267]: shorter == longer
Out[267]:
          a          b          c  bools
7   True   True   True   True
```

Chapter 12. Indexing and Selecting Data
12.16.7 Performance of query()

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames.

**Note:** You will only see the performance benefits of using the `numexpr` engine with `DataFrame.query()` if your frame has more than approximately 200,000 rows.

This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

12.17 Duplicate Data

If you want to identify and remove duplicate rows in a DataFrame, there are two methods that will help: `duplicated` and `drop_duplicates`. Each takes as an argument the columns to use to identify duplicated rows.
• `duplicated` returns a boolean vector whose length is the number of rows, and which indicates whether a row is duplicated.
• `drop_duplicates` removes duplicate rows.

By default, the first observed row of a duplicate set is considered unique, but each method has a `keep` parameter to specify targets to be kept.
• `keep='first'` (default): mark / drop duplicates except for the first occurrence.
• `keep='last'`: mark / drop duplicates except for the last occurrence.
• `keep=False`: mark / drop all duplicates.

```
In [268]: 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 [269]: df2
Out[269]:
   a    b          c
0  one   x -1.067137
1  one   y  0.309500
2  two   x -0.211056
3  two   y -1.842023
4  two   x -0.390820
5  three  x -1.964475
6   four  x  1.298329

In [270]: df2.duplicated('a')
Out[270]:
0   False
1   True
2   False
3   True
4   True
5   False
6   False
   dtype: bool

In [271]: df2.duplicated('a', keep='last')
Out[271]:
0   True
1   False
2   True
3   True
4   False
5   False
6   False
   dtype: bool

In [272]: df2.duplicated('a', keep=False)
Out[272]:
0   True
1   True
```

(continues on next page)
In [273]: df2.drop_duplicates('a')

   a  b  c  
0  one  x -1.067137
2  two  x -0.211056
5  three x -1.964475
6  four x  1.298329

In [274]: df2.drop_duplicates('a', keep='last')

   a  b  c  
1  one  y  0.309500
4  two  x -0.390820
5  three x -1.964475
6  four x  1.298329

In [275]: df2.drop_duplicates('a', keep=False)

   a  b  c  
5  three x -1.964475
6  four x  1.298329

Also, you can pass a list of columns to identify duplications.

In [276]: df2.duplicated(['a', 'b'])

Out[276]:
0   False
1   False
2   False
3   False
4    True
5   False
6   False
dtype: bool

In [277]: df2.drop_duplicates(['a', 'b'])

   a  b  c  
0  one  x -1.067137
1  one  y  0.309500
2  two  x -0.211056
3  two  y -1.842023
5  three x -1.964475
6  four x  1.298329

To drop duplicates by index value, use Index.duplicated then perform slicing. The same set of options are
available for the keep parameter.

```python
In [278]: df3 = pd.DataFrame({'a': np.arange(6),
                         'b': np.random.randn(6)},
                         index=['a', 'a', 'b', 'c', 'b', 'a'])

In [279]: df3
Out[279]:
   a    b
a 0  1.440455
a 1  2.456086
b 2  1.038402
c 3  0.894409
b 4  0.683536
a 5  3.082764

In [280]: df3.index.duplicated()
\                                          array([False,  True, False, False,  True,  True], dtype=bool)

In [281]: df3[~df3.index.duplicated()]
\                                     a    b
a 0  1.440455
b 2  1.038402
c 3  0.894409

In [282]: df3[~df3.index.duplicated(keep='last')]
\                                              a    b
   c    3  0.894409
      b  4  0.683536
      a  5  3.082764

In [283]: df3[~df3.index.duplicated(keep=False)]
\                                               a    b
   c    3  0.894409
```

### 12.18 Dictionary-like get() method

Each of Series, DataFrame, and Panel have a `get` method which can return a default value.

```python
In [284]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [285]: s.get('a') # equivalent to s['a']
Out[285]: 1

In [286]: s.get('x', default=-1)
\                     Out[286]: -1
```
12.19 The `lookup()` Method

Sometimes you want to extract a set of values given a sequence of row labels and column labels, and the `lookup` method allows for this and returns a NumPy array. For instance:

```
In [287]: dflookup = pd.DataFrame(np.random.rand(20,4), columns = ['A','B','C','D'])
In [288]: dflookup.lookup(list(range(0,10,2)), ['B','C','A','B','D'])
Out[288]: array([ 0.3506, 0.4779, 0.4825, 0.9197, 0.5019])
```

12.20 Index objects

The pandas `Index` class and its subclasses can be viewed as implementing an *ordered multiset*. Duplicates are allowed. However, if you try to convert an `Index` object with duplicate entries into a set, an exception will be raised.

`Index` also provides the infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create an `Index` directly is to pass a list or other sequence to `Index`:

```
In [289]: index = pd.Index(['e', 'd', 'a', 'b'])
In [290]: index
Out[290]: Index(['e', 'd', 'a', 'b'], dtype='object')
In [291]: 'd' in index
Out[291]: True
```

You can also pass a name to be stored in the index:

```
In [292]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')
In [293]: index.name
Out[293]: 'something'
```

The name, if set, will be shown in the console display:

```
In [294]: index = pd.Index(list(range(5)), name='rows')
In [295]: columns = pd.Index(['A', 'B', 'C'], name='cols')
In [296]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)
In [297]: df
Out[297]:
    A       B       C
  rows
 0  1.295989  0.185778  0.436259
 1  0.678101  0.311369 -0.528378
 2 -0.674808 -1.103529 -0.656157
 3  1.889957  2.076651 -1.102192
 4 -1.211795 -0.791746  0.634724
```

(continues on next page)
12.20.1 Setting metadata

Indexes are “mostly immutable”, but it is possible to set and change their metadata, like the index name (or, for MultiIndex, levels and 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.

```python
In [299]: ind = pd.Index([1, 2, 3])
In [300]: ind.rename("apple")
Out[300]: Int64Index([1, 2, 3], dtype='int64', name='apple')
In [301]: ind.set_names(['apple'], inplace=True)
In [302]: ind
Out[302]: Int64Index([1, 2, 3], dtype='int64', name='bob')
set_names, set_levels, and set_labels also take an optional level’ argument

In [305]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])
In [306]: index
Out[306]: MultiIndex(levels=[[0, 1, 2], ['one', 'two']],
                   labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
                   names=['first', 'second'])
In [307]: index.levels[1]
Index(['one', 'two'], dtype='object', name='second')
In [308]: index.set_levels(["a", "b"], level=1)
MultiIndex(levels=[[0, 1, 2], ['a', 'b']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=['first', 'second'])
```
12.20.2 Set operations on Index objects

The two main operations are union (|) and intersection (&). These can be directly called as instance methods or used via overloaded operators. Difference is provided via the .difference() method.

```python
In [309]: a = pd.Index(['c', 'b', 'a'])
In [310]: b = pd.Index(['c', 'e', 'd'])
In [311]: a | b
Out[311]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
In [312]: a & b
Out[312]: Index(['c'], dtype='object')
In [313]: a.difference(b)
Out[313]: Index(['a', 'b'], dtype='object')
```

Also available is the `symmetric_difference (^)` operation, which returns elements that appear in either `idx1` or `idx2`, but not in both. This is equivalent to the Index created by `idx1.difference(idx2).union(idx2.difference(idx1))`, with duplicates dropped.

```python
In [314]: idx1 = pd.Index([1, 2, 3, 4])
In [315]: idx2 = pd.Index([2, 3, 4, 5])
In [316]: idx1.symmetric_difference(idx2)
Out[316]: Int64Index([1, 5], dtype='int64')
In [317]: idx1 ^ idx2
Out[317]: Int64Index([1, 5], dtype='int64')
```

Note: The resulting index from a set operation will be sorted in ascending order.

12.20.3 Missing values

Important: Even though Index can hold missing values (NaN), it should be avoided if you do not want any unexpected results. For example, some operations exclude missing values implicitly.

`Index.fillna` fills missing values with specified scalar value.

```python
In [318]: idx1 = pd.Index([1, np.nan, 3, 4])
In [319]: idx1
Out[319]: Float64Index([1.0, nan, 3.0, 4.0], dtype='float64')
In [320]: idx1.fillna(2)
Out[320]: Float64Index([1.0, 2.0, 3.0, 4.0], dtype='float64')
```
In [321]: idx2 = pd.DatetimeIndex([pd.Timestamp('2011-01-01'), pd.NaT, pd.Timestamp('2011-01-03'))

In [322]: idx2
Out[322]: DatetimeIndex(['2011-01-01', 'NaT', '2011-01-03'], dtype='datetime64[ns]',
                   freq=None)

In [323]: idx2.fillna(pd.Timestamp('2011-01-02'))

12.21 Set / Reset Index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you’ve already done so. There are a couple of different ways.

12.21.1 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, re-indexed DataFrame:

In [324]: data
Out[324]:
    a   b   c   d
0  bar  one  z  1.0
1  bar  two  y  2.0
2  foo  one  x  3.0
3  foo  two  w  4.0

In [325]: indexed1 = data.set_index('c')

In [326]: indexed1
Out[326]:
    a   b   d
   c
 z  bar  one  1.0
 y  bar  two  2.0
 x  foo  one  3.0
 w  foo  two  4.0

In [327]: indexed2 = data.set_index(['a', 'b'])

In [328]: indexed2
Out[328]:
   c   d
   a   b
   bar  one  1.0
   two  y  2.0
   foo  one  3.0
   two  w  4.0
The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [329]: frame = data.set_index('c', drop=False)
In [330]: frame = frame.set_index(['a', 'b'], append=True)
In [331]: frame
```
```
c d
  c a b
  z bar one z 1.0
  y bar two y 2.0
  x foo one x 3.0
  w foo two w 4.0
```

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 [332]: data.set_index('c', drop=False)
Out[332]:
   a   b   c   d
  c
  z bar one z 1.0
  y bar two y 2.0
  x foo one x 3.0
  w foo two w 4.0
In [333]: data.set_index(['a', 'b'], inplace=True)
In [334]: data
```
```
c d
  a   b
  bar one z 1.0
    two y 2.0
    foo one x 3.0
    two w 4.0
```

### 12.21.2 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 of `set_index()`.

```
In [335]: data
Out[335]:
   c   d
  a   b
  bar one z 1.0
    two y 2.0
    foo one x 3.0
    two w 4.0
In [336]: data.reset_index()
```
```
  a   b   c   d
```

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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 [337]: frame
Out[337]:
   c a b
z bar one z 1.0
y bar two y 2.0
x foo one x 3.0
w foo two w 4.0
```

```
In [338]: frame.reset_index(level=1)
Out[338]:
   a c d
   b c
z one bar z 1.0
y two bar y 2.0
x one foo x 3.0
w two foo w 4.0
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame’s columns.

### 12.21.3 Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

### 12.22 Returning a view versus a copy

When setting values in a pandas object, care must be taken to avoid what is called chained indexing. Here is an example.

```
In [339]: dfmi = pd.DataFrame([list('abcd'),
                          list('efgh'),
                          list('ijkl'),
                          list('mnop')],
                          columns=pd.MultiIndex.from_product([['one','two'],
                                                          ['first','second']]))
```

```
In [340]: dfmi
```

(continues on next page)
Compare these two access methods:

```python
In [341]: dfmi['one']['second']
Out[341]:
   0   b
   1   f
   2   j
   3   n
Name: second, dtype: object
```

```python
In [342]: dfmi.loc[:,('one','second')]
Out[342]:
   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 DataFrame that is singly-indexed. Then another Python operation dfmi_with_one['second'] selects the series indexed by 'second'. This is indicated by the variable dfmi_with_one because pandas sees these operations as separate events. e.g. separate calls to `__getitem__`, so it has to treat them as linear operations, they happen one after another.

Contrast this to df.loc[:,('one','second')] which passes a nested tuple of (slice(0), ('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.

### 12.22.1 Why does assignment fail when using chained indexing?

The problem in the previous section is just a performance issue. What’s up with the `SettingWithCopy` warning? We don’t usually throw warnings around when you do something that might cost a few extra milliseconds!

But it turns out that assigning to the product of chained indexing has inherently unpredictable results. To see this, think about how the Python interpreter executes this code:

```python
dfmi.loc[:,('one','second')] = value
# becomes
dfmi.loc.__setitem__((slice(None), ('one', 'second')), value)
```

But this code is handled differently:

```python
dfmi['one']['second'] = value
# becomes
dfmi.__getitem__('one').__setitem__('second', value)
```
See that \_\_getitem\_\_ in there? Outside of simple cases, it's very hard to predict whether it will return a view or a copy (it depends on the memory layout of the array, about which pandas makes no guarantees), and therefore whether the \_\_setitem\_\_ will modify dfmi or a temporary object that gets thrown out immediately afterward. That's what SettingWithCopy is warning you about!

**Note:** You may be wondering whether we should be concerned about the loc property in the first example. But dfmi.loc is guaranteed to be dfmi itself with modified indexing behavior, so dfmi.loc.__getitem__ / dfmi.loc.__setitem__ operate on dfmi directly. Of course, dfmi.loc.__getitem__(idx) may be a view or a copy of dfmi.

Sometimes a SettingWithCopy warning will arise at times when there's no obvious chained indexing going on. These are the bugs that SettingWithCopy is designed to catch! Pandas is probably trying to warn you that you've done this:

```python
def do_something(df):
    foo = df[['bar', 'baz']]  # Is foo a view? A copy? Nobody knows!
    # ... many lines here ...
    foo['quux'] = value  # We don't know whether this will modify df or not!
    return foo
```

Yikes!

### 12.22.2 Evaluation order matters

When you use chained indexing, the order and type of the indexing operation partially determine whether the result is a slice into the original object, or a copy of the slice.

Pandas has the SettingWithCopyWarning because assigning to a copy of a slice is frequently not intentional, but a mistake caused by chained indexing returning a copy where a slice was expected.

If you would like pandas to be more or less trusting about assignment to a chained indexing expression, you can set the option mode.chained_assignment to one of these values:

- 'warn', the default, means a SettingWithCopyWarning is printed.
- 'raise' means pandas will raise a SettingWithCopyException you have to deal with.
- None will suppress the warnings entirely.

```
In [343]: 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 [344]: dfb['c'][dfb.a.str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```python
>>> pd.set_option('mode.chained_assignment', 'warn')
>>> dfb[dfb.a.str.startswith('o')]['c'] = 42
Traceback (most recent call last)
...
SettingWithCopyWarning:
```

(continues on next page)
A chained assignment can also crop up in setting in a mixed dtype frame.

**Note:** These setting rules apply to all of `.loc/.iloc`.

This is the correct access method:

```python
In [345]: dfc = pd.DataFrame({'A':['aaa','bbb','ccc'],'B':[1,2,3]})
In [346]: dfc.loc[0,'A'] = 11
In [347]: dfc
Out[347]:
   A  B
0  11  1
1  bbb  2
2  ccc  3
```

This *can* work at times, but it is not guaranteed to, and therefore should be avoided:

```python
In [348]: dfc = dfc.copy()
In [349]: dfc['A'][0] = 111
In [350]: dfc
Out[350]:
   A  B
0  111  1
1  bbb  2
2  ccc  3
```

This will **not** work at all, and so should be avoided:

```python
>>> 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.
CHAPTER

THIRTEEN

MULTIINDEX / ADVANCED INDEXING

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`.

See the `cookbook` for some advanced strategies.

13.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like Series (1d) and DataFrame (2d).

In this section, we will show what exactly we mean by “hierarchical” indexing and how it integrates with all of the pandas indexing functionality described above and in prior sections. Later, when discussing group by and pivoting and reshaping data, we’ll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the `cookbook` for some advanced strategies.

13.1.1 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` as an array of tuples where each tuple is unique. A `MultiIndex` can be created from a list of arrays (using `MultiIndex.from_arrays`), an array of tuples (using `MultiIndex.from_tuples`), 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 demonstrate different ways to initialize MultiIndexes.

```python
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'), ...
```

(continues on next page)
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'])
```

As a convenience, you can pass a list of arrays directly into Series or DataFrame to construct a MultiIndex automatically:

```
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)
```

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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:

```python
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:

```python
In [16]: df = pd.DataFrame(np.random.randn(3, 8), index=['A', 'B', 'C'], columns=index)
In [17]: df
```

```
0 1 2 3 4 5 6 7
--- --- --- --- --- --- --- ---
A 0.895717 0.805244 -1.206412 2.565646 1.431256 1.343039 -1.170299 -0.226169
B 0.410835 0.813850 0.132003 -0.827317 -0.076467 -1.187678 1.130127 -1.436737
C -1.413681 1.607920 1.024180 0.569605 0.875906 -2.211372 0.974466 -2.006747
```

```python
In [18]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
```

```
  bar   baz   foo
--- --- --- --- --- --- --- --- --- --- --- ---
 first  second  one  two  one  two  one  two  one  two  one  two
                                                                                      --- --- --- --- --- --- --- --- --- --- --- ---
A   0.895717 0.805244 -1.206412 2.565646 1.431256 1.343039 -1.170299 -0.226169
B   0.410835 0.813850 0.132003 -0.827317 -0.076467 -1.187678 1.130127 -1.436737
C  -1.413681 1.607920 1.024180 0.569605 0.875906 -2.211372 0.974466 -2.006747
```

We’ve “sparsified” the higher levels of the indexes to make the console output a bit easier on the eyes. Note that how the index is displayed can be controlled using the `multi_sparse` option in `pandas.set_options()`:
It’s worth keeping in mind that there’s nothing preventing you from using tuples as atomic labels on an axis:

```python
In [20]: pd.Series(np.random.randn(8), index=tuples)
Out[20]:
(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.

### 13.1.2 Reconstructing the level labels

The method `get_level_values` will return a vector of the labels for each location at a particular level:

```python
In [21]: index.get_level_values(0)
Out[21]:
Index(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], dtype='object', name='first')
```

```python
In [22]: index.get_level_values('second')
Out[22]:
Index(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'], dtype='object', name='second')
```

### 13.1.3 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:

```python
In [23]: df['bar']
Out[23]:
     second  one     two
   A   0.895717  0.805244
   B   0.410835  0.813850
   C  -1.413681  1.607920
```

```python
In [24]: df['bar', 'one']
```

(continues on next page)
C  -1.413681
Name: (bar, one), dtype: float64

In [25]: df['bar']['one']

→
A   0.895717
B   0.410835
C  -1.413681
Name: one, dtype: float64

In [26]: s['qux']

→
one  -1.039575
two   0.271860
dtype: float64

See Cross-section with hierarchical index for how to select on a deeper level.

13.1.4 Defined Levels

The repr of a MultiIndex shows all the defined levels of an index, even if the they are not actually used. When slicing an index, you may notice this. For example:

```
In [27]: df.columns  # original MultiIndex
Out[27]:
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'])

In [28]: df[['foo','qux']].columns  # sliced

→
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 only the used levels, you can use the `MultiIndex.get_level_values()` method.

```
In [29]: df[['foo','qux']].columns.values
Out[29]: array([('foo', 'one'), ('foo', 'two'), ('qux', 'one'), ('qux', 'two')],
              dtype=object)

# for a specific level
In [30]: df[['foo','qux']].columns.get_level_values(0)
→Index([('foo', 'foo', 'qux', 'qux'), dtypes.object, name='first')
```

To reconstruct the MultiIndex with only the used levels, the `remove_unused_levels` method may be used. New in version 0.20.0.
In [31]: df[['foo', 'qux']].columns.remove_unused_levels()
Out[31]:
MultiIndex(levels=[['foo', 'qux'], ['one', 'two']],
      labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
     names=['first', 'second'])

13.1.5 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 [32]: s + s[:-2]
Out[32]:
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 [33]: s + s[:2]

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 [34]: s.reindex(index[:3])
Out[34]:
first second
bar one -0.861849
    two -2.104569
baz one -0.494929
dtype: float64

In [35]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])

foo two  -0.706771
bar one -0.861849
qux one -1.039575
baz one  -0.494929
dtype: float64
13.2 Advanced indexing with hierarchical index

Syntactically integrating `MultiIndex` in advanced indexing with `.loc` is a bit challenging, but we’ve made every effort to do so. In general, `MultiIndex` keys take the form of tuples. For example, the following works as you would expect:

```
In [36]: df = df.T

In [37]: df
Out[37]:
          A     B     C
first  
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  2.565646 -0.827317  0.569605

In [38]: df.loc[('bar', 'two'),]
   ...: 
   ...:
   ...:     A       B       C
   ...: 0  0.805244  0.813850  1.607920

In [39]: df.loc[('bar', 'two'), 'A']
Out[39]: 0.80524402538637851
```

Note that `df.loc['bar', 'two']` would also work in this example, but this shorthand notation can lead to ambiguity in general.

If you also want to index a specific column with `.loc`, you must use a tuple like this:

```
In [39]: df.loc[('bar', 'two'), 'A']
Out[39]: 0.80524402538637851
```

You don’t have to specify all levels of the `MultiIndex` by passing only the first elements of the tuple. For example, you can use “partial” indexing to get all elements with `bar` in the first level as follows:

```
df.loc['bar']
```

This is a shortcut for the slightly more verbose notation `df.loc[('bar',),]` (equivalent to `df.loc['bar',]` in this example).

“Partial” slicing also works quite nicely.

```
In [40]: df.loc['baz':'foo']
Out[40]:
          A     B     C
first  
baz  one -1.206412  0.132003  1.024180
two  2.565646 -0.827317  0.569605
foo  one  1.431256 -0.076467  0.875906
two  1.340309 -1.187678 -2.211372
```

You can slice with a ‘range’ of values, by providing a slice of tuples.

13.2. Advanced indexing with hierarchical index 751
In [41]: df.loc[('baz', 'two'):('qux', 'one')]
Out[41]:
      A     B     C
first second
baz  two  2.565646 -0.827317  0.569605
foo  one  1.431256 -0.076467  0.875906
two  1.340309 -1.187678 -2.211372
qux  one -1.170299  1.130127  0.974466

In [42]: df.loc[('baz', 'two'):'foo']

In [43]: df.loc[[(('bar', 'two'), ('qux', 'one'))]]
Out[43]:
      A    B    C
first second
bar  two  0.805244  0.813850  1.607920
qux  one -1.170299  1.130127  0.974466

Passing a list of labels or tuples works similar to reindexing:

In [43]: df.loc[[['bar', 'two'], ['qux', 'one']]]
Out[43]:
      A    B    C
first second
bar  two  0.805244  0.813850  1.607920
qux  one -1.170299  1.130127  0.974466

Note: It is important to note that tuples and lists are not treated identically in pandas when it comes to indexing. Whereas a tuple is interpreted as one multi-level key, a list is used to specify several keys. Or in other words, tuples go horizontally (traversing levels), lists go vertically (scanning levels).

Importantly, a list of tuples indexes several complete MultiIndex keys, whereas a tuple of lists refer to several values within a level:

In [44]: s = pd.Series([1, 2, 3, 4, 5, 6],
                  index=pd.MultiIndex.from_product([['A', 'B'], ['c', 'd', 'e']]))

In [45]: s.loc[['A', 'c'], ('B', 'd')]] # list of tuples
Out[45]:
       A  c  1
      B  d  5
dtype: int64

In [46]: s.loc[['A', 'B'], ['c', 'd']]] # tuple of lists
Out[46]:
       A   c   1
      d   2
      B   c   4
      d   5
dtype: int64
13.2.1 Using slicers

You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see Selection by Label, including slices, lists of labels, labels, and boolean indexers.

You can use slice(None) to select all the contents of that level. You do not need to specify all the deeper levels, they will be implied as slice(None).

As usual, both sides of the slicers are included as this is label indexing.

**Warning:** You should specify all axes in the .loc specifier, meaning the indexer for the index and for the columns. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing both axes, rather than into say the MultiIndex for the rows.

You should do this:
```
df.loc[{slice('A1','A3'),......}, :]
```

You should not do this:
```
df.loc[{slice('A1','A3'),......}]
```

In [47]: def mklbl(prefix,n):
    ....:     return ["%s%s" % (prefix,i) for i in range(n)]
    ....:

In [48]: miindex = pd.MultiIndex.from_product([mklbl('A',4),
    ....:     mklbl('B',2),
    ....:     mklbl('C',4),
    ....:     mklbl('D',2)])
    ....:

In [49]: micolumns = pd.MultiIndex.from_tuples([('a','foo'),('a','bar'),
    ....:     ('b','foo'),('b','bah')],
    ....:     names=['lvl0', 'lvl1'])
    ....:

In [50]: 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 [51]: dfmi
Out[51]:
   lvl0  lvl1  a  b  foo  bah  foo
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
  D0  29  28  31  30
  ...   ...   ...   ...
A3  B1  C0  D1 229 228 231 230

(continues on next page)
Basic multi-index slicing using slices, lists, and labels.

```
In [52]: dfmi.loc[(slice('A1','A3'), slice(None), ['C1', 'C3']), :]
Out[52]:
   lvl0 a b
   lvl1 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 `pandas.IndexSlice` to facilitate a more natural syntax using `:`, rather than using `slice(None)`.  

```
In [53]: idx = pd.IndexSlice

In [54]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[54]:
   lvl0  a  b
   lvl1 foo foo
  A0 B0 C1 D0  8 10
  D1  12  14
  C3 D0  24  26
  D1  28  30
  B1 C1 D0  40  42
  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
```

(continues on next page)
It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```python
In [55]: dfmi.loc['A1', (slice(None), 'foo')]
Out[55]:
lvl0  a  b  
lvl1  foo  foo
B0  C0  D0  64  66
   D1   68   70
   C1  D0  72   74
   D1   76   78
   C2  D0  80   82
   D1   84   86
   C3  D0  88   90
   ... ... ...
   B1  C0  D1  100  102
   C1  D0  104  106
   D1  108  110
   C2  D0  112  114
   D1  116  118
   C3  D0  120  122
   D1  124  126
B1  C1  D0  8  10
   D1  12  14
   C3  D0  24  26
   D1  28  30
   C3  D0  24  26
   D1  28  30
   ... ... ...
   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]
```

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

```python
In [56]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]  
Out[56]:
lvl0  a  b  
lvl1  foo  foo
A0  B0  C1  8  10
   D1  12  14
   C3  D0  24  26
   D1  28  30
   C3  D0  56  58
   ... ... ...
   A3  B0  C1  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]
```

In [57]: mask = dfmi[('a', 'foo')] > 200

In [58]: dfmi.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]  
Out[58]:
lvl0  a  b  
lvl1  foo  foo
(continues on next page)
You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [59]: dfmi.loc(axis=0)[:, :, ['C1', 'C3']]
Out[59]:
   a  b
--- ---
  lvl0 9 10
    8 11
A0  13 14
   12 15
D1  19 18
   17 16
C2  23 24
   22 21
C2  27 26
   25 24
C1  31 30
   29 28
D1  36 35
   34 33
B1  41 42
   40 41
D1  47 48
   45 46
C3  57 58
   56 57
D1  65 66
   63 64
C3  75 76
   73 74
D1  83 84
   81 82
...
[32 rows x 4 columns]
```

Furthermore you can set the values using the following methods.

```
In [60]: df2 = dfmi.copy()
In [61]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10
In [62]: df2
Out[62]:
   a  b
--- ---
  lvl0 1 2
    0 1
A0  5 6
   4 5
D1  11 12
   10 11
C1  17 18
   16 17
D1  23 24
   22 23
C2  31 32
   30 31
C2  37 38
   36 37
C1  47 48
   46 47
D1  55 56
   54 55
C3  67 68
   66 67
D1  75 76
   74 75
C3  87 88
   86 87
D1  95 96
   94 95
...
[32 rows x 4 columns]
```
You can use a right-hand-side of an alignable object as well.

```python
In [63]: df2 = dfmi.copy()

In [64]: df2.loc[idx[:, :, ['C1', 'C3']]] = df2 * 1000

In [65]: df2
```

```
Out[65]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>lvl0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lvl1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
</tr>
<tr>
<td>D1</td>
<td>5</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>C1</td>
<td>9000</td>
<td>8000</td>
<td>11000</td>
</tr>
<tr>
<td>D1</td>
<td>13000</td>
<td>12000</td>
<td>15000</td>
</tr>
<tr>
<td>C2</td>
<td>17</td>
<td>16</td>
<td>19</td>
</tr>
<tr>
<td>D1</td>
<td>21</td>
<td>20</td>
<td>23</td>
</tr>
<tr>
<td>C3</td>
<td>25000</td>
<td>24000</td>
<td>27000</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>A3</td>
<td>B1</td>
<td>C0</td>
<td>D1</td>
</tr>
<tr>
<td>D1</td>
<td>229</td>
<td>228</td>
<td>231</td>
</tr>
<tr>
<td>C1</td>
<td>233000</td>
<td>232000</td>
<td>235000</td>
</tr>
<tr>
<td>D1</td>
<td>237000</td>
<td>236000</td>
<td>239000</td>
</tr>
<tr>
<td>C2</td>
<td>241</td>
<td>240</td>
<td>243</td>
</tr>
<tr>
<td>D1</td>
<td>245</td>
<td>244</td>
<td>247</td>
</tr>
<tr>
<td>C3</td>
<td>249000</td>
<td>248000</td>
<td>251000</td>
</tr>
<tr>
<td>D1</td>
<td>253000</td>
<td>252000</td>
<td>255000</td>
</tr>
</tbody>
</table>
```

[64 rows x 4 columns]

### 13.2.2 Cross-section

The `xs` method of `DataFrame` additionally takes a level argument to make selecting data at a particular level of a MultiIndex easier.

```python
In [66]: df

Out[66]:

<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>first</td>
<td>second</td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>one</td>
<td>0.895717 0.410835 -1.413681</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>0.805244 0.813850 1.607920</td>
</tr>
<tr>
<td>baz</td>
<td>one</td>
<td>-1.206412 0.132003 1.024180</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>2.565646 -0.827317 0.569605</td>
</tr>
<tr>
<td>foo</td>
<td>one</td>
<td>1.431256 -0.076467 0.875906</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>1.340309 -1.187678 -2.211372</td>
</tr>
<tr>
<td>qux</td>
<td>one</td>
<td>-1.170299 1.130127 0.974466</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>-0.226169 -1.436737 -2.006747</td>
</tr>
</tbody>
</table>

In [67]: df.xs('one', level='second')

```

```
→

<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>first</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>one</td>
<td>0.895717 0.410835 -1.413681</td>
</tr>
</tbody>
</table>
```

(continues on next page)
# using the slicers

```python
In [68]: df.loc[(slice(None),'one'),:]
Out[68]:
   first second
  bar   one    0.895717   0.410835  -1.413681
  baz   one   -1.206412   0.132003   1.024180
  foo   one    1.431256  -0.076467   0.875906
  qux   one  -1.170299   1.130127   0.974466
```

You can also select on the columns with `xs()`, by providing the axis argument.

```python
In [69]: df = df.T

In [70]: df.xs('one', level='second', axis=1)
Out[70]:
    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
```

`xs()` also allows selection with multiple keys.

```python
In [71]: df.xs(('one', 'bar'), level=('second', 'first'), axis=1)
Out[71]:
   first  bar
   A    0.895717
   B    0.410835
   C  -1.413681
```

You can pass `drop_level=False` to `xs()` to retain the level that was selected.
In [74]: df.xs('one', level='second', axis=1, drop_level=False)
Out[74]:
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

Compare the above with the result using drop_level=True (the default value).

In [75]: df.xs('one', level='second', axis=1, drop_level=True)
Out[75]:
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

13.2.3 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 [76]: midx = pd.MultiIndex(levels=[['zero', 'one'], ['x','y']],
label=[1,1,0,0],[1,0,1,0]])
....:
....:

In [77]: df = pd.DataFrame(np.random.randn(4,2), index=midx)
In [78]: df
Out[78]:
   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 [79]: df2 = df.mean(level=0)
In [80]: df2
Out[80]:
   0    1
one 1.060074 -0.109716
zero 1.271532  0.713416

In [81]: df2.reindex(df.index, level=0)

# aligning
In [82]: df_aligned, df2_aligned = df.align(df2, level=0)
(continues on next page)
13.2.4 Swapping levels with `swaplevel()`

The `swaplevel` function can switch the order of two levels:

```python
In [85]: df[:5]
Out[85]:
    0    1
   ---
one 1.519970 -0.493662
   x  0.600178  0.274230
zero 0.132885 -0.023688
   x  2.410179  1.450520

In [86]: df[:5].swaplevel(0, 1, axis=0)
```

13.2.5 Reordering levels with `reorder_levels()`

The `reorder_levels` function generalizes the `swaplevel` function, allowing you to permute the hierarchical index levels in one step:

```python
In [87]: df[:5].reorder_levels([1, 0], axis=0)
```

---
13.3 Sorting a MultiIndex

For MultiIndex-ed objects to be indexed and sliced effectively, they need to be sorted. As with any index, you can use `sort_index`.

```python
In [88]: import random; random.shuffle(tuples)
In [89]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))
In [90]: s
Out[90]:
baz one 0.206053
qux two -0.251905
foo one -2.213588
baz two 1.063327
bar one 1.266143
foo two 0.299368
qux one -0.863838
bar two 0.408204
dtype: float64
In [91]: s.sort_index()
In [92]: s.sort_index(level=0)
In [93]: s.sort_index(level=1)
```

(continues on next page)
You may also pass a level name to `sort_index` if the MultiIndex levels are named.

```
In [94]: s.index.set_names(['L1', 'L2'], inplace=True)

In [95]: s.sort_index(level='L1')
Out[95]:
     L1 L2
bar one 1.266143
   two 0.408204
baz one 0.206053
   two 1.063327
foo one -2.213588
   two 0.299368
qux one -0.863838
   two -0.251905
dtype: float64

In [96]: s.sort_index(level='L2')

In [97]: df.T.sort_index(level=1, axis=1)
Out[97]:
      one zero  one zero
        x     x    y     y
   0  0.600178 2.410179 1.519970 0.132885
   1  0.274230 1.450520 -0.493662 -0.023688

Indexing will work even if the data are not sorted, but will be rather inefficient (and show a `PerformanceWarning`). It will also return a copy of the data rather than a view:

```
In [98]: dfm = pd.DataFrame({'jim': [0, 0, 1, 1],
                      'joe': ['x', 'x', 'z', 'y'],
                      'jolie': np.random.rand(4)})

In [99]: dfm = dfm.set_index(['jim', 'joe'])

In [100]: dfm
Out[100]:
    jolie
   ..
   ...
   ...
   ...
   ..
   ...
   ...

(continues on next page)
Furthermore if you try to index something that is not fully lexsorted, this can raise:

```python
In [5]: dfm.loc[(0,'y'):(1, 'z')]
UnsortedIndexError: 'Key length (2) was greater than MultiIndex lexsort depth (1)'
```

The `is_lexsorted()` method on an `Index` show if the index is sorted, and the `lexsort_depth` property returns the sort depth:

```python
In [101]: dfm.index.is_lexsorted()
Out[101]: False

In [102]: dfm.index.lexsort_depth
Out[102]: 1
```

```python
In [103]: dfm = dfm.sort_index()

In [104]: dfm
Out[104]:
    x  0.490671 0.120248
  0  x  0.120248
  1  x  0.110968 0.537020
  y  0.110968
```

```python
In [105]: dfm.index.is_lexsorted()
Out[105]: True

In [106]: dfm.index.lexsort_depth
Out[106]: 2
```

And now selection works as expected.

```python
In [107]: dfm.loc[(0,'y'):(1, 'z')]
```

```python
jolie
  jim joe
  0 x  0.490671 0.120248
  1 x  0.110968 0.537020
```

And now selection works as expected.
13.4 Take Methods

Similar to NumPy ndarrays, pandas Index, Series, and DataFrame also provides the `take` method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [108]: index = pd.Index(np.random.randint(0, 1000, 10))
In [109]: index
Out[109]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64')
In [110]: positions = [0, 9, 3]
In [111]: index[positions]
Out[111]: Int64Index([214, 329, 567], dtype='int64')
In [112]: index.take(positions)
Out[112]: Int64Index([214, 329, 567], dtype='int64')
In [113]: ser = pd.Series(np.random.randn(10))
In [114]: ser.iloc[positions]
Out[114]:
0 -0.179666
9  1.824375
3  0.392149
dtype: float64
In [115]: ser.take(positions)
Out[115]:
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 [116]: frm = pd.DataFrame(np.random.randn(5, 3))
In [117]: frm.take([1, 4, 3])
Out[117]:
   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 [118]: frm.take([0, 2], axis=1)
Out[118]:
     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.

```python
In [119]: arr = np.random.randn(10)
In [120]: arr.take([False, False, True, True])
Out[120]: array([-1.1935, -1.1935, 0.6775, 0.6775])

In [121]: arr[[0, 1]]
Out[121]: array([-1.1935, 0.6775])

In [122]: ser = pd.Series(np.random.randn(10))
In [123]: ser.take([False, False, True, True])
Out[123]:
0   0.233141
0   0.233141
1  -0.223540
1  -0.223540
dtype: float64

In [124]: ser.iloc[[0, 1]]
Out[124]:
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.

## 13.5 Index Types

We have discussed `MultiIndex` in the previous sections pretty extensively. `DatetimeIndex` and `PeriodIndex` are shown [here](#), and information about `TimedeltaIndex` is found [here](#).

In the following sub-sections we will highlight some other index types.

### 13.5.1 CategoricalIndex

`CategoricalIndex` is a type of index that is useful for supporting indexing with duplicates. This is a container around a `Categorical` and allows efficient indexing and storage of an index with a large number of duplicated elements.

```python
In [125]: from pandas.api.types import CategoricalDtype
In [126]: df = pd.DataFrame({'A': np.arange(6),
                         'B': list('aabbca')})
In [127]: df['B'] = df['B'].astype(CategoricalDtype(list('cab')))
In [128]: df
```

(continues on next page)
Setting the index will create a CategoricalIndex.

Indexing with __getitem__/ .iloc/.loc works similarly to an Index with duplicates. The indexers must be in the category or the operation will raise a KeyError.

The CategoricalIndex is preserved after indexing:

Sorting the index will sort by the order of the categories (recall that we created the index with CategoricalDtype(list('cab')), so the sorted order is cab).
Groupby operations on the index will preserve the index nature as well.

```python
In [136]: df2.groupby(level=0).sum()
Out[136]:
   A  B
a  6  5
b  4  3
c  2  1

In [137]: df2.groupby(level=0).sum().index
Out[137]: CategoricalIndex([u'c', u'a', u'b'], ordered=False, name='B', dtype='category')
```

Reindexing operations will return a resulting index based on the type of the passed indexer. Passing a list will return a plain-old Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the passed Categorical dtype. This allows one to arbitrarily index these even with values not in the categories, similarly to how you can reindex any pandas index.

```python
In [138]: df2.reindex([u'a','e'])
Out[138]:
   A  B
a  0.0  0.0
a  1.0  1.0
a  5.0  5.0
e  NaN  NaN

In [139]: df2.reindex([u'a','e']).index
Out[139]: Index([u'a', u'a', u'a', u'e'], dtype='object', name='B')

In [140]: df2.reindex(pd.Categorical([u'a','e'],categories=list('abcde')))
Out[140]:
   A  B
a  0.0  0.0
a  1.0  1.0
a  5.0  5.0
e  NaN  NaN

In [141]: df2.reindex(pd.Categorical([u'a','e'],categories=list('abcde'))).index
Out[141]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'b', u'c', u'd', u'e'], ordered=False, name='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('aabbca')).astype('category')})

In [11]: df3 = df3.set_index('B')

In [11]: df3.index
Out[11]: CategoricalIndex([u'u'a', u'u'a', u'u'b', u'u'b', u'u'c', u'u'a'], categories=[u'u'a', u'
   'u'b', u'u'c'], ordered=False, name=u'B', dtype='category')

In [12]: pd.concat([df2, df3])
```

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13.5.2 Int64Index and RangeIndex

**Warning:** Indexing on an integer-based Index with floats has been clarified in 0.18.0, for a summary of the changes, see [here](#).

Int64Index is a fundamental basic index in pandas. This is an Immutable array implementing an ordered, sliceable set. Prior to 0.18.0, the Int64Index would provide the default index for all NDFrame objects.

RangeIndex is a sub-class of Int64Index added in version 0.18.0, now providing the default index for all NDFrame objects. RangeIndex is an optimized version of Int64Index that can represent a monotonic ordered set. These are analogous to Python range types.

13.5.3 Float64Index

By default a Float64Index will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes [],ix,loc for scalar indexing and slicing work exactly the same.

```python
In [122]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])
In [123]: indexf
Out[123]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')
In [124]: sf = pd.Series(range(5), index=indexf)
In [125]: sf
Out[125]:
1.5 0
2.0 1
3.0 2
4.5 3
5.0 4
dtype: int64
```

Scalar selection for [],.loc will always be label based. An integer will match an equal float index (e.g. 3 is equivalent to 3.0).

```python
In [126]: sf[3]
Out[126]: 2
In [127]: sf[3.0]
Out[127]: 2
In [128]: sf.loc[3]
Out[128]: 2
In [129]: sf.loc[3.0]
Out[129]: 2
```

The only positional indexing is via iloc.
A scalar index that is not found will raise a KeyError. Slicing is primarily on the values of the index when using [], ix, loc, and always positional when using iloc. The exception is when the slice is boolean, in which case it will always be positional.

Float indexes, slicing using floats is allowed.

In non-float indexes, slicing using floats will raise a TypeError.

**Warning:** Using a scalar float indexer for .iloc has been removed in 0.18.0, so the following will raise a TypeError:
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.

```python
In [156]: dfir = pd.concat([pd.DataFrame(np.random.randn(5,2),
                   index=np.arange(5) * 250.0,
                   columns=list('AB')),
                   pd.DataFrame(np.random.randn(6,2),
                   index=np.arange(4,10) * 250.1,
                   columns=list('AB'))])

In [157]: dfir
Out[157]:
    A   B
0.0 0.99729 -1.69332
250.0 -0.17913 -1.59806
500.0 0.93691 0.91256
750.0 -1.00340 1.63278
1000.0 -0.72463 0.17822
1000.4 0.31061 -0.10800
1250.5 -0.97423 -1.14771
1500.6 -2.28137 0.76001
1750.7 -0.74253 1.53332
2000.8 2.49536 -0.43277
2250.9 -0.06895 0.04352
```

Selection operations then will always work on a value basis, for all selection operators.

```python
In [158]: dfir[0:1000.4]
Out[158]:
    A   B
0.0 0.99729 -1.69332
250.0 -0.17913 -1.59806
500.0 0.93691 0.91256
750.0 -1.00340 1.63278
1000.0 -0.72463 0.17822
1000.4 0.31061 -0.10800
```

```python
In [159]: dfir.loc[0:1000,'A']
\n    A
0.0  0.99729
250.0 -0.17913
500.0  0.93691
750.0 -1.00340
1000.0 -0.72463
1000.4  0.31061
Name: A, dtype: float64
```

```python
In [160]: dfir.loc[1000.4]
\nA 0.31061
B -0.10800
Name: 1000.4, dtype: float64
```

You could retrieve the first 1 second (1000 ms) of data as such:
If you need integer based selection, you should use `iloc`:

```
In [162]: dfir.iloc[0:5]
Out[162]:
     A     B
0 0.00  0.997289 -1.693316
250.00 -0.179129 -1.598062
500.00  0.936914  0.912560
750.00 -1.003401  1.632781
1000.00 -0.724626  0.178219
```

### 13.5.4 IntervalIndex

New in version 0.20.0.

`IntervalIndex` together with its own `dtype`, `interval` as well as the `Interval` scalar type, allow first-class support in pandas for interval notation.

The `IntervalIndex` allows some unique indexing and is also used as a return type for the categories in `cut()` and `qcut()`.

**Warning:** These indexing behaviors are provisional and may change in a future version of pandas.

An `IntervalIndex` can be used in `Series` and in `DataFrame` as the index.

```
In [163]: df = pd.DataFrame({'A': [1, 2, 3, 4]},
                   index=pd.IntervalIndex.from_breaks([0, 1, 2, 3, 4]))

In [164]: df.loc[2]
Out[164]:
     A
0 1
1 2
2 3
3 4
```

Label based indexing via `.loc` along the edges of an interval works as you would expect, selecting that particular interval.

```
In [165]: df.loc[2]
Out[165]:
     A
0 2
Name: (1, 2], dtype: int64
```

(continues on next page)
If you select a label contained within an interval, this will also select the interval.

Interval and IntervalIndex are used by cut and qcut:

Furthermore, IntervalIndex allows one to bin other data with these same bins, with NaN representing a missing value similar to other dtypes.

13.5.4.1 Generating Ranges of Intervals

If we need intervals on a regular frequency, we can use the interval_range() function to create an IntervalIndex using various combinations of start, end, and periods. The default frequency for interval_range is a 1 for numeric intervals, and calendar day for datetime-like intervals:
In [174]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4)

IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03], (2017-01-03, 2017-01-04], (2017-01-04, 2017-01-05]
closed='right',
dtype='interval[datetime64[ns]]')

In [175]: pd.interval_range(end=pd.Timedelta('3 days'), periods=3)

IntervalIndex([(0 days 00:00:00, 1 days 00:00:00], (1 days 00:00:00, 2 days 00:00:00],
(2 days 00:00:00, 3 days 00:00:00]
closed='right',
dtype='interval[timedelta64[ns]]')

The freq parameter can be used to specify non-default frequencies, and can utilize a variety of frequency aliases with datetime-like intervals:

In [176]: pd.interval_range(start=0, periods=5, freq=1.5)

IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0], (6.0, 7.5]
closed='right',
dtype='interval[float64]')

In [177]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4, freq='W')

closed='right',
dtype='interval[datetime64[ns]]')

In [178]: pd.interval_range(start=pd.Timedelta('0 days'), periods=3, freq='9H')

IntervalIndex([(0 days 00:00:00, 0 days 09:00:00], (0 days 09:00:00, 0 days 18:00:00],
(0 days 18:00:00, 1 days 03:00:00]
closed='right',
dtype='interval[timedelta64[ns]]')

Additionally, the closed parameter can be used to specify which side(s) the intervals are closed on. Intervals are closed on the right side by default.

In [179]: pd.interval_range(start=0, end=4, closed='both')

IntervalIndex([(0, 1], [1, 2], [2, 3], [3, 4]
closed='both',
dtype='interval[int64]')

In [180]: pd.interval_range(start=0, end=4, closed='neither')

IntervalIndex([(0, 1), (1, 2), (2, 3), (3, 4]
closed='neither',
dtype='interval[int64]')
New in version 0.23.0.

Specifying start, end, and periods will generate a range of evenly spaced intervals from start to end inclusively, with periods number of elements in the resulting IntervalIndex:

```python
In [181]: pd.interval_range(start=0, end=6, periods=4)
Out[181]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]
    closed='right',
    dtype='interval[float64]')

In [182]: pd.interval_range(pd.Timestamp('2018-01-01'), pd.Timestamp('2018-02-28'),
   periods=3)
   IntervalIndex([(2018-01-01, 2018-01-20 08:00:00], (2018-01-20 08:00:00, 2018-02-08
   16:00:00], (2018-02-08 16:00:00, 2018-02-28]
    closed='right',
    dtype='interval[datetime64[ns]]')
```

13.6 Miscellaneous indexing FAQ

13.6.1 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 .loc. The following code will generate exceptions:

```python
s = pd.Series(range(5))
s[-1]
df = pd.DataFrame(np.random.randn(5, 4))
df
df.loc[-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).

13.6.2 Non-monotonic indexes require exact matches

If the index of a Series or DataFrame is monotonically increasing or decreasing, then the bounds of a label-based slice can be outside the range of the index, much like slice indexing a normal Python list. Monotonicity of an index can be tested with the is_monotonic_increasing and is_monotonic_decreasing attributes.

```python
In [183]: df = pd.DataFrame(index=[2,3,3,4,5], columns=['data'], data=list(range(5)))
In [184]: df.index.is_monotonic_increasing
Out[184]: True

# no rows 0 or 1, but still returns rows 2, 3 (both of them), and 4:
In [185]: df.loc[0:4, :]
```

(continues on next page)
On the other hand, if the index is not monotonic, then both slice bounds must be *unique* members of the index.

```python
In [187]: df = pd.DataFrame(index=[2, 3, 1, 4, 3, 5], columns=['data'],
       ...: data=list(range(6)))

In [188]: df.index.is_monotonic_increasing
Out[188]: False

# OK because 2 and 4 are in the index
In [189]: df.loc[2:4, :]
Out[189]:
   data
2  0
3  1
1  2
4  3

# 0 is not in the index
In [9]: df.loc[0:4, :]
KeyError: 0

# 3 is not a unique label
In [11]: df.loc[2:3, :]
KeyError: 'Cannot get right slice bound for non-unique label: 3'
```

`Index.is_monotonic_increasing()` and `Index.is_monotonic_decreasing()` only check that an index is weakly monotonic. To check for strict montonicity, you can combine one of those with `Index.is_unique()`.

```python
In [190]: weakly_monotonic = pd.Index(['a', 'b', 'c', 'c'])

In [191]: weakly_monotonic.is_monotonic_increasing
Out[191]: Index(['a', 'b', 'c', 'c'], dtype='object')

In [192]: weakly_monotonic.is_monotonic_increasing
Out[192]: True

In [193]: weakly_monotonic.is_monotonic_increasing & weakly_monotonic.is_unique
Out[193]: False
```
13.6.3 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 [194]: s = pd.Series(np.random.randn(6), index=list('abcdef'))
```

```
In [195]: s
Out[195]:
a  0.112246
b  0.871721
c  0.816064
d -0.784880
e  1.030659
f  0.187483
dtype: float64
```

Suppose we wished to slice from c to e, using integers this would be accomplished as such:

```
In [196]: s[2:5]
Out[196]:
c  0.816064
d -0.784880
e  1.030659
dtype: float64
```

However, if you only had c and e, determining the next element in the index can be somewhat complicated. For example, the following does not work:

```
s.loc['c':'e'+1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design to make label-based slicing include both endpoints:

```
In [197]: s.loc['c':'e']
Out[197]:
c  0.816064
d -0.784880
e  1.030659
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.

13.6.4 Indexing potentially changes underlying Series dtype

The different indexing operation can potentially change the dtype of a Series.

```
In [198]: series1 = pd.Series([1, 2, 3])
In [199]: series1.dtype
Out[199]: dtype('int64')
In [200]: res = series1.reindex([0, 4])
```

(continues on next page)
In [201]: res.dtype
Out[201]: dtype('float64')

In [202]: res
Out[202]:
\n0   1.0
4   NaN
\ndtype: float64

In [203]: series2 = pd.Series([True])

In [204]: series2.dtype
Out[204]: dtype('bool')

In [205]: res = series2.reindex_like(series1)

In [206]: res.dtype
Out[206]: dtype('O')

In [207]: res
Out[207]:
0   True
1   NaN
2   NaN
\ndtype: object

This is because the (re)indexing operations above silently inserts NaNs and the dtype changes accordingly. This can cause some issues when using numpy ufuncs such as numpy.logical_and.

See the this old issue for a more detailed discussion.
14.1 Statistical Functions

14.1.1 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 -0.218320 -1.054001 1.987147 -0.510183
4 -0.439121 -1.816454 0.649715 -4.822809
5 -0.127833 -3.042065 -5.866604 -1.776977
6 -2.596833 -1.959538 -2.111697 -3.798900
7 -0.117826 -2.169058 0.036094 -0.067696
8  2.492606 -1.357320 -1.205802 -1.558697
9 -1.012977  2.324558 -1.003744 -0.371806
```

14.1.2 Covariance

`Series.cov()` can be used to compute covariance between series (excluding missing values).
Analogously, `DataFrame.cov()` to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

Note: Assuming the missing data are missing at random this results in an estimate for the covariance matrix which is unbiased. However, for many applications this estimate may not be acceptable because the estimated covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimated correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

DataFrame.cov also supports an optional `min_periods` keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.
14.1.3 Correlation

Correlation may be computed using the `corr()` method. Using the `method` parameter, several methods for computing correlations are provided:

<table>
<thead>
<tr>
<th>Method name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pearson</td>
<td>Standard correlation coefficient</td>
</tr>
<tr>
<td>kendall</td>
<td>Kendall Tau correlation coefficient</td>
</tr>
<tr>
<td>spearman</td>
<td>Spearman rank correlation coefficient</td>
</tr>
</tbody>
</table>

All of these are currently computed using pairwise complete observations. Wikipedia has articles covering the above correlation coefficients:

- Pearson correlation coefficient
- Kendall rank correlation coefficient
- Spearman’s rank correlation coefficient

**Note:** Please see the caveats associated with this method of calculating correlation matrices in the covariance section.

```
In [15]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
In [16]: frame.iloc[::2] = np.nan
# Series with Series
In [17]: frame['a'].corr(frame['b'])
Out[17]: 0.013479040400098794
In [18]: frame['a'].corr(frame['b'], method='spearman')
Out[18]: -0.0072898851595406371
```

# Pairwise correlation of DataFrame columns
```
In [19]: frame.corr()
```

```
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.loc[frame.index[:5], 'a'] = np.nan
In [22]: frame.loc[frame.index[5:10], 'b'] = np.nan
In [23]: frame.corr()
```

(continues on next page)
A related method `corrwith()` is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

```python
In [25]: index = ['a', 'b', 'c', 'd', 'e']
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
a -0.125501  NaN  0.344056  0.004183
d  0.458296  0.493244  0.344056  0.004183
d  0.344056  0.493244  0.344056  0.004183
d  0.004183  0.344056  0.004183  0.004183
```

14.1.4 Data ranking

The `rank()` method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```python
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    1.5
```

(continues on next page)
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  0.369552 -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   NaN   0.463347
6  0.376892  0.959292  0.095572  0.593740   NaN   0.069180
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
```

```
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

14.2 Window Functions

For working with data, a number of window functions are provided for computing common window or rolling statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and
kurtosis.

The `rolling()` and `expanding()` functions can be used directly from `DataFrameGroupBy` objects, see the `groupby docs`.

**Note:** The API for window statistics is quite similar to the way one works with `GroupBy` objects, see the documentation `here`.

We work with `rolling`, `expanding` and exponentially weighted data through the corresponding objects, `Rolling`, `Expanding` and `EWM`.

```python
In [38]: s = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
In [39]: s = s.cumsum()
In [40]: s
Out[40]:
2000-01-01   -0.268824
2000-01-02   -1.771855
2000-01-03   -0.818003
2000-01-04   -0.659244
2000-01-05   -1.942133
2000-01-06   -1.869391
2000-01-07    0.563674
   ... 
2002-09-20  -68.233054
2002-09-21  -66.765687
2002-09-22  -67.457323
2002-09-23  -69.253182
2002-09-24  -70.296818
2002-09-25  -70.844674
2002-09-26  -72.475016
Freq: D, Length: 1000, dtype: float64
```

These are created from methods on `Series` and `DataFrame`.

```python
In [41]: r = s.rolling(window=60)
```

```python
In [42]: r
Out[42]: Rolling [window=60, center=False, axis=0]
```

These object provide tab-completion of the available methods and properties.

```python
In [14]: r.
   r.agg r.apply r.count r.exclusions r.max r.median r.
   r.name r.skew r.sum   r.
   r.aggregate r.corr r.cov r.kurt r.mean r.min r.
   r.quantile r.std r.var
```

Generally these methods all have the same interface. They all accept the following arguments:

- `window`: size of moving window
- `min_periods`: threshold of non-null data points to require (otherwise result is NA)
- `center`: boolean, whether to set the labels at the center (default is False)

We can then call methods on these `rolling` objects. These return like-indexed objects:
In [43]: `r.mean()`
Out[43]:
    2000-01-01   NaN
    2000-01-02   NaN
    2000-01-03   NaN
    2000-01-04   NaN
    2000-01-05   NaN
    2000-01-06   NaN
    2000-01-07   NaN
    ...  
    2002-09-20 -62.694135
    2002-09-21 -62.812190
    2002-09-22 -62.914971
    2002-09-23 -63.061867
    2002-09-24 -63.213876
    2002-09-25 -63.375074
    2002-09-26 -63.539734
Freq: D, Length: 1000, dtype: float64

In [44]: `s.plot(style='k--')`
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1a27e8e208>

In [45]: `r.mean().plot(style='k')`

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1a27e8e208>
They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window operator to all of the DataFrame’s columns:

```python
In [46]: df = pd.DataFrame(np.random.randn(1000, 4),
                 index=pd.date_range('1/1/2000', periods=1000),
                 columns=['A', 'B', 'C', 'D'])

In [47]: df = df.cumsum()

In [48]: df.rolling(window=60).sum().plot(subplots=True)
```

14.2.1 Method Summary

We provide a number of common statistical functions:
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count()</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>sum()</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean()</td>
<td>Mean of values</td>
</tr>
<tr>
<td>median()</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min()</td>
<td>Minimum</td>
</tr>
<tr>
<td>max()</td>
<td>Maximum</td>
</tr>
<tr>
<td>std()</td>
<td>Bessel-corrected sample standard deviation</td>
</tr>
<tr>
<td>var()</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>skew()</td>
<td>Sample skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt()</td>
<td>Sample kurtosis (4th moment)</td>
</tr>
<tr>
<td>quantile()</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>apply()</td>
<td>Generic apply</td>
</tr>
<tr>
<td>cov()</td>
<td>Unbiased covariance (binary)</td>
</tr>
<tr>
<td>corr()</td>
<td>Correlation (binary)</td>
</tr>
</tbody>
</table>

The `apply()` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an ndarray input. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```python
In [49]: mad = lambda x: np.fabs(x - x.mean()).mean()
In [50]: s.rolling(window=60).apply(mad, raw=True).plot(style='k')
Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x1a284ef898>```
14.2.2 Rolling Windows

Passing win_type to .rolling generates a generic rolling window computation, that is weighted according the win_type. The following methods are available:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum()</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean()</td>
<td>Mean of values</td>
</tr>
</tbody>
</table>

The weights used in the window are specified by the win_type keyword. The list of recognized types are the scipy.signal window functions:

- boxcar
- triang
- blackman
- hamming
- bartlett
- parzen
- bohman
- blackmanharris
- nuttall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general_gaussian (needs power, width)
- slepian (needs width).

In [51]: ser = pd.Series(np.random.randn(10), index=pd.date_range('1/1/2000', periods=10))

In [52]: ser.rolling(window=5, win_type='triang').mean()
Out[52]:
2000-01-01     NaN
2000-01-02     NaN
2000-01-03     NaN
2000-01-04     NaN
2000-01-05  -1.037870
2000-01-06  -0.767705
2000-01-07  -0.383197
2000-01-08  -0.395513
2000-01-09  -0.558440
2000-01-10  -0.672416
Freq: D, dtype: float64

Note that the boxcar window is equivalent to mean().

In [53]: ser.rolling(window=5, win_type='boxcar').mean()
Out[53]:
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 [54]: ser.rolling(window=5).mean()

14.2. Window Functions
For some windowing functions, additional parameters must be specified:

```
In [55]: ser.rolling(window=5, win_type='gaussian').mean(std=0.1)
Out[55]:
2000-01-01 NaN
2000-01-02 NaN
2000-01-03 NaN
2000-01-04 NaN
2000-01-05 -1.309989
2000-01-06 -1.153000
2000-01-07 0.606382
2000-01-08 -0.681101
2000-01-09 -0.289724
2000-01-10 -0.996632
Freq: D, dtype: float64
```

**Note:** For `.sum()` with a `win_type`, there is no normalization done to the weights for the window. Passing custom weights of `[1, 1, 1]` will yield a different result than passing weights of `[2, 2, 2]`, for example. When passing a `win_type` instead of explicitly specifying the weights, the weights are already normalized so that the largest weight is 1.

In contrast, the nature of the `.mean()` calculation is such that the weights are normalized with respect to each other. Weights of `[1, 1, 1]` and `[2, 2, 2]` yield the same result.

### 14.2.3 Time-aware Rolling

New in version 0.19.0.

New in version 0.19.0 are the ability to pass an offset (or convertible) to a `.rolling()` method and have it produce variable sized windows based on the passed time window. For each time point, this includes all preceding values occurring within the indicated time delta.

This can be particularly useful for a non-regular time frequency index.

```
In [56]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                       index=pd.date_range('20130101 09:00:00', periods=5, freq='s'))

In [57]: dft
Out[57]:
     B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  2.0
2013-01-01 09:00:03  NaN
2013-01-01 09:00:04  4.0
```

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

```
In [58]: dft.rolling(2).sum()
Out[58]:
          B
2013-01-01 09:00:00  NaN
2013-01-01 09:00:01  1.0
(continues on next page)
```
Specifying an offset allows a more intuitive specification of the rolling frequency.

```python
In [60]: dft.rolling('2s').sum()
Out[60]:
   B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0
```

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

```python
In [61]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                       index = pd.Index([pd.Timestamp('20130101 09:00:00'),
                                         pd.Timestamp('20130101 09:00:02'),
                                         pd.Timestamp('20130101 09:00:03'),
                                         pd.Timestamp('20130101 09:00:05'),
                                         pd.Timestamp('20130101 09:00:06')],
                                         name='foo'))
In [62]: dft
Out[62]:
   B
foo
2013-01-01 09:00:00    0.0
2013-01-01 09:00:02    1.0
2013-01-01 09:00:03    2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06    4.0
In [63]: dft.rolling(2).sum()
```

## 14.2. Window Functions
Using the time-specification generates variable windows for this sparse data.

```python
In [64]: dft.rolling('2s').sum()
Out[64]:
    B
foo
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```python
In [65]: dft = dft.reset_index()
In [66]: dft
Out[66]:
   foo    B
0  0  2013-01-01 09:00:00  0.0
1  1  2013-01-01 09:00:02  1.0
2  2  2013-01-01 09:00:03  2.0
3  3  2013-01-01 09:00:05  NaN
4  4  2013-01-01 09:00:06  4.0
```

```python
In [67]: dft.rolling('2s', on='foo').sum()
```

### 14.2.4 Rolling Window Endpoints

New in version 0.20.0.

The inclusion of the interval endpoints in rolling window calculations can be specified with the `closed` parameter:

<table>
<thead>
<tr>
<th>closed</th>
<th>Description</th>
<th>Default for</th>
</tr>
</thead>
<tbody>
<tr>
<td>right</td>
<td>close right endpoint</td>
<td>time-based windows</td>
</tr>
<tr>
<td>left</td>
<td>close left endpoint</td>
<td></td>
</tr>
<tr>
<td>both</td>
<td>close both endpoints</td>
<td>fixed windows</td>
</tr>
<tr>
<td>neither</td>
<td>open endpoints</td>
<td></td>
</tr>
</tbody>
</table>

For example, having the right endpoint open is useful in many problems that require that there is no contamination from present information back to past information. This allows the rolling window to compute statistics “up to that point in time”, but not including that point in time.

```python
In [68]: df = pd.DataFrame({'x': 1},
                      index=[pd.Timestamp('20130101 09:00:01'),
                             pd.Timestamp('20130101 09:00:02')},
                      columns=['x'])
```

(continues on next page)
In [69]: df["right"] = df.rolling('2s', closed='right').x.sum()  # default
In [70]: df["both"] = df.rolling('2s', closed='both').x.sum()
In [71]: df["left"] = df.rolling('2s', closed='left').x.sum()
In [72]: df["neither"] = df.rolling('2s', closed='neither').x.sum()

In [73]: df
Out[73]:
          x  right  both  left  neither
2013-01-01 09:00:01 1  1.0  1.0    NaN     NaN
2013-01-01 09:00:02 1  2.0  2.0  1.0    1.0
2013-01-01 09:00:03 1  2.0  3.0  2.0  1.0
2013-01-01 09:00:04 1  2.0  3.0  2.0  1.0
2013-01-01 09:00:06 1  1.0  2.0  1.0     NaN

Currently, this feature is only implemented for time-based windows. For fixed windows, the closed parameter cannot be set and the rolling window will always have both endpoints closed.

### 14.2.5 Time-aware Rolling vs. Resampling

Using `.rolling()` with a time-based index is quite similar to `resampling`. They both operate and perform reductive operations on time-indexed pandas objects.

When using `.rolling()` with an offset. The offset is a time-delta. Take a backwards-in-time looking window, and aggregate all of the values in that window (including the end-point, but not the start-point). This is the new value at that point in the result. These are variable sized windows in time-space for each point of the input. You will get a same sized result as the input.

When using `.resample()` with an offset. Construct a new index that is the frequency of the offset. For each frequency bin, aggregate points from the input within a backwards-in-time looking window that fall in that bin. The result of this aggregation is the output for that frequency point. The windows are fixed size in the frequency space. Your result will have the shape of a regular frequency between the min and the max of the original input object.

To summarize, `.rolling()` is a time-based window operation, while `.resample()` is a frequency-based window operation.

### 14.2.6 Centering Windows

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center.

In [74]: ser.rolling(window=5).mean()
Out[74]:
2000-01-01     NaN
2000-01-02     NaN
2000-01-03     NaN
2000-01-04     NaN

(continues on next page)
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 [75]: ser.rolling(window=5, center=True).mean()

Out[75]:
   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
Freq: D, dtype: float64

14.2.7 Binary Window Functions

cov() and 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 MultiIndexed DataFrame whose index are the dates in question (see the next section).

For example:

In [76]: df = pd.DataFrame(np.random.randn(1000, 4),
  ....:                   index=pd.date_range('1/1/2000', periods=1000),
  ....:                   columns=['A', 'B', 'C', 'D'])
  ....:

In [77]: df = df.cumsum()

In [78]: df2 = df[:20]

In [79]: df2.rolling(window=5).corr(df2['B'])

Out[79]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>B</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>C</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>D</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>
14.2.8 Computing rolling pairwise covariances and correlations

**Warning:** Prior to version 0.20.0 if `pairwise=True` was passed, a Panel would be returned. This will now return a 2-level MultiIndexed DataFrame, see the whatsnew [here](#).

In financial data analysis and other fields it's common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of DataFrame inputs will yield a MultiIndexed DataFrame whose index are the dates in question. In the case of a single DataFrame argument the `pairwise` argument can even be omitted:

**Note:** Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the covariance section for caveats associated with this method of calculating covariance and correlation matrices.

```
In [80]: covs = df[['B','C','D']].rolling(window=50).cov(df[['A','B','C']],                  -> pairwise=True)

In [81]: covs.loc['2002-09-22':]
Out[81]:
```

```
   B   C   D
2002-09-22 A 1.367467 8.676734 -8.047366
   B  3.067315 0.865946 -1.052533
   C  0.865946 7.739761 -4.943924
2002-09-23 A 0.910343 8.669065 -8.443062
   B  2.625456 0.565152 -0.907654
   C  0.565152 7.825521 -5.367526
2002-09-24 A 0.463332 8.514509 -8.776514
   B  2.306695 0.267746 -0.732186
   C  0.267746 7.771425 -5.696962
2002-09-25 A 0.467976 8.198236 -9.162599
   B  2.307129 0.267287 -0.754080
   C  0.267287 7.466559 -5.822650
2002-09-26 A 0.545781 7.899084 -9.326238
   B  2.311058 0.322295 -0.844451
   C  0.322295 7.038237 -5.684445
```
In [82]: correls = df.rolling(window=50).corr()

In [83]: correls.loc['2002-09-22':]

Out[83]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002-09-22</td>
<td>1.000000</td>
<td>0.186397</td>
<td>0.744551</td>
<td>-0.769767</td>
</tr>
<tr>
<td></td>
<td>0.186397</td>
<td>1.000000</td>
<td>0.177725</td>
<td>-0.240802</td>
</tr>
<tr>
<td></td>
<td>0.744551</td>
<td>0.177725</td>
<td>1.000000</td>
<td>-0.712051</td>
</tr>
<tr>
<td></td>
<td>-0.769767</td>
<td>-0.240802</td>
<td>-0.712051</td>
<td>1.000000</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>1.000000</td>
<td>0.134723</td>
<td>0.743113</td>
<td>-0.758758</td>
</tr>
<tr>
<td></td>
<td>0.134723</td>
<td>1.000000</td>
<td>0.124683</td>
<td>-0.209934</td>
</tr>
<tr>
<td></td>
<td>0.743113</td>
<td>0.124683</td>
<td>1.000000</td>
<td>-0.719088</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>0.075157</td>
<td>1.000000</td>
<td>0.064399</td>
<td>-0.164179</td>
</tr>
<tr>
<td></td>
<td>0.731888</td>
<td>0.064399</td>
<td>1.000000</td>
<td>-0.704686</td>
</tr>
<tr>
<td></td>
<td>-0.739160</td>
<td>-0.164179</td>
<td>-0.704686</td>
<td>1.000000</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>1.000000</td>
<td>0.087756</td>
<td>0.727792</td>
<td>-0.736562</td>
</tr>
<tr>
<td></td>
<td>0.087756</td>
<td>1.000000</td>
<td>0.079913</td>
<td>-0.179477</td>
</tr>
<tr>
<td></td>
<td>0.727792</td>
<td>0.079913</td>
<td>1.000000</td>
<td>-0.692303</td>
</tr>
<tr>
<td></td>
<td>-0.736562</td>
<td>-0.179477</td>
<td>-0.692303</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

[20 rows x 4 columns]

You can efficiently retrieve the time series of correlations between two columns by reshaping and indexing:

In [84]: correls.unstack(1)[('A', 'C')].plot()

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1c28c4a710>
14.3 Aggregation

Once the Rolling, Expanding or EWM objects have been created, several methods are available to perform multiple computations on the data. These operations are similar to the aggregating API, groupby API, and resample API.

```
In [85]: dfa = pd.DataFrame(np.random.randn(1000, 3),
                   index=pd.date_range('1/1/2000', periods=1000),
                   columns=['A', 'B', 'C'])

In [86]: r = dfa.rolling(window=60,min_periods=1)

In [87]: r
Out[87]: Rolling [window=60,min_periods=1,center=False,axis=0]
```

We can aggregate by passing a function to the entire DataFrame, or select a Series (or multiple Series) via standard `__getitem__`.

```
In [88]: r.aggregate(np.sum)
Out[88]:
          A           B           C
2000-01-01 -0.289838 -0.370545 -1.284206
2000-01-02 -0.216612 -1.675528 -1.169415
```

(continues on next page)
In [89]: r['A'].aggregate(np.sum)

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-03</td>
<td>1.154661</td>
<td>-1.634017</td>
<td>-1.566620</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>2.969393</td>
<td>-4.003274</td>
<td>-1.816179</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>4.690630</td>
<td>-4.682017</td>
<td>-2.717209</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.880630</td>
<td>-4.477000</td>
<td>-1.078947</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>4.001957</td>
<td>-2.884072</td>
<td>-3.116903</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2002-09-20</td>
<td>2.652493</td>
<td>-10.528875</td>
<td>9.867805</td>
</tr>
<tr>
<td>2002-09-21</td>
<td>0.844497</td>
<td>-9.280944</td>
<td>9.522649</td>
</tr>
<tr>
<td>2002-09-22</td>
<td>2.860036</td>
<td>-9.270337</td>
<td>6.415245</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>3.510163</td>
<td>-8.151439</td>
<td>5.177219</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>6.524983</td>
<td>-10.168078</td>
<td>5.792639</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>6.409626</td>
<td>-9.956226</td>
<td>5.704050</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>5.093787</td>
<td>-7.074515</td>
<td>6.905823</td>
</tr>
</tbody>
</table>

[1000 rows x 3 columns]

In [90]: r[['A','B']].aggregate(np.sum)

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>-0.289838</td>
<td>-0.370545</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-0.216612</td>
<td>-1.675528</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.154661</td>
<td>-1.634017</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>2.969393</td>
<td>-4.003274</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>4.690630</td>
<td>-4.682017</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.880630</td>
<td>-4.477000</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>4.001957</td>
<td>-2.884072</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2002-09-20</td>
<td>2.652493</td>
<td>-10.528875</td>
</tr>
<tr>
<td>2002-09-21</td>
<td>0.844497</td>
<td>-9.280944</td>
</tr>
<tr>
<td>2002-09-22</td>
<td>2.860036</td>
<td>-9.270337</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>3.510163</td>
<td>-8.151439</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>6.524983</td>
<td>-10.168078</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>6.409626</td>
<td>-9.956226</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>5.093787</td>
<td>-7.074515</td>
</tr>
</tbody>
</table>

[1000 rows x 2 columns]
As you can see, the result of the aggregation will have the selected columns, or all columns if none are selected.

### 14.3.1 Applying multiple functions

With windowed `Series` you can also pass a list of functions to do aggregation with, outputting a DataFrame:

```
In [91]: r['A'].agg([np.sum, np.mean, np.std])
Out[91]:
     sum     mean     std
2000-01-01 -0.289838 -0.289838 NaN
2000-01-02 -0.216612 -0.108306 0.256725
2000-01-03  1.154661  0.384887  0.873311
2000-01-04  2.969393  0.742348  1.009734
2000-01-05  4.690630  0.938126  0.977914
2000-01-06  3.880630  0.646772  1.128883
2000-01-07  4.001957  0.571708  1.049487
      ...      ...      ...  ...
2002-09-20  2.652493  0.044208  1.164919
2002-09-21  0.844497  0.014075  1.148231
2002-09-22  2.860036  0.047667  1.132051
2002-09-23  3.510163  0.058503  1.134296
2002-09-24  6.524983  0.108750  1.144204
2002-09-25  6.409626  0.106827  1.142913
2002-09-26  5.093787  0.084896  1.151416
[1000 rows x 3 columns]
```

On a windowed DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [92]: r.agg([np.sum, np.mean])
Out[92]:
       A     sum   mean
2000-01-01 -0.289838 -0.289838
2000-01-02 -0.216612 -0.108306
2000-01-03  1.154661  0.384887
2000-01-04  2.969393  0.742348
2000-01-05  4.690630  0.938126
2000-01-06  3.880630  0.646772
2000-01-07  4.001957  0.571708
      ...      ...      ...
2002-09-20  2.652493  0.044208
2002-09-21  0.844497  0.014075
2002-09-22  2.860036  0.047667
2002-09-23  3.510163  0.058503
2002-09-24  6.524983  0.108750
2002-09-25  6.409626  0.106827
2002-09-26  5.093787  0.084896
[1000 rows x 6 columns]
```

Passing a dict of functions has different behavior by default, see the next section.

14.3. Aggregation
14.3.2 Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```python
In [93]: r.agg({'A' : np.sum,
          ....:     'B' : lambda x: np.std(x, ddof=1)})

Out[93]:
   A     B
0  2000-01-01 -0.289838  NaN
1  2000-01-02 -0.216612  0.660747
2  2000-01-03   1.154661  0.689929
3  2000-01-04   2.969393  1.072199
4  2000-01-05   4.690630  0.939657
5  2000-01-06   3.880630  0.966848
6  2000-01-07   4.001957  1.240137
... ... 
994  2002-09-20  2.652493  1.114814
995  2002-09-21  0.844497  1.113220
996  2002-09-22  2.860036  1.132208
997  2002-09-23  3.510163  1.132381
998  2002-09-24  6.524983  1.080963
999  2002-09-25  6.409626  1.082911
1000  2002-09-26  5.093787  1.136199
[1000 rows x 2 columns]
```

The function names can also be strings. In order for a string to be valid it must be implemented on the windowed object.

```python
In [94]: r.agg({'A' : 'sum', 'B' : 'std'})

Out[94]:
   A     B
0  2000-01-01 -0.289838  NaN
1  2000-01-02 -0.216612  0.660747
2  2000-01-03   1.154661  0.689929
3  2000-01-04   2.969393  1.072199
4  2000-01-05   4.690630  0.939657
5  2000-01-06   3.880630  0.966848
6  2000-01-07   4.001957  1.240137
... ... 
994  2002-09-20  2.652493  1.114814
995  2002-09-21  0.844497  1.113220
996  2002-09-22  2.860036  1.132208
997  2002-09-23  3.510163  1.132381
998  2002-09-24  6.524983  1.080963
999  2002-09-25  6.409626  1.082911
1000  2002-09-26  5.093787  1.136199
[1000 rows x 2 columns]
```

Furthermore you can pass a nested dict to indicate different aggregations on different columns.

```python
In [95]: r.agg({'A' : ['sum','std'], 'B' : ['mean','std']})

Out[95]:
     A  B
    sum std  mean std
0  2000-01-01 -0.289838 NaN  0.370545 NaN
```

(continues on next page)
Pandas: powerful Python data analysis toolkit, Release 0.23.1

(continued from previous page)

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-02</td>
<td>-0.216612</td>
<td>0.256725</td>
<td>-0.837764</td>
<td>0.660747</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.154661</td>
<td>0.873311</td>
<td>-0.544672</td>
<td>0.689929</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>2.969393</td>
<td>1.009734</td>
<td>-1.000819</td>
<td>1.072199</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>4.690630</td>
<td>0.977914</td>
<td>-0.936403</td>
<td>0.939657</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.880630</td>
<td>1.128883</td>
<td>-0.741283</td>
<td>0.966848</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>4.001957</td>
<td>1.049487</td>
<td>-0.412010</td>
<td>1.240137</td>
</tr>
</tbody>
</table>

... ... ... ...

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002-09-20</td>
<td>2.652493</td>
<td>1.164919</td>
<td>-0.175481</td>
<td>1.114814</td>
</tr>
<tr>
<td>2002-09-21</td>
<td>0.844497</td>
<td>1.148231</td>
<td>-0.154682</td>
<td>1.113220</td>
</tr>
<tr>
<td>2002-09-22</td>
<td>2.860036</td>
<td>1.132051</td>
<td>-0.154506</td>
<td>1.113208</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>3.510163</td>
<td>1.134296</td>
<td>-0.135857</td>
<td>1.132381</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>6.524983</td>
<td>1.144204</td>
<td>-0.169468</td>
<td>1.080963</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>6.409626</td>
<td>1.142913</td>
<td>-0.165937</td>
<td>1.082911</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>5.093787</td>
<td>1.151416</td>
<td>-0.117909</td>
<td>1.136199</td>
</tr>
</tbody>
</table>

[1000 rows x 4 columns]

14.4 Expanding Windows

A common alternative to rolling statistics is to use an expanding window, which yields the value of the statistic with all the data available up to that point in time.

These follow a similar interface to .rolling, with the .expanding method returning an Expanding object.

As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [96]: df.rolling(window=len(df), min_periods=1).mean()[:5]
Out[96]:
   A      B      C      D
2000-01-01  0.3142  -0.0017  0.0718  0.8926
2000-01-02  0.6545  -0.1714  0.1792  0.8535
2000-01-03  0.7087  -0.0645  -0.2383  1.3711
2000-01-04  0.9876  0.1635  -0.9197  1.5664
2000-01-05  1.4269  0.2883  -1.359  1.8086
```

```
In [97]: df.expanding(min_periods=1).mean()[:5]
```

These have a similar set of methods to .rolling methods.

14.4. Expanding Windows
14.4.1 Method Summary

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count()</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>sum()</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean()</td>
<td>Mean of values</td>
</tr>
<tr>
<td>median()</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min()</td>
<td>Minimum</td>
</tr>
<tr>
<td>max()</td>
<td>Maximum</td>
</tr>
<tr>
<td>std()</td>
<td>Unbiased standard deviation</td>
</tr>
<tr>
<td>var()</td>
<td>Unbiased variance</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>apply()</td>
<td>Generic apply</td>
</tr>
<tr>
<td>cov()</td>
<td>Unbiased covariance (binary)</td>
</tr>
<tr>
<td>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 counterparts. Like above, the parameters they all accept are:

- min_periods: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No NaNs will be output once min_periods non-null data points have been seen.
- center: boolean, whether to set the labels at the center (default is False).

**Note:** The output of the .rolling and .expanding methods do not return a NaN if there are at least min_periods non-null values in the current window. For example:

```python
In [98]: sn = pd.Series([1, 2, np.nan, 3, np.nan, 4])

In [99]: sn
Out[99]:
0    1.0
1    2.0
2    NaN
3    3.0
4    NaN
5    4.0
dtype: float64

In [100]: sn.rolling(2).max()
Out[100]:
0    NaN
1    2.0
2    NaN
3    NaN
4    NaN
5    NaN
dtype: float64

In [101]: sn.rolling(2, min_periods=1).max()
```

(continues on next page)
In case of expanding functions, this differs from `cumsum()`, `cumprod()`, `cummax()`, and `cummin()`, which return NaN in the output wherever a NaN is encountered in the input. In order to match the output of `cumsum` with expanding, use `fillna()`:

```python
In [102]: sn.expanding().sum()
Out[102]:
   0  1.0
   1  3.0
   2  3.0
   3  6.0
   4  6.0
   5 10.0
 dtype: float64
```

```python
In [103]: sn.cumsum()
Out[103]:
   0  1.0
   1  3.0
   2  NaN
   3  6.0
   4  NaN
   5 10.0
 dtype: float64
```

```python
In [104]: sn.cumsum().fillna(method='ffill')
Out[104]:
   0  1.0
   1  3.0
   2  3.0
   3  6.0
   4  6.0
   5 10.0
 dtype: float64
```

An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the `mean()` output for the previous time series dataset:

```python
In [105]: s.plot(style='k--')
Out[105]: <matplotlib.axes._subplots.AxesSubplot at 0x1c28e93860>
```

```python
In [106]: s.expanding().mean().plot(style='k')
Out[106]: <matplotlib.axes._subplots.AxesSubplot at 0x1c28e93860>
```
14.5 Exponentially Weighted Windows

A related set of functions are exponentially weighted versions of several of the above statistics. A similar interface to `.rolling` and `.expanding` is accessed through the `.ewm` method to receive an EWM object. A number of expanding EW (exponentially weighted) methods are provided:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>mean()</code></td>
<td>EW moving average</td>
</tr>
<tr>
<td><code>var()</code></td>
<td>EW moving variance</td>
</tr>
<tr>
<td><code>std()</code></td>
<td>EW moving standard deviation</td>
</tr>
<tr>
<td><code>corr()</code></td>
<td>EW moving correlation</td>
</tr>
<tr>
<td><code>cov()</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, \( y_t \) is the result and the \( w_i \) are the weights.

The EW functions support two variants of exponential weights. The default, `adjust=True`, uses the weights \( w_i = \frac{1}{2^i} \).
\[(1 - \alpha)^i\] which gives

\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots + (1 - \alpha)^i x_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + \ldots + (1 - \alpha)^t}
\]

When \texttt{adjust=False} is specified, moving averages are calculated as

\[
y_0 = x_0 \\
y_t = (1 - \alpha)y_{t-1} + \alpha x_t,
\]

which is equivalent to using weights

\[
w_i = \begin{cases} 
\alpha(1 - \alpha)^i & \text{if } i < t \\
(1 - \alpha)^i & \text{if } i = t.
\end{cases}
\]

**Note:** These equations are sometimes written in terms of \(\alpha' = 1 - \alpha\), e.g.

\[
y_t = \alpha'y_{t-1} + (1 - \alpha')x_t.
\]

The difference between the above two variants arises because we are dealing with series which have finite history. Consider a series of infinite history:

\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots}{1 - (1 - \alpha)}
\]

Noting that the denominator is a geometric series with initial term equal to 1 and a ratio of \(1 - \alpha\) we have

\[
y_t = x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots
\]

\[
= \alpha x_t + [(1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots] \alpha
\]

\[
= \alpha x_t + (1 - \alpha)[x_{t-1} + (1 - \alpha)x_{t-2} + \ldots] \alpha
\]

\[
= \alpha x_t + (1 - \alpha)y_{t-1}
\]

which shows the equivalence of the above two variants for infinite series. When \texttt{adjust=True} we have \(y_0 = x_0\) and from the last representation above we have \(y_t = \alpha x_t + (1 - \alpha)y_{t-1}\), therefore there is an assumption that \(x_0\) is not an ordinary value but rather an exponentially weighted moment of the infinite series up to that point.

One must have \(0 < \alpha \leq 1\), and while since version 0.18.0 it has been possible to pass \(\alpha\) directly, it’s often easier to think about either the \texttt{span}, \texttt{center of mass (com)} or \texttt{half-life} of an EW moment:

\[
\alpha = \begin{cases} 
\frac{s}{s + 1}, & \text{for span } s \geq 1 \\
\frac{1}{1 + c}, & \text{for center of mass } c \geq 0 \\
1 - \exp\left(-\frac{\alpha}{h}\right), & \text{for half-life } h > 0
\end{cases}
\]

One must specify precisely one of \texttt{span}, \texttt{center of mass}, \texttt{half-life} and \texttt{alpha} to the EW functions:

- **Span** corresponds to what is commonly called an “\(N\)-day EW moving average”.
- **Center of mass** has a more physical interpretation and can be thought of in terms of span: \(c = (s - 1)/2\).
- **Half-life** is the period of time for the exponential weight to reduce to one half.
- **Alpha** specifies the smoothing factor directly.

Here is an example for a univariate time series:
In [107]: s.plot(style='k--')
Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0x1c29087d68>

In [108]: s.ewm(span=20).mean().plot(style='k')
Out[108]: <matplotlib.axes._subplots.AxesSubplot at 0x1c29087d68>

EWM has a `min_periods` argument, which has the same meaning it does for all the `.expanding` and `.rolling` methods: no output values will be set until at least `min_periods` non-null values are encountered in the (expanding) window.

EWM also has an `ignore_na` argument, which determines how intermediate null values affect the calculation of the weights. When `ignore_na=False` (the default), weights are calculated based on absolute positions, so that intermediate null values affect the result. When `ignore_na=True`, weights are calculated by ignoring intermediate null values. For example, assuming `adjust=True`, if `ignore_na=False`, the weighted average of 3, NaN, 5 would be calculated as

\[
\frac{(1-\alpha)^3 + 1 \cdot 5}{(1-\alpha)^2 + 1}.
\]

Whereas if `ignore_na=True`, the weighted average would be calculated as

\[
\frac{(1-\alpha) \cdot 3 + 1 \cdot 5}{(1-\alpha) + 1}.
\]

The `var()`, `std()`, and `cov()` functions have a `bias` argument, specifying whether the result should contain biased or unbiased statistics. For example, if `bias=True`, `ewmvar(x)` is calculated as `ewmvar(x) =
ewma(x**2) - ewma(x)**2; whereas if bias=False (the default), the biased variance statistics are scaled by debiasing factors

\[
\frac{\left( \sum_{i=0}^{t} w_i \right)^2}{\left( \sum_{i=0}^{t} w_i \right)^2 - \sum_{i=0}^{t} w_i^2}
\]

(For \( w_i = 1 \), this reduces to the usual \( N/(N - 1) \) factor, with \( N = t + 1 \).) See Weighted Sample Variance on Wikipedia for further details.
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.

### 15.1 Missing data basics

#### 15.1.1 When / why does data become missing?

Some might quibble over our usage of `missing`. By “missing” we simply mean `NA` (“not available”) 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 -0.166778  0.501113 -0.355322  bar  False
   c -0.337890  0.580967  0.983801  bar  False
   e  0.057802  0.761948 -0.712964  bar   True
   f -0.443160 -0.974602  1.047704  bar  False
   h -0.717852 -1.053898 -0.019369  bar  False

In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

In [6]: df2
Out[6]:
```

(continues on next page)
15.1.2 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 “not available” or “NA”.

Note: If you want to consider inf and -inf to be “NA” in computations, you can set pandas.options.mode.use_inf_as_na = True.

To make detecting missing values easier (and across different array dtypes), pandas provides the isna() and notna() functions, which are also methods on Series and DataFrame objects:

```python
In [7]: df2['one']
Out[7]:
a -0.166778
b NaN
c -0.337890
d NaN
e 0.057802
f -0.443160
g NaN
h -0.717852
Name: one, dtype: float64
In [8]: pd.isna(df2['one'])
→ a False
   b True
c False
d True
e False
   f False
g True
   h False
Name: one, dtype: bool
In [9]: df2['four'].notna()
→ a True
   b False
```
Warning: One has to be mindful that in Python (and NumPy), the nan's don't compare equal, but None's do. Note that pandas/NumPy uses the fact that np.nan != np.nan, and treats None like np.nan.

So as compared to above, a scalar equality comparison versus a None/np.nan doesn't provide useful information.

15.2 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.
15.3 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:

```python
In [20]: s = pd.Series([1, 2, 3])
In [21]: s.loc[0] = None
In [22]: s
Out[22]:
0    NaN
1     2.0
2     3.0
dtype: float64
```

Likewise, datetime containers will always use NaT.

For object containers, pandas will use the value given:

```python
In [23]: s = pd.Series(["a", "b", "c"])
In [24]: s.loc[0] = None
```

(continues on next page)
15.4 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

In [27]: a
Out[27]:
   one     two
a  NaN   0.501113
b  NaN   0.580967
c  NaN   0.578020
f -0.443160 -0.974602
e  0.057802  0.761948
h -0.443160 -1.053898

In [28]: b
   →
   one     two    three
   a  NaN   0.501113 -0.355322
   c  NaN   0.580967  0.983801
   e  0.057802  0.761948 -0.712964
   f -0.443160 -0.974602  1.047704
   h  NaN  -1.053898 -0.019369

In [29]: a + b
   →
   one    three     two
   a  NaN  NaN   1.002226
   c  NaN  NaN   1.161935
   e  0.115604  NaN  1.523896
   f -0.886321  NaN -1.949205
   h  NaN  NaN  -2.107796

The descriptive statistics and computational methods discussed in the *data structure overview* (and listed *here* and *here*) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero.
- If the data are all NA, the result will be 0.
- Cumulative methods like `cumsum()` and `cumprod()` ignore NA values by default, but preserve them in the resulting arrays. To override this behaviour and include NA values, use `skipna=False`.

In [30]: df
Out[30]:
   (continues on next page)
The sum of an empty or all-NA Series or column of a DataFrame is 0.

**Warning:** This behavior is now standard as of v0.22.0 and is consistent with the default in *numpy*; previously sum/prod of all-NA or empty Series/DataFrames would return NaN. See [v0.22.0 what's new](#) for more.

The sum of an empty or all-NA Series or column of a DataFrame is 0.

## 15.4.1 Sum/Prod of Empties/Nans

The sum of an empty or all-NA Series or column of a DataFrame is 0.
The product of an empty or all-NA Series or column of a DataFrame is 1.

```
In [37]: pd.Series([np.nan]).prod()
Out[37]: 1.0

In [38]: pd.Series([]).prod()
Out[38]: 1.0
```

15.4.2 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example:

```
In [39]: df
Out[39]:
     one     two     three
   a  NaN  0.501113 -0.355322
   c  NaN  0.580967  0.983801
  e  0.057802  0.761948 -0.712964
  f -0.443160 -0.974602  1.047704
  h  NaN  1.053898  1.047704

In [40]: df.groupby('one').mean()
```

See the groupby section [here](#) for more information.

15.5 Cleaning / filling missing data

Pandas objects are equipped with various data manipulation methods for dealing with missing data.

15.5.1 Filling missing values: `fillna`

`fillna()` can “fill in” NA values with non-NA data in a couple of ways, which we illustrate:

Replace NA with a scalar value

```
In [41]: df2
Out[41]:
     one     two     three     four    five  timestamp
   a  NaN  0.501113 -0.355322  False  bar  NaT
   c  NaN  0.580967  0.983801  False  bar  NaT
  e  0.057802  0.761948 -0.712964   True  2012-01-01
  f -0.443160 -0.974602  1.047704  False  2012-01-01
  h  NaN  1.053898 -0.019369  False  bar  NaT

In [42]: df2.fillna(0)
```

(continues on next page)
Fill gaps forward or backward

Using the same filling arguments as reindexing, we can propagate non-NA values forward or backward:

```python
In [44]: df
Out[44]:
     one  two  three
a  NaN  0.501113 -0.355322
b  NaN  0.580967  0.983801
c  NaN  0.580967  0.983801
d  NaN  0.580967  0.983801
```

```python
In [45]: df.fillna(method='pad')
```

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:

```python
In [46]: df
Out[46]:
     one  two  three
a  NaN  0.501113 -0.355322
b  NaN  0.580967  0.983801
c  NaN  0.580967  0.983801
d  NaN  0.580967  0.983801
e  NaN  NaN     NaN
f  NaN  NaN     NaN
g  NaN  NaN     NaN
h  NaN  -1.053898 -0.019369
```

```python
In [47]: df.fillna(method='pad', limit=1)
```
To remind you, these are the available filling methods:

<table>
<thead>
<tr>
<th>Method</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>pad / ffill</td>
<td>Fill values forward</td>
</tr>
<tr>
<td>bfill / backfill</td>
<td>Fill values backward</td>
</tr>
</tbody>
</table>

With time series data, using pad/ffill is extremely common so that the “last known value” is available at every time point.

`ffill()` is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

### 15.5.2 Filling with a PandasObject

You can also fillna using a dict or Series that is alignable. The labels of the dict or index of the Series must match the columns of the frame you wish to fill. The use case of this is to fill a DataFrame with the mean of that column.

```python
In [48]: dff = pd.DataFrame(np.random.randn(10,3), columns=list('ABC'))
In [49]: dff.iloc[3:5,0] = np.nan
In [50]: dff.iloc[4:6,1] = np.nan
In [51]: dff.iloc[5:8,2] = np.nan

In [52]: dff
```

```
    A       B       C
0  0.758887  2.340598  0.219039
1 -1.235583  0.031785  0.701683
2 -1.557016 -0.636986 -1.238610
3 NaN      -1.002278  0.654052
4 NaN      NaN      1.053999
5  0.651981  NaN      NaN
6  0.109001  0.533294  NaN
7 -1.037831  0.150016  NaN
8 -0.258742  0.706329  0.402547
9 -1.037831  0.150016  NaN
```

```
In [53]: dff.fillna(dff.mean())
```

```
    A       B       C
0  0.758887  2.340598  0.219039
1 -1.235583  0.031785  0.701683
2 -1.557016 -0.636986 -1.238610
3 -0.407125 -1.002278  0.654052
4 -0.407125  0.033067  1.053999
5  0.651981  NaN      NaN
6  0.109001  0.533294  NaN
7 -1.037831  0.150016  NaN
8 -0.687693  1.921056  0.121113
9 -0.258742  0.706329  0.402547
```

(continues on next page)
5 0.651981 0.033067 0.238800
6 0.109001 -0.533294 0.238800
7 -1.037831 -1.150016 0.238800
8 -0.687693 1.921056 -0.121113
9 0.258742 0.706392 0.402547

In [54]: dff.fillna(dff.mean()['B': 'C'])

\[
\begin{array}{ccc}
A & B & C \\
0 & 0.758887 & 2.340598 & 0.219039 \\
1 & -1.235583 & 0.031785 & 0.701683 \\
2 & -1.557016 & -0.636986 & -1.238610 \\
3 & NaN & -1.002278 & 0.654052 \\
4 & NaN & 0.033067 & 1.053999 \\
5 & 0.651981 & 0.033067 & 0.238800 \\
6 & 0.109001 & -0.533294 & 0.238800 \\
7 & -1.037831 & -1.150016 & 0.238800 \\
8 & 0.687693 & 1.921056 & -0.121113 \\
9 & 0.258742 & 0.706392 & 0.402547 \\
\end{array}
\]

Same result as above, but is aligning the ‘fill’ value which is a Series in this case.

In [55]: dff.where(pd.notna(dff), dff.mean(), axis='columns')

Out [55]:
\[
\begin{array}{ccc}
A & B & C \\
0 & 0.758887 & 2.340598 & 0.219039 \\
1 & -1.235583 & 0.031785 & 0.701683 \\
2 & -1.557016 & -0.636986 & -1.238610 \\
3 & -0.407125 & -1.002278 & 0.654052 \\
4 & -0.407125 & 0.033067 & 1.053999 \\
5 & 0.651981 & 0.033067 & 0.238800 \\
6 & -0.500000 & -0.533294 & 0.238800 \\
7 & -1.037831 & -1.150016 & 0.238800 \\
8 & -0.687693 & 1.921056 & -0.121113 \\
9 & 0.258742 & 0.706392 & 0.402547 \\
\end{array}
\]

15.5.3 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 dropna():

In [56]: df

Out [56]:
\[
\begin{array}{ccc}
one & two & three \\
a & NaN & 0.501113 & -0.355322 \\
c & NaN & 0.580967 & 0.983801 \\
e & NaN & 0.000000 & 0.000000 \\
f & NaN & 0.000000 & 0.000000 \\
h & NaN & -1.053898 & -0.019369 \\
\end{array}
\]

In [57]: df.dropna(axis=0)

\[
\begin{array}{ccc}
one & two & three \\
a & NaN & 0.501113 & -0.355322 \\
c & NaN & 0.580967 & 0.983801 \\
f & NaN & 0.000000 & 0.000000 \\
h & NaN & -1.053898 & -0.019369 \\
\end{array}
\]

(continues on next page)
An equivalent `dropna()` is available for Series. DataFrame.dropna has considerably more options than Series.dropna, which can be examined in the API.

### 15.5.4 Interpolation

New in version 0.21.0: The `limit_area` keyword argument was added.

Both Series and DataFrame objects have `interpolate()` that, by default, performs linear interpolation at missing datapoints.
Index aware interpolation is available via the `method` keyword:

```python
In [64]: ts2
Out[64]:
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 [65]: ts2.interpolate()
...

In [66]: ts2.interpolate(method='time')
```
2002-07-31 -5.689738
2005-01-31 -7.095568
2008-04-30 -8.916232
dtype: float64

For a floating-point index, use `method='values'`:

```python
In [67]: ser
Out[67]:
0.0   0.0
1.0   NaN
10.0  10.0
dtype: float64

In [68]: ser.interpolate()
Out[68]:
0.0   0.0
1.0   1.0
10.0  10.0
```

You can also interpolate with a DataFrame:

```python
In [70]: 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 [71]: df
Out[71]:
  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 [72]: df.interpolate()
```

The `method` argument gives access to fancier interpolation methods. If you have `scipy` installed, you can pass the
name of a 1-d interpolation routine to `method`. You’ll want to consult the full scipy interpolation documentation and reference guide for details. The appropriate interpolation method will depend on the type of data you are working with.

- If you are dealing with a time series that is growing at an increasing rate, `method='quadratic'` may be appropriate.
- If you have values approximating a cumulative distribution function, then `method='pchip'` should work well.
- To fill missing values with goal of smooth plotting, consider `method='akima'`.

**Warning:** These methods require scipy.

```python
In [73]: df.interpolate(method='barycentric')
Out[73]:
     A     B
0  1.00  0.250
1  2.10 -7.660
2  3.53 -4.515
3  4.70  4.000
4  5.60 12.200
5  6.80 14.400

In [74]: df.interpolate(method='pchip')
     →
     A     B
0  1.00000  0.250000
1  2.10000  0.672808
2  3.43454  1.928950
3  4.70000  4.000000
4  5.60000 12.200000
5  6.80000 14.400000

In [75]: df.interpolate(method='akima')
     →
     A     B
0  1.000000  0.250000
1  2.100000 -0.873316
2  3.406667  1.206900
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:

```python
In [76]: df.interpolate(method='spline', order=2)
Out[76]:
     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
```

(continues on next page)
In [77]: df.interpolate(method='polynomial', order=2)

\begin{verbatim}
  →
        A    B
0  1.000000  0.250000
1  2.100000 -2.703846
2  3.451351 -1.453846
3  4.700000  4.000000
4  5.600000  12.200000
5  6.800000  14.400000
\end{verbatim}

Compare several methods:

In [78]: np.random.seed(2)
In [79]: ser = pd.Series(np.arange(1, 10.1, .25)**2 + np.random.randn(37))
In [80]: bad = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])
In [81]: ser[bad] = np.nan
In [82]: methods = ['linear', 'quadratic', 'cubic']
In [83]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})
In [84]: df.plot()
Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1c39fbd160>
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.

```
In [85]: ser = pd.Series(np.sort(np.random.uniform(size=100)))
# interpolate at new_index
In [86]: new_index = ser.index | pd.Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])
In [87]: interp_s = ser.reindex(new_index).interpolate(method='pchip')

In [88]: interp_s[49:51]
Out [88]:
        0.471410
49.25   0.476841
49.50   0.481780
49.75   0.485998
50.00   0.489266
50.25   0.491814
50.50   0.493995
50.75   0.495763
51.00   0.497074
dtype: float64
```
15.5.4.1 Interpolation Limits

Like other pandas fill methods, `interpolate()` accepts a `limit` keyword argument. Use this argument to limit the number of consecutive NaN values filled since the last valid observation:

```python
In [89]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13, np.nan, np.nan])

# fill all consecutive values in a forward direction
In [90]: ser.interpolate()
Out[90]:
0    NaN
1    NaN
2    5.0
3    7.0
4    9.0
5   11.0
6   13.0
7   13.0
8   13.0
dtype: float64

# fill one consecutive value in a forward direction
In [91]: ser.interpolate(limit=1)
Out[91]:
0    NaN
1    5.0
2    5.0
3    NaN
4    NaN
5   11.0
6   13.0
7   13.0
8    NaN
dtype: float64
```

By default, NaN values are filled in a forward direction. Use `limit_direction` parameter to fill backward or from both directions.

```python
# fill one consecutive value backwards
In [92]: ser.interpolate(limit=1, limit_direction='backward')
Out[92]:
0    NaN
1    5.0
2    5.0
3    NaN
4    NaN
5   11.0
6   13.0
7    NaN
8    NaN
dtype: float64

# fill one consecutive value in both directions
In [93]: ser.interpolate(limit=1, limit_direction='both')
```

(continues on next page)
0   NaN
1    5.0
2    5.0
3    7.0
4    NaN
5   11.0
6   13.0
7   13.0
8    NaN
dtype: float64

# fill all consecutive values in both directions
In [94]: ser.interpolate(limit_direction='both')
Out[94]:
0    5.0
1    5.0
2    5.0
3    7.0
4    9.0
5   11.0
6   13.0
7   13.0
8   13.0
dtype: float64

By default, NaN values are filled whether they are inside (surrounded by) existing valid values, or outside existing valid values. Introduced in v0.23 the limit_area parameter restricts filling to either inside or outside values.

# fill one consecutive inside value in both directions
In [95]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[95]:
0    NaN
1    NaN
2    5.0
3    7.0
4    NaN
5    NaN
6    11.0
7    NaN
8    NaN
dtype: float64

# fill all consecutive outside values backward
In [96]: ser.interpolate(limit_direction='backward', limit_area='outside')
Out[96]:
0    5.0
1    5.0
2    5.0
3    NaN
4    NaN
5    NaN
6    13.0
7    NaN
8    NaN
dtype: float64

(continues on next page)
15.5.5 Replacing Generic Values

Often times we want to replace arbitrary values with other values. `replace()` in Series and `replace()` in DataFrame provides an efficient yet flexible way to perform such replacements.

For a Series, you can replace a single value or a list of values by another value:

```python
In [98]: ser = pd.Series([0., 1., 2., 3., 4.])
In [99]: ser.replace(0, 5)
Out[99]:
0   5.0
1   1.0
2   2.0
3   3.0
4   4.0
dtype: float64
```

You can replace a list of values by a list of other values:

```python
In [100]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[100]:
0   4.0
1   3.0
2   2.0
3   1.0
4   0.0
dtype: float64
```

You can also specify a mapping dict:

```python
In [101]: ser.replace({0: 10, 1: 100})
Out[101]:
0   10.0
1  100.0
2    2.0
```

(continues on next page)
For a DataFrame, you can specify individual values by column:

```
In [102]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})
In [103]: df.replace({'a': 0, 'b': 5}, 100)
```

```
Out[103]:
   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 [104]: ser.replace([1, 2, 3], method='pad')
```

```
Out[104]:
0  0.0
1  0.0
2  0.0
3  0.0
4  4.0
dtype: float64
```

## 15.5.6 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 NaN (str -> str):

```
In [105]: d = {'a': list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}
In [106]: df = pd.DataFrame(d)
In [107]: df.replace('.', np.nan)
```

```
Out[107]:
   a  b  c
0  0  a  a
1  1  b  b
2  NaN NaN
3  3 NaN  d
```

Now do it with a regular expression that removes surrounding whitespace (regex -> regex):

```
In [108]: df.replace(r'\s*\.\s*', np.nan, regex=True)
```

```
Out[108]:
   a  b  c
0  0  a  a
1  1  b  b
2  NaN NaN
3  3 NaN  d
```
Replace a few different values (list -> list):

```
In [109]: df.replace(['a', '.'], ['b', np.nan])
Out[109]:
        a   b   c
0  0 b   b
1  1 b   b
2  NaN NaN
3  NaN d
```

list of regex -> list of regex:

```
In [110]: df.replace([r'\.', r'(a)'], ['dot', '\1stuff'], regex=True)
Out[110]:
         a   b   c
0  dot {stuff {stuff
1  1 b   b
2  dot NaN
3  NaN d
```

Only search in column 'b' (dict -> dict):

```
In [111]: df.replace({'b': '.'}, {'b': np.nan})
Out[111]:
         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 [112]: df.replace({'b': {'b': r''}}, regex=True)
Out[112]:
         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 [113]: df.replace({'b': {'b': r''}}, regex=True)
Out[113]:
         a   b   c
0  0 a   a
1  1 b
2  . NaN
3  . d
```

Alternatively, you can pass the nested dictionary like so:

15.5. Cleaning / filling missing data
pandas: powerful Python data analysis toolkit, Release 0.23.1

In [114]: df.replace(regex={'b': {r'\s*\.\s*': np.nan}})
Out[114]:
   a  b  c
0  0  a  a
1  1  b  b
2  NaN NaN
3  NaN d

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well.

In [115]: df.replace({'b': r'\s*(\.\s*)', 'b': r'\1ty'}, regex=True)
Out[115]:
   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 [116]: df.replace([r'\s*\.\s*', r'a|b'], np.nan, regex=True)
Out[116]:
   a  b  c
0  NaN  NaN
1  NaN  NaN
2  NaN  NaN
3  NaN  d

All of the regular expression examples can also be passed with the to_replace argument as the regex argument. In this case the value argument must be passed explicitly by name or regex must be a nested dictionary. The previous example, in this case, would then be:

In [117]: df.replace(regex=[r'\s*\.\s*', r'a|b'], value=np.nan)
Out[117]:
   a  b  c
0  NaN  NaN
1  NaN  NaN
2  NaN  NaN
3  NaN  d

This can be convenient if you do not want to pass regex=True every time you want to use a regular expression.

Note: Anywhere in the above replace examples that you see a regular expression a compiled regular expression is valid as well.

15.5.7 Numeric Replacement

replace() is similar to fillna().

In [118]: df = pd.DataFrame(np.random.randn(10, 2))
In [119]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5
(continues on next page)
In [120]: df.replace(1.5, np.nan)
Out[120]:
   0    1
 0 -0.844214 -1.021415
 1  0.432396 -0.323580
 2  0.423825  0.799180
 3  1.262614  0.751965
 4    NaN        NaN
 5    NaN        NaN
 6 -0.498174 -1.060799
 7  0.591667 -0.183257
 8  1.019855 -1.482465
 9    NaN        NaN

Replacing more than one value is possible by passing a list.

In [121]: df00 = df.values[0, 0]
In [122]: df.replace([1.5, df00], [np.nan, 'a'])
Out[122]:
   0    1
 0    a -1.02141
 1  0.432396 -0.32358
 2  0.423825  0.79918
 3  1.262614  0.751965
 4    NaN        NaN
 5    NaN        NaN
 6 -0.498174 -1.060799
 7  0.591667 -0.183257
 8  1.019855 -1.48247
 9    NaN        NaN

In [123]: df[1].dtype

    dtype('float64')

You can also operate on the DataFrame in place:

In [124]: df.replace(1.5, np.nan, inplace=True)

Warning:  When replacing multiple bool or datetime64 objects, the first argument to replace (to_replace) must match the type of the value being replaced. For example,

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,
15.6 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 a reindexing operation introduces missing data, the Series will be cast according to the rules introduced in the table below.

<table>
<thead>
<tr>
<th>data type</th>
<th>Cast to</th>
</tr>
</thead>
<tbody>
<tr>
<td>integer</td>
<td>float</td>
</tr>
<tr>
<td>boolean</td>
<td>object</td>
</tr>
<tr>
<td>float</td>
<td>no cast</td>
</tr>
<tr>
<td>object</td>
<td>no cast</td>
</tr>
</tbody>
</table>

For example:

```
In [127]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])
In [128]: s > 0
Out[128]:
0    True
2    True
4    True
6    True
7    True
dtype: bool

In [129]: (s > 0).dtype
Out[129]: dtype('bool')

In [130]: crit = (s > 0).reindex(list(range(8)))
In [131]: crit
Out[131]:
0    True
1   NaN
2    True
3   NaN
4    True
5   NaN
6    True
```

(continues on next page)
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:

```python
In [133]: reindexed = s.reindex(list(range(8))).fillna(0)
In [134]: reindexed[crit]
```

```
ValueError: cannot index with vector containing NA / NaN values
```

However, these can be filled in using `fillna()` and it will work fine:

```python
In [135]: reindexed[crit.fillna(False)]
```

```
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
```

```python
In [136]: reindexed[crit.fillna(True)]
```

```
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.

Out of these, the split step is the most straightforward. In fact, in many situations we may wish to split the data set into groups and do something with those groups. In the apply step, we might wish to one of the following:

- **Aggregation**: compute a summary statistic (or statistics) for each group. Some examples:
  - Compute group sums or means.
  - Compute group sizes / counts.
- **Transformation**: perform some group-specific computations and return a like-indexed object. Some examples:
  - Standardize data (zscore) within a group.
  - Filling NAs within groups with a value derived from each group.
- **Filtration**: discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
  - Discard data that belongs to groups with only a few members.
  - Filter out data based on the group sum or mean.
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn’t fit into either of the above two categories.

Since the set of object instance methods on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or *itertools*), in which you can write code like:

```sql
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We’ll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the *cookbook* for some advanced strategies.
16.1 Splitting an object into groups

pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you may do the following:

```python
# default is axis=0
>>> 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.
- For DataFrame objects, a string indicating an index level to be used to group.
- A list of any of the above things.

Collectively we refer to the grouping objects as the keys. For example, consider the following DataFrame:

```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))
```

```python
In [2]: df
Out[2]:
       A     B     C     D
   0 foo foo  0.469112 -0.861849
   1 bar one  0.282863 -2.104569
   2 foo two -1.509059 -0.494929
   3 bar three -1.135632  1.071804
   4 foo two  1.212112  0.721555
   5 bar two  0.173215 -0.706771
   6 foo one -1.19209 -1.039575
   7 foo three -1.044236  0.271860
```

On a DataFrame, we obtain a GroupBy object by calling `groupby()`. We could naturally group by either the A or B columns, or both:
In [3]: grouped = df.groupby('A')

In [4]: grouped = df.groupby(['A', 'B'])

These will split the DataFrame on its index (rows). We could also split by the columns:

In [5]: def get_letter_type(letter):
   ...:     if letter.lower() in 'aeiou':
   ...:         return 'vowel'
   ...:     else:
   ...:         return 'consonant'
   ...

In [6]: grouped = df.groupby(get_letter_type, axis=1)

pandas Index objects support duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

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.

---

16.1. Splitting an object into groups 837
16.1.1 GroupBy sorting

By default the group keys are sorted during the groupby operation. You may however pass sort=False for potential speedups:

```python
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()
```

Note that groupby will preserve the order in which observations are sorted within each group. For example, the groups created by groupby() below are in the order they appeared in the original DataFrame:

```python
In [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')
```

16.1.2 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': Int64Index([1, 3, 5], dtype='int64'),
 'foo': Int64Index([0, 2, 4, 6, 7], dtype='int64')} 
In [20]: df.groupby(get_letter_type, axis=1).groups
```

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:
In [21]: grouped = df.groupby(['A', 'B'])

In [22]: grouped.groups
Out[22]:
(('bar', 'one'): Int64Index([1], dtype='int64'),
 ('bar', 'three'): Int64Index([3], dtype='int64'),
 ('bar', 'two'): Int64Index([5], dtype='int64'),
 ('foo', 'one'): Int64Index([0, 6], dtype='int64'),
 ('foo', 'three'): Int64Index([7], dtype='int64'),
 ('foo', 'two'): Int64Index([2, 4], dtype='int64'))

In [23]: len(grouped)
Out[23]:
→ 6

**GroupBy** will tab complete column names (and other attributes):

In [24]: df
Out[24]:
height  weight  gender
2000-01-01 42.849980 157.500553  male
2000-01-02 49.607315 177.340407  male
2000-01-03 56.293531 171.524640  male
2000-01-04 48.421077 144.251986  female
2000-01-05 46.556882 152.526206  male
2000-01-06 68.448851 168.272968  female
2000-01-07 70.757698 136.431469  male
2000-01-08 58.909500 176.499753  female
2000-01-09 76.435631 174.094104  female
2000-01-10 45.306120 177.540920  male

In [25]: gb = df.groupby('gender')

16.1.3 GroupBy with MultiIndex

With **hierarchically-indexed data**, it’s quite natural to group by one of the levels of the hierarchy.

Let’s create a Series with a two-level MultiIndex.

In [27]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]

In [28]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])
In [29]: s = pd.Series(np.random.randn(8), index=index)

In [30]: s
Out[30]:
first  second
bar    one     -0.919854
       two      -0.042379
baz    one      1.247642
       two     -0.009920
foo    one      0.290213
       two      0.495767
qux    one      0.362949
       two      1.548106
dtype: float64

We can then group by one of the levels in `s`.

In [31]: grouped = s.groupby(level=0)

In [32]: grouped.sum()
Out[32]:
first
bar  -0.962232
baz   1.237723
foo   0.785980
qux   1.911055
dtype: float64

If the MultiIndex has names specified, these can be passed instead of the level number:

In [33]: s.groupby(level='second').sum()
Out[33]:
second
one   0.980950
two   1.991575
dtype: float64

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

In [34]: s.sum(level='second')
Out[34]:
second
one   0.980950
two   1.991575
dtype: float64

Grouping with multiple levels is supported.

In [35]: s
Out[35]:
first  second  third
bar    doo    one   -1.131345
       two     0.970051
baz    bee    one    0.337863
       two    -0.945867
foo bop one -0.932132
two 1.956030
qux bop one 0.017587
two -0.016692
dtype: float64

```
In [36]: s.groupby(level=['first', 'second']).sum()

   first second
bar  doo   -1.220674
baz  bee   -0.608004
foo  bop    1.023898
qux  bop    0.000895
dtype: float64
```

New in version 0.20.

Index level names may be supplied as keys.

```
In [37]: s.groupby(["first", "second"]).sum()

Out[37]:
   first second
bar  doo   -1.220674
baz  bee   -0.608004
foo  bop    1.023898
qux  bop    0.000895
dtype: float64
```

More on the `sum` function and aggregation later.

### 16.1.4 Grouping DataFrame with Index Levels and Columns

A DataFrame may be grouped by a combination of columns and index levels by specifying the column names as strings and the index levels as `pd.Grouper` objects.

```
In [38]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]

In [39]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])

In [40]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3], 'B': np.arange(8)}, index=index)

In [41]: df

```

```
A   B
bar one 1 0
two 1 1
baz one 1 2
two 1 3
```

See more on `pd.DataFrame` and the MultiIndex class.

---

16.1. Splitting an object into groups
The following example groups df by the second index level and the A column.

```python
In [42]: df.groupby([pd.Grouper(level=1), 'A']).sum()
Out[42]:
   B
  second A
  one  1  2
      2  4
      3  6
  two  1  4
      2  5
      3  7
```

Index levels may also be specified by name.

```python
In [43]: df.groupby([pd.Grouper(level='second'), 'A']).sum()
Out[43]:
   B
  second A
  one  1  2
      2  4
      3  6
  two  1  4
      2  5
      3  7
```

New in version 0.20.

Index level names may be specified as keys directly to groupby.

```python
In [44]: df.groupby(['second', 'A']).sum()
Out[44]:
   B
  second A
  one  1  2
      2  4
      3  6
  two  1  4
      2  5
      3  7
```

### 16.1.5 DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, you might want to do something different for each of the columns. Thus, using [] similar to getting a column from a DataFrame, you can do:

```python
In [45]: grouped = df.groupby(['A'])
In [46]: grouped_C = grouped['C']
In [47]: grouped_D = grouped['D']
```
This is mainly syntactic sugar for the alternative and much more verbose:

```
In [48]: df['C'].groupby(df['A'])
Out[48]: <pandas.core.groupby.groupby.SeriesGroupBy object at 0x1c32da08d0>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

### 16.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```
In [49]: grouped = df.groupby('A')

In [50]: for name, group in grouped:
   ....:     print(name)
   ....:     print(group)
   ....:
bar
   A  B  C  D
   1 bar one 0.254161 1.511763
   3 bar three 0.215897 -0.990582
   5 bar two -0.077118 1.211526

foo
   A  B  C  D
   0 foo one -0.575247 1.346061
   2 foo two -1.143704 1.627081
   4 foo two 1.193555 -0.441652
   6 foo one -0.408530 0.268520
   7 foo three -0.862495 0.024580
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [51]: for name, group in df.groupby(['A', 'B']):
   ....:     print(name)
   ....:     print(group)
   ....:
('bar', 'one')
   A  B  C  D
   1 bar one 0.254161 1.511763
('bar', 'three')
   A  B  C  D
   3 bar three 0.215897 -0.990582
('bar', 'two')
   A  B  C  D
   5 bar two -0.077118 1.211526
('foo', 'one')
   A  B  C  D
   0 foo one -0.575247 1.346061
('foo', 'three')
   A  B  C  D
   6 foo one -0.408530 0.268520
('foo', 'two')
   A  B  C  D
   7 foo three -0.862495 0.024580
```

(continues on next page)
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:

### 16.3 Selecting a group

A single group can be selected using `get_group()`:

```python
In [52]: grouped.get_group('bar')
Out[52]:
   A  B  C  D
0  bar one 0.254161 1.511763
1  bar   3 0.215897 -0.990582
2  bar   2 -0.077118 1.211526
```

Or for an object grouped on multiple columns:

```python
In [53]: df.groupby(['A', 'B']).get_group(('bar', 'one'))
Out[53]:
   A  B  C  D
0  bar one 0.254161 1.511763
```

### 16.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data. These operations are similar to the aggregating API, window functions API, and resample API.

An obvious one is aggregation via the `aggregate()` or equivalently `agg()` method:

```python
In [54]: grouped = df.groupby('A')

In [55]: grouped.aggregate(np.sum)
Out [55]:
   C  D
0  0.392940 1.732707
1 -1.796421 2.824590
```

```python
In [56]: grouped = df.groupby(['A', 'B'])

In [57]: grouped.aggregate(np.sum)
Out [57]:
   C  D
0  0.254161 1.511763
1  0.215897 -0.990582
2 -0.077118 1.211526
3 -0.983776 1.614581
4 -0.862495 0.024580
5  0.049851 1.185429
```
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:

```
In [58]: grouped = df.groupby(['A', 'B'], as_index=False)

In [59]: grouped.aggregate(np.sum)
Out[59]:
   A   B   C   D
0  bar  one  0.254161  1.511763
1  bar  three  0.215897 -0.990582
2  bar  two  -0.077118  1.211526
3  foo  one  -0.983776  1.614581
4  foo  three  -0.862495  0.024580
5  foo  two   0.049851  1.185429
```

```
In [59]: grouped.aggregate(np.sum)[2:5]
```

```
In [60]: df.groupby('A', as_index=False).sum()
```

```
A   C   D
0  bar  0.392940  1.732707
1  foo -1.796421  2.824590
```

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 [61]: df.groupby(['A', 'B']).sum().reset_index()
```

```
A   B   C   D
0  bar  one  0.254161  1.511763
1  bar  three  0.215897 -0.990582
2  bar  two  -0.077118  1.211526
3  foo  one  -0.983776  1.614581
4  foo  three  -0.862495  0.024580
5  foo  two   0.049851  1.185429
```

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 [62]: grouped.size()
```

```
In [62]: grouped.size()[:5]
A   B
bar one 1
    three 1
two 1
```

```
In [63]: grouped.describe()
Out[63]:
   C  ...
->D
   count  mean   std  min  25%  50%  75% ...
   mean  std   min  25%  50%  75%  max
0  1.0  0.254161 NaN  0.254161 0.254161 0.254161 0.254161 ...
   1.511763 1.511763 1.511763 1.511763 1.511763 1.511763
(continues on next page)
Note: Aggregation functions will not return the groups that you are aggregating over if they are named columns, when as_index=True, the default. The grouped columns will be the indices of the returned object.

Passing as_index=False will return the groups that you are aggregating over, if they are named columns.

Aggregating functions are the ones that reduce the dimension of the returned objects. Some common aggregating functions are tabulated below:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean()</td>
<td>Compute mean of groups</td>
</tr>
<tr>
<td>sum()</td>
<td>Compute sum of group values</td>
</tr>
<tr>
<td>size()</td>
<td>Compute group sizes</td>
</tr>
<tr>
<td>count()</td>
<td>Compute count of group</td>
</tr>
<tr>
<td>std()</td>
<td>Standard deviation of groups</td>
</tr>
<tr>
<td>var()</td>
<td>Compute variance of groups</td>
</tr>
<tr>
<td>sem()</td>
<td>Standard error of the mean of groups</td>
</tr>
<tr>
<td>describe()</td>
<td>Generates descriptive statistics</td>
</tr>
<tr>
<td>first()</td>
<td>Compute first of group values</td>
</tr>
<tr>
<td>last()</td>
<td>Compute last of group values</td>
</tr>
<tr>
<td>nth()</td>
<td>Take nth value, or a subset if n is a list</td>
</tr>
<tr>
<td>min()</td>
<td>Compute min of group values</td>
</tr>
<tr>
<td>max()</td>
<td>Compute max of group values</td>
</tr>
</tbody>
</table>

The aggregating functions above will exclude NA values. Any function which reduces a Series to a scalar value is an aggregation function and will work, a trivial example is `df.groupby('A').agg(lambda ser: 1)`. Note that nth() can act as a reducer or a filter, see here.

### 16.4.1 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 [64]: grouped = df.groupby('A')
In [65]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[65]:
        sum    mean     std
     A
-990582 -0.990582 -0.990582 -0.990582
  211526  1.211526  1.211526  1.211526
  807291  0.807291  0.537905  0.807291
  024580  0.024580  0.024580  0.024580
  592714  1.592714  0.592714  1.592714
```
On a grouped DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```python
In [66]: grouped.agg([np.sum, np.mean, np.std])
Out[66]:
   C    D
  sum  mean  std  sum  mean  std
A  bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
    foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```

The resulting aggregations are named for the functions themselves. If you need to rename, then you can add in a chained operation for a Series like this:

```python
In [67]: (grouped['C'].agg([np.sum, np.mean, np.std])
    
    ....: .rename(columns={'sum': 'foo',
    ....:                     'mean': 'bar',
    ....:                     'std': 'baz'})

Out[67]:
   foo  bar  baz
A  bar  0.392940  0.130980  0.181231
    foo -1.796421 -0.359284  0.912265
```

For a grouped DataFrame, you can rename in a similar manner:

```python
In [68]: (grouped.agg([np.sum, np.mean, np.std])
    
    ....: .rename(columns={'sum': 'foo',
    ....:                     'mean': 'bar',
    ....:                     'std': 'baz'})

Out[68]:
   C    D
  foo  bar  baz  foo  bar  baz
A  bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
    foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```

### 16.4.2 Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```python
In [69]: grouped.agg({'C' : np.sum,

    ....:     'D' : lambda x: np.std(x, ddof=1)})

Out[69]:
   C    D
A  bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
    foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```
The function names can also be strings. In order for a string to be valid it must be either implemented on GroupBy or available via \textit{dispatching}:

\begin{verbatim}
In [70]: grouped.agg({'C': 'sum', 'D': 'std'})
Out[70]:
\begin{tabular}{cc}
  C  & D \\
bar & 0.392940 1.366330 \\
foo & -1.796421 0.884785 \\
\end{tabular}
\end{verbatim}

\textbf{Note:} If you pass a dict to \texttt{aggregate}, the ordering of the output columns is non-deterministic. If you want to be sure the output columns will be in a specific order, you can use an \texttt{OrderedDict}. Compare the output of the following two commands:

\begin{verbatim}
In [71]: grouped.agg({'D': 'std', 'C': 'mean'})
Out[71]:
\begin{tabular}{cc}
  D  & C \\
bar & 1.366330 0.130980 \\
foo & 0.884785 -0.359284 \\
\end{tabular}

In [72]: grouped.agg(OrderedDict([('D', 'std'), ('C', 'mean')]))
\end{verbatim}

\subsection*{16.4.3 Cython-optimized aggregation functions}

Some common aggregations, currently only \texttt{sum}, \texttt{mean}, \texttt{std}, and \texttt{sem}, have optimized Cython implementations:

\begin{verbatim}
In [73]: df.groupby('A').sum()
Out[73]:
\begin{tabular}{cc}
  C  & D \\
bar & 0.392940 1.732707 \\
foo & -1.796421 2.824590 \\
\end{tabular}

In [74]: df.groupby(['A', 'B']).mean()
\end{verbatim}
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).

### 16.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. The transform function must:

- Return a result that is either the same size as the group chunk or broadcastable to the size of the group chunk (e.g., a scalar, `grouped.transform(lambda x: x.iloc[-1])`).
- Operate column-by-column on the group chunk. The transform is applied to the first group chunk using `chunk.apply`.
- Not perform in-place operations on the group chunk. Group chunks should be treated as immutable, and changes to a group chunk may produce unexpected results. For example, when using `fillna`, `inplace` must be `False` (`grouped.transform(lambda x: x.fillna(inplace=False))`).
- (Optionally) operates on the entire group chunk. If this is supported, a fast path is used starting from the second chunk.

For example, suppose we wished to standardize the data within each group:

```python
In [75]: index = pd.date_range('10/1/1999', periods=1100)
In [76]: ts = pd.Series(np.random.normal(0.5, 2, 1100), index)
In [77]: ts = ts.rolling(window=100, min_periods=100).mean().dropna()
In [78]: ts.head()
Out[78]:
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 [79]: ts.tail()
Out[79]:
2002-09-30  0.660294
2002-10-01  0.631095
2002-10-02  0.705176
2002-10-03  0.709213
2002-10-04  0.719369
Freq: D, dtype: float64
In [80]: key = lambda x: x.year
In [81]: zscore = lambda x: (x - x.mean()) / x.std()
In [82]: 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 [83]: grouped = ts.groupby(key)

In [84]: grouped.mean()
Out[84]:
   2000    0.442441
   2001    0.526246
   2002    0.459365
   dtype: float64

In [85]: grouped.std()
Out[85]:
   2000    0.131752
   2001    0.210945
   2002    0.128753
   dtype: float64

# Transformed Data
In [86]: grouped_trans = transformed.groupby(key)

In [87]: grouped_trans.mean()
Out[87]:
   2000    1.168208e-15
   2001    1.454544e-15
   2002    1.726657e-15
   dtype: float64

In [88]: grouped_trans.std()
Out[88]:
   2000    1.0
   2001    1.0
   2002    1.0
   dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [89]: compare = pd.DataFrame({'Original': ts, 'Transformed': transformed})

In [90]: compare.plot()
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x1c32d61a90>
```
Transformation functions that have lower dimension outputs are broadcast to match the shape of the input array.

```
In [91]: data_range = lambda x: x.max() - x.min()

In [92]: ts.groupby(key).transform(data_range)
Out[92]:
2000-01-08  0.623893
2000-01-09  0.623893
2000-01-10  0.623893
2000-01-11  0.623893
2000-01-12  0.623893
2000-01-13  0.623893
2000-01-14  0.623893
   ...        ...
2002-09-28  0.558275
2002-09-29  0.558275
2002-09-30  0.558275
2002-10-01  0.558275
2002-10-02  0.558275
2002-10-03  0.558275
2002-10-04  0.558275
Freq: D, Length: 1001, dtype: float64
```

Alternatively the built-in methods can be could be used to produce the same outputs
Another common data transform is to replace missing data with the group mean.

In [94]: data_df
Out[94]:
   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 [95]: countries = np.array(['US', 'UK', 'GR', 'JP'])

In [96]: key = countries[np.random.randint(0, 4, 1000)]

In [97]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [98]: grouped.count()
In [99]: f = lambda x: x.fillna(x.mean())

In [100]: 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 [101]: grouped_trans = transformed.groupby(key)

In [102]: grouped.mean()  # original group means

Out[102]:
        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 [103]: grouped_trans.mean()  # transformation did not change group means

Out[103]:
        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 [104]: grouped.count()  # original has some missing data points

Out[104]:
       A  B  C
    GR 209 217 189
    JP 240 255 217
    UK 216 231 193
    US 239 250 217

In [105]: grouped_trans.count()  # counts after transformation

Out[105]:
       A  B  C
    GR 228 228 228
    JP 267 267 267
    UK 247 247 247
    US 258 258 258

In [106]: grouped_trans.size()  # Verify non-NA count equals group size

Out[106]:
       GR    JP    UK    US
dtype: int64

Note: Some functions will automatically transform the input when applied to a GroupBy object, but returning an object of the same shape as the original. Passing as_index=False will not affect these transformation methods.
For example: `fillna`, `ffill`, `bfill`, `shift`.

```
In [107]: grouped.ffill()
Out[107]:
   NaN     A     B     C
0   US  1.539708 -1.166480  0.533026
1   US  1.302092 -0.505754  0.533026
2   US -0.371983  1.104803 -0.651520
3   JP -1.309622  1.118697 -1.161657
4   JP -1.924296  0.396437  0.812436
5   US  0.815643  0.367816 -0.469478
6   GR -0.030651  0.376106 -0.645129
..   ..    ...    ...    ...
993 US  0.012359  0.554602 -1.976159
994 GR  0.042312 -1.628835  1.013822
995 JP  0.093110  0.683847 -0.774753
996 JP  0.185043  1.435792 -0.774753
997 GR  0.394469 -0.642343  0.113747
998 JP  1.174126  1.857148 -0.774753
999 UK  0.234564  0.517098  0.393534
[1000 rows x 4 columns]
```

### 16.5.1 New syntax to window and resample operations

New in version 0.18.1.

Working with the resample, expanding or rolling operations on the groupby level used to require the application of helper functions. However, now it is possible to use `resample()`, `expanding()` and `rolling()` as methods on groupbys.

The example below will apply the `rolling()` method on the samples of the column B based on the groups of column A.

```
                           'B': np.arange(20)}
In [109]: df_re
Out[109]:
   A   B
0  0   0
1  1   1
2  2   2
3  3   3
4  4   4
5  5   5
6  6   6
.. .. ..
13 13 13
14 14 14
15 15 15
16 16 16
17 17 17
18 18 18
19 19 19
```

(continues on next page)
In [110]: df_re.groupby('A').rolling(4).B.mean()

Out[110]:
A     1  0  NaN
      1  NaN
      2  NaN
      3  1.5
      4  2.5
      5  3.5
      6  4.5
      ... ...
      5  13  11.5
      14  12.5
      15  13.5
      16  14.5
      17  15.5
      18  16.5
      19  17.5
Name: B, Length: 20, dtype: float64

The `expanding()` method will accumulate a given operation (`sum()` in the example) for all the members of each particular group.

In [111]: df_re.groupby('A').expanding().sum()

Out[111]:
A   B
A
1  0  1.0  0.0
1  2.0  1.0
2  3.0  3.0
3  4.0  6.0
4  5.0  10.0
5  6.0  15.0
6  7.0  21.0
... ... ...
5  13  20.0  46.0
14  25.0  60.0
15  30.0  75.0
16  35.0  91.0
17  40.0  108.0
18  45.0  126.0
19  50.0  145.0
[20 rows x 2 columns]

Suppose you want to use the `resample()` method to get a daily frequency in each group of your dataframe and wish to complete the missing values with the `ffill()` method.

In [112]: df_re = pd.DataFrame({'date': pd.date_range(start='2016-01-01', periods=4, freq='W'),
                          'group': [1, 1, 2, 2],
                          'val': [1, 2, 3, 4]})

(continues on next page)
......:                            'val': [5, 6, 7, 8])).set_index('date')
......:

In [113]: df_re
Out[113]:
    group  val
date
2016-01-03  1   5
2016-01-10  1   6
2016-01-17  2   7
2016-01-24  2   8

In [114]: df_re.groupby('group').resample('1D').ffill()

→

    group  val
group date
1  2016-01-03  1   5
    2016-01-04  1   5
    2016-01-05  1   5
    2016-01-06  1   5
    2016-01-07  1   5
    2016-01-08  1   5
    2016-01-09  1   5
...
2  2016-01-18  2   7
    2016-01-19  2   7
    2016-01-20  2   7
    2016-01-21  2   7
    2016-01-22  2   7
    2016-01-23  2   7
    2016-01-24  2   8

[16 rows x 2 columns]

16.6 Filtration

The filter method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

In [115]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [116]: sf.groupby(sf).filter(lambda x: x.sum() > 2)

Out[116]:
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.
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.

For DataFrames with multiple columns, filters should explicitly specify a column as the filter criterion.

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`.

16.6. Filtration
16.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```python
In [123]: grouped = df.groupby('A')
In [124]: grouped.agg(lambda x: x.std())
Out[124]:
   C      D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

But, it’s rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, GroupBy now has the ability to “dispatch” method calls to the groups:

```python
In [125]: grouped.std()
Out[125]:
   C      D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the gluing, documented next). This enables some operations to be carried out rather succinctly:

```python
In [126]: tsdf = pd.DataFrame(np.random.randn(1000, 3),
   .....:       index=pd.date_range('1/1/2000', periods=1000),
   .....:       columns=['A', 'B', 'C'])
   
In [127]: tsdf.iloc[::2] = np.nan
In [128]: grouped = tsdf.groupby(lambda x: x.year)
In [129]: grouped.fillna(method='pad')
```

(continues on next page)
In this example, we chopped the collection of time series into yearly chunks then independently called `fillna` on the groups.

The `nlargest` and `nsmallest` methods work on Series style groupbys:

```python
In [130]: s = pd.Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])
In [131]: g = pd.Series(list('abababab'))
In [132]: gb = s.groupby(g)
In [133]: gb.nlargest(3)
Out[133]:
    a       19.0
           0    9.0
           2    7.0
    b       8.0
           3    5.0
           7    3.3
dtype: float64

In [134]: gb.nsmallest(3)
Out[134]:
    a       4.2
           2    7.0
           0    9.0
    b       1.0
           7    3.3
           3    5.0
dtype: float64
```

### 16.8 Flexible apply

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want GroupBy to infer how to combine the results. For these, use the `apply` function, which can be substituted for `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```python
In [135]: df
Out[135]:
   A  B      C      D
0  foo  one -0.575247  1.346061
1   bar  one  0.254161  1.511763
2  foo   two -1.143704  1.627081
3   bar  three  0.215897 -0.990582
4  foo   two  1.193555 -0.441652
5   bar   two -0.077118  1.211526
6  foo   one  0.408530  0.268520
7  foo  three -0.862495  0.024580
```

(continues on next page)
In [136]: grouped = df.groupby('A')

# could also just call .describe()
In [137]: grouped['C'].apply(lambda x: x.describe())
Out[137]:
A
bar  count 3.000000
  mean 0.130980
  std  0.181231
  min -0.077118
  25%  0.069390
  50%  0.215897
  75%  0.235029
...
foo  mean -0.359284
  std  0.912265
  min -1.143704
  25% -0.862495
  50% -0.575247
  75% -0.408530
  max  1.193555
Name: C, Length: 16, dtype: float64

The dimension of the returned result can also change:

In [138]: grouped = df.groupby('A')['C']

In [139]: def f(group):
   .....:     return pd.DataFrame({'original': group,
   .....:                     'demeaned': group - group.mean()})
   .....:
In [140]: grouped.apply(f)
Out[140]:
original  demeaned
0  -0.575247  -0.215962
1   0.254161   0.123181
2  -1.143704  -0.784420
3   0.215897   0.084917
4   1.193555   1.552839
5  -0.077118  -0.208098
6  -0.408530  -0.049245
7  -0.862495   0.503211

apply on a Series can operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame:

In [141]: def f(x):
   .....:     return pd.Series([x, x**2], index = ['x', 'x^2'])
   .....:
In [142]: s
Out[142]:
0   9.0
1   8.0
2   7.0
In [143]: s.apply(f)

\[ x \ x^2 \\
0 9.0 81.00 \\
1 8.0 64.00 \\
2 7.0 49.00 \\
3 5.0 25.00 \\
4 19.0 361.00 \\
5 1.0 1.00 \\
6 4.2 17.64 \\
7 3.3 10.89 \\
\]

Note: apply can act as a reducer, transformer, or filter function, depending on exactly what is passed to it. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

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 [144]: d = pd.DataFrame({"a": ["x", "y"], "b": [1, 2]})

In [145]: def identity(df):
   ....:     print(df)
   ....:     return df
   ....:

In [146]: d.groupby("a").apply(identity)

a b
0 x 1
a b
0 x 1
a b
1 y 2

Out[146]:

a b
0 x 1
1 y 2
16.9 Other useful features

16.9.1 Automatic exclusion of “nuisance” columns

Again consider the example DataFrame we’ve been looking at:

```
In [147]: df
Out[147]:
   A  B       C        D
0  foo  one -0.575247  1.346061
1  bar  one  0.254161  1.511763
2  foo  two -1.143704  1.627081
3  bar  three  0.215897 -0.990582
4  foo  two  1.193555 -0.441652
5  bar  two -0.077118  1.211526
6  foo  one -0.408530  0.268520
7  foo  three -0.862495  0.024580
```

Suppose we wish to compute the standard deviation grouped by the A column. There is a slight problem, namely that we don’t care about the data in column B. We refer to this as a “nuisance” column. If the passed aggregation function can’t be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

```
In [148]: df.groupby('A').std()
Out[148]:
   C   D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

Note that `df.groupby('A').colname.std()`, is more efficient than `df.groupby('A').std().colname`, so if the result of an aggregation function is only interesting over one column (here `colname`), it may be filtered before applying the aggregation function.

16.9.2 Handling of (un)observed Categorical values

When using a Categorical grouper (as a single grouper, or as part of multiplier groupers), the observed keyword controls whether to return a cartesian product of all possible groupers values (`observed=False`) or only those that are observed groupers (`observed=True`).

Show all values:

```
In [149]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=False).count()
Out[149]:
    a  3
   b  0
dtype: int64
```

Show only the observed values:

```
In [150]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=True).count()
Out[150]:
   a  2
```

(continues on next page)
The returned dtype of the grouped will *always* include *all* of the categories that were grouped.

```
In [151]: s = pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=False).count()
```

```
In [152]: s.index.dtype
Out[152]: CategoricalDtype(categories=['a', 'b'], ordered=False)
```

### 16.9.3 NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. In other words, there will never be an “NA group” or “NaT group”. This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

### 16.9.4 Grouping with ordered factors

Categorical variables represented as instance of pandas’s `Categorical` class can be used as group keys. If so, the order of the levels will be preserved:

```
In [153]: data = pd.Series(np.random.randn(100))
In [154]: factor = pd.qcut(data, [0, .25, .5, .75, 1.])
In [155]: data.groupby(factor).mean()
```

```
Out[155]:
(2.618, 0.684] -1.531461
(0.684, 0.0232] -0.272816
(-0.0232, 0.541] 0.263607
(0.541, 2.369] 1.166038
dtype: float64
```

### 16.9.5 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.

```
In [156]: import datetime
In [157]: df = pd.DataFrame(
......:   'Branch' : 'A A A A A A A B'.split(),
......:   'Buyer' : 'Carl Mark Carl Carl Joe Joe Joe Carl'.split(),
......:   'Quantity': [1,3,5,1,8,1,9,3],
......:   'Date' : [
......:     datetime.datetime(2013,1,1,13,0),
......:     datetime.datetime(2013,1,1,13,5),
......:     datetime.datetime(2013,10,1,20,0),
......:     datetime.datetime(2013,10,2,10,0),
......:     datetime.datetime(2013,10,1,20,0),
......:     datetime.datetime(2013,10,1,20,0),
```

(continues on next page)
Groupby a specific column with the desired frequency. This is like resampling.

In [159]: df.groupby([pd.Grouper(freq='1M',key='Date'),'Buyer']).sum()

Out[159]:

<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>2013-01-31</td>
<td>Mark</td>
<td>3</td>
</tr>
<tr>
<td>2013-10-31</td>
<td>Carl</td>
<td>6</td>
</tr>
<tr>
<td>2013-10-31</td>
<td>Joe</td>
<td>9</td>
</tr>
<tr>
<td>2013-12-31</td>
<td>Carl</td>
<td>3</td>
</tr>
<tr>
<td>2013-12-31</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 [160]: df = df.set_index('Date')

In [161]: df['Date'] = df.index + pd.offsets.MonthEnd(2)

In [162]: df.groupby([pd.Grouper(freq='6M',level='Date'),'Buyer']).sum()

Out[162]:

<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>2013-02-28</td>
<td>Mark</td>
<td>3</td>
</tr>
<tr>
<td>2014-02-28</td>
<td>Carl</td>
<td>9</td>
</tr>
<tr>
<td>2014-02-28</td>
<td>Joe</td>
<td>18</td>
</tr>
</tbody>
</table>
16.9.6 Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

```
In [164]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [165]: df
Out[165]:
   A  B
0  1  2
1  1  4
2  5  6

In [166]: g = df.groupby('A')

In [167]: g.head(1)
Out[167]:
   A  B
0  1  2
2  5  6

In [168]: g.tail(1)
Out[168]:
   A  B
1  1  4
2  5  6
```

This shows the first or last n rows from each group.

16.9.7 Taking the nth row of each group

To select from a DataFrame or Series the nth item, use `n.\text{th}(\cdot)`. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [169]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [170]: g = df.groupby('A')

In [171]: g.nth(0)
Out[171]:
   B
A
1  NaN
5  6.0

In [172]: g.nth(-1)
Out[172]:
   B
A
1  4.0
5  6.0

In [173]: g.nth(1)
Out[173]:
   →
   B
(continues on next page)
```

16.9. Other useful features

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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`:

```python
# nth(0) is the same as g.first()
In [174]: g.nth(0, dropna='any')
Out[174]:
   B
A  
  1 4.0
  5 6.0

In [175]: g.first()
Out[175]:
   B
A  
  1 4.0
  5 6.0

# nth(-1) is the same as g.last()
In [176]: g.nth(-1, dropna='any')  # NaNs denote group exhausted when using dropna
Out[176]:
   B
A  
  1 4.0
  5 6.0

In [177]: g.last()
Out[177]:
   B
A  
  1 4.0
  5 6.0

In [178]: g.B.nth(0, dropna='all')
Out[178]:
   A  B
   0  NaN
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```python
In [179]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
In [180]: g = df.groupby('A', as_index=False)
In [181]: g.nth(0)
Out[181]:
   A  B
  0  1  NaN
```

(continues on next page)
2 5 6.0

In [182]: g.nth(-1)
Out[182]:
   A  B
1 1 4.0
2 5 6.0

You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

In [183]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq='B')

In [184]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [185]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
Out[185]:
   a  b
2014 4 1 1
     4 1 1
     5 1 1
     5 1 1
     6 1 1
     6 1 1
     6 1 1

16.9.8 Enumerate group items

To see the order in which each row appears within its group, use the \texttt{cumcount} method:

In [186]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])

In [187]: dfg
Out[187]:
   A
0 a
1 a
2 a
3 b
4 b
5 a

In [188]: dfg.groupby('A').cumcount()
Out[188]:
   0
0 0
1 1
2 2
3 0
4 1
5 3
dtype: int64

In [189]: dfg.groupby('A').cumcount(ascending=False)

(continues on next page)
16.9.9 Enumerate groups

New in version 0.20.2.

To see the ordering of the groups (as opposed to the order of rows within a group given by \texttt{cumcount}) you can use \texttt{ngroup}().

Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the \texttt{groupby} object, not the order they are first observed.

\begin{verbatim}
In [190]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])

In [191]: dfg
Out[191]:
   A
0   a
1   a
2   b
3   b
4   b
5   a

In [192]: dfg.groupby('A').ngroup()
Out[192]:
   0  0
   1  0
   2  0
   3  0
   4  0
   5  0
dtype: int64

In [193]: dfg.groupby('A').ngroup(ascending=False)
Out[193]:
   0  1
   1  1
   2  1
   3  0
   4  0
   5  1
dtype: int64
\end{verbatim}
16.9.10 Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame may differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

```python
In [194]: np.random.seed(1234)
In [195]: df = pd.DataFrame(np.random.randn(50, 2))
In [196]: df['g'] = np.random.choice(['A', 'B'], size=50)
In [197]: df.loc[df['g'] == 'B', 1] += 3

We can easily visualize this with a boxplot:

```python
In [198]: df.groupby('g').boxplot()
Out[198]:
A AxesSubplot(0.1,0.15;0.363636x0.75)
B AxesSubplot(0.536364,0.15;0.363636x0.75)
dtype: object
```

The result of calling `boxplot` is a dictionary whose keys are the values of our grouping column `g` (“A” and “B”). The values of the resulting dictionary can be controlled by the `return_type` keyword of `boxplot`. See the `visualization documentation` for more.
Warning: For historical reasons, `df.groupby("g").boxplot()` is not equivalent to `df.boxplot(by="g")`. See here for an explanation.

### 16.9.11 Piping function calls

New in version 0.21.0.

Similar to the functionality provided by DataFrame and Series, functions that take `GroupBy` objects can be chained together using a `pipe` method to allow for a cleaner, more readable syntax. To read about `.pipe` in general terms, see here.

Combining `.groupby` and `.pipe` is often useful when you need to reuse `GroupBy` objects.

As an example, imagine having a DataFrame with columns for stores, products, revenue and quantity sold. We’d like to do a groupwise calculation of `prices` (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable. First we set the data:

```python
In [199]: import numpy as np
In [200]: n = 1000
In [201]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
       ....:       'Product': np.random.choice(['Product_1',
       ....:         'Product_2'], n),
       ....:       'Revenue': (np.random.random(n)*50+10).round(2),
       ....:       'Quantity': np.random.randint(1, 10, size=n)})
In [202]: df.head(2)
Out[202]:
      Store Product  Revenue  Quantity
0  Store_2  Product_1   26.12       1
1  Store_2  Product_1   28.86       1
```

Now, to find prices per store/product, we can simply do:

```python
In [203]: (df.groupby(['Store', 'Product']).pipe(
       ....:     lambda grp: grp.Revenue.sum()/grp.Quantity.sum())
       ....:     .unstack().round(2))
```

Piping can also be expressive when you want to deliver a grouped object to some arbitrary function, for example:

```python
(df.groupby(['Store', 'Product'])).pipe(report_func)
```

where `report_func` takes a `GroupBy` object and creates a report from that.
pandas: powerful Python data analysis toolkit, Release 0.23.1

16.10 Examples
16.10.1 Regrouping by factor
Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.
In [204]: df = pd.DataFrame({'a':[1,0,0], 'b':[0,1,0], 'c':[1,0,0], 'd':[2,3,4]})
In [205]: df
Out[205]:
a b c d
0 1 0 1 2
1 0 1 0 3
2 0 0 0 4
In [206]: df.groupby(df.sum(), axis=1).sum()
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\Out[206]:
1 9
0 2 2
1 1 3
2 0 4

16.10.2 Multi-column factorization
By using ngroup(), we can extract information about the groups in a way similar to factorize() (as described
further in the reshaping API) but which applies naturally to multiple columns of mixed type and different sources.
This can be useful as an intermediate categorical-like step in processing, when the relationships between the group
rows are more important than their content, or as input to an algorithm which only accepts the integer encoding.
(For more information about support in pandas for full categorical data, see the Categorical introduction and the API
documentation.)
In [207]: dfg = pd.DataFrame({"A": [1, 1, 2, 3, 2], "B": list("aaaba")})
In [208]: dfg
Out[208]:
A B
0 1 a
1 1 a
2 2 a
3 3 b
4 2 a
In [209]: dfg.groupby(["A", "B"]).ngroup()
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\Out[209]:
0
0
1
0
2
1
3
2
4
1
dtype: int64

In [210]: dfg.groupby(["A", [0, 0, 0, 1, 1]]).ngroup()
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
˓→

0

0
(continues on next page)

16.10. Examples

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16.10.3 Groupby by Indexer to ‘resample’ data

Resampling produces new hypothetical samples (resamples) from already existing observed data or from a model that generates data. These new samples are similar to the pre-existing samples.

In order to resample to work on indices that are non-datetime-like, the following procedure can be utilized.

In the following examples, `df.index // 5` returns a binary array which is used to determine what gets selected for the groupby operation.

**Note:** The below example shows how we can downsample by consolidation of samples into fewer samples. Here by using `df.index // 5`, we are aggregating the samples in bins. By applying `std()` function, we aggregate the information contained in many samples into a small subset of values which is their standard deviation thereby reducing the number of samples.

```
In [211]: df = pd.DataFrame(np.random.randn(10,2))
In [212]: df
Out[212]:
   0       1
0 -0.793893  0.321153
1  0.342250  1.618906
2 -0.975807  1.918201
3 -0.810847 -1.405919
4 -0.810847 -1.405919
5  0.730057 -1.316938
6  0.730057 -1.316938
7 -0.751328  0.528290
8 -0.257759 -1.081009
9 -1.006349  0.020208
```

```
In [213]: df.index // 5
Out[213]:
   0  0  0  0  0  1  1  1  1  1
```

```
In [214]: df.groupby(df.index // 5).std()
Out[214]:
   0  1
0  0.823647  1.312912
1  0.760109  0.942941
```

16.10.4 Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the
column index name will be used as the name of the inserted column:

```python
In [215]: df = pd.DataFrame({
.....:    'a': [0, 0, 0, 1, 1, 1, 2, 2, 2, 2],
.....:    'b': [0, 0, 1, 1, 0, 1, 0, 0, 1, 1],
.....:    'c': [1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
.....:    'd': [0, 0, 0, 0, 1, 0, 0, 0, 1, 1],
.....:  })

In [216]: def compute_metrics(x):
.....:      result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
.....:      return pd.Series(result, name='metrics')

In [217]: result = df.groupby('a').apply(compute_metrics)
In [218]: result
Out[218]:
metrics  b_sum  c_mean
a  
  0  2.0  0.5
  1  2.0  0.5
  2  2.0  0.5

In [219]: result.stack()

Out[219]:
  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
```
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.

### 17.1 Concatenating objects

The `concat()` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say “if any” because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```python
In [1]: df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                        'B': ['B0', 'B1', 'B2', 'B3'],
                        'C': ['C0', 'C1', 'C2', 'C3'],
                        'D': ['D0', 'D1', 'D2', 'D3'],
                        index=[0, 1, 2, 3])

In [2]: df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
                        'B': ['B4', 'B5', 'B6', 'B7'],
                        'C': ['C4', 'C5', 'C6', 'C7'],
                        'D': ['D4', 'D5', 'D6', 'D7'],
                        index=[4, 5, 6, 7])

In [3]: df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
                        'B': ['B8', 'B9', 'B10', 'B11'],
                        'C': ['C8', 'C9', 'C10', 'C11'],
                        'D': ['D8', 'D9', 'D10', 'D11'],
                        index=[8, 9, 10, 11])

In [4]: frames = [df1, df2, df3]

In [5]: result = pd.concat(frames)
```
Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

```python
def concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, copy=True)
```

- **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 axis(es). Outer for union and inner for intersection.
- **ignore_index**: boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.
- **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. Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.
- **names**: list, default None. Names for the levels in the resulting hierarchical index.
- **verify_integrity**: boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.
- `copy`: boolean, default True. If False, do not copy data unnecessarily.

Without a little bit of context many of these arguments don’t make much sense. Let’s revisit the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```python
In [6]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

As you can see (if you’ve read the rest of the documentation), the resulting object’s index has a hierarchical index. This means that we can now select out each chunk by key:

```python
In [7]: result.loc['y']
Out [7]:
A  B  C  D
4  A4 B4 C4 D4
5  A5 B5 C5 D5
6  A6 B6 C6 D6
7  A7 B7 C7 D7
```

It’s not a stretch to see how this can be very useful. More detail on this functionality below.

**Note:** It is worth noting that `concat()` (and therefore `append()`) makes a full copy of the data, and that constantly reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```python
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```
17.1.1 Set logic on the other axes

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following three ways:

- Take the union of them all, `join='outer'`. This is the default option as it results in zero information loss.
- Take the intersection, `join='inner'`.
- Use a specific index, as passed to 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, sort=False)
```

```
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>A1</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
<td></td>
<td>A1</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
</tr>
<tr>
<td>1</td>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
<td></td>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
</tr>
<tr>
<td>2</td>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
<td></td>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
</tr>
<tr>
<td>3</td>
<td>A4</td>
<td>B4</td>
<td>C4</td>
<td>D4</td>
<td></td>
<td>A4</td>
<td>B4</td>
<td>C4</td>
<td>D4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>D</th>
<th>F</th>
<th></th>
<th>B</th>
<th>D</th>
<th>F</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>B2</td>
<td>D2</td>
<td>F2</td>
<td></td>
<td>B2</td>
<td>D2</td>
<td>F2</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B3</td>
<td>D3</td>
<td>F3</td>
<td></td>
<td>B3</td>
<td>D3</td>
<td>F3</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>B4</td>
<td>D4</td>
<td>F4</td>
<td></td>
<td>B4</td>
<td>D4</td>
<td>F4</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>B5</td>
<td>D5</td>
<td>F5</td>
<td></td>
<td>B5</td>
<td>D5</td>
<td>F5</td>
<td></td>
</tr>
</tbody>
</table>
```

**Warning:** Changed in version 0.23.0.

The default behavior with `join='outer'` is to sort the other axis (columns in this case). In a future version of pandas, the default will be to not sort. We specified `sort=False` to opt in to the new behavior now.

Here is the same thing with `join='inner'`:

```
In [10]: result = pd.concat([df1, df4], axis=1, join='inner')
```

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:
17.1.2 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:

```python
In [12]: result = df1.append(df2)
```

In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

```python
In [13]: result = df1.append(df4)
```
append may take multiple objects to concatenate:

```python
In [14]: result = df1.append([df2, df3])
```
### 17.1.3 Ignoring indexes on the concatenation axis

For DataFrame’s which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the `ignore_index` argument:

```python
In [15]: result = pd.concat([df1, df4], ignore_index=True)
```

This is also a valid argument to `DataFrame.append()`:

```python
In [16]: result = df1.append(df4, ignore_index=True)
```

### 17.1.4 Concatenating with mixed ndims

You can concatenate a mix of Series and DataFrame’s. The `Series` will be transformed to `DataFrame` with the column name as the name of the `Series`. 

---

**17.1. Concatenating objects**

881
In [17]: s1 = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')

In [18]: result = pd.concat([df1, s1], axis=1)

Note: Since we're concatenating a Series to a DataFrame, we could have achieved the same result with DataFrame.assign(). To concatenate an arbitrary number of pandas objects (DataFrame or Series), use concat.

If unnamed Series are passed they will be numbered consecutively.

In [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)
17.1.5 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 inherit 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
1         1 1
2         2 4
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 a variation of 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):

```python
In [28]: pieces = {'x': df1, 'y': df2, 'z': df3}

In [29]: result = pd.concat(pieces)
```
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:

17.1. Concatenating objects
If you wish to specify other levels (as will occasionally be the case), you can do so using the levels argument:

```python
In [32]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
                     ....:     levels=[['z', 'y', 'x', 'w'],
                     ....:     names=['group_key'])
```

This is fairly esoteric, but it is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

### 17.1.6 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.

```python
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:

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)

17.2 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 the internal layout of the data in DataFrame.

See the cookbook for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a comparison with SQL.

pandas provides a single function, `merge()`, as the entry point for all standard database join operations between DataFrame objects:

17.2. Database-style DataFrame joining/merging
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
left_index=False, right_index=False, sort=True,
suffixes=('_x', '_y'), copy=True, indicator=False,
validate=None)

- **left**: A DataFrame object.
- **right**: Another DataFrame object.
- **on**: Column or index level 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 or index levels from the left DataFrame to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame.
- **right_on**: Columns or index levels from the right DataFrame to use as keys. Can either be column names, index level 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.
- **validate**: string, default None. If specified, checks if merge is of specified type.
  - “one_to_one” or “1:1”: checks if merge keys are unique in both left and right datasets.
  - “one_to_many” or “1:m”: checks if merge keys are unique in left dataset.
  - “many_to_one” or “m:1”: checks if merge keys are unique in right dataset.
  - “many_to_many” or “m:m”: allowed, but does not result in checks.

New in version 0.21.0.

**Note**: Support for specifying index levels as the on, left_on, and right_on parameters was added in version 0.23.0.

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 merge(), with the calling DataFrame being implicitly considered the left object in the join.
The related `join()` method, uses `merge` internally for the index-on-index (by default) and column(s)-on-index join. If you are joining on index only, you may wish to use `DataFrame.join` to save yourself some typing.

### 17.2.1 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 different `DataFrame`.
- **many-to-many** joins: joining columns on columns.

**Note:** When joining columns on columns (potentially a many-to-many join), any indexes on the passed `DataFrame` objects will be discarded.

It is worth spending some time understanding the result of the many-to-many join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```python
In [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. Only the keys appearing in `left` and `right` are present (the intersection), since `how='inner'` by default.

```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']})
```

(continues on next page)
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>

In [44]: result = pd.merge(left, right, how='left', on=['key1', 'key2'])

In [45]: result = pd.merge(left, right, how='right', on=['key1', 'key2'])
In [46]: result = pd.merge(left, right, how='outer', on=['key1', 'key2'])

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>key1</td>
<td>key2</td>
<td>A</td>
</tr>
<tr>
<td>0</td>
<td>K0</td>
<td>K0</td>
</tr>
<tr>
<td>1</td>
<td>K0</td>
<td>K1</td>
</tr>
<tr>
<td>2</td>
<td>K1</td>
<td>K0</td>
</tr>
<tr>
<td>3</td>
<td>K2</td>
<td>K1</td>
</tr>
</tbody>
</table>

In [47]: result = pd.merge(left, right, how='inner', on=['key1', 'key2'])

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>key1</td>
<td>key2</td>
<td>A</td>
</tr>
<tr>
<td>0</td>
<td>K0</td>
<td>K0</td>
</tr>
<tr>
<td>1</td>
<td>K0</td>
<td>K1</td>
</tr>
<tr>
<td>2</td>
<td>K1</td>
<td>K0</td>
</tr>
<tr>
<td>3</td>
<td>K2</td>
<td>K1</td>
</tr>
</tbody>
</table>

Here is another example with duplicate join keys in DataFrames:

In [48]: left = pd.DataFrame({'A': [1,2], 'B': [2,2]})

In [49]: right = pd.DataFrame({'A': [4,5,6], 'B': [2,2,2]})

In [50]: result = pd.merge(left, right, on='B', how='outer')

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>key1</td>
<td>key2</td>
<td>A</td>
</tr>
<tr>
<td>0</td>
<td>K0</td>
<td>K0</td>
</tr>
<tr>
<td>1</td>
<td>K0</td>
<td>K1</td>
</tr>
<tr>
<td>2</td>
<td>K1</td>
<td>K0</td>
</tr>
<tr>
<td>3</td>
<td>K2</td>
<td>K1</td>
</tr>
</tbody>
</table>
Warning: Joining / merging on duplicate keys can cause a returned frame that is the multiplication of the row dimensions, which may result in memory overflow. It is the user’s responsibility to manage duplicate values in keys before joining large DataFrames.

17.2.2 Checking for duplicate keys

New in version 0.21.0.

Users can use the validate argument to automatically check whether there are unexpected duplicates in their merge keys. Key uniqueness is checked before merge operations and so should protect against memory overflows. Checking key uniqueness is also a good way to ensure user data structures are as expected.

In the following example, there are duplicate values of B in the right DataFrame. As this is not a one-to-one merge – as specified in the validate argument – an exception will be raised.

In [51]: left = pd.DataFrame({'A' : [1,2], 'B' : [1, 2]})
In [52]: right = pd.DataFrame({'A' : [4,5,6], 'B': [2, 2, 2]})
In [53]: result = pd.merge(left, right, on='B', how='outer', validate="one_to_one")
...  
MergeError: Merge keys are not unique in right dataset; not a one-to-one merge

If the user is aware of the duplicates in the right DataFrame but wants to ensure there are no duplicates in the left DataFrame, one can use the validate='one_to_many' argument instead, which will not raise an exception.

In [53]: pd.merge(left, right, on='B', how='outer', validate="one_to_many")
Out[53]:
   A_x  B  A_y
0  1  1  NaN
1  2  2  4.0
2  2  2  5.0
3  2  2  6.0

17.2.3 The merge indicator

merge() accepts the argument indicator. If True, a Categorical-type column called _merge will be added to the output object that takes on values:
<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 [54]: `df1 = pd.DataFrame({'col1': [0, 1], 'col_left': ['a', 'b']})`

In [55]: `df2 = pd.DataFrame({'col1': [1, 2, 2], 'col_right': [2, 2, 2]})`

In [56]: `pd.merge(df1, df2, on='col1', how='outer', indicator=True)`

Out[56]:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>_merge</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>a</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>b</td>
<td>2.0</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>NaN</td>
<td>2.0</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>NaN</td>
<td>2.0</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 [57]: `pd.merge(df1, df2, on='col1', how='outer', indicator='indicator_column')`

Out[57]:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>indicator_column</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>a</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>b</td>
<td>2.0</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>NaN</td>
<td>2.0</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>NaN</td>
<td>2.0</td>
</tr>
</tbody>
</table>

### 17.2.4 Merge Dtypes

New in version 0.19.0.

Merging will preserve the dtype of the join keys.

In [58]: `left = pd.DataFrame({'key': [1], 'v1': [10]})`

In [59]: `left`

Out[59]:

<table>
<thead>
<tr>
<th>key</th>
<th>v1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>10</td>
</tr>
</tbody>
</table>

In [60]: `right = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})`

In [61]: `right`

Out[61]:

<table>
<thead>
<tr>
<th>key</th>
<th>v1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>1</td>
<td>30</td>
</tr>
</tbody>
</table>

We are able to preserve the join keys:

In [62]: `pd.merge(left, right, how='outer')`

Out[62]:

<table>
<thead>
<tr>
<th>key</th>
<th>v1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
</tr>
</tbody>
</table>

(continues on next page)
In [63]: pd.merge(left, right, how='outer').dtypes
Out[63]:
key   int64
v1    int64
dtype: object

Of course if you have missing values that are introduced, then the resulting dtype will be upcast.

In [64]: pd.merge(left, right, how='outer', on='key')
Out[64]:
    key  v1_x  v1_y
0   1    10.0  20
1   2   NaN   30

In [65]: pd.merge(left, right, how='outer', on='key').dtypes
Out[65]:
key   int64
v1_x  float64
v1_y  int64
dtype: object

New in version 0.20.0.

Merging will preserve category dtypes of the mergands. See also the section on categoricals.

The left frame.

In [66]: from pandas.api.types import CategoricalDtype
In [67]: X = pd.Series(np.random.choice(['foo', 'bar'], size=(10,)))
In [68]: X = X.astype(CategoricalDtype(categories=['foo', 'bar']))
In [69]: left = pd.DataFrame({
    'X': X,
    'Y': np.random.choice(['one', 'two', 'three'], size=(10,))
})

In [70]: left
Out[70]:
   X  Y
0  bar one
1  foo one
2  foo three
3  bar three
4  foo one
5  bar one
6  bar three
7  bar three
8  bar three
9  foo three

In [71]: left.dtypes
(continues on next page)
The right frame.

```
In [72]: right = pd.DataFrame({
   ....:     'X': pd.Series(['foo', 'bar'],
   ....:                  dtype=CategoricalDtype(['foo', 'bar'])),
   ....:     'Z': [1, 2]
   ....: })
   ....:

In [73]: right
Out[73]:
   X  Z
0 foo 1
1 bar 2
```

The merged result:

```
In [75]: result = pd.merge(left, right, how='outer')
```

```
In [76]: result
Out[76]:
   X  Y  Z
0 bar one 2
1 bar three 2
2 bar one 2
3 bar three 2
4 bar three 2
5 bar three 2
6 foo one 1
7 foo three 1
8 foo one 1
9 foo three 1
```

```
In [77]: result.dtypes
   ...
X  category
Y  object
Z  int64
```

**Note:** The category dtypes must be *exactly* the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to *object* dtype.

---

**17.2. Database-style DataFrame joining/merging** 895
Note: Merging on category dtypes that are the same can be quite performant compared to object dtype merging.

17.2.5 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 [78]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                          'B': ['B0', 'B1', 'B2'],
                          index=['K0', 'K1', 'K2'])

In [79]: right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
                           'D': ['D0', 'D2', 'D3'],
                           index=['K0', 'K2', 'K3'])

In [80]: result = left.join(right)
```

The output of `df1.join(df2)` is a DataFrame with columns from both `df1` and `df2`, left-justified (when possible). This amounts to the `left = pd.merge(left, right, how='left')` approach. The output of `df1.join(df2, how='right')` is the DataFrame counterpart to `right.join(left)`. The output of `df1.join(df2, how='outer')` is the equivalent of `pd.concat([df1, df2], axis=1)`. Here is a more complex example:

```python
In [81]: result = left.join(right, how='outer')
```

In [82]: result = left.join(right, how='inner')

The same as above, but with `how='inner'`.

```python
In [82]: 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:

```python
In [83]: result = pd.merge(left, right, left_index=True, right_index=True, how='outer')
```

### 17.2.6 Joining key columns on an index

`join()` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed DataFrame is to be aligned on that column in the DataFrame. These two function calls are completely equivalent:

```python
left.join(right, on=key_or_keys)
pd.merge(left, right, left_on=key_or_keys, right_index=True, how='left', sort=False)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the DataFrame’s is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```python
In [85]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                       'B': ['B0', 'B1', 'B2', 'B3'],
                       'key': ['K0', 'K1', 'K0', 'K1']})

In [86]: right = pd.DataFrame({'C': ['C0', 'C1'],
                        'D': ['D0', 'D1']})

In [87]: result = left.join(right, on='key')
```
In 

```python
result = pd.merge(left, right, left_on='key', right_index=True,
                   how='left', sort=False);
```

To join on multiple keys, the passed DataFrame must have a MultiIndex:

```python
left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                     'B': ['B0', 'B1', 'B2', 'B3'],
                     'key1': ['K0', 'K0', 'K1', 'K2'],
                     'key2': ['K0', 'K1', 'K0', 'K1']})
index = pd.MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'), ('K2', 'K0'), ('K2', 'K1')])
right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                      'D': ['D0', 'D1', 'D2', 'D3']},
                      index=index)
result = left.join(right, on=['key1', 'key2'])
```

The default for DataFrame.join is to perform a left join (essentially a “VLOOKUP” operation, for Excel users), which
uses only the keys found in the calling DataFrame. Other join types, for example inner join, can be just as easily performed:

```python
In [93]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

As you can see, this drops any rows where there was no match.

### 17.2.7 Joining a single Index to a Multi-index

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.

```python
In [94]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                         'B': ['B0', 'B1', 'B2'],
                         index=pd.Index(['K0', 'K1', 'K2'], name='key'))
In [95]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
                                          ('K2', 'Y2'), ('K2', 'Y3')],
                                         names=['key', 'Y'])
In [96]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                           'D': ['D0', 'D1', 'D2', 'D3'],
                           index=index)
In [97]: result = left.join(right, how='inner')
```

This is equivalent but less verbose and more memory efficient / faster than this.

```python
In [98]: result = pd.merge(left.reset_index(), right.reset_index(),
                        on=['key'], how='inner').set_index(['key','Y'])
```

17.2. Database-style DataFrame joining/merging
17.2.8 Joining with two multi-indexes

This is not implemented via `join` at-the-moment, however it can be done using the following code.

```python
In [99]: index = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
                                         ('K1', 'X2')],
                                         names=['key', 'X'])

In [100]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                          'B': ['B0', 'B1', 'B2'],
                          'key2': ['K0', 'K1', 'K2']},
                          index=index)

In [101]: result = pd.merge(left.reset_index(), right.reset_index(),
                          on='key', how='inner').set_index(['key', 'X', 'Y'])
```

17.2.9 Merging on a combination of columns and index levels

New in version 0.22.

Strings passed as the `on`, `left_on`, and `right_on` parameters may refer to either column names or index level names. This enables merging DataFrame instances on a combination of index levels and columns without resetting indexes.

```python
In [102]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [103]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                         'B': ['B0', 'B1', 'B2', 'B3'],
                         'key2': ['K0', 'K1', 'K0', 'K1']},
                         index=left_index)
```

(continues on next page)
In [104]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [105]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                           'D': ['D0', 'D1', 'D2', 'D3'],
                           'key2': ['K0', 'K0', 'K0', 'K1'],
                           index=right_index)

In [106]: result = left.merge(right, on=['key1', 'key2'])

Note: When DataFrames are merged on a string that matches an index level in both frames, the index level is preserved as an index level in the resulting DataFrame.

Note: If a string matches both a column name and an index level name, then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

17.2.10 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 [107]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [108]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

In [109]: result = pd.merge(left, right, on='k')

17.2. Database-style DataFrame joining/merging
In [110]: result = pd.merge(left, right, on='k', suffixes=['_l', '_r'])

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>v</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>K0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>K1</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>K2</td>
<td>3</td>
</tr>
</tbody>
</table>

**DataFrame.join()** has `lsuffix` and `rsuffix` arguments which behave similarly.

In [111]: left = left.set_index('k')

In [112]: right = right.set_index('k')

In [113]: result = left.join(right, lsuffix='_l', rsuffix='_r')

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<thead>
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<td></td>
<td></td>
</tr>
<tr>
<td>k</td>
<td>v_l</td>
<td>v_r</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>K0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>K0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>K0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>4.0</td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>5.0</td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>NaN</td>
</tr>
<tr>
<td>K1</td>
<td>2</td>
<td>NaN</td>
</tr>
<tr>
<td>K2</td>
<td>3</td>
<td>NaN</td>
</tr>
</tbody>
</table>

**17.2.11 Joining multiple DataFrame or Panel objects**

A list or tuple of DataFrames can also be passed to `join()` to join them together on their indexes.

In [114]: right2 = pd.DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])

In [115]: result = left.join([right, right2])

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>k</td>
<td>v</td>
<td>v</td>
<td>v</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>4</td>
<td>4.0</td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>5</td>
<td>NaN</td>
</tr>
<tr>
<td>K1</td>
<td>2</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>K2</td>
<td>3</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>K0</td>
<td>1</td>
<td>7</td>
<td>7.0</td>
</tr>
<tr>
<td>K1</td>
<td>2</td>
<td>NaN</td>
<td>8.0</td>
</tr>
<tr>
<td>K2</td>
<td>3</td>
<td>NaN</td>
<td>9.0</td>
</tr>
</tbody>
</table>
17.2.12 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 [116]: df1 = pd.DataFrame([[np.nan, 3., 5.], [-4.6, np.nan, np.nan],
                     ........:     [np.nan, 7., np.nan]])
In [117]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4.]],
                     ........:     index=[1, 2])
```

For this, use the `combine_first()` method:

```
In [118]: 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 [119]: df1.update(df2)
```

17.3 Timeseries friendly merging

17.3.1 Merging Ordered Data

A `merge_ordered()` function allows combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [120]: left = pd.DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
                      ........:     'lv': [1, 2, 3, 4],
                      ........:     's': ['a', 'b', 'c', 'd']})
In [121]: right = pd.DataFrame({'k': ['K1', 'K2', 'K4'],
                         ........:     'lv': [1, 2, 3, 4],
                         ........:     's': ['a', 'b', 'c', 'd']})
```

(continues on next page)
In [122]: pd.merge_ordered(left, right, fill_method='ffill', left_by='s')
Out[122]:
   k  lv  s  rv
0  K0 1.0  a  NaN
1  K1 1.0  a  1.0
2  K2 1.0  a  2.0
3  K4 1.0  a  3.0
4  K1 2.0  b  1.0
5  K2 2.0  b  2.0
6  K4 2.0  b  3.0
7  K1 3.0  c  1.0
8  K2 3.0  c  2.0
9  K4 3.0  c  3.0
10 K1  NaN  d  1.0
11 K2  4.0  d  2.0
12 K4  4.0  d  3.0

17.3.2 Merging AsOf

New in version 0.19.0.

A `merge_asof()` is similar to an ordered left-join except that we match on nearest key rather than equal keys. For each row in the `leftDataFrame`, we select the last row in the `rightDataFrame` whose `on` key is less than the left’s key. Both DataFrames must be sorted by the key.

Optionally an asof merge can perform a group-wise merge. This matches the `by` key equally, in addition to the nearest match on the `on` key.

For example; we might have `trades` and `quotes` and we want to `asof` merge them.

In [123]: trades = pd.DataFrame({
   .....:     'time': pd.to_datetime(['20160525 13:30:00.023',
   .....:       '20160525 13:30:00.038',
   .....:       '20160525 13:30:00.048',
   .....:       '20160525 13:30:00.048',
   .....:       '20160525 13:30:00.048'],
   .....:     'ticker': ['MSFT', 'MSFT',
   .....:                   'GOOG', 'GOOG', 'AAPL'],
   .....:     'price': [51.95, 51.95,
   .....:                  720.77, 720.92, 98.00],
   .....:     'quantity': [75, 155,
   .....:                        100, 100, 100]})

In [124]: quotes = pd.DataFrame({
   .....:     'time': pd.to_datetime(['20160525 13:30:00.023',
   .....:       '20160525 13:30:00.030',
   .....:       '20160525 13:30:00.041',
   .....:       '20160525 13:30:00.048',
   .....:       '20160525 13:30:00.049',
   .....:       '20160525 13:30:00.072'],
   .....:     'ticker': ['MSFT', 'GOOG', 'AAPL'],
   .....:     'price': [51.95, 51.95, 98.00],
   .....:     'quantity': [75, 155, 100],
   .....:     'columns': ['time', 'ticker', 'price', 'quantity']})
In [125]: trades
Out[125]:

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
</tr>
</tbody>
</table>

In [126]: quotes

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>51.96</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.99</td>
<td>52.00</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>AAPL</td>
<td>97.99</td>
<td>98.01</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.50</td>
<td>720.88</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>52.01</td>
<td>52.03</td>
</tr>
</tbody>
</table>

By default we are taking the `asof` of the quotes.

In [127]: pd.merge_asof(trades, quotes,
                          on='time',
                          by='ticker')
Out[127]:

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>51.95</td>
<td>51.96</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>720.5</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>720.5</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

We only `asof` within 2ms between the quote time and the trade time.

In [128]: pd.merge_asof(trades, quotes,
                          on='time',
                          by='ticker',
                          tolerance=pd.Timedelta('2ms'))
Out[128]:

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>51.95</td>
<td>51.96</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>720.5</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>720.5</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

(continues on next page)
We only `asof` within 10ms between the quote time and the trade time and we exclude exact matches on time. Note that though we exclude the exact matches (of the quotes), prior quotes do propagate to that point in time.

```python
In [129]: pd.merge_asof(trades, quotes,
               on='time',
               by='ticker',
               tolerance=pd.Timedelta('10ms'),
               allow_exact_matches=False)
```

```plaintext
Out[129]:

<table>
<thead>
<tr>
<th></th>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2</td>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>3</td>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>4</td>
<td>2016-05-25</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>
```
18.1 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, we use the `DataFrame.pivot()` method (also implemented as a top level function `pivot()`):

```
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
    date     2000-01-03  2000-01-04  2000-01-05
variable
A         0.469112    -0.282863   -1.509059
B         -1.135632    1.212112    -0.173215
C         0.119209    -1.044236   -0.861849
D        -2.104569   -0.494929    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
```

You can then select subsets from the pivoted DataFrame:
Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

18.2 Reshaping by stacking and unstacking

Stack

Closely related to the `pivot()` method are the related `stack()` and `unstack()` methods available on `Series` and `DataFrame`. These methods are designed to work together with `MultiIndex` objects (see the section on `hierarchical indexing`). Here are essentially what these methods do:

- **stack**: “pivot” a level of the (possibly hierarchical) column labels, returning a `DataFrame` with an index with a new inner-most level of row labels.
- **unstack**: (inverse operation of `stack`) “pivot” a level of the (possibly hierarchical) row index to the column axis, producing a reshaped `DataFrame` with a new inner-most level of column labels.
Unstack

The clearest way to explain is by example. Let’s take a prior example data set from the hierarchical indexing section:

```python
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]:

<table>
<thead>
<tr>
<th>first</th>
<th>second</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>bar</td>
<td>one</td>
<td>0.721555</td>
<td>-0.706771</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>-1.039575</td>
<td>0.271860</td>
</tr>
<tr>
<td>baz</td>
<td>one</td>
<td>-0.424972</td>
<td>0.567020</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>0.276232</td>
<td>-1.087401</td>
</tr>
</tbody>
</table>

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)

In [17]: stacked.unstack(0)
Unstack(1)

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  0.567020 -1.087401
      B  0.276232 -1.087401
```

```
In [18]: stacked.unstack('second')
Out[18]:
    second   one    two
first  
bar   A  1.039575  0.721555
      B -0.706771  0.271860
baz   A  0.276232 -1.087401
      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())
          ˓→ True
```

The above code will raise a `TypeError` if the call to `sort_index` is removed.

### 18.2.1 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'])
(continues on next page)
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'])

exp   A     B
animal hair_length
0       cat   cat   1.075770 -0.109050
       dog   dog   1.643563 -1.469388
1       cat   cat   0.357021 -0.674600
       dog   dog  -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])

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

18.2.2 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’])

(continues on next page)
In 

```
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.iloc[[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 0.875906 -2.211372 0.974466 -2.006747
foo     one -1.413681 1.607920 1.024180 0.569605
      two 0.875906 -2.211372 0.974466 -2.006747
qux     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]:
exp  A   B   A
animal   cat  dog  cat  dog
first second
bar     one A  0.895717 2.565646
      B -1.206412 0.805244
      two A 1.431256 -0.226169
              B -1.170299 1.340309
baz     one A 0.410835 -0.827317
      B 0.132003 0.813850
foo     one A -1.413681 0.569605
      B 1.024180 1.607920
      two A 0.875906 -2.006747
              B 0.974466 -2.211372
qux     two A -1.226825 -0.727707
      B -1.281247 0.769804
```

```
In [34]: df2.stack('animal')
```

```
Out[34]:
animal  A   B
first second
bar     cat 0.895717 -1.206412
        dog 2.565646 0.805244
      cat 1.431256 -1.170299
              dog -0.226169 1.340309
baz     cat 0.410835 0.132003
        dog -0.827317 0.813850
foo     cat -1.413681 1.024180
        dog 0.569605 1.607920
      cat 0.875906 0.974466
              dog -2.006747 -2.211372
```

(continues on next page)
Unstacking can result in missing values if subgroups do not have the same set of labels. By default, missing values will be replaced with the default fill value for that data type, NaN for float, NaT for datetimelike, etc. For integer types, by default data will converted to float and missing values will be set to NaN.

In [35]: df3 = df.iloc[[0, 1, 4, 7], [1, 2]]

In [36]: df3
Out[36]:
exp B
animal dog cat
first second
bar one 0.805244 -1.206412
two 1.340309 -1.170299
foo one 1.607920 1.024180
qux two 0.769804 -1.281247

In [37]: df3.unstack()  
...
Out[37]:
exp B
animal dog cat
second one two one two
first bar 0.805244 1.340309 -1.206412 -1.170299
foo 1.607920 NaN 1.024180 NaN
qux NaN 0.769804 NaN -1.281247

New in version 0.18.0.

Alternatively, unstack takes an optional fill_value argument, for specifying the value of missing data.

In [38]: df3.unstack(fill_value=-1e9)
Out[38]:
exp B
animal dog cat
second one two one two
first bar 8.052440e-01 1.340309e+00 -1.206412e+00 -1.170299e+00
foo 1.607920e+00 -1.000000e+09 1.024180e+00 -1.000000e+09
qux -1.000000e+09 7.698036e-01 -1.000000e+09 -1.281247e+00

18.2.3 With a MultiIndex

Unstacking when the columns are a MultiIndex is also careful about doing the right thing:

In [39]: df[:3].unstack(0)
Out[39]:
exp A B A
animal cat dog cat dog
first bar baz bar baz bar baz baz
second one 0.895717 0.410835 0.805244 0.81385 -1.206412 0.132003 2.565646 -0.827317
In [40]: df2.unstack(1)

Out[40]:

animal  
    exp  A    B  
    cat  one  two  one  two  
    dog  one  two  one  two  

18.3 Reshaping by Melt

Melt

The top-level \texttt{melt()} function and the corresponding \texttt{DataFrame.melt()} are useful to massage a \texttt{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 \texttt{var_name} and \texttt{value_name} parameters.

For instance,

\begin{verbatim}
In [41]: cheese = pd.DataFrame({'first': ['John', 'Mary'], 
                          'last': ['Doe', 'Bo'], 
                          'height': [5.5, 6.0], 
                          'weight': [130, 150]})

In [42]: cheese
\end{verbatim}

\begin{verbatim}
Out[42]:
\end{verbatim}
first  last  height  weight
0  John  Doe     5.5   130
1    Mary   Bo    6.0   150

In [43]: cheese.melt(id_vars=['first', 'last'])

Out[43]:
  first last variable  value
0  John  Doe   height 5.5
1    Mary   Bo  height 6.0
2  John  Doe   weight 130.0
3    Mary   Bo  weight 150.0

In [44]: cheese.melt(id_vars=['first', 'last'], var_name='quantity')

Out[44]:
  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 `wide_to_long()` panel data convenience function. It is less flexible than `melt()`, but more user-friendly.

In [45]: 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 : .7},
                           "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
                           "X" : dict(zip(range(3), np.random.randn(3)))
                       })

In [46]: dft["id"] = dft.index

In [47]: dft
Out[47]:
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 [48]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")

Out[48]:
   X  A  B
id  year
0 1970 -0.121306   a   2.5
1 1970  0.097883   b   1.2
2 1970  0.695775   c   0.7
0 1980 -0.121306   d   3.2
1 1980  0.097883   e   1.3
2 1980  0.695775   f   0.1
18.4 Combining with stats and GroupBy

It should be no shock that combining `pivot`/`stack`/`unstack` with `GroupBy` and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

```
In [49]: df
Out[49]:
exp       A     B
animal    cat   dog  cat   dog
first second
bar       one  0.895717 0.805244 -1.206412 2.565646
         two  1.431256 1.340309 -1.170299 -0.226169
baz       one  0.410835 0.813850 0.132003 -0.827317
         two -0.076467 -1.187678 1.130127 -1.436737
foo       one -1.413681 1.607920 1.024180 0.569605
         two  0.875906 -2.211372 0.974466 -2.006747
qux       one -0.410001 -0.078638 0.545952 -1.219217
         two -1.226825 0.769804 -1.281247 -0.727707
```

```
In [50]: df.stack().mean(1).unstack()
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 [51]: df.groupby(level=1, axis=1).mean()
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 [52]: df.stack().groupby(level=1).mean()
exp     A     B
second
one    0.071448 0.455513
two   -0.424186 -0.204486
```

```
In [53]: df.mean().unstack(0)
(continues on next page)
18.5 Pivot tables

While `pivot()` provides general purpose pivoting with various data types (strings, numerics, etc.), pandas also provides `pivot_table()` for pivoting with aggregation of numeric data.

The function `pivot_table()` can be used to create spreadsheet-style pivot tables. See the cookbook for some advanced strategies.

It takes a number of arguments:

- `data`: a DataFrame object.
- `values`: a column or a list of columns to aggregate.
- `index`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`.

Consider a data set like this:

```
In [54]: import datetime
In [55]: 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 [56]: df
```

```
Out[56]:
     A    C         D       E         F
0  one  foo  0.341734 -0.317441  2013-01-01
1  one    B  0.959726 -1.236269  2013-02-01
2  two    C -1.110336  0.896171  2013-03-01
3  three    A -0.619976  0.487602  2013-04-01
4      one    B  0.149748 -0.082240  2013-05-01
5      one    C  0.732339 -2.182937  2013-06-01
6      two    A  0.687738  0.380396  2013-07-01
7      ...    ...        ...        ...        ...
17     one    C -0.345352  0.206053  2013-06-15
18     two    A  1.314232 -0.251905  2013-07-15
```
We can produce pivot tables from this data very easily:

```
In [57]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[57]:
     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 0.000985
     B 0.158248 NaN
     C NaN 0.176180
In [58]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.
   → sum)
   
   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 [59]: pd.pivot_table(df, values=['D','E'], index=['B'], columns=['A', 'C'],
   → aggfunc=np.sum)
   
   D       E
   A  one  three  two  one  three  two
   C  bar  foo  bar  foo  bar  foo
   B
   A  2.241830 -1.028115 -2.363137 NaN NaN 2.001971 2.786113 -0.043211 1.
   → 922577 NaN NaN 0.128491
   B -0.676843  0.005518 NaN 0.867024 0.316495 NaN 1.368280 -1.103384 -2.
   → 1.94294 NaN
   C -1.077692  1.399070  1.177566 NaN NaN 0.352360 -1.976883 1.495717 -0.
   → 263660 NaN 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.

18.5. Pivot tables
In [60]: `pd.pivot_table(df, index=['A', 'B'], columns=['C'])`

Out[60]:

<table>
<thead>
<tr>
<th></th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>one</td>
<td>A 1.120915</td>
<td>-0.514058</td>
</tr>
<tr>
<td></td>
<td>B -0.338421</td>
<td>0.002759</td>
</tr>
<tr>
<td></td>
<td>C -0.538846</td>
<td>0.699535</td>
</tr>
<tr>
<td>three</td>
<td>A -1.181568</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>B NaN</td>
<td>0.433512</td>
</tr>
<tr>
<td></td>
<td>C 0.588783</td>
<td>NaN -0.131830</td>
</tr>
<tr>
<td>two</td>
<td>A NaN</td>
<td>1.000985</td>
</tr>
<tr>
<td></td>
<td>B 0.158248</td>
<td>NaN -0.097147</td>
</tr>
<tr>
<td></td>
<td>C NaN</td>
<td>0.176180</td>
</tr>
</tbody>
</table>

Also, you can use Grouper for index and columns keywords. For detail of Grouper, see Grouping with a Grouper specification.

In [61]: `pd.pivot_table(df, values='D', index=pd.Grouper(freq='M', key='F'), columns='C')`

Out[61]:

<table>
<thead>
<tr>
<th></th>
<th>bar</th>
<th>foo</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2013-01-31</td>
<td>NaN</td>
<td>-0.514058</td>
</tr>
<tr>
<td>2013-02-28</td>
<td>NaN</td>
<td>0.002759</td>
</tr>
<tr>
<td>2013-03-31</td>
<td>NaN</td>
<td>0.176180</td>
</tr>
<tr>
<td>2013-04-30</td>
<td>-1.181568</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-05-31</td>
<td>-0.338421</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-06-30</td>
<td>-0.538846</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-07-31</td>
<td>NaN</td>
<td>1.000985</td>
</tr>
<tr>
<td>2013-08-31</td>
<td>NaN</td>
<td>0.433512</td>
</tr>
<tr>
<td>2013-09-30</td>
<td>NaN</td>
<td>0.699535</td>
</tr>
<tr>
<td>2013-10-31</td>
<td>1.120915</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-11-30</td>
<td>0.158248</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-12-31</td>
<td>0.588783</td>
<td>NaN</td>
</tr>
</tbody>
</table>

You can render a nice output of the table omitting the missing values by calling to_string if you wish:

In [62]: `table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])`

In [63]: `print(table.to_string(na_rep=''))`

<table>
<thead>
<tr>
<th></th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>one</td>
<td>A 1.120915</td>
<td>-0.514058</td>
</tr>
<tr>
<td></td>
<td>B -0.338421</td>
<td>0.002759</td>
</tr>
<tr>
<td></td>
<td>C -0.538846</td>
<td>0.699535</td>
</tr>
<tr>
<td>three</td>
<td>A -1.181568</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>B 0.433512</td>
<td>NaN -1.064372</td>
</tr>
<tr>
<td></td>
<td>C 0.588783</td>
<td>NaN -0.131830</td>
</tr>
<tr>
<td>two</td>
<td>A 1.000985</td>
<td>NaN 0.064245</td>
</tr>
<tr>
<td></td>
<td>B 0.158248</td>
<td>NaN -0.097147</td>
</tr>
<tr>
<td></td>
<td>C 0.176180</td>
<td>NaN 0.436241</td>
</tr>
</tbody>
</table>

Note that pivot_table is also available as an instance method on DataFrame, i.e. DataFrame.pivot_table().
18.5.1 Adding margins

If you pass margins=True to pivot_table, special All columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [64]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[64]:
       D   E
     bar  foo All  bar  foo All
A
one  1.804346  1.210272  1.569879  0.179483  0.418374  0.858005
B  0.690376  1.353355  0.898998  1.083825  0.968138  1.101401
C  0.273641  0.419826  0.771139  1.689271  0.446140  1.142136
three  0.794212  NaN  2.049040  2.049040
B  NaN  0.363548  0.363548  1.625237  1.625237
C  3.915454  NaN  3.915454  1.035215  1.035215
two  0.894298  0.894298  0.447104  0.447104
B  0.202765  NaN  0.202765  0.560757  0.560757
C  NaN  1.819408  1.819408  0.650439  0.650439
All  1.556868  0.952552  1.246608  1.250924  0.899904  1.059389
```

18.6 Cross tabulations

Use crosstab() to compute a cross-tabulation of two (or more) factors. By default crosstab computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments:

- **index**: array-like, values to group by in the rows.
- **columns**: array-like, values to group by in the columns.
- **values**: array-like, optional, array of values to aggregate according to the factors.
- **aggfunc**: function, optional, If no values array is passed, computes a frequency table.
- **rownames**: sequence, default None, must match number of row arrays passed.
- **colnames**: sequence, default None, if passed, must match number of column arrays passed.
- **margins**: boolean, default False, Add row/column margins (subtotals)
- **normalize**: boolean, {'all', 'index', 'columns'}, or {0,1}, default False. Normalize by dividing all values by the sum of values.

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

For example:

```
In [65]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'
In [66]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)
In [67]: b = np.array([one, one, two, one, two, one], dtype=object)
In [68]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)
In [69]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
```

(continues on next page)
If `crosstab` receives only two series, it will provide a frequency table.

```
In [70]: df = pd.DataFrame({'A': [1, 2, 2, 2, 2], 'B': [3, 3, 4, 4, 4],
                      'C': [1, 1, np.nan, 1, 1]})
....:

In [71]: df
Out[71]:
   A  B  C
0  1  3  1.0
1  2  3  1.0
2  2  4  NaN
3  2  4  1.0
4  2  4  1.0

In [72]: pd.crosstab(df.A, df.B)
```

Any input passed containing `Categorical` data will have all of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

```
In [73]: foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])

In [74]: bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])

In [75]: pd.crosstab(foo, bar)
```

### 18.6.1 Normalization

New in version 0.18.1.

Frequency tables can also be normalized to show percentages rather than counts using the `normalize` argument:

```
In [76]: pd.crosstab(df.A, df.B, normalize=True)
```
normalize can also normalize values within each row or within each column:

```python
In [77]: pd.crosstab(df.A, df.B, normalize='columns')
Out[77]:
     B 3 4
A    
1 0.5 0.0
2 0.5 1.0
```

crosstab can also be passed a third Series and an aggregation function (aggfunc) that will be applied to the values of the third Series within each group defined by the first two Series:

```python
In [78]: pd.crosstab(df.A, df.B, values=df.C, aggfunc=np.sum)
Out[78]:
     B 3 4
A    
1 1.0 NaN
2 1.0 2.0
```

### 18.6.2 Adding Margins

Finally, one can also add margins or normalize this output.

```python
In [79]: pd.crosstab(df.A, df.B, values=df.C, aggfunc=np.sum, normalize=True,
....:     margins=True)
```

```python
Out[79]:
     B 3 4 All
A    
1 0.25 0.0 0.25
2 0.25 0.5 0.75
All 0.50 0.5 1.00
```

### 18.7 Tiling

The `cut()` function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```python
In [80]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [81]: pd.cut(ages, bins=3)
```

```python
Out[81]:
[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (26.667, 43.333], (43.333, 60.0]
Categories (3, interval[float64]): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60.0]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```python
In [82]: c = pd.cut(ages, bins=[0, 18, 35, 70])

In [83]: c
```

(continues on next page)
New in version 0.20.0.

If the `bins` keyword is an `IntervalIndex`, then these will be used to bin the passed data:

```
pd.cut([25, 20, 50], bins=c.categories)
```

## 18.8 Computing indicator / dummy variables

To convert a categorical variable into a “dummy” or “indicator” DataFrame, for example a column in a DataFrame (a Series) which has \( k \) distinct values, can derive a DataFrame containing \( k \) columns of 1s and 0s using `get_dummies()`:

```
In [84]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})
In [85]: pd.get_dummies(df['key'])
```

```
Out[85]:
   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 [86]: dummies = pd.get_dummies(df['key'], prefix='key')
In [87]: dummies
```

```
Out[87]:
   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 [88]: df[['data1']].join(dummies)
```

```
   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 [89]: values = np.random.randn(10)

In [90]: values
Out[90]:
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29 ,
       0.0824, -0.0558,  0.5366])

In [91]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [92]: pd.get_dummies(pd.cut(values, bins))
Out[92]:

<table>
<thead>
<tr>
<th></th>
<th>(0.0, 0.2]</th>
<th>(0.2, 0.4]</th>
<th>(0.4, 0.6]</th>
<th>(0.6, 0.8]</th>
<th>(0.8, 1.0]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

See also `Series.str.get_dummies`.

`get_dummies()` also accepts a DataFrame. By default all categorical variables (categorical in the statistical sense, those with `object` or `categorical` dtype) are encoded as dummy variables.

In [93]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
                       'C': [1, 2, 3]})

In [94]: pd.get_dummies(df)
Out[94]:

<table>
<thead>
<tr>
<th>C</th>
<th>A_a</th>
<th>A_b</th>
<th>B_b</th>
<th>B_c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

All non-object columns are included untouched in the output. You can control the columns that are encoded with the `columns` keyword.

In [95]: pd.get_dummies(df, columns=['A'])
Out[95]:

<table>
<thead>
<tr>
<th>B</th>
<th>C</th>
<th>A_a</th>
<th>A_b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>c</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>c</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>b</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Notice that the `B` column is still included in the output, it just hasn’t been encoded. You can drop `B` before calling `get_dummies` if you don’t want to include it in the output.

As with the `Series` version, you can pass values for the `prefix` and `prefix_sep`. By default the column name is used as the prefix, and ` '_'` as the prefix separator. You can specify `prefix` and `prefix_sep` in 3 ways:

- string: Use the same value for `prefix` or `prefix_sep` for each column to be encoded.
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix.
Sometimes it will be useful to only keep k-1 levels of a categorical variable to avoid collinearity when feeding the result to statistical models. You can switch to this mode by turn on drop_first.

When a column contains only one level, it will be omitted in the result.
18.9 Factorizing values

To encode 1-d values as an enumerated type use `factorize()`:

```
In [110]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])

In [111]: x
Out[111]:
0    A
1    A
2  NaN
3    B
4  3.14
5     inf
dtype: object

In [112]: labels, uniques = pd.factorize(x)

In [113]: labels
Out[113]: array([ 0,  0, -1,  1,  2,  3])

In [114]: uniques
```

New in version 0.23.0.
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.

```python
In [2]: pd.factorize(x, sort=True)
Out[2]:
(array([ 2, 2, -1, 3, 0, 1]),
     Index([3.14, inf, u'A', u'B'], dtype='object'))

In [3]: np.unique(x, return_inverse=True)[::-1]
Out[3]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

**Note:** If you just want to handle one column as a categorical variable (like R’s `factor`), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on `Categorical`, see the `Categorical introduction` and the `API documentation`.

---

*Chapter 18. Reshaping and Pivot Tables*
pandas has proven very successful as a tool for working with time series data, especially in the financial data analysis space. Using the NumPy `datetime64` and `timedelta64` dtypes, we have consolidated a large number of features from other Python libraries like `scikit.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 = pd.date_range('1/1/2011', periods=72, freq='H')

In [2]: rng[:5]
Out[2]:
```

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2011-01-01 00:00:00</td>
</tr>
<tr>
<td>2011-01-01 01:00:00</td>
</tr>
<tr>
<td>2011-01-01 02:00:00</td>
</tr>
<tr>
<td>2011-01-01 03:00:00</td>
</tr>
<tr>
<td>2011-01-01 04:00:00</td>
</tr>
</tbody>
</table>
```

Index pandas objects with dates:

```python
In [3]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [4]: ts.head()
Out[4]:
```

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2011-01-01 00:00:00</td>
</tr>
<tr>
<td>2011-01-01 01:00:00</td>
</tr>
<tr>
<td>2011-01-01 02:00:00</td>
</tr>
<tr>
<td>2011-01-01 03:00:00</td>
</tr>
<tr>
<td>2011-01-01 04:00:00</td>
</tr>
</tbody>
</table>
```

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')
```

(continues on next page)
Resample the series to a daily frequency:

```python
# Daily means
In [7]: ts.resample('D').mean()
Out[7]:
2011-01-01 -0.319569
2011-01-02 -0.337703
2011-01-03 0.117258
Freq: D, dtype: float64
```

19.1 Overview

The 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 timestamp</td>
<td>to_datetime, Timestamp</td>
</tr>
<tr>
<td>DatetimeIndex</td>
<td>Index of Timestamp</td>
<td>to_datetime, date_range, bdate_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>

19.2 Timestamps vs. Time Spans

Timestamped data is the most basic type of time series data that associates values with points in time. For pandas objects it means using the points in time.

```python
In [8]: pd.Timestamp(datetime(2012, 5, 1))
Out[8]: Timestamp('2012-05-01 00:00:00')
In [9]: pd.Timestamp('2012-05-01')
Out[9]: Timestamp('2012-05-01 00:00:00')
In [10]: pd.Timestamp(2012, 5, 1)
Out[10]: 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:
pandas: powerful Python data analysis toolkit, Release 0.23.1

In [11]: pd.Period('2011-01')
Out[11]: Period('2011-01', 'M')

In [12]: pd.Period('2012-05', freq='D')
Out[12]: Period('2012-05-01', 'D')

Timestamp and Period can serve as an index. Lists of Timestamp and Period are automatically coerced to DatetimeIndex and PeriodIndex respectively.

In [14]: ts = pd.Series(np.random.randn(3), dates)
In [15]: type(ts.index)
Out[15]: pandas.core.indexes.datetimes.DatetimeIndex
In [16]: ts.index
Out[16]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
In [17]: ts
Out[17]:
2012-05-01 -0.410001
2012-05-02 -0.078638
2012-05-03  0.545952
dtype: float64
In [18]: periods = [pd.Period('2012-01'), pd.Period('2012-02'), pd.Period('2012-03')]
In [19]: ts = pd.Series(np.random.randn(3), periods)
In [20]: type(ts.index)
Out[20]: pandas.core.indexes.period.PeriodIndex
In [21]: ts.index
Out[21]: PeriodIndex(['2012-01', '2012-02', '2012-03'], dtype='period[M]', freq='M')
In [22]: ts
Out[22]:
2012-01  -1.219217
2012-02  -1.226825
2012-03   0.769804
Freq: M, dtype: float64

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.

19.2. Timestamps vs. Time Spans 933
19.3 Converting to Timestamps

To convert a `Series` or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the `to_datetime` function. When passed a `Series`, this returns a `Series` (with the same index), while a list-like is converted to a `DatetimeIndex`:

```python
In [23]: pd.to_datetime(pd.Series(['Jul 31, 2009', '2010-01-10', None]))
Out[23]:
0    2009-07-31
1    2010-01-10
2      NaT
dtype: datetime64[ns]
```

```python
In [24]: pd.to_datetime(['2005/11/23', '2010.12.31'])
Out[24]:
\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:

```python
In [25]: pd.to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[25]:
\DatetimeIndex(['2012-01-04 10:00:00'],
dtype='datetime64[ns]', freq=None)
```

```python
In [26]: pd.to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[26]:
\DatetimeIndex(['2012-01-14', '2012-01-14'],
dtype='datetime64[ns]', freq=None)
```

**Warning:** You see in the above example that `dayfirst` isn’t strict, so if a date can’t be parsed with the day being first it will be parsed as if `dayfirst` were False.

If you pass a single string to `to_datetime`, it returns a single `Timestamp`. `Timestamp` can also accept string input, but it doesn’t accept string parsing options like `dayfirst` or `format`, so use `to_datetime` if these are required.

```python
In [27]: pd.to_datetime('2010/11/12')
Out[27]:
\Timestamp('2010-11-12 00:00:00')
```

```python
In [28]: pd.Timestamp('2010/11/12')
Out[28]:
\Timestamp('2010-11-12 00:00:00')
```

19.3.1 Providing a Format Argument

In addition to the required datetime string, a `format` argument can be passed to ensure specific parsing. This could also potentially speed up the conversion considerably.

```python
In [29]: pd.to_datetime('2010/11/12', format='%Y/%m/%d')
Out[29]:
\Timestamp('2010-11-12 00:00:00')
```

```python
In [30]: pd.to_datetime('12-11-2010 00:00', format='%d-%m-%Y %H:%M')
Out[30]:
\Timestamp('2010-11-12 00:00:00')
```

For more information on the choices available when specifying the `format` option, see the Python `datetime` documentation.
19.3.2 Assembling Datetime from Multiple DataFrame Columns

New in version 0.18.1.

You can also pass a DataFrame of integer or string columns to assemble into a Series of Timestamps.

```
In [31]: df = pd.DataFrame({'year': [2015, 2016],
        ....:                'month': [2, 3],
        ....:                'day': [4, 5],
        ....:                'hour': [2, 3]})

In [32]: pd.to_datetime(df)
Out[32]:
0  2015-02-04 02:00:00
1  2016-03-05 03:00:00
dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```
In [33]: pd.to_datetime(df[['year', 'month', 'day']])
Out[33]:
0  2015-02-04
1  2016-03-05
dtype: datetime64[ns]
```

`pd.to_datetime` looks for standard designations of the datetime component in the column names, including:

- **required**: `year`, `month`, `day`
- **optional**: `hour`, `minute`, `second`, `millisecond`, `microsecond`, `nanosecond`

19.3.3 Invalid Data

The default behavior, `errors='raise'`, is to raise when unparsable:

```
In [2]: pd.to_datetime(['2009/07/31', 'asd'], errors='raise')
ValueError: Unknown string format
```

Pass `errors='ignore'` to return the original input when unparsable:

```
In [34]: pd.to_datetime(['2009/07/31', 'asd'], errors='ignore')
Out[34]: array(['2009/07/31', 'asd'], dtype=object)
```

Pass `errors='coerce'` to convert unparsable data to `NaT` (not a time):

```
In [35]: pd.to_datetime(['2009/07/31', 'asd'], errors='coerce')
Out[35]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
```

19.3.4 Epoch Timestamps

`pandas` supports converting integer or float epoch times to `Timestamp` and `DatetimeIndex`. The default unit is nanoseconds, since that is how `Timestamp` objects are stored internally. However, epochs are often stored in another unit which can be specified. These are computed from the starting point specified by the `origin` parameter.
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```
In [36]: pd.to_datetime([1349720105, 1349806505, 1349892905,
                     1349979305, 1350065705], unit='s')
Out[36]:
             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 [37]: pd.to_datetime([1349720105100, 1349720105200, 1349720105300,
                     1349720105400, 1349720105500], unit='ms')
Out[37]:
          DatetimeIndex(['2012-10-08 18:15:05.100000', '2012-10-08 18:15:05.200000',
                         '2012-10-08 18:15:05.300000', '2012-10-08 18:15:05.400000',
                         '2012-10-08 18:15:05.500000'],
                         dtype='datetime64[ns]', freq=None)

Note: Epoch times will be rounded to the nearest nanosecond.

Warning: Conversion of float epoch times can lead to inaccurate and unexpected results. Python floats have about 15 digits precision in decimal. Rounding during conversion from float to high precision Timestamp is unavoidable. The only way to achieve exact precision is to use a fixed-width types (e.g. an int64).

In [38]: pd.to_datetime([1490195805.433, 1490195805.433502912], unit='s')
Out[38]:
          DatetimeIndex(['2017-03-22 15:16:45.433000088', '2017-03-22 15:16:45.433502913'],
                         dtype='datetime64[ns]', freq=None)

In [39]: pd.to_datetime(1490195805433502912, unit='ns')
Out[39]:
          Timestamp('2017-03-22 15:16:45.433502912')

See also: Using the origin Parameter

19.3.5 From Timestamps to Epoch

To invert the operation from above, namely, to convert from a Timestamp to a ‘unix’ epoch:

In [40]: stamps = pd.date_range('2012-10-08 18:15:05', periods=4, freq='D')
In [41]: stamps
Out[41]:
          DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
                         '2012-10-10 18:15:05', '2012-10-11 18:15:05'],
                         dtype='datetime64[ns]', freq='D')

We subtract the epoch (midnight at January 1, 1970 UTC) and then floor divide by the “unit” (1 second).

In [42]: (stamps - pd.Timestamp("1970-01-01")) // pd.Timedelta('1s')
Out[42]:
          Int64Index([1349720105, 1349806505, 1349892905, 1349979305], dtype='int64')
19.3.6 Using the origin Parameter

New in version 0.20.0.

Using the `origin` parameter, one can specify an alternative starting point for creation of a `DatetimeIndex`. For example, to use 1960-01-01 as the starting date:

```python
In [43]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[43]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype='datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00. Commonly called ‘unix epoch’ or POSIX time.

```python
In [44]: pd.to_datetime([1, 2, 3], unit='D')
Out[44]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype='datetime64[ns]', freq=None)
```

19.4 Generating Ranges of Timestamps

To generate an index with timestamps, you can use either the `DatetimeIndex` or `Index` constructor and pass in a list of datetime objects:

```python
In [45]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]
# Note the frequency information
In [46]: index = pd.DatetimeIndex(dates)

In [47]: index
Out[47]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)

# Automatically converted to DatetimeIndex
In [48]: index = pd.Index(dates)

In [49]: index
Out[49]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

In practice this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the `date_range()` and `bdate_range()` functions to create a `DatetimeIndex`. The default frequency for `date_range` is a calendar day while the default for `bdate_range` is a business day:

```python
In [50]: start = datetime(2011, 1, 1)
In [51]: end = datetime(2012, 1, 1)
In [52]: index = pd.date_range(start, end)

In [53]: index
  '2011-01-09', '2011-01-10'],
  dtype='datetime64[ns]', freq='D')
```

(continues on next page)
... '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 [54]: index = pd.bdate_range(start, end)

In [55]: index
Out[55]:
               '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=366, freq='D')

Convenience functions like `date_range` and `bdate_range` can utilize a variety of frequency aliases:

In [56]: pd.date_range(start, periods=1000, freq='M')
Out[56]:
               '2011-09-30', '2011-10-31',
               ...
'2093-07-31', '2093-08-31', '2093-09-30', '2093-10-31',
'2093-11-30', '2093-12-31', '2094-01-31', '2094-02-28',
'2094-03-31', '2094-04-30'],
dtype='datetime64[ns]', length=1000, freq='M')

In [57]: pd.bdate_range(start, periods=250, freq='BQS')

               '2012-01-01', '2012-04-02', '2012-07-02', '2012-10-01',
               '2013-01-01', '2013-04-01',
               ...
'2071-01-01', '2071-04-01', '2071-07-01', '2071-10-01',
'2072-01-01', '2072-04-02', '2072-07-02', '2072-10-03',
'2073-01-02', '2073-04-03'],
dtype='datetime64[ns]', length=250, freq='BQS-JAN')

date_range and bdate_range make it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`. The start and end dates are strictly inclusive, so dates outside of those specified will not be generated:

In [58]: pd.date_range(start, end, freq='BM')
Out[58]:
dtype='datetime64[ns]', freq='BM')

In [59]: pd.date_range(start, end, freq='W')

(continues on next page)
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               '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 [60]: pd.bdate_range(end=end, periods=20)

Out[60]:

DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-10', '2011-12-11', '2011-12-12',
               '2011-12-13', '2011-12-14', '2011-12-15', '2011-12-16',
               '2011-12-17', '2011-12-18', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-24',
               '2011-12-25', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
                      dtype='datetime64[ns]', freq='B')

In [61]: pd.bdate_range(start=start, periods=20)

Out[61]:

                      dtype='datetime64[ns]', freq='B')

New in version 0.23.0.

Specifying start, end, and periods will generate a range of evenly spaced dates from start to end inclusively, with periods number of elements in the resulting DatetimeIndex:

In [62]: pd.date_range('2018-01-01', '2018-01-05', periods=5)
Out[62]:

               '2018-01-05'],
                      dtype='datetime64[ns]', freq=None)

In [63]: pd.date_range('2018-01-01', '2018-01-05', periods=10)

Out[63]:

DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 01:00:00',
               '2018-01-01 02:00:00', '2018-01-01 03:00:00',
               '2018-01-01 04:00:00', '2018-01-01 05:00:00',
               '2018-01-01 06:00:00', '2018-01-01 07:00:00',
               '2018-01-01 08:00:00', '2018-01-01 09:00:00',
               '2018-01-01 10:00:00', '2018-01-01 11:00:00',
               '2018-01-01 12:00:00', '2018-01-01 13:00:00',
               '2018-01-01 14:00:00', '2018-01-01 15:00:00',
               '2018-01-01 16:00:00', '2018-01-01 17:00:00',
               '2018-01-01 18:00:00', '2018-01-01 19:00:00',
               '2018-01-01 20:00:00', '2018-01-01 21:00:00',
               '2018-01-01 22:00:00', '2018-01-01 23:00:00'],
                      dtype='datetime64[ns]', freq=None)
19.4.1 Custom Frequency Ranges

**Warning:** This functionality was originally exclusive to `cdate_range`, which is deprecated as of version 0.21.0 in favor of `bdate_range`. Note that `cdate_range` only utilizes the `weekmask` and `holidays` parameters when custom business day, 'C', is passed as the frequency string. Support has been expanded with `bdate_range` to work with any custom frequency string.

New in version 0.21.0.

`bdate_range` can also generate a range of custom frequency dates by using the `weekmask` and `holidays` parameters. These parameters will only be used if a custom frequency string is passed.

```python
In [64]: weekmask = 'Mon Wed Fri'
In [65]: holidays = [datetime(2011, 1, 5), datetime(2011, 3, 14)]
In [66]: pd.bdate_range(start, end, freq='C', weekmask=weekmask, holidays=holidays)
Out[66]:
   '2011-01-24', '2011-01-26',
   ...
   '2011-12-09', '2011-12-12', '2011-12-14', '2011-12-16',
   '2011-12-19', '2011-12-21', '2011-12-23', '2011-12-26',
   '2011-12-28', '2011-12-30'],
   dtype='datetime64[ns]', length=154, freq='C')
```

```python
In [67]: pd.bdate_range(start, end, freq='CBMS', weekmask=weekmask)
```

See also:

*Custom Business Days*

19.5 Timestamp Limitations

Since pandas represents timestamps in nanosecond resolution, the time span that can be represented using a 64-bit integer is limited to approximately 584 years:

```python
In [68]: pd.Timestamp.min
Out[68]: Timestamp('1677-09-21 00:12:43.145225')
```

```python
In [69]: pd.Timestamp.max
```
See also:
Representing Out-of-Bounds Spans

19.6 Indexing

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many time series related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice).
- Fast shifting using the `shift` 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 have all the basic functionality of regular `Index` objects, and a smorgasbord of advanced time series specific methods for easy frequency processing.

See also:
Reindexing methods

Note: While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted.

`DatetimeIndex` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```python
In [70]: rng = pd.date_range(start, end, freq='BM')
In [71]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
In [72]: ts.index
dtype='datetime64[ns]', freq='BM')
In [73]: ts[:5].index
dtype='datetime64[ns]', freq='BM')
In [74]: ts[::2].index
```

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19.6.1 Partial String Indexing

Dates and strings that parse to timestamps can be passed as indexing parameters:

```python
In [75]: ts['1/31/2011']
Out[75]: -1.2812473076599531

In [76]: ts[datetime(2011, 12, 25):]
   ...:
Out[76]:
2011-12-30 0.687738
Freq: BM, dtype: float64

In [77]: ts['10/31/2011':'12/31/2011']
   ...:
Out[77]:
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:

```python
In [78]: ts['2011']
Out[78]:
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 [79]: ts['2011-6']
```

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:

```python
In [80]: dft = pd.DataFrame(randn(100000,1),
   ....:     index=pd.date_range('20130101',periods=100000,freq='T'))
```

(continues on next page)
In [81]: dft
Out[81]:
    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]

In [82]: dft['2013']
    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 and time for the month:

In [83]: dft["2013-1":"2013-2"]
    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]

(continues on next page)
This specifies a stop time that includes all of the times on the last day:

```
In [84]: dft['2013-1':'2013-2-28']
Out[84]:
    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
   ...         ...          ...
2013-02-28 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
[84960 rows x 1 columns]
```

This specifies an exact stop time (and is not the same as the above):

```
In [85]: dft['2013-1':'2013-2-28 00:00:00']
Out[85]:
    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]
```

We are stopping on the included end-point as it is part of the index:
In [86]: dft['2013-1-15':'2013-1-15 12:30:00']
Out[86]:
    A
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
2013-01-15 00:06:00  -1.188774
... ... 
2013-01-15 12:24:00  1.358314
2013-01-15 12:25:00  -0.737727
2013-01-15 12:26:00  1.838323
2013-01-15 12:27:00  -0.774090
2013-01-15 12:28:00  0.622261
2013-01-15 12:29:00  -0.631649
2013-01-15 12:30:00  0.193284
[751 rows x 1 columns]

New in version 0.18.0.

DatetimeIndex partial string indexing also works on a DataFrame with a MultiIndex:

In [87]: dft2 = pd.DataFrame(np.random.randn(20, 1),
                        columns=['A'],
                        index=pd.MultiIndex.from_product([pd.date_range('20130101'
                                -> ',
                        periods=10,
                        freq='12H'
                        )))

In [88]: dft2
Out[88]:
    A
2013-01-01 00:00:00  a  -0.659574
   b  1.494522
2013-01-01 12:00:00  a  -0.778425
   b  -0.253355
2013-01-02 00:00:00  a  -2.816159
   b  -1.210929
2013-01-02 12:00:00  a  0.144669
   b  -0.631649
... ... 
2013-01-04 00:00:00  b  -1.624463
2013-01-04 12:00:00  a  0.056912
   b  0.149867
2013-01-05 00:00:00  a  -1.256173
   b  2.324544
2013-01-05 12:00:00  a  -1.067396
   b  -0.660996
[20 rows x 1 columns]

In [89]: dft2.loc['2013-01-05']
(continues on next page)
19.6.2 Slice vs. Exact Match

Changed in version 0.20.0.

The same string used as an indexing parameter can be treated either as a slice or as an exact match depending on the resolution of the index. If the string is less accurate than the index, it will be treated as a slice, otherwise as an exact match.

Consider a Series object with a minute resolution index:

```python
In [93]: series_minute = pd.Series([1, 2, 3],
                              pd.DatetimeIndex(['2011-12-31 23:59:00',
                              '2012-01-01 00:00:00',
                              '2012-01-01 00:02:00']))

In [94]: series_minute.index.resolution
Out[94]: 'minute'
```

A timestamp string less accurate than a minute gives a Series object.

```python
In [95]: series_minute['2011-12-31 23']
Out[95]:
2011-12-31 23:59:00    1
dtype: int64
```

A timestamp string with minute resolution (or more accurate), gives a scalar instead, i.e. it is not casted to a slice.

```python
In [96]: series_minute['2011-12-31 23:59']
Out[96]: 1
```

```python
In [97]: series_minute['2011-12-31 23:59:00']

Out[97]: 1
```

If index resolution is second, then the minute-accurate timestamp gives a Series.
In [98]: series_second = pd.Series([1, 2, 3],
                        index=pd.DatetimeIndex(['2011-12-31 23:59:59',
                        '2012-01-01 00:00:00',
                        '2012-01-01 00:00:01']))
In [99]: series_second.index.resolution
Out[99]: 'second'
In [100]: series_second['2011-12-31 23:59']
Out[100]:

If the timestamp string is treated as a slice, it can be used to index DataFrame with [] as well.

In [101]: dft_minute = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6]},
                          index=series_minute.index)
In [102]: dft_minute['2011-12-31 23:59']
Out[102]:

Warning: However, if the string is treated as an exact match, the selection in DataFrame's [] will be column-wise and not row-wise, see Indexing Basics. For example dft_minute['2011-12-31 23:59'] will raise KeyError as '2012-12-31 23:59' has the same resolution as the index and there is no column with such name:

To always have unambiguous selection, whether the row is treated as a slice or a single selection, use .loc.

In [103]: dft_minute.loc['2011-12-31 23:59']
Out[103]:

Note also that DatetimeIndex resolution cannot be less precise than day.

In [104]: series_monthly = pd.Series([1, 2, 3],
                        index=pd.DatetimeIndex(['2011-12',
                        '2012-01',
                        '2012-02']))
In [105]: series_monthly.index.resolution
Out[105]: 'day'
In [106]: series_monthly['2011-12'] # returns Series
Out[106]:

19.6. Indexing
19.6.3 Exact Indexing

As discussed in previous section, indexing a DatetimeIndex with a partial string depends on the “accuracy” of the period, in other words how specific the interval is in relation to the resolution of the index. In contrast, indexing with Timestamp or datetime objects is exact, because the objects have exact meaning. These also follow the semantics of including both endpoints.

These Timestamp and datetime objects have exact hours, minutes, and seconds, even though they were not explicitly specified (they are 0).

In [107]: dft[datetime(2013, 1, 1):datetime(2013,2,28)]
Out[107]:
      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.

In [108]: dft[datetime(2013, 1, 1, 10, 12, 0):datetime(2013,2,28,10,12,0)]
Out[108]:
      A
2013-01-01 10:12:00 -0.246733
2013-01-01 10:13:00 -1.429225
2013-01-01 10:14:00 -1.265339
2013-01-01 10:15:00  0.710986
2013-01-01 10:16:00 -0.818200
2013-01-01 10:17:00  0.543542
2013-01-01 10:18:00  1.577713
   ...         ...    ...
2013-02-27 23:56:00  0.897051
2013-02-27 23:57:00 -0.309230
2013-02-27 23:58:00  1.944713
2013-02-27 23:59:00 -0.019734
2013-02-28 00:00:00  1.388189

[83521 rows x 1 columns]
19.6.4 Truncating & Fancy Indexing

A `truncate()` convenience function is provided that is similar to slicing. Note that `truncate` assumes a 0 value for any unspecified date component in a `DatetimeIndex` in contrast to slicing which returns any partially matching dates:

```
In [109]: rng2 = pd.date_range('2011-01-01', '2012-01-01', freq='W')
In [110]: ts2 = pd.Series(np.random.randn(len(rng2)), index=rng2)
In [111]: ts2.truncate(before='2011-11', after='2011-12')
Out[111]:
2011-11-06 -0.773743
2011-11-13 0.247216
2011-11-20 0.591308
2011-11-27 2.228500
Freq: W-SUN, dtype: float64
```

```
In [112]: ts2['2011-11':'2011-12']
```

Even complicated fancy indexing that breaks the `DatetimeIndex` frequency regularity will result in a `DatetimeIndex`, although frequency is lost:

```
In [113]: ts2[[0, 2, 6]].index
Out[113]: DatetimeIndex(['2011-01-02', '2011-01-16', '2011-02-13'], dtype='datetime64[ns]', freq=None)
```

19.7 Time/Date Components

There are several time/date properties that one can access from `Timestamp` or a collection of timestamps like a `DatetimeIndex`. 
## 19.8 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 `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</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>
</tbody>
</table>
## Table 1 – continued from previous page

<table>
<thead>
<tr>
<th>Class name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBMonthBegin</td>
<td>custom business month begin</td>
</tr>
<tr>
<td>SemiMonthEnd</td>
<td>15th (or other day_of_month) and calendar month end</td>
</tr>
<tr>
<td>SemiMonthBegin</td>
<td>15th (or other day_of_month) and calendar 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>CustomBusinessHour</td>
<td>custom 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 as follows:

```python
In [114]: d = datetime(2008, 8, 18, 9, 0)

In [115]: d + relativedelta(months=4, days=5)
Out[115]: datetime.datetime(2008, 12, 23, 9, 0)
```

We could have done the same thing with `DateOffset`:

```python
In [116]: from pandas.tseries.offsets import *

In [117]: d + DateOffset(months=4, days=5)
Out[117]: 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:

```python
class BDay(DateOffset):
    """DateOffset increments between business days""
    def apply(self, other):
        ...
```

### 19.8. DateOffset Objects
In [118]: d - 5 * BDay()
Out[118]: Timestamp('2008-08-11 09:00:00')

In [119]: d + BMonthEnd()
Out[119]: Timestamp('2008-08-29 09:00:00')

The rollforward and rollback methods do exactly what you would expect:

In [120]: d
Out[120]: datetime.datetime(2008, 8, 18, 9, 0)

In [121]: offset = BMonthEnd()

In [122]: offset.rollforward(d)
Out[122]: Timestamp('2008-08-29 09:00:00')

In [123]: offset.rollback(d)
Out[123]: 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) preserve time (hour, minute, etc) information by default. To reset time, use normalize=True when creating the offset instance. If normalize=True, the result is normalized after the function is applied.

In [124]: day = Day()

In [125]: day.apply(pd.Timestamp('2014-01-01 09:00'))
Out[125]: Timestamp('2014-01-02 09:00:00')

In [126]: day = Day(normalize=True)

In [127]: day.apply(pd.Timestamp('2014-01-01 09:00'))
Out[127]: Timestamp('2014-01-02 00:00:00')

In [128]: hour = Hour()

In [129]: hour.apply(pd.Timestamp('2014-01-01 22:00'))
Out[129]: Timestamp('2014-01-01 23:00:00')

In [130]: hour = Hour(normalize=True)

In [131]: hour.apply(pd.Timestamp('2014-01-01 22:00'))
Out[131]: Timestamp('2014-01-01 00:00:00')

In [132]: hour.apply(pd.Timestamp('2014-01-01 23:00'))
Out[132]: Timestamp('2014-01-02 00:00:00')

19.8.1 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 [133]: d
Out[133]: datetime.datetime(2008, 8, 18, 9, 0)
In [134]: d + Week()
Out[134]: Timestamp('2008-08-25 09:00:00')

In [135]: d + Week(weekday=4)
Out[135]: Timestamp('2008-08-22 09:00:00')

In [136]: (d + Week(weekday=4)).weekday()
Out[136]: 4

In [137]: d - Week()
Out[137]: Timestamp('2008-08-11 09:00:00')

The `normalize` option will be effective for addition and subtraction.

In [138]: d + Week(normalize=True)
Out[138]: Timestamp('2008-08-25 00:00:00')

In [139]: d - Week(normalize=True)
Out[139]: Timestamp('2008-08-11 00:00:00')

Another example is parameterizing `YearEnd` with the specific ending month:

In [140]: d + YearEnd()
Out[140]: Timestamp('2008-12-31 09:00:00')

In [141]: d + YearEnd(month=6)
Out[141]: Timestamp('2009-06-30 09:00:00')

### 19.8.2 Using Offsets with Series / DatetimeIndex

Offsets can be used with either a `Series` or `DatetimeIndex` to apply the offset to each element.

In [142]: rng = pd.date_range('2012-01-01', '2012-01-03')

In [143]: s = pd.Series(rng)

In [144]: rng
Out[144]: DatetimeIndex(['2012-01-01', '2012-01-02', '2012-01-03'], dtype='datetime64[ns]', freq='D')

In [145]: rng + DateOffset(months=2)
Out[145]: DatetimeIndex(['2012-03-01', '2012-03-02', '2012-03-03'], dtype='datetime64[ns]', freq='D')

In [146]: s + DateOffset(months=2)
Out[146]:
   0  2012-03-01
   1  2012-03-02
2  2012-03-03
dtype: datetime64[ns]

In [147]: s - DateOffset(months=2)
   →
0  2011-11-01
1  2011-11-02
2  2011-11-03
dtype: datetime64[ns]

If the offset class maps directly to a Timedelta (Day, Hour, Minute, Second, Micro, Milli, Nano) it can be
used exactly like a Timedelta - see the Timedelta section for more examples.

In [148]: s - Day(2)
Out[148]:
0  2011-12-30
1  2011-12-31
2  2012-01-01
dtype: datetime64[ns]

In [149]: td = s - pd.Series(pd.date_range('2011-12-29', '2011-12-31'))

In [150]: td
Out[150]:
0  3 days
1  3 days
2  3 days
dtype: timedelta64[ns]

In [151]: td + Minute(15)
   →
Out[151]:
0  3 days 00:15:00
1  3 days 00:15:00
2  3 days 00:15:00
dtype: timedelta64[ns]

Note that some offsets (such as BQuarterEnd) do not have a vectorized implementation. They can still be used but
may calculate significantly slower and will show a PerformanceWarning

In [152]: rng + BQuarterEnd()
Out[152]: DatetimeIndex(['2012-03-30', '2012-03-30', '2012-03-30'], dtype=
˓→'datetime64[ns]', freq='D')

19.8.3 Custom Business Days

The CDay or CustomBusinessDay class provides a parametric BusinessDay class which can be used to create
customized business day calendars which account for local holidays and local weekend conventions.

As an interesting example, let's look at Egypt where a Friday-Saturday weekend is observed.

In [153]: from pandas.tseries.offsets import CustomBusinessDay

In [154]: weekmask_egypt = 'Sun Mon Tue Wed Thu'
They also observe International Workers' Day so let's add that for a couple of years:

```
In [155]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]

In [156]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [157]: dt = datetime(2013, 4, 30)

In [158]: dt + 2 * bday_egypt
```

Out[158]: Timestamp('2013-05-05 00:00:00')

Let's map to the weekday names:

```
In [159]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)

In [160]: pd.Series(dts.weekday, dts).map(pd.Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
```

Out[160]:

| 2013-04-30Tue
| 2013-05-02Thu
| 2013-05-05Sun
| 2013-05-06Mon
| 2013-05-07Tue

Freq: C, dtype: object

Holiday calendars can be used to provide the list of holidays. See the holiday calendar section for more information.

```
In [161]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [162]: bday_us = CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [163]: dt = datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [164]: dt + bday_us
```

Out[164]: Timestamp('2014-01-21 00:00:00')

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [165]: from pandas.tseries.offsets import CustomBusinessMonthBegin

In [166]: bmth_us = CustomBusinessMonthBegin(calendar=USFederalHolidayCalendar())

# Skip new years
In [167]: dt = datetime(2013, 12, 17)

In [168]: dt + bmth_us
```

Out[168]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
```
In [169]: pd.DatetimeIndex(start='20100101', end='20120101', freq=bmth_us)
```

(continues on next page)
'2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
dtype='datetime64[ns]', freq='CBMS')

Note: The frequency string ‘C’ is used to indicate that a CustomBusinessDay DateOffset is used, it is important to
note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is
not detectable from the ‘C’ frequency string. The user therefore needs to ensure that the ‘C’ frequency string is used
consistently within the user’s application.

19.8.4 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 frequency. If target Timestamp is out of business hours, move to the next business hour
then increment it. If the result exceeds the business hours end, the remaining hours are added to the next business day.

```
In [170]: bh = BusinessHour()

In [171]: bh
Out[171]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [172]: pd.Timestamp('2014-08-01 10:00').weekday()

Out[172]: 4

In [173]: pd.Timestamp('2014-08-01 10:00') + bh

Out[173]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as: pd.Timestamp('2014-08-01 09:00') + bh
In [174]: pd.Timestamp('2014-08-01 08:00') + bh

Out[174]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [175]: pd.Timestamp('2014-08-01 16:00') + bh

Out[175]: Timestamp('2014-08-02 09:00:00')

# Remainings are added to the next day
In [176]: pd.Timestamp('2014-08-01 16:30') + bh

Out[176]: Timestamp('2014-08-02 09:30:00')

# Adding 2 business hours
In [177]: pd.Timestamp('2014-08-01 10:00') + BusinessHour(2)

Out[177]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
```

(continues on next page)
In [178]: pd.Timestamp('2014-08-01 10:00') + BusinessHour(-3)
→ Timestamp('2014-07-31 15:00:00')

You can also specify start and end time by keywords. The argument must be a str with an hour:minute representation or a datetime.time instance. Specifying seconds, microseconds and nanoseconds as business hour results in ValueError.

In [179]: bh = BusinessHour(start='11:00', end=time(20, 0))
In [180]: bh
Out[180]: <BusinessHour: BH=11:00-20:00>
In [181]: pd.Timestamp('2014-08-01 13:00') + bh
→ Timestamp('2014-08-01 14:00:00')
In [182]: pd.Timestamp('2014-08-01 09:00') + bh
→ Timestamp('2014-08-01 12:00:00')
In [183]: pd.Timestamp('2014-08-01 18:00') + bh
→ Timestamp('2014-08-01 19:00:00')

Passing start time later than end represents midnight business hour. In this case, business hour exceeds midnight and overlap to the next day. Valid business hours are distinguished by whether it started from valid BusinessDay.

In [184]: bh = BusinessHour(start='17:00', end='09:00')
In [185]: bh
Out[185]: <BusinessHour: BH=17:00-09:00>
In [186]: pd.Timestamp('2014-08-01 17:00') + bh
→ Timestamp('2014-08-01 18:00:00')
In [187]: pd.Timestamp('2014-08-01 21:00') + bh
→ Timestamp('2014-08-02 00:00:00')

# Although 2014-08-02 is Saturday,
# it is valid because it starts from 08-01 (Friday).
In [188]: pd.Timestamp('2014-08-02 04:00') + bh
→ Timestamp('2014-08-02 05:00:00')

# Although 2014-08-04 is Monday,
# it is out of business hours because it starts from 08-03 (Sunday).
In [189]: pd.Timestamp('2014-08-04 04:00') + bh
→ Timestamp('2014-08-04 18:00:00')

Applying BusinessHour.rollforward and rollback to out of business hours results in the next business hour start or previous day’s end. Different from other offsets, BusinessHour.rollforward may output different results from apply by definition.

This is because one day’s business hour end is equal to next day’s business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between 2014-08-01 17:00 and 2014-08-04...
# This adjusts a Timestamp to business hour edge

```
In [190]: BusinessHour().rollback(pd.Timestamp('2014-08-02 15:00'))
Out[190]: Timestamp('2014-08-01 17:00:00')
```

```
In [191]: BusinessHour().rollforward(pd.Timestamp('2014-08-02 15:00'))
Out[191]: Timestamp('2014-08-04 09:00:00')
```

# It is the same as BusinessHour().apply(pd.Timestamp('2014-08-01 17:00')).
# And it is the same as BusinessHour().apply(pd.Timestamp('2014-08-04 09:00'))

```
In [192]: BusinessHour().apply(pd.Timestamp('2014-08-02 15:00'))
Out[192]: Timestamp('2014-08-04 10:00:00')
```

BusinessHour regards Saturday and Sunday as holidays. To use arbitrary holidays, you can use `CustomBusinessHour` offset, as explained in the following subsection.

### 19.8.5 Custom Business Hour

New in version 0.18.1.

The `CustomBusinessHour` is a mixture of `BusinessHour` and `CustomBusinessDay` which allows you to specify arbitrary holidays. `CustomBusinessHour` works as the same as `BusinessHour` except that it skips specified custom holidays.

```
In [195]: from pandas.tseries.holiday import USFederalHolidayCalendar
```

```
In [196]: bhour_us = CustomBusinessHour(calendar=USFederalHolidayCalendar())
```

```
# Friday before MLK Day
In [197]: dt = datetime(2014, 1, 17, 15)

In [198]: dt + bhour_us
Out[198]: Timestamp('2014-01-17 16:00:00')
```

# Tuesday after MLK Day (Monday is skipped because it's a holiday)

```
In [199]: dt + bhour_us * 2
Out[199]: Timestamp('2014-01-21 09:00:00')
```

You can use keyword arguments supported by either `BusinessHour` and `CustomBusinessDay`.

```
In [200]: bhour_mon = CustomBusinessHour(start='10:00', weekmask='Tue Wed Thu Fri')
```

# Monday is skipped because it's a holiday, business hour starts from 10:00

(continues on next page)
19.8.6 Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as offset aliases.

<table>
<thead>
<tr>
<th>Alias</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>business day frequency</td>
</tr>
<tr>
<td>C</td>
<td>custom business day frequency</td>
</tr>
<tr>
<td>D</td>
<td>calendar day frequency</td>
</tr>
<tr>
<td>W</td>
<td>weekly frequency</td>
</tr>
<tr>
<td>M</td>
<td>month end frequency</td>
</tr>
<tr>
<td>SM</td>
<td>semi-month end frequency (15th and end of month)</td>
</tr>
<tr>
<td>BM</td>
<td>business month end frequency</td>
</tr>
<tr>
<td>CBM</td>
<td>custom business month end frequency</td>
</tr>
<tr>
<td>MS</td>
<td>month start frequency</td>
</tr>
<tr>
<td>SMS</td>
<td>semi-month start frequency (1st and 15th)</td>
</tr>
<tr>
<td>BMS</td>
<td>business month start frequency</td>
</tr>
<tr>
<td>CBMS</td>
<td>custom business month start frequency</td>
</tr>
<tr>
<td>Q</td>
<td>quarter end frequency</td>
</tr>
<tr>
<td>BQ</td>
<td>business quarter end frequency</td>
</tr>
<tr>
<td>QS</td>
<td>quarter start frequency</td>
</tr>
<tr>
<td>BQS</td>
<td>business quarter start frequency</td>
</tr>
<tr>
<td>A, Y</td>
<td>year end frequency</td>
</tr>
<tr>
<td>BA, BY</td>
<td>business year end frequency</td>
</tr>
<tr>
<td>AS, YS</td>
<td>year start frequency</td>
</tr>
<tr>
<td>BAS, BYS</td>
<td>business year start frequency</td>
</tr>
<tr>
<td>BH</td>
<td>business hour frequency</td>
</tr>
<tr>
<td>H</td>
<td>hourly frequency</td>
</tr>
<tr>
<td>T, min</td>
<td>minutely frequency</td>
</tr>
<tr>
<td>S</td>
<td>secondly frequency</td>
</tr>
<tr>
<td>L, ms</td>
<td>milliseconds</td>
</tr>
<tr>
<td>U, us</td>
<td>microseconds</td>
</tr>
<tr>
<td>N</td>
<td>nanoseconds</td>
</tr>
</tbody>
</table>

19.8.7 Combining Aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

In [202]: pd.date_range(start, periods=5, freq='B')
Out[202]:
dtype='datetime64[ns]', freq='B')

In [203]: pd.date_range(start, periods=5, freq=BDay())

(continues on next page)
You can combine together day and intraday offsets:

```python
In [204]: pd.date_range(start, periods=10, freq='2h20min')
Out[204]:
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')
```

You can use anchored offsets:

```python
In [205]: pd.date_range(start, periods=10, freq='1D10U')
```

<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>
</tbody>
</table>
Table 2 – continued from previous page

<table>
<thead>
<tr>
<th>Alias</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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.

### 19.8.9 Anchored Offset Semantics

For those offsets that are anchored to the start or end of specific frequency (`MonthEnd`, `MonthBegin`, `WeekEnd`, etc), the following rules apply to rolling forward and backwards.

When \( n \) is not 0, if the given date is not on an anchor point, it snapped to the next(previous) anchor point, and moved \(|n| - 1\) additional steps forwards or backwards.

```python
In [206]: pd.Timestamp('2014-01-02') + MonthBegin(n=1)
Out[206]: Timestamp('2014-02-01 00:00:00')

In [207]: pd.Timestamp('2014-01-02') + MonthEnd(n=1)
Out[207]: Timestamp('2014-01-31 00:00:00')
```

(continues on next page)
If the given date is on an anchor point, it is moved \(|n|\) points forwards or backwards.

For the case when \(n=0\), the date is not moved if on an anchor point, otherwise it is rolled forward to the next anchor point.
19.8.10 Holidays / Holiday Calendars

Holidays and calendars provide a simple way to define holiday rules to be used with CustomBusinessDay or in other analysis that requires a predefined set of holidays. The AbstractHolidayCalendar class provides all the necessary methods to return a list of holidays and only rules need to be defined in a specific holiday calendar class. Furthermore, the start_date and end_date class attributes determine over what date range holidays are generated. These should be overwritten on the AbstractHolidayCalendar class to have the range apply to all calendar subclasses. USFederalHolidayCalendar is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

<table>
<thead>
<tr>
<th>Rule</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>nearest_workday</td>
<td>move Saturday to Friday and Sunday to Monday</td>
</tr>
<tr>
<td>sunday_to_monday</td>
<td>move Sunday to following Monday</td>
</tr>
<tr>
<td>next_monday_or_tuesday</td>
<td>Saturday to Monday and Sunday/Monday to Tuesday</td>
</tr>
<tr>
<td>previous_friday</td>
<td>move Saturday and Sunday to previous Friday</td>
</tr>
<tr>
<td>next_monday</td>
<td>move Saturday and Sunday to following Monday</td>
</tr>
</tbody>
</table>

An example of how holidays and holiday calendars are defined:

In [222]: from pandas.tseries.holiday import Holiday, USMemorialDay, AbstractHolidayCalendar, nearest_workday, MO

In [223]: 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 [224]: cal = ExampleCalendar()

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th). For example, the below defines a custom business day offset using the ExampleCalendar. Like any other offset, it can be used to create a DatetimeIndex or added to datetime or Timestamp objects.

In [226]: from pandas.tseries.offsets import CDay

In [227]: pd.DatetimeIndex(start='7/1/2012', end='7/10/2012',
                        freq=CDay(calendar=cal)).to_pydatetime()

Out[227]: 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='datetime64[ns]')

(continues on next page)
Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are shown below.

```python
In [233]: AbstractHolidayCalendar.start_date
Out[233]: Timestamp('1970-01-01 00:00:00')

In [234]: AbstractHolidayCalendar.end_date
Out[234]: Timestamp('2030-12-31 00:00:00')
```

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

```python
In [235]: AbstractHolidayCalendar.start_date = datetime(2012, 1, 1)
In [236]: AbstractHolidayCalendar.end_date = datetime(2012, 12, 31)

In [237]: cal.holidays()
Out[237]: 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.

```python
In [238]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory,
.....: USLaborDay
.....:

In [239]: cal = get_calendar('ExampleCalendar')

In [240]: cal.rules
Out[240]: [Holiday: MemorialDay (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x1c31164378>),
Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>)]

In [241]: new_cal = HolidayCalendarFactory('NewExampleCalendar', cal, USLaborDay)
```

(continues on next page)
In [242]: new_cal.rules
Out [242]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: weekday=MO(+1)>),
 Holiday: MemorialDay (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at˓→0x1c31164378>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>)]

19.9 Time Series-Related Instance Methods

19.9.1 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 [243]: ts = ts[:5]
In [244]: ts.shift(1)
Out [244]:
2011-01-31 NaN
2011-02-28 -1.281247
2011-03-31 -0.727707
2011-04-29 -0.121306
2011-05-31 -0.097883
Freq: BM, dtype: float64

The shift method accepts an freq argument which can accept a DateOffset class or other timedelta-like object or also an offset alias:

In [245]: ts.shift(5, freq=offsets.BDay())
Out [245]:
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
dtype: float64

In [246]: ts.shift(5, freq='BM')
Out [246]:
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 tshift() convenience method that changes all the dates in the index by a specified number of offsets:

In [247]: ts.tshift(5, freq='D')
Out [247]:
(continues on next page)
Note that with `tshift`, the leading entry is no longer NaN because the data is not being realigned.

### 19.9.2 Frequency Conversion

The primary function for changing frequencies is the `asfreq()` method. For a `DatetimeIndex`, this is basically just a thin, but convenient wrapper around `reindex()` which generates a `date_range` and calls `reindex`.

```python
In [248]: dr = pd.date_range('1/1/2010', periods=3, freq=3 * offsets.BDay())
In [249]: ts = pd.Series(randn(3), index=dr)
In [250]: ts
Out[250]:
2010-01-01  0.155932
2010-01-06  1.486218
2010-01-11 -2.148675
Freq: 3B, dtype: float64
```

`asfreq` provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion.

```python
In [251]: ts.asfreq(BDay(), method='pad')
Out[251]:
2010-01-01  0.155932
2010-01-04  NaN
2010-01-05  NaN
2010-01-06  1.486218
2010-01-07  NaN
2010-01-08  NaN
2010-01-11 -2.148675
Freq: B, dtype: float64
```

### 19.9.3 Filling Forward / Backward

Related to `asfreq` and `reindex` is `fillna()`, which is documented in the missing data section.
19.9.4 Converting to Python Datetimes

DatetimeIndex can be converted to an array of Python native `datetime.datetime` objects using the `to_pydatetime` method.

19.10 Resampling

**Warning:** The interface to `.resample` has changed in 0.18.0 to be more groupby-like and hence more flexible. See the `whatsnew docs` for a comparison with prior versions.

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.

Starting in version 0.18.1, the `resample()` function can be used directly from `DataFrameGroupBy` objects, see the `groupby docs`.

**Note:** `.resample()` is similar to using a `rolling()` operation with a time-based offset, see a discussion `here`.

19.10.1 Basics

```
In [253]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
In [254]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
In [255]: ts.resample('5Min').sum()
Out[255]: 2012-01-01 25653
Freq: 5T, dtype: int64
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

Any function available via `dispatching` is available as a method of the returned object, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`:

```
In [256]: ts.resample('5Min').mean()
Out[256]: 2012-01-01  256.53
Freq: 5T, dtype: float64

In [257]: ts.resample('5Min').ohlc()
Out[257]: 2012-01-01  296  496  6  449
```

(continues on next page)
For downsampling, closed can be set to ‘left’ or ‘right’ to specify which end of the interval is closed:

```
In [258]: ts.resample('5Min', closed='right').mean()
Out[258]:
2011-12-31 23:55:00 296.000000
2012-01-01 00:00:00 256.131313
Freq: 5T, dtype: float64
```

```
In [259]: ts.resample('5Min', closed='left').mean()
```

```
In [260]: ts.resample('5Min').mean()  # by default label='left'
Out[260]:
2012-01-01 256.53
Freq: 5T, dtype: float64
```

Note: The default values for label and closed is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

```
In [261]: ts.resample('5Min').mean()  # by default label='left'
Out[261]:
2012-01-01 256.53
Freq: 5T, dtype: float64
```

```
In [262]: ts.resample('5Min', label='left').mean()
```

```
In [263]: ts.resample('5Min', label='left', loffset='1s').mean()
```

```
In [264]: rng2 = pd.date_range('1/1/2012', end='3/31/2012', freq='D')
```

```
In [265]: ts2 = pd.Series(range(len(rng2)), index=rng2)
```

```
# default: label='right', closed='right'
In [266]: ts2.resample('M').max()
Out[266]:
2012-01-31 30
2012-02-29 59
2012-03-31 90
Freq: M, dtype: int64
```

```
# default: label='left', closed='left'
In [267]: ts2.resample('SM').max()
```

(continues on next page)
The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a DataFrame. The `kind` parameter can be set to ‘timestamp’ or ‘period’ to convert the resulting index to/from timestamp and time span representations. By default, `resample` retains the input representation. The `convention` parameter 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.

### 19.10.2 Upsampling

For upsampling, you can specify a way to upsample and the `limit` parameter to interpolate over the gaps that are created:

```python
# from secondly to every 250 milliseconds
In [269]: ts[:2].resample('250L').asfreq()
```

```
2012-01-01 00:00:00.000 296.0
2012-01-01 00:00:00.250 NaN
2012-01-01 00:00:00.500 NaN
2012-01-01 00:00:00.750 NaN
2012-01-01 00:00:01.000 199.0
Freq: 250L, dtype: float64
```

```python
In [270]: ts[:2].resample('250L').ffill()
```

```
2012-01-01 00:00:00.000 296
2012-01-01 00:00:00.250 296
2012-01-01 00:00:00.500 296
2012-01-01 00:00:00.750 296
2012-01-01 00:00:01.000 199
Freq: 250L, dtype: int64
```
19.10.3 Sparse Resampling

Sparse timeseries are the ones where you have a lot fewer points relative to the amount of time you are looking to resample. Naively upsampling a sparse series can potentially generate lots of intermediate values. When you don’t want to use a method to fill these values, e.g. `fill_method` is `None`, then intermediate values will be filled with `NaN`.

Since `resample` is a time-based groupby, the following is a method to efficiently resample only the groups that are not all `NaN`.

```python
In [272]: rng = pd.date_range('2014-1-1', periods=100, freq='D') + pd.Timedelta('1s')
In [273]: ts = pd.Series(range(100), index=rng)
```

If we want to resample to the full range of the series:

```python
In [274]: ts.resample('3T').sum()
```

We can instead only resample those groups where we have points as follows:

```python
In [275]: from functools import partial
In [276]: from pandas.tseries.frequencies import to_offset
In [277]: def round(t, freq):
   ....:     freq = to_offset(freq)
   ....:     return pd.Timestamp((t.value // freq.delta.value) * freq.delta.value)
```
..:

In [278]: ts.groupby(partial(round, freq='3T')).sum()
Out[278]:
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
Length: 100, dtype: int64

19.10.4 Aggregation

Similar to the aggregating API, groupby API, and the window functions API, a Resampler can be selectively resampled.

Resampling a DataFrame, the default will be to act on all columns with the same function.

In [279]: df = pd.DataFrame(np.random.randn(1000, 3),
.....:
index=pd.date_range('1/1/2012', freq='S', periods=1000),
.....:
columns=['A', 'B', 'C'])
.....:

In [280]: r = df.resample('3T')

In [281]: r.mean()
Out[281]:
A    B    C
2012-01-01 00:00:00 -0.038580 -0.085117 -0.024750
2012-01-01 00:03:00 0.052387 -0.061477 0.029548
2012-01-01 00:06:00 0.121377 -0.010630 -0.043691
2012-01-01 00:09:00 -0.106814 -0.053819 0.097222
2012-01-01 00:12:00 0.060486 -0.057602 -0.106213
2012-01-01 00:15:00 0.060486 -0.057602 -0.106213

We can select a specific column or columns using standard getitem.

In [282]: r['A'].mean()
Out[282]:
A
2012-01-01 00:00:00 -0.038580
2012-01-01 00:03:00 0.052387
2012-01-01 00:06:00 0.121377
2012-01-01 00:09:00 -0.106814
2012-01-01 00:12:00 0.060486
2012-01-01 00:15:00 0.060486

(continues on next page)
Freq: 3T, Name: A, dtype: float64

In [283]: r[['A', 'B']].mean()
→

    A   B
2012-01-01 00:00:00 -0.038580 -0.085117
2012-01-01 00:03:00  0.052387  -0.061477
2012-01-01 00:06:00  0.121377   -0.010630
2012-01-01 00:09:00 -0.106814  -0.053819
2012-01-01 00:12:00  0.032560   0.080543
2012-01-01 00:15:00  0.060486  -0.057602

You can pass a list or dict of functions to do aggregation with, outputting a DataFrame:

In [284]: r['A'].agg([np.sum, np.mean, np.std])
Out[284]:

   sum    mean    std
2012-01-01 00:00:00 -6.944481 -0.038580  0.985150
2012-01-01 00:03:00  9.429707  0.052387  1.078022
2012-01-01 00:06:00 21.847876  0.121377  0.996365
2012-01-01 00:09:00 -19.226593 -0.106814  0.914070
2012-01-01 00:12:00  5.860874  0.032560  1.100055
2012-01-01 00:15:00  6.048588  0.060486  1.001532

On a resampled DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

In [285]: r.agg([np.sum, np.mean])
Out[285]:

   A   B   C
2012-01-01 00:00:00 -15.320993 -0.085117 -4.454941
2012-01-01 00:03:00 -11.065916 -0.061477  5.318688
2012-01-01 00:06:00  -1.913420 -0.010630 -7.864429
2012-01-01 00:09:00 -9.687468  -0.053819 17.499920
2012-01-01 00:12:00 14.497725  0.080543 30.128432
2012-01-01 00:15:00 -5.760208 -0.057602 -10.621260

By passing a dict to aggregate you can apply a different aggregation to the columns of a DataFrame:

In [286]: r.agg({'A': np.sum, 'B': lambda x: np.std(x, ddof=1)})

Out[286]:

   A   B
2012-01-01 00:00:00 -6.944481  1.087752
2012-01-01 00:03:00  9.429707  1.014552
2012-01-01 00:06:00 21.847876  0.954588
2012-01-01 00:09:00 -19.226593  1.027990
2012-01-01 00:12:00  5.860874  1.021503
2012-01-01 00:15:00  6.048588  1.004984

The function names can also be strings. In order for a string to be valid it must be implemented on the resampled object:
In [287]: r.agg({'A' : 'sum', 'B' : 'std'})
Out[287]:
    A      B
2012-01-01 00:00:00 -6.944481 1.087752
2012-01-01 00:03:00  9.429707 1.014552
2012-01-01 00:06:00 21.847876 0.954588
2012-01-01 00:09:00 -19.226593 1.027990
2012-01-01 00:12:00  5.860874 1.021503
2012-01-01 00:15:00  6.048588 1.004984

Furthermore, you can also specify multiple aggregation functions for each column separately.

In [288]: r.agg({'A' : ['sum','std'], 'B' : ['mean','std'] })
Out[288]:
    A         B
             sum     std     mean     std
2012-01-01 00:00:00 -6.944481 0.985150 -0.085117 1.087752
2012-01-01 00:03:00  9.429707 1.078022 -0.061477 1.014552
2012-01-01 00:06:00 21.847876 0.996365 -0.010630 0.954588
2012-01-01 00:09:00 -19.226593 0.914070 -0.053819 1.027990
2012-01-01 00:12:00  5.860874 1.100055  0.080543 1.021503
2012-01-01 00:15:00  6.048588 1.001532 -0.057602 1.004984

If a DataFrame does not have a datetimelike index, but instead you want to resample based on datetimelike column in the frame, it can passed to the on keyword.

In [289]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W', periods=5),
                        'a': np.arange(5),
                        index=pd.MultiIndex.from_arrays=[[1,2,3,4,5],
                                       pd.date_range('2015-01-01', freq='W',
                                       periods=5)],
                        names=['v','d'])

In [290]: df
Out[290]:
    date  a
   v d
1 2015-01-04  2015-01-04 0
2 2015-01-11  2015-01-11 1
3 2015-01-18  2015-01-18 2
4 2015-01-25  2015-01-25 3
5 2015-02-01  2015-02-01 4

In [291]: df.resample('M', on='date').sum()
Out[291]:
   a
   date
2015-01-31 6
2015-02-28 4

Similarly, if you instead want to resample by a datetimelike level of MultiIndex, its name or location can be passed to the level keyword.

In [292]: df.resample('M', level='d').sum()

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19.11 Time Span Representation

Regular intervals of time are represented by Period objects in pandas while sequences of Period objects are collected in a PeriodIndex, which can be created with the convenience function period_range.

19.11.1 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”.

```python
In [293]: pd.Period('2012', freq='A-DEC')
Out[293]: Period('2012', 'A-DEC')
In [294]: pd.Period('2012-1-1', freq='D')
Out[294]: Period('2012-01-01', 'D')
In [295]: pd.Period('2012-1-1 19:00', freq='H')
Out[295]: Period('2012-01-01 19:00', 'H')
In [296]: pd.Period('2012-1-1 19:00', freq='5H')
```

Adding and subtracting integers from periods shifts the period by its own frequency. Arithmetic is not allowed between Period with different freq (span).

```python
In [297]: p = pd.Period('2012', freq='A-DEC')
In [298]: p + 1
Out[298]: Period('2013', 'A-DEC')
In [299]: p - 3
Out[299]: Period('2009', 'A-DEC')
In [300]: p = pd.Period('2012-01', freq='2M')
In [301]: p + 2
Out[301]: Period('2012-05', '2M')
In [302]: p - 1
Out[302]: Period('2011-11', '2M')
In [303]: p == pd.Period('2012-01', freq='3M')
```

IncompatibleFrequency Traceback (most recent call last)
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 [304]: p == pd.Period('2012-01', freq='3M')
```

```
~/sandbox/pandas-release/pandas-docs/pandas/_libs/tslibs/period.pyx in pandas._libs.tslibs.period._Period.__richcmp__()
IncompatibleFrequency: Input has different freq=3M from Period(freq=2M)
```

```
In [1]: p + pd.Period('2014-07-01 09:00', freq='H')
```

```
In [305]: p + Hour(2)
Out[305]: Period('2014-07-01 11:00', 'H')
```

```
In [306]: p + timedelta(minutes=120)
```

```
Out[306]: Period('2014-07-01 11:00', 'H')
```

```
In [307]: p + np.timedelta64(7200, 's')
```

```
Out[307]: 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 [308]: p = pd.Period('2014-07', freq='M')
```

```
In [309]: p + MonthEnd(3)
Out[309]: 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:

```
Out[310]: 10
```

### 19.11.2 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 [311]: prng = pd.period_range('1/1/2011', '1/1/2012', freq='M')
```

```
In [312]: prng
```
The `PeriodIndex` constructor can also be used directly:

```python
In [313]: pd.PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[313]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

Passing multiplied frequency outputs a sequence of `Period` which has multiplied span.

```python
In [314]: pd.PeriodIndex(start='2014-01', freq='3M', periods=4)
```

If `start` or `end` are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `PeriodIndex` constructor.

```python
In [315]: pd.PeriodIndex(start=pd.Period('2017Q1', freq='Q'),
                   end=pd.Period('2017Q2', freq='Q'), freq='M')
Out[315]: PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'], dtype='period[M]', freq='M')
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```python
In [316]: ps = pd.Series(np.random.randn(len(prng)), prng)
In [317]: ps
Out[317]:
          2011-01  0.258318
            2011-02 -2.503700
            2011-03 -0.303053
            2011-04  0.270509
            2011-05  1.004841
            2011-06 -1.406335
            2011-07 -1.310412
            2011-08  0.769439
            2011-09 -0.542325
            2011-10  2.010541
            2011-11  1.001558
            2011-12 -0.087453
Freq: M, dtype: float64
```

`PeriodIndex` supports addition and subtraction with the same rule as `Period`.

```python
In [318]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')
In [319]: idx
Out[319]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00'], dtype='period[H]',频=f'H')
```
PeriodIndex has its own dtype named period. refer to Period Dtypes.

19.11.3 Period Dtypes

New in version 0.19.0.

PeriodIndex has a custom period dtype. This is a pandas extension dtype similar to the timezone aware dtype (datetime64[ns, tz]).

The period dtype holds the freq attribute and is represented with period[freq] like period[D] or period[M], using frequency strings.

```python
In [324]: pi = pd.period_range('2016-01-01', periods=3, freq='M')
```

In [325]: pi

Out[325]: PeriodIndex(['2016-01', '2016-02', '2016-03'], dtype='period[M]', freq='M')

The period dtype can be used in .astype(...). It allows one to change the freq of a PeriodIndex like .asfreq() and convert a DatetimeIndex to PeriodIndex like to_period().

```python
In [326]: pi.dtype
```

Out[326]: period[M]

```python
# change monthly freq to daily freq
In [327]: pi.astype('period[D]')
```

Out[327]: PeriodIndex(['2016-01-31', '2016-02-29', '2016-03-31'], dtype='period[D]', freq='D')

```python
# convert to DatetimeIndex
In [328]: pi.astype('datetime64[ns]')
```

Out[328]: DatetimeIndex(['2016-01-01', '2016-02-01', '2016-03-01'], dtype='datetime64[ns]', freq='MS')

```python
# convert to PeriodIndex
In [329]: dti = pd.date_range('2011-01-01', freq='M', periods=3)
```

(continues on next page)
In [330]: dti
Out[330]: DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31'], dtype='datetime64[ns]', freq='M')

In [331]: dti.astype('period[M]')
Out[331]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')

19.11.4 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 [332]: ps['2011-01']
Out[332]: 0.25831819727391592

In [333]: ps[datetime(2011, 12, 25):]
Out[333]:
2011-12 1.001558
2012-01 -0.087453
Freq: M, dtype: float64

In [334]: ps['10/31/2011':'12/31/2011']
Out[334]:
2011-10 -0.542325
2011-11 2.010541
2011-12 1.001558
Freq: M, dtype: float64

Passing a string representing a lower frequency than PeriodIndex returns partial sliced data.

In [335]: ps['2011']
Out[335]:
2011-01  0.258318
2011-02 -2.503700
2011-03 -0.303053
2011-04  0.270509
2011-05  1.004841
2011-06 -0.129044
2011-07 -1.406335
2011-08 -1.310412
2011-09  0.769439
2011-10 -0.542325
2011-11  2.010541
2011-12  1.001558
Freq: M, dtype: float64

In [336]: dfp = pd.DataFrame(np.random.randn(600,1),
                   columns=['A'],
                   index=pd.period_range('2013-01-01 9:00', periods=600,
                                      freq='T'))
As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```
In [339]: dfp['2013-01-01 10H':'2013-01-01 11H']
Out[339]:
               A
2013-01-01 10:00  -0.148998
2013-01-01 10:01   2.154810
2013-01-01 10:02  -1.605646
2013-01-01 10:03   0.021024
2013-01-01 10:04  -0.623737
2013-01-01 10:05   1.451612
2013-01-01 10:06   1.062463
...  ...  ...  ...  ...
2013-01-01 11:53   0.273119
2013-01-01 11:54  -0.994071
2013-01-01 11:55  -1.222179
2013-01-01 11:56  -1.167118
2013-01-01 11:57   0.262822
2013-01-01 11:58  -0.283786
2013-01-01 11:59   1.190726
[60 rows x 1 columns]
```
19.11.5 Frequency Conversion and Resampling with PeriodIndex

The frequency of Period and PeriodIndex can be converted via the \texttt{asfreq} method. Let’s start with the fiscal year 2011, ending in December:

\begin{verbatim}
In [340]: p = pd.Period('2011', freq='A-DEC')
In [341]: p
Out[341]: Period('2011', 'A-DEC')
\end{verbatim}

We can convert it to a monthly frequency. Using the \texttt{how} parameter, we can specify whether to return the starting or ending month:

\begin{verbatim}
In [342]: p.asfreq('M', how='start')
Out[342]: Period('2011-01', 'M')
In [343]: p.asfreq('M', how='end')
Out[343]: Period('2011-12', 'M')
\end{verbatim}

The shorthands ‘s’ and ‘e’ are provided for convenience:

\begin{verbatim}
In [344]: p.asfreq('M', 's')
Out[344]: Period('2011-01', 'M')
In [345]: p.asfreq('M', 'e')
Out[345]: Period('2011-12', 'M')
\end{verbatim}

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:

\begin{verbatim}
In [346]: p = pd.Period('2011-12', freq='M')
In [347]: p.asfreq('A-NOV')
Out[347]: Period('2012', 'A-NOV')
\end{verbatim}

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 \texttt{Q-JAN} through \texttt{Q-DEC}.

\texttt{Q-DEC} define regular calendar quarters:
Q-MAR defines fiscal year end in March:

```python
In [351]: p = pd.Period('2011Q4', freq='Q-MAR')
In [352]: p.asfreq('D', 's')
Out[352]: Period('2011-01-01', 'D')
In [353]: p.asfreq('D', 'e')
Out[353]: Period('2011-03-31', 'D')
```

### 19.12 Converting Between Representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```python
In [354]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
In [355]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
In [356]: ts
Out[356]:
2012-01-31 -0.898547
2012-02-29 -1.332247
2012-03-31 -0.741645
2012-04-30  0.094321
2012-05-31 -0.438813
Freq: M, dtype: float64
In [357]: ps = ts.to_period()
In [358]: ps
Out[358]:
2012-01  -0.898547
2012-02  -1.332247
2012-03  -0.741645
2012-04   0.094321
2012-05  -0.438813
Freq: M, dtype: float64
In [359]: ps.to_timestamp()
```

(continues on next page)
Remember that ‘s’ and ‘e’ can be used to return the timestamps at the start or end of the period:

```python
In [360]: ps.to_timestamp('D', how='s')
Out[360]:
2012-01-01 -0.898547
2012-02-01 -1.332247
2012-03-01 -0.741645
2012-04-01  0.094321
2012-05-01 -0.438813
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```python
In [361]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
In [362]: ts = pd.Series(np.random.randn(len(prng)), prng)
In [363]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
In [364]: ts.head()
Out[364]:
1990-03-01 09:00 -0.564874
1990-06-01 09:00 -1.426510
1990-09-01 09:00  1.295437
1990-12-01 09:00  1.124017
1991-03-01 09:00  0.840428
Freq: H, dtype: float64
```

## 19.13 Representing Out-of-Bounds Spans

If you have data that is outside of the Timestamp bounds, see [Timestamp limitations](#), then you can use a PeriodIndex and/or Series of Periods to do computations.

```python
In [365]: span = pd.period_range('1215-01-01', '1381-01-01', freq='D')
In [366]: span
Out[366]:
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',
            '1215-01-11', '1215-01-12', '1215-01-13', '1215-01-14',
            '1215-01-15', '1215-01-16', '1215-01-17', '1215-01-18',
            '1215-01-19', '1215-01-20', '1215-01-21', '1215-01-22',
            '1215-01-23', '1215-01-24', '1215-01-25', '1215-01-26',
            '1215-01-27', '1215-01-28', '1215-01-29', '1215-01-30',
            '1215-01-31', '1215-01-32'],
       dtype='period[D]', length=60632, freq='D')
```

To convert from an `int64` based YYYYMMDD representation.
In [367]: s = pd.Series([20121231, 20141130, 99991231])

In [368]: s
Out[368]:
0  20121231
1  20141130
2  99991231
dtype: int64

In [369]: def conv(x):
    .....:     return pd.Period(year = x // 10000, month = x//100 % 100, day = x%100,
    .....:                     freq='D')
    .....:

In [370]: s.apply(conv)
Out[370]:
0  2012-12-31
1  2014-11-30
2  9999-12-31
dtype: object

In [371]: s.apply(conv)[2]
Out[371]: Period('9999-12-31', 'D')

These can easily be converted to a PeriodIndex:

In [372]: span = pd.PeriodIndex(s.apply(conv))

In [373]: span
Out[373]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'],
                       freq='D')

19.14 Time Zone Handling

Pandas provides rich support for working with timestamps in different time zones using pytz and dateutil libraries. dateutil currently is 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.

19.14.1 Working with Time Zones

By default, pandas objects are time zone unaware:

In [374]: rng = pd.date_range('3/6/2012 00:00', periods=15, freq='D')

In [375]: rng.tz is None
Out[375]: True

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*.

```python
# pytz
In [366]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                           tz='Europe/London')
                           
In [367]: rng_pytz.tz
Out[367]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>

# dateutil
In [368]: rng_dateutil = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                                tz='dateutil/Europe/London')

In [369]: rng_dateutil.tz
Out[369]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case
In [370]: rng_utc = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                            tz=dateutil.tz.tzutc())

In [371]: rng_utc.tz
Out[371]: 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:

```python
# pytz
In [372]: tz_pytz = pytz.timezone('Europe/London')

In [373]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                               tz=tz_pytz)

In [374]: rng_pytz.tz == tz_pytz
Out[374]: True

# dateutil
In [375]: tz_dateutil = dateutil.tz.gettz('Europe/London')

In [376]: rng_dateutil = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                                 tz=tz_dateutil)

In [377]: rng_dateutil.tz == tz_dateutil
Out[377]: 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`:

```python
In [378]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [379]: ts_utc = ts.tz_localize('UTC')
```

(continues on next page)
In [390]: ts_utc
Out[390]:
2012-03-06 00:00:00+00:00  0.037206
2012-03-07 00:00:00+00:00  2.313998
2012-03-08 00:00:00+00:00  1.458296
2012-03-09 00:00:00+00:00 -0.620431
2012-03-10 00:00:00+00:00 -0.000111
2012-03-11 00:00:00+00:00 -0.342783
2012-03-12 00:00:00+00:00 -0.664322
2012-03-13 00:00:00+00:00  0.654814
2012-03-14 00:00:00+00:00  1.550680
2012-03-15 00:00:00+00:00  0.174511
2012-03-16 00:00:00+00:00  1.360491
2012-03-17 00:00:00+00:00  0.799737
2012-03-18 00:00:00+00:00  0.449149
2012-03-19 00:00:00+00:00  0.111346
2012-03-20 00:00:00+00:00 -0.435531
Freq: D, dtype: float64

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 [391]: ts_utc.tz_convert('US/Eastern')
Out[391]:
2012-03-05 19:00:00-05:00  0.037206
2012-03-06 19:00:00-05:00  2.313998
2012-03-07 19:00:00-05:00  1.458296
2012-03-08 19:00:00-05:00 -0.620431
2012-03-09 19:00:00-05:00 -0.000111
2012-03-10 19:00:00-05:00 -0.342783
2012-03-11 20:00:00-04:00 -0.664322
2012-03-12 20:00:00-04:00  0.654814
2012-03-13 20:00:00-04:00  1.550680
2012-03-14 20:00:00-04:00  0.174511
2012-03-15 20:00:00-04:00  1.360491
2012-03-16 20:00:00-04:00  0.799737
2012-03-17 20:00:00-04:00  0.449149
2012-03-18 20:00:00-04:00  0.111346
2012-03-19 20:00:00-04:00 -0.435531
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...
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:

```python
In [392]: rng_eastern = rng_utc.tz_convert('US/Eastern')
In [393]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')
In [394]: rng_eastern[5]
Out[394]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', freq='D')
In [395]: rng_berlin[5]
Out[395]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', freq='D')
Out[396]: True
```

Like Series, DataFrame, and DatetimeIndex, Timestamp``s can be converted to other time zones using ``tz_convert``:

```python
In [397]: rng_eastern[5]
Out[397]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', freq='D')
In [398]: rng_berlin[5]
Out[398]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', freq='D')
In [399]: rng_eastern[5].tz_convert('Europe/Berlin')
Out[399]: Timestamp('2012-03-11 01:00:00+0100')
```

Localization of Timestamp functions just like DatetimeIndex and Series:

```python
In [400]: rng[5]
Out[400]: Timestamp('2012-03-11 00:00:00', freq='D')
In [401]: rng[5].tz_localize('Asia/Shanghai')
Out[401]: Timestamp('2012-03-11 00:00:00+0800')
```

Operations between Series in different time zones will yield UTC Series, aligning the data on the UTC timestamps:

```python
In [402]: eastern = ts_utc.tz_convert('US/Eastern')
In [403]: berlin = ts_utc.tz_convert('Europe/Berlin')
In [404]: result = eastern + berlin
In [405]: result
Out[405]:
2012-03-06 00:00:00+00:00 0.074412
(continues on next page)
pandas: powerful Python data analysis toolkit, Release 0.23.1

19.14. Time Zone Handling

<table>
<thead>
<tr>
<th>Date</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-03-07</td>
<td>4.627997</td>
</tr>
<tr>
<td>2012-03-08</td>
<td>2.916592</td>
</tr>
<tr>
<td>2012-03-09</td>
<td>-1.240863</td>
</tr>
<tr>
<td>2012-03-10</td>
<td>-0.000221</td>
</tr>
<tr>
<td>2012-03-11</td>
<td>-0.685566</td>
</tr>
<tr>
<td>2012-03-12</td>
<td>-1.328643</td>
</tr>
<tr>
<td>2012-03-13</td>
<td>1.309628</td>
</tr>
<tr>
<td>2012-03-14</td>
<td>3.101359</td>
</tr>
<tr>
<td>2012-03-15</td>
<td>0.349022</td>
</tr>
<tr>
<td>2012-03-16</td>
<td>2.720983</td>
</tr>
<tr>
<td>2012-03-17</td>
<td>1.599475</td>
</tr>
<tr>
<td>2012-03-18</td>
<td>0.898297</td>
</tr>
<tr>
<td>2012-03-19</td>
<td>0.222691</td>
</tr>
<tr>
<td>2012-03-20</td>
<td>-0.871062</td>
</tr>
</tbody>
</table>

Freq: D, dtype: float64

In [406]: result.index

Out[406]:

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 [407]: didx = pd.DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz=
    'US/Eastern')

In [408]: didx

Out[408]:

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 [409]: didx.tz_localize(None)

Out[409]:

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'],
dtype='datetime64[ns]', freq='H')

In [410]: didx.tz_convert(None)

Out[410]:

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'],
dtype='datetime64[ns]', freq='H')
19.14.2 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'` 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 [412]: rng_hourly = pd.DatetimeIndex(['11/06/2011 00:00', '11/06/2011 01:00',
                  .....:
                  '11/06/2011 01:00', '11/06/2011 02:00',
                  .....:
                  '11/06/2011 03:00'])

This will fail as there are ambiguous times

In [2]: rng_hourly.tz_localize('US/Eastern')
AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try using the 'ambiguous' argument

Infer the ambiguous times

In [413]: rng_hourly_eastern = rng_hourly.tz_localize('US/Eastern', ambiguous='infer')
In [414]: rng_hourly_eastern.tolist()
Out[414]:
[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 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 [415]: rng_hourly_dst = np.array([1, 1, 0, 0, 0])
In [416]: rng_hourly.tz_localize('US/Eastern', ambiguous=rng_hourly_dst).tolist()
Out[416]:
[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 [417]:
rng_hourly.tz_localize('US/Eastern', ambiguous='NaT').tolist()

Out[417]:
[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 [418]:
didx = pd.DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [419]:
didx
Out[419]:
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 [420]:
didx.tz_localize(None)

Out[420]:
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 [421]:
didx.tz_convert(None)

Out[421]:
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'],
       dtype='datetime64[ns]', freq='H')

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)

In [422]:
didx.tz_convert('UTC').tz_localize(None)

Out[422]:
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'],
       dtype='datetime64[ns]', freq='H')

(continues on next page)
### 19.14.3 TZ Aware Dtypes

Series/DatetimeIndex with a timezone **naive** value are represented with a dtype of `datetime64[ns]`

```
In [423]: s_naive = pd.Series(pd.date_range('20130101', periods=3))
In [424]: s_naive
Out[424]:
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]`

```
In [425]: s_aware = pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern'))
In [426]: s_aware
Out[426]:
0   2013-01-01 00:00:00-05:00
1   2013-01-02 00:00:00-05:00
2   2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Both of these Series can be manipulated via the `.dt` accessor, see [here](#).

For example, to localize and convert a naive stamp to timezone aware.

```
In [427]: s_naive.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[427]:
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.

```
# localize and convert a naive timezone
In [428]: s_naive.astype('datetime64[ns, US/Eastern]')
Out[428]:
0   2012-12-31 19:00:00-05:00
1   2013-01-01 19:00:00-05:00
2   2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]

# make an aware tz naive
In [429]: s_aware.astype('datetime64[ns]')
→
0   2013-01-01 05:00:00
1   2013-01-02 05:00:00
```

(continues on next page)
# convert to a new timezone

```
In [430]: s_aware.astype('datetime64[ns, CET]')

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 an 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!).

```
In [431]: s_naive.values
Out[431]:
array(['2013-01-01T00:00:00.000000000', '2013-01-02T00:00:00.000000000',
      '2013-01-03T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
In [432]: s_aware.values
Out[432]:
array(['2013-01-01T05:00:00.000000000', '2013-01-02T05:00:00.000000000',
      '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

Further note that once converted to a NumPy array these would lose the tz tenor.

```
In [433]: pd.Series(s_aware.values)
Out[433]:
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 [434]: pd.Series(s_aware.values).dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[434]:
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]
```
Chapter 19. Time Series / Date functionality
Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

Timedelta is a subclass of datetime.timedelta, and behaves in a similar manner, but allows compatibility with np.timedelta64 types as well as a host of custom representation, parsing, and attributes.

## 20.1 Parsing

You can construct a Timedelta scalar through various arguments:

```python
# strings
In [1]: pd.Timedelta('1 days')
Out[1]: Timedelta('1 days 00:00:00')

In [2]: pd.Timedelta('1 days 00:00:00')

In [3]: pd.Timedelta('1 days 2 hours')

In [4]: pd.Timedelta('-1 days 2 min 3us')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [5]: pd.Timedelta(days=1, seconds=1)

In [6]: pd.Timedelta(1, unit='d')

# from a datetime.timedelta/np.timedelta64
In [7]: pd.Timedelta(datetime.timedelta(days=1, seconds=1))

In [8]: pd.Timedelta(np.timedelta64(1, 'ms'))
```

(continues on next page)
Timedelta('0 days 00:00:00.001000')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [9]: pd.Timedelta('-1us')

Timedelta('-1 days +23:59:59.999999')

# a NaT
In [10]: pd.Timedelta('nan')

NaT

In [11]: pd.Timedelta('nat')

NaT

# ISO 8601 Duration strings
In [12]: pd.Timedelta('P0DT0H1M0S')

Timedelta('0 days 00:01:00')

In [13]: pd.Timedelta('P0DT0H0M0.000000123S')

Timedelta('0 days 00:00:00.000000')

New in version 0.23.0: Added constructor for ISO 8601 Duration strings

DateOffsets (Day, Hour, Minute, Second, Milli, Micro, Nano) can also be used in construction.

In [14]: pd.Timedelta(Day(2))
Out[14]: Timedelta('0 days 00:00:02')

Further, operations among the scalars yield another scalar Timedelta.

In [15]: pd.Timedelta(Day(2)) + pd.Timedelta(Second(2)) + pd.Timedelta('00:00:00.000123')
Out[15]: Timedelta('2 days 00:00:02.000123')

20.1.1 to_timedelta

Using the top-level pd.to_timedelta, you can convert a scalar, array, list, or Series from a recognized timedelta format / value into a Timedelta type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise it will output a TimedeltaIndex.

You can parse a single string to a Timedelta:

In [16]: pd.to_timedelta('1 days 06:05:01.00003')
Out[16]: Timedelta('1 days 06:05:01.000030')

In [17]: pd.to_timedelta('15.Sus')
Out[17]: Timedelta('0 days 00:00:00.000015')

or a list/array of strings:
In [18]: pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[18]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT],
    dtype='timedelta64[ns]', freq=None)

The `unit` keyword argument specifies the unit of the Timedelta:

In [19]: pd.to_timedelta(np.arange(5), unit='s')
Out[19]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'],
    dtype='timedelta64[ns]', freq=None)

In [20]: pd.to_timedelta(np.arange(5), unit='d')
Out[20]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
    dtype='timedelta64[ns]', freq=None)

20.1.2 Timedelta limitations

Pandas represents Timedeltas in nanosecond resolution using 64 bit integers. As such, the 64 bit integer limits determine the Timedelta limits.

In [21]: pd.Timedelta.min
Out[21]: Timedelta('-106752 days +00:12:43.145224')

In [22]: pd.Timedelta.max
Out[22]: Timedelta('106751 days +23:47:16.854775')

20.2 Operations

You can operate on Series/DataFrames and construct timedelta64[ns] Series through subtraction operations on datetime64[ns] Series, or Timestamps.

In [23]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))
In [24]: td = pd.Series([pd.Timedelta(days=i) for i in range(3)])
In [25]: df = pd.DataFrame(dict(A = s, B = td))
In [26]: df
Out[26]:
   A       B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [27]: df['C'] = df['A'] + df['B']
In [28]: df
Out[28]:
   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

(continues on next page)
In [29]: df.dtypes
   →
   A   datetime64[ns]
   B   timedelta64[ns]
   C   datetime64[ns]
dtype: object

In [30]: s - s.max()
   →
   0   -2 days
   1   -1 days
   2    0 days
dtype: timedelta64[ns]

In [31]: s - datetime.datetime(2011, 1, 1, 3, 5)
   →
   0   364 days 20:55:00
   1   365 days 20:55:00
   2   366 days 20:55:00
dtype: timedelta64[ns]

In [32]: s + datetime.timedelta(minutes=5)
   →
   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 [33]: s + Minute(5)
   →
   0   2012-01-01 00:05:00
   1   2012-01-02 00:05:00
   2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [34]: s + Minute(5) + Milli(5)
   →
   0   2012-01-01 00:05:00.005
   1   2012-01-02 00:05:00.005
   2   2012-01-03 00:05:00.005
dtype: datetime64[ns]

Operations with scalars from a timedelta64[ns] series:

In [35]: y = s - s[0]

In [36]: y
Out[36]:
   0    0 days
   1    1 days
Series of timedeltas with NaT values are supported:

```python
In [37]: y = s - s.shift()

In [38]: y
Out[38]:
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 [39]: y[1] = np.nan

In [40]: y
Out[40]:
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 [41]: s.max() - s
Out[41]:
0  2 days
1  1 days
2  0 days
dtype: timedelta64[ns]

In [42]: datetime.datetime(2011, 1, 1, 3, 5) - s
Out[42]:
0 -365 days +03:05:00
1 -366 days +03:05:00
2 -367 days +03:05:00
dtype: timedelta64[ns]

In [43]: datetime.timedelta(minutes=5) + s
Out[43]:
0 2012-01-01 00:05:00
1 2012-01-02 00:05:00
2 2012-01-03 00:05:00
dtype: datetime64[ns]
```

min, max and the corresponding idxmin, idxmax operations are supported on frames:

```python
In [44]: A = s - pd.Timestamp('20120101') - pd.Timedelta('00:05:05')
In [45]: B = s - pd.Series(pd.date_range('2012-1-2', periods=3, freq='D'))
In [46]: df = pd.DataFrame(dict(A=A, B=B))
```
In [47]: df
Out[47]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1 days</td>
<td>+23:54:55</td>
</tr>
<tr>
<td>1</td>
<td>0 days</td>
<td>23:54:55</td>
</tr>
<tr>
<td>2</td>
<td>1 days</td>
<td>23:54:55</td>
</tr>
</tbody>
</table>

In [48]: df.min()

Out[48]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1 days</td>
<td>+00:00:00</td>
</tr>
</tbody>
</table>

In [49]: df.min(axis=1)

Out[49]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1 days</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1 days</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-1 days</td>
<td></td>
</tr>
</tbody>
</table>

dtype: timedelta64[ns]

In [50]: df.idxmin()

Out[50]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

dtype: int64

In [51]: df.idxmax()

Out[51]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

dtype: int64

min, max, idxmin, idxmax operations are supported on Series as well. A scalar result will be a Timedelta.

In [52]: df.min().max()
Out[52]: Timedelta('-1 days +23:54:55')

In [53]: df.min(axis=1).min()
Out[53]: Timedelta('-1 days +00:00:00')

In [54]: df.min().idxmax()

Out[54]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

In [55]: df.min(axis=1).idxmin()

Out[55]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

You can fillna on timedeltas. Integers will be interpreted as seconds. You can pass a timedelta to get a particular value.

In [56]: y.fillna(0)
Out[56]:

(continues on next page)
You can also negate, multiply and use abs on Timedeltas:

```python
In [59]: tdl = pd.Timedelta('-1 days 2 hours 3 seconds')

In [60]: tdl
Out[60]: Timedelta('-2 days +21:59:57')

In [61]: -1 * tdl
Out[61]: Timedelta('1 days 02:00:03')

In [62]: - tdl
Out[62]: Timedelta('1 days 02:00:03')

In [63]: abs(tdl)
Out[63]: Timedelta('1 days 02:00:03')
```

### 20.3 Reductions

Numeric reduction operation for `timedelta64[ns]` will return `Timedelta` objects. As usual NaT are skipped during evaluation.

```python
In [64]: y2 = pd.Series(pd.to_timedelta(['-1 days +00:00:05', 'nat', '-1 days +00:00:05', '1 days']))

In [65]: y2
Out[65]:
0   -1 days +00:00:05
1      NaT
2   -1 days +00:00:05
3     1 days
dtype: timedelta64[ns]
```

(continues on next page)
In [66]: y2.mean()
Timedelta('-1 days +16:00:03.333333')

In [67]: y2.median()
Timedelta('-1 days +00:00:05')

In [68]: y2.quantile(.1)
Timedelta('-1 days +00:00:05')

In [69]: y2.sum()
Timedelta('-1 days +00:00:10')

20.4 Frequency Conversion

Timedelta Series, TimedeltaIndex, and Timedelta scalars can be converted to other ‘frequencies’ by dividing
by another timedelta, or by astyping to a specific timedelta type. These operations yield Series and propagate NaT ->
nan. Note that division by the NumPy scalar is true division, while astyping is equivalent of floor division.

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

In [71]: td[2] += datetime.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  NaT
   dtype: timedelta64[ns]

# to days
In [74]: td / np.timedelta64(1, 'D')

    0  31.00000000
    1  31.00000000
    2  31.00350707
    3  NaN
   dtype: float64

In [75]: td.astype('timedelta64[D]')

    0  31.0
    1  31.0
    2  31.0

(continues on next page)


3   NaN
dtype: float64

# to seconds
In [76]: td / np.timedelta64(1, 's')

→
0   2678400.0
1   2678400.0
2   2678703.0
3   NaN
dtype: float64

In [77]: td.astype('timedelta64[s]')

→
0   2678400.0
1   2678400.0
2   2678703.0
3   NaN
dtype: float64

# to months (these are constant months)
In [78]: td / np.timedelta64(1, 'M')

→
0   1.018501
1   1.018501
2   1.018617
3   NaN
dtype: float64

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

In [79]: td * -1

Out[79]:
0   -31 days 00:00:00
1   -31 days 00:00:00
2   -32 days 23:54:57
3        NaT
dtype: timedelta64[ns]

In [80]: td * pd.Series([1, 2, 3, 4])

→
0    31 days 00:00:00
1    62 days 00:00:00
2    93 days 00:15:09
3        NaT
dtype: timedelta64[ns]

Rounded division (floor-division) of a `timedelta64[ns]` Series by a scalar `Timedelta` gives a series of integers.

In [81]: td // pd.Timedelta(days=3, hours=4)

Out[81]:
0  9.0
1  9.0
2  9.0
3  NaN
dtype: float64

In [82]: pd.Timedelta(days=3, hours=4) // td
\large\textbf{Out}[82]:
0  0.0
1  0.0
2  0.0
3  NaN
dtype: float64

The mod (%) and divmod operations are defined for `Timedelta` when operating with another timedelta-like or with a numeric argument.

In [83]: pd.Timedelta(hours=37) % datetime.timedelta(hours=2)
Out[83]: Timedelta('0 days 01:00:00')

# divmod against a timedelta-like returns a pair (int, Timedelta)
In [84]: divmod(datetime.timedelta(hours=2), pd.Timedelta(minutes=11))
\large\textbf{Out}[84]: (10, Timedelta('0 days 00:10:00'))

# divmod against a numeric returns a pair (Timedelta, Timedelta)
In [85]: divmod(pd.Timedelta(hours=25), 86400000000000)
\large\textbf{Out}[85]:
→(Timedelta('0 days 00:00:00.000000'), Timedelta('0 days 01:00:00'))

## 20.5 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 $\geq 0$ 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 [86]: td.dt.days
Out[86]:
0  31.0
1  31.0
2  31.0
3  NaN
dtype: float64

In [87]: td.dt.seconds
(continues on next page)
You can access the value of the fields for a scalar `Timedelta` directly.

```python
In [88]: tds = pd.Timedelta('31 days 5 min 3 sec')
In [89]: tds.days
Out[89]: 31
In [90]: tds.seconds
Out[90]: 303
In [91]: (-tds).seconds
Out[91]: 86097
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a DataFrame indexed similarly to the `Series`. These are the displayed values of the `Timedelta`.

```python
In [92]: tds.dt.components
Out[92]:
          days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0      31.0    0.0     0.0     0.0       0.0           0.0          0.0
1      31.0    0.0     0.0     0.0       0.0           0.0          0.0
2      31.0    0.0     5.0     3.0       0.0           0.0          0.0
3       NaN    NaN    NaN     NaN      NaN           NaN          NaN

In [93]: tds.dt.components.seconds
Out[93]:
          0  0.0
1      3.0
2  303.0
3     NaN
```

You can convert a `Timedelta` to an ISO 8601 Duration string with the `.isoformat` method.

```python
New in version 0.20.0.
In [94]: pd.Timedelta(days=6, minutes=50, seconds=3,
                ....:       milliseconds=10, microseconds=10,
                ....:       nanoseconds=12).isoformat()
Out[94]: 'P6DT0H50M3.010010012S'
```

## 20.6 TimedeltaIndex

To generate an index with time delta, you can use either the `TimedeltaIndex` or the `timedelta_range()` constructor.
Using `TimedeltaIndex` you can pass string-like, `Timedelta`, `timedelta`, or `np.timedelta64` objects. Passing `np.nan/pd.NaT/nat` will represent missing values.

```
In [95]: pd.TimedeltaIndex(['1 days', '1 days, 00:00:05',
                       ....:       np.timedelta64(2,'D'),
                       ....:       datetime.timedelta(days=2,
                       ....:                       seconds=2))
Out[95]:
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)
```

### 20.6.1 Generating Ranges of Time Deltas

Similar to `date_range()`, you can construct regular ranges of a `TimedeltaIndex` using `timedelta_range()`. The default frequency for `timedelta_range` is calendar day:

```
In [96]: pd.timedelta_range(start='1 days', periods=5)
Out[96]:
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'],
               dtype='timedelta64[ns]', freq='D')
```

Various combinations of `start`, `end`, and `periods` can be used with `timedelta_range`:

```
In [97]: pd.timedelta_range(start='1 days', end='5 days')
Out[97]:
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'],
               dtype='timedelta64[ns]', freq='D')
```

```
In [98]: pd.timedelta_range(end='10 days', periods=4)
```

```
TimedeltaIndex(['7 days', '8 days', '9 days', '10 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `freq` parameter can passed a variety of `frequency aliases`:

```
In [99]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[99]:
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')
```

```
In [100]: pd.timedelta_range(start='1 days', periods=5, freq='2D5H')
(continues on next page)
```
New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced `timedelta` objects from `start` to `end` inclusively, with `periods` number of elements in the resulting `TimedeltaIndex`:

```
In [101]: pd.timedelta_range('0 days', '4 days', periods=5)
Out[101]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]', freq=None)
```

```
In [102]: pd.timedelta_range('0 days', '4 days', periods=10)
```

```
TimedeltaIndex(['0 days 00:00:00', '0 days 10:40:00', '0 days 21:20:00', '1 days 08:00:00', '1 days 18:40:00', '2 days 05:20:00', '2 days 16:00:00', '3 days 02:40:00', '3 days 13:20:00', '4 days 00:00:00'], dtype='timedelta64[ns]', freq=None)
```

### 20.6.2 Using the TimedeltaIndex

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```
In [103]: s = pd.Series(np.arange(100),
                index=pd.timedelta_range('1 days', periods=100, freq='h'))
```

```
In [104]: s
Out[104]:
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
Freq: H, Length: 100, dtype: int64
```

Selections work similarly, with coercion on string-likes and slices:
In [105]: s['1 day':'2 day']
Out[105]:
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
..  
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, Length: 48, dtype: int64

In [106]: s['1 day 01:00:00']

In [107]: s[pd.Timedelta('1 day 1h')]

Furthermore you can use partial string selection and the range will be inferred:

In [108]: s['1 day':'1 day 5 hours']
Out[108]:
1 days 00:00:00 0
1 days 01:00:00 1
1 days 02:00:00 2
1 days 03:00:00 3
1 days 04:00:00 4
1 days 05:00:00 5
Freq: H, dtype: int64

20.6.3 Operations

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

In [109]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])
In [110]: tdi.tolist()
Out[110]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [111]: dti = pd.date_range('20130101', periods=3)
In [112]: dti.tolist()
Out[112]: [Timestamp('2013-01-01 00:00:00', freq='D'),
Timestamp('2013-01-02 00:00:00', freq='D'),
Timestamp('2013-01-03 00:00:00', freq='D')]

(continues on next page)
In [113]: (dti + tdi).tolist()
    → [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [114]: (dti - tdi).tolist()
    → [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]

20.6.4 Conversions

Similarly to frequency conversion on a Series above, you can convert these indices to yield another Index.

In [115]: tdi / np.timedelta64(1,'s')
Out[115]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [116]: tdi.astype('timedelta64[s]')
    → Float64Index([86400.0, nan, 172800.0], dtype='float64')

Scalars type ops work as well. These can potentially return a different type of index.

In [117]: tdi + pd.Timestamp('20130101')
Out[117]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]',
    → freq=None)

In [118]: (pd.Timestamp('20130101') - tdi).tolist()
    → [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

In [119]: tdi + pd.Timedelta('10 days')
    → TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]', freq=None)

In [120]: tdi / 2
    → TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype='timedelta64[ns]',
    → freq=None)

In [121]: tdi / tdi[0]
    → Float64Index([1.0, nan, 2.0], dtype='float64')

20.7 Resampling

Similar to timeseries resampling, we can resample with a TimedeltaIndex.
In [122]: s.resample('D').mean()
Out[122]:
1 days  11.5
2 days  35.5
3 days  59.5
4 days  83.5
5 days  97.5
Freq: D, dtype: float64
CATEGORICAL DATA

This is an introduction to pandas categorical data type, including a short comparison with R’s factor.

Categoricals are a pandas data type corresponding to categorical variables in statistics. A categorical variable takes on a limited, and usually fixed, number of possible values (categories; levels in R). Examples are gender, social class, blood type, country affiliation, observation time or rating via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. ‘strongly agree’ vs ‘agree’ or ‘first observation’ vs. ‘second observation’), but numerical operations (additions, divisions, . . . ) are not possible.

All values of categorical data are either in categories or np.nan. Order is defined by the order of categories, not lexical order of the values. Internally, the data structure consists of a categories array and an integer array of codes which point to the real value in the categories array.

The categorical data type is useful in the following cases:

• A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory, see here.

• The lexical order of a variable is not the same as the logical order (“one”, “two”, “three”). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order, see here.

• As a signal to other Python libraries that this column should be treated as a categorical variable (e.g. to use suitable statistical methods or plot types).

See also the API docs on categoricals.

21.1 Object Creation

21.1.1 Series Creation

Categorical Series or columns in a DataFrame can be created in several ways:

By specifying dtype="category" when constructing a Series:

```
In [1]: s = pd.Series(["a","b","c","a"], dtype="category")

In [2]: s
Out[2]:
   0  a
   1  b
   2  c
   3  a
```
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')

In [5]: df
```
```
   A  B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using special functions, such as `cut()`, which groups data into discrete bins. See the `example on tiling` in the docs.

```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)

In [9]: df.head(10)
```
```
   value    group
0    65  60 - 69
1    49  40 - 49
2    56  50 - 59
3    43  40 - 49
4    43  40 - 49
5    91  90 - 99
6    32  30 - 39
7    87  80 - 89
8    36  30 - 39
9     8  0 - 9
```

By passing a `pandas.Categorical` object to a `Series` or assigning it to a `DataFrame`.

```python
In [10]: raw_cat = pd.Categorical(["a","b","c","a"], categories=["b","c","d"],
                    ordered=False)

In [11]: s = pd.Series(raw_cat)

In [12]: s
```
```
0   NaN
1    b
2    c
3   NaN
dtype: category
Categories (3, object): [b, c, d]
```

(continues on next page)
21.1.2 DataFrame Creation

Similar to the previous section where a single column was converted to categorical, all columns in a DataFrame can be batch converted to categorical either during or after construction.

This can be done during construction by specifying `dtype="category"` in the DataFrame constructor:

```python
In [17]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')}, dtype="category")
```

```python
In [18]: df.dtypes
Out[18]:
A category
B category
dtype: object
```

Note that the categories present in each column differ; the conversion is done column by column, so only labels present in a given column are categories:

```python
In [19]: df['A']
Out[19]:
  0  a
  1  b
  2  c
  3  a
Name: A, dtype: category
Categories (3, object): [a, b, c]
```

```python
In [20]: df['B']
```

(continues on next page)
New in version 0.23.0.

Analogously, all columns in an existing DataFrame can be batch converted using \texttt{DataFrame.astype()}:  

```
In [21]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))
In [22]: df_cat = df.astype('category')
In [23]: df_cat.dtypes
Out[23]:
A category
B category
dtype: object
```

This conversion is likewise done column by column:

```
In [24]: df_cat['A']
Out[24]:
0 a
1 b
2 c
3 a
Name: A, dtype: category
Categories (3, object): [a, b, c]

In [25]: df_cat['B']
Out[25]:
0 b
1 c
2 c
3 d
Name: B, dtype: category
Categories (3, object): [b, c, d]
```

### 21.1.3 Controlling Behavior

In the examples above where we passed \texttt{dtype='category'}, we used the default behavior:

1. Categories are inferred from the data.
2. Categories are unordered.

To control those behaviors, instead of passing \texttt{'category'}, use an instance of \texttt{CategoricalDtype}.

```
In [26]: from pandas.api.types import CategoricalDtype
In [27]: s = pd.Series(['a', 'b', 'c', 'a'])
In [28]: cat_type = CategoricalDtype(categories=['b', 'c', 'd'], ordered=True)
```

(continues on next page)
Similarly, a `CategoricalDtype` can be used with a `DataFrame` to ensure that categories are consistent among all columns.

```python
In [31]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))

In [32]: cat_type = CategoricalDtype(categories=list('abcd'), ordered=True)

In [33]: df_cat = df.astype(cat_type)

In [34]: df_cat['A']
Out[34]:
0  a
1  b
2  c
3  a
Name: A, dtype: category
Categories (4, object): [a < b < c < d]

In [35]: df_cat['B']
\[...
0  b
1  c
2  c
3  d
Name: B, dtype: category
Categories (4, object): [a < b < c < d]
```

**Note:** To perform table-wise conversion, where all labels in the entire DataFrame are used as categories for each column, the `categories` parameter can be determined programmatically by `categories = pd.unique(df.values.ravel())`.

If you already have codes and categories, you can use the `from_codes()` constructor to save the factorize step during normal constructor mode:

```python
In [36]: splitter = np.random.choice([0, 1], 5, p=[0.5, 0.5])

In [37]: s = pd.Series(pd.Categorical.from_codes(splitter, categories=['train', 'test']))
```
21.1.4 Regaining Original Data

To get back to the original Series or NumPy array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

```
In [38]: s = pd.Series(["a", "b", "c", "a"])

In [39]: s
Out[39]:
0 a
1 b
2 c
3 a
dtype: object

In [40]: s2 = s.astype('category')

In [41]: s2
Out[41]:
0 a
1 b
2 c
3 a
dtype: category
Categories (3, object): [a, b, c]

In [42]: s2.astype(str)
Out[42]:
0 a
1 b
2 c
3 a
dtype: object

In [43]: np.asarray(s2)
Out[43]:
array(['a', 'b', 'c', 'a'], dtype=object)
```

**Note:** In contrast to R’s `factor` function, categorical data is not converting input values to strings; categories will end up the same data type as the original values.

**Note:** In contrast to R’s `factor` function, there is currently no way to assign/change labels at creation time. Use `categories` to change the categories after creation time.

### 21.2 CategoricalDtype

Changed in version 0.21.0.

A categorical’s type is fully described by

1. `categories`: a sequence of unique values and no missing values
2. ordered: a boolean

This information can be stored in a `CategoricalDtype`. The `categories` argument is optional, which implies that the actual categories should be inferred from whatever is present in the data when the `pandas.Categorical` is created. The categories are assumed to be unordered by default.

```python
In [44]: from pandas.api.types import CategoricalDtype

In [45]: CategoricalDtype(['a', 'b', 'c'])
Out[45]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=None)

In [46]: CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[46]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=True)

In [47]: CategoricalDtype()
Out[47]: CategoricalDtype(categories=None, ordered=None)
```

A `CategoricalDtype` can be used in any place pandas expects a `dtype`. For example `pandas.read_csv()`, `pandas.DataFrame.astype()`, or in the `Series` constructor.

**Note:** As a convenience, you can use the string 'category' in place of a `CategoricalDtype` when you want the default behavior of the categories being unordered, and equal to the set values present in the array. In other words, `dtype='category'` is equivalent to `dtype=CategoricalDtype()`.

### 21.2.1 Equality Semantics

Two instances of `CategoricalDtype` compare equal whenever they have the same categories and order. When comparing two unordered categoricals, the order of the categories is not considered.

```python
In [48]: c1 = CategoricalDtype(['a', 'b', 'c'], ordered=False)

# Equal, since order is not considered when ordered=False
In [49]: c1 == CategoricalDtype(['b', 'c', 'a'], ordered=False)
Out[49]: True

# Unequal, since the second CategoricalDtype is ordered
In [50]: c1 == CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[50]: False
```

All instances of `CategoricalDtype` compare equal to the string 'category'.

```python
In [51]: c1 == 'category'
Out[51]: True
```

**Warning:** Since `dtype='category'` is essentially `CategoricalDtype(None, False)`, and since all instances `CategoricalDtype` compare equal to 'category', all instances of `CategoricalDtype` compare equal to a `CategoricalDtype(None, False)`, regardless of categories or ordered.
21.3 Description

Using `describe()` on categorical data will produce similar output to a `Series` or `DataFrame` of type `string`.

```python
In [52]: cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c")
In [53]: df = pd.DataFrame({"cat":cat, "s":["a", "c", "c", np.nan]})
In [54]: df.describe()
Out[54]:
          cat    s
count   3   3
unique  2   2
top     c   c
freq    2   2
```

```python
In [55]: df["cat"].describe()
Out[55]:
       count
Name: cat, dtype: object
```

21.4 Working with categories

Categorical data has a `categories` and a `ordered` property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don’t manually specify categories and ordering, they are inferred from the passed arguments.

```python
In [56]: s = pd.Series(["a","b","c","a"], dtype="category")
In [57]: s.cat.categories
Out[57]: Index(["a", "b", "c"], dtype='object')
In [58]: s.cat.ordered
Out[58]: False
```

It’s also possible to pass in the categories in a specific order:

```python
In [59]: s = pd.Series(pd.Categorical(["a","b","c","a"], categories=["c","b","a")))
In [60]: s.cat.categories
Out[60]: Index(["c", "b", "a"], dtype='object')
In [61]: s.cat.ordered
Out[61]: False
```

**Note:** New categorical data are not automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered Categorical.
Note: The result of `unique()` is not always the same as `Series.cat.categories`, because `Series.unique()` has a couple of guarantees, namely that it returns categories in the order of appearance, and it only includes values that are actually present.

```python
In [62]: s = pd.Series(list('babc')).astype(CategoricalDtype(list('abcd')))

In [63]: s
Out[63]:
0   b
1   a
2   b
3   c
dtype: category
Categories (4, object): [a, b, c, d]

# categories
In [64]: s.cat.categories
Out[64]:
Index(['a', 'b', 'c', 'd'], dtype='object')

# uniques
In [65]: s.unique()
Out[65]:
[b, a, c]
Categories (3, object): [b, a, c]
```

### 21.4.1 Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `rename_categories()` method:

```python
In [66]: s = pd.Series(['a', 'b', 'c', 'a'], dtype='category')

In [67]: s
Out[67]:
0   a
1   b
2   c
3   a
dtype: category
Categories (3, object): [a, b, c]

In [68]: s.cat.categories = ['Group %s' % g for g in s.cat.categories]

In [69]: s
Out[69]:
0   Group a
1   Group b
2   Group c
3   Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
```

(continues on next page)
In [70]: s.cat.rename_categories([1,2,3])

→
0 1  
1 2  
2 3  
3 1

dtype: category
Categories (3, int64): [1, 2, 3]

In [71]: s

→
0 Group a  
1 Group b  
2 Group c  
3 Group a  
dtype: category
Categories (3, object): [Group a, Group b, Group c]

# You can also pass a dict-like object to map the renaming
In [72]: s.cat.rename_categories({1: 'x', 2: 'y', 3: 'z'})

→
0 Group a  
1 Group b  
2 Group c  
3 Group a  
dtype: category
Categories (3, object): [Group a, Group b, Group c]

In [73]: s

→
0 Group a  
1 Group b  
2 Group c  
3 Group a  
dtype: category
Categories (3, object): [Group a, Group b, Group c]

Note: In contrast to R’s factor, categorical data can have categories of other types than string.

Note: Be aware that assigning new categories is an inplace operation, while most other operations under Series.
cat per default return a new Series of dtype category.

Categories must be unique or a ValueError is raised:

In [74]: try:
.....: s.cat.categories = [1,1,1]
.....: except ValueError as e:
.....: print("ValueError: " + str(e))
.....:
Categories must also not be Na\text{N} or a \texttt{ValueError} is raised:

```
In [75]: try:
    ...:     s.cat.categories = [1,2,np.nan]
    ...: except ValueError as e:
    ...:     print("ValueError: " + str(e))
    ...:
ValueError: Categorical categories cannot be null
```

### 21.4.2 Appending new categories

Appending categories can be done by using the \texttt{add\_categories()} method:

```
In [76]: s = s.cat.add\_categories([4])

In [77]: s.cat.categories
Out[77]: Index(['Group a', 'Group b', 'Group c', 4], dtype='object')

In [78]: s
Out[78]:
0  Group a
1  Group b
2  Group c
3  Group a
dtype: category
Categories (4, object): [Group a, Group b, Group c, 4]
```

### 21.4.3 Removing categories

Removing categories can be done by using the \texttt{remove\_categories()} method. Values which are removed are replaced by \texttt{np.nan}:

```
In [79]: s = s.cat.remove\_categories([4])

In [80]: s
Out[80]:
0  Group a
1  Group b
2  Group c
3  Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
```

### 21.4.4 Removing unused categories

Removing unused categories can also be done:

```
In [81]: s = pd.Series(pd.Categorical(['a','b','a'], categories=['a','b','c','d']))
```

(continues on next page)
21.4.5 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 `set_categories()`.

```python
In [84]: s = pd.Series(["one","two","four", ":"], dtype="category")

In [85]: s
Out[85]:
0   one
1   two
2   four
3   NaN
dtype: category
Categories (4, object): [one, two, four]

In [86]: s = s.cat.set_categories(["one","two","three","four"])

In [87]: s
Out[87]:
0   one
1   two
2   four
3   NaN
dtype: category
Categories (4, object): [one, two, three, four]
```

**Note:** Be aware that `Categorical.set_categories()` cannot know whether some category is omitted
intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., NumPy S1 dtype and Python
strings). This can result in surprising behaviour!
21.5 Sorting and Order

If categorical data is ordered (s.cat.ordered == True), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, .min()/.max() will raise a TypeError.

```
In [88]: s = pd.Series(pd.Categorical(["a","b","c","a"], ordered=False))
In [89]: s.sort_values(inplace=True)
In [90]: s = pd.Series(["a","b","c","a"]).astype(
   ....:     CategoricalDtype(ordered=True)
   ....: )
   ....:
In [91]: s.sort_values(inplace=True)
In [92]: s
Out[92]:
0   a
3   a
1   b
2   c
dtype: category
Categories (3, object): [a < b < c]
In [93]: s.min(), s.max()
```

You can set categorical data to be ordered by using `as_ordered()` or unordered by using `as_unordered()`. These will by default return a new object.

```
In [94]: s.cat.as_ordered()
Out[94]:
0   a
3   a
1   b
2   c
dtype: category
Categories (3, object): [a < b < c]
In [95]: s.cat.as_unordered()
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [96]: s = pd.Series([1,2,3,1], dtype="category")
In [97]: s = s.cat.set_categories([2,3,1], ordered=True)
```

(continues on next page)
In [98]: s
Out[98]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [99]: s.sort_values(inplace=True)

In [100]: s
Out[100]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [101]: s.min(), s.max()
Out[101]: (2, 1)

21.5.1 Reordering

Reordering the categories is possible via the `Categorical.reorder_categories()` and the `Categorical.set_categories()` methods. For `Categorical.reorder_categories()`, all old categories must be included in the new categories and no new categories are allowed. This will necessarily make the sort order the same as the categories order.

In [102]: s = pd.Series([1,2,3,1], dtype="category")

In [103]: s = s.cat.reorder_categories([2,3,1], ordered=True)

In [104]: s
Out[104]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [105]: s.sort_values(inplace=True)

In [106]: s
Out[106]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]
In [107]: s.min(), s.max()

Out[107]:
(2, 1)

Note: Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the Series, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the Series are changed.

Note: If the Categorical is not ordered, Series.min() and Series.max() will raise TypeError. Numeric operations like +, -, *, / and operations based on them (e.g. Series.median(), which would need to compute the mean between two values if the length of an array is even) do not work and raise a TypeError.

### 21.5.2 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.

```
In [108]: dfs = pd.DataFrame({'A' : pd.Categorical(list('bbeebbaa'), categories=['e', 'a', 'b'], ordered=True),
       'B' : [1,2,1,2,2,1,2,1] })

In [109]: dfs.sort_values(by=['A', 'B'])
```

Reordering the categories changes a future sort.

```
In [110]: dfs['A'] = dfs['A'].cat.reorder_categories(['a','b','e'])

In [111]: dfs.sort_values(by=['A', 'B'])
```

---

**21.5. Sorting and Order**

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21.6 Comparisons

Comparing categorical data with other objects is possible in three cases:

- Comparing equality (== and !=) to a list-like object (list, Series, array, ...) of the same length as the categorical data.
- All comparisons (==, !=, >, >=, <, and <=) of categorical data to another categorical Series, when ordered=True and the categories are the same.
- All comparisons of a categorical data to a scalar.

All other comparisons, especially “non-equality” comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a TypeError.

**Note:** Any “non-equality” comparisons of categorical data with a Series, np.array, list or categorical data with different categories or ordering will raise a TypeError because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

```python
In [112]: cat = pd.Series([1,2,3]).astype(CategoricalDtype([3, 2, 1], ordered=True))
In [113]: cat_base = pd.Series([2,2,2]).astype(CategoricalDtype([3, 2, 1], ordered=True))
In [114]: cat_base2 = pd.Series([2,2,2]).astype(CategoricalDtype(ordered=True))
In [115]: cat
Out[115]:
0 1
1 2
2 3
dtype: category
Categories (3, int64): [3 < 2 < 1]
In [116]: cat_base
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\Out[116]:
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\0 2
1 2
2 2
dtype: category
Categories (3, int64): [3 < 2 < 1]
In [117]: cat_base2
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\0 2
1 2
```
Comparing to a categorical with the same categories and ordering or to a scalar works:

```python
In [118]: cat > cat_base
Out[118]:
0   True
1   False
2   False
dtype: bool

In [119]: cat > 2
Out[119]:
0   True
1   False
2   False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```python
In [120]: cat == cat_base
Out[120]:
0   False
1   True
2   False
dtype: bool

In [121]: cat == np.array([1,2,3])
Out[121]:
0   True
1   True
2   True
dtype: bool

In [122]: cat == 2
```

This doesn’t work because the categories are not the same:

```python
In [123]: try:
    ....:     cat > cat_base2
    ....:     except TypeError as e:
    ....:         print("TypeError: " + str(e))
    ....:TypeError: Categoricals can only be compared if 'categories' are the same. Categories are different lengths
```

If you want to do a “non-equality” comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:
When you compare two unordered categoricals with the same categories, the order is not considered:

```
In [127]: cl = pd.Categorical(['a', 'b'], categories=['a', 'b'], ordered=False)
In [128]: c2 = pd.Categorical(['a', 'b'], categories=['b', 'a'], ordered=False)
In [129]: cl == c2
Out[129]: array([ True, True], dtype=bool)
```

### 21.7 Operations

Apart from `Series.min()`, `Series.max()` and `Series.mode()`, the following operations are possible with categorical data:

Series methods like `Series.value_counts()` will use all categories, even if some categories are not present in the data:

```
In [130]: s = pd.Series(pd.Categorical(['a','b','c','c'], categories=['c','a','b','d']))
In [131]: s.value_counts()
Out[131]:
   c    2
   b    1
   a    1
   d    0
 dtype: int64
```

Groupby will also show “unused” categories:

```
In [132]: cats = pd.Categorical(['a','b','b','b','c','c','c'], categories=['a','b','c','d'])
In [133]: df = pd.DataFrame({'cats':cats, 'values':[1,2,2,2,3,4,5]})
In [134]: df.groupby('cats').mean()
Out[134]:
   values
cats  
   a    1.0
```

(continues on next page)
In [135]: cats2 = pd.Categorical(["a","a","b","b"], categories=["a","b","c"])  
In [136]: df2 = pd.DataFrame({"cats":cats2,"B":["c","d","c","d"], "values":[1,2,3,4]})  
In [137]: df2.groupby(["cats","B"]).mean()  
Out[137]:  
        values  
   cats B          
a  c  1.0  
    d  2.0  
b  c  3.0  
    d  4.0  
c  c  NaN  
    d  NaN  

Pivot tables:  
In [138]: raw_cat = pd.Categorical(["a","a","b","b"], categories=["a","b","c"])  
In [139]: df = pd.DataFrame({"A":raw_cat,"B":["c","d","c","d"], "values":[1,2,3,4]})  
In [140]: pd.pivot_table(df, values='values', index=['A', 'B'])  
Out[140]:  
          values  
   A  B  
a  c   1  
    d   2  
b  c   3  
    d   4  

21.8 Data munging  
The optimized pandas data access methods .loc, .iloc, .at, and .iat, work as normal. The only difference is the return type (for getting) and that only values already in categories can be assigned.  

21.8.1 Getting  
If the slicing operation returns either a DataFrame or a column of type Series, the category dtype is preserved.  
In [141]: idx = pd.Index(["h","i","j","k","l","m","n",])  
In [142]: cats = pd.Series(["a","b","b","b","c","c","c"], dtype="category", index=idx)  
In [143]: values= [1,2,2,2,3,4,5]  
In [144]: df = pd.DataFrame({"cats":cats,"values":values}, index=idx)  
In [145]: df.iloc[2:4,:]  
Out[145]: (continues on next page)
An example where the category type is not preserved is if you take one single row: the resulting `Series` is of dtype `object`:

```python
In [149]: df.loc["h", :]
Out[149]:
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”.

```python
In [150]: df.iat[0,0]
Out[150]: 'a'
```

```python
In [151]: df["cats"].cat.categories = ["x","y","z"]
```

```python
In [152]: df.at["h","cats"] # returns a string
Out[152]: 'x'
```

**Note:** The is in contrast to R’s `factor` function, where `factor(c(1,2,3))[1]` returns a single value `factor`.

To get a single value `Series` of type `category`, you pass in a list with a single value:

```python
In [153]: df.loc["h","cats"]
Out[153]:
h  x
```
21.8.2 String and datetime accessors

The accessors .dt and .str will work if the s.cat.categories are of an appropriate type:

```python
In [154]: str_s = pd.Series(list('aabb'))
In [155]: str_cat = str_s.astype('category')
In [156]: str_cat
Out[156]:
0   a
1   a
2   b
3   b
dtype: category
Categories (2, object): [a, b]
In [157]: str_cat.str.contains("a")
Out[157]:
0   True
1   True
2  False
3  False
dtype: bool
In [158]: date_s = pd.Series(pd.date_range('1/1/2015', periods=5))
In [159]: date_cat = date_s.astype('category')
In [160]: date_cat
Out[160]:
0  2015-01-01
1  2015-01-02
2  2015-01-03
3  2015-01-04
4  2015-01-05
dtype: category
In [161]: date_cat.dt.day
Out[161]:
0   1
1   2
2   3
3   4
4   5
dtype: int64
```

Note: The returned Series (or DataFrame) is of the same type as if you used the .str.<method> / .dt.
<method> on a Series of that type (and not of type category!).

That means, that the returned values from methods and properties on the accessors of a Series and the returned values from methods and properties on the accessors of this Series transformed to one of type category will be equal:

```python
In [162]: ret_s = str_s.str.contains("a")
In [163]: ret_cat = str_cat.str.contains("a")
In [164]: ret_s.dtype == ret_cat.dtype
Out[164]: True
In [165]: ret_s == ret_cat
```

```
 0    True
 1    True
 2    True
 3    True
dtype: bool
```

Note: The work is done on the categories and then a new Series is constructed. This has some performance implication if you have a Series of type string, where lots of elements are repeated (i.e. the number of unique elements in the Series is a lot smaller than the length of the Series). In this case it can be faster to convert the original Series to one of type category and use .str.<method> or .dt.<property> on that.

### 21.8.3 Setting

Setting values in a categorical column (or Series) works as long as the value is included in the categories:

```python
In [166]: idx = pd.Index(["h","i","j","k","l","m","n"])
In [167]: cats = pd.Categorical(["a","a","a","a","a","a","a"], categories=["a","b"])
In [168]: values = [1,1,1,1,1,1,1]
In [169]: df = pd.DataFrame({"cats":cats,"values":values}, index=idx)
In [170]: df.iloc[2:4,:] = [["b",2],["b",2]]
In [171]: df
Out[171]:
   cats values
  h    a    1
  i    a    1
  j    b    2
  k    b    2
  l    a    1
  m    a    1
  n    a    1
```

```python
In [172]: try:
.....:   df.iloc[2:4,:] = [["c",3],["c",3]]
```
Setting values by assigning categorical data will also check that the categories match:

```
In [173]: df.loc["j":"k","cats"] = pd.Categorical(["a","a"], categories=["a","b"])

In [174]: df
Out[174]:
      cats     values
    h  a  1
    i  a  1
    j  a  2
    k  a  2
    l  a  1
    m  a  1
    n  a  1

In [175]: try:
    ....:     df.loc["j":"k","cats"] = pd.Categorical(["b","b"], categories=["a","b", "c"])
    ....: except ValueError as e:
    ....:     print("ValueError: " + str(e))
    ....:     print("Cannot setitem on a Categorical with a new category, set the categories first")
```

Assigning a Categorical to parts of a column of other types will use the values:

```
In [176]: df = pd.DataFrame({"a":\[1,1,1,1,1\], "b":\["a","a","a","a","a"\]})

In [177]: df.loc[1:2,"a"] = pd.Categorical(["b","b"], categories=["a","b"])

In [178]: df.loc[2:3,"b"] = pd.Categorical(["b","b"], categories=["a","b"])

In [179]: df
Out[179]:
   a   b
  0  a  1
  1  b  a
  2  b  b
  3  l  b
  4  l  a

In [180]: df.dtypes
Out[180]:
a   object
b   object
dtype: object
```
21.8.4 Merging

You can concat two DataFrame containing categorical data together, but the categories of these categoricals need to be the same:

```python
In [181]: cat = pd.Series(["a","b"], dtype="category")
In [182]: vals = [1,2]
In [183]: df = pd.DataFrame({"cats":cat, "vals":vals})
In [184]: res = pd.concat([df,df])
In [185]: res
Out[185]:
cats  vals
  0  a  1
  1  b  2
  0  a  1
  1  b  2
```

In this case the categories are not the same, and therefore an error is raised:

```python
In [186]: res.dtypes

In [186]: res.dtypes

```

The same applies to `df.append(df_different)`.

See also the section on `merge dtypes` for notes about preserving merge dtypes and performance.

21.8.5 Unioning

New in version 0.19.0.

If you want to combine categoricals that do not necessarily have the same categories, the `union_categoricals()` function will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```python
In [190]: from pandas.api.types import union_categoricals
In [191]: a = pd.Categorical(["b", "c")
In [192]: b = pd.Categorical(["a", "b")
In [193]: union_categoricals([a, b])
```
By default, the resulting categories will be ordered as they appear in the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```python
In [194]: union_categoricals([a, b], sort_categories=True)
Out[194]:
[b, c, a, b]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with the “easy” case of combining two categoricals of the same categories and order information (e.g. what you could also append for).

```python
In [195]: a = pd.Categorical(['a', 'b'], ordered=True)
In [196]: b = pd.Categorical(['a', 'b', 'a'], ordered=True)
In [197]: union_categoricals([a, b])
Out[197]:
[a, b, a, b, a]
Categories (2, object): [a < b]
```

The below raises `TypeError` because the categories are ordered and not identical.

```python
In [1]: a = pd.Categorical(['a', 'b'], ordered=True)
In [2]: b = pd.Categorical(['a', 'b', 'c'], ordered=True)
In [3]: union_categoricals([a, b])
```

```
TypeError: to union ordered Categoricals, all categories must be the same
```

New in version 0.20.0.

Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```python
In [198]: a = pd.Categorical(['a', 'b', 'c'], ordered=True)
In [199]: b = pd.Categorical(['c', 'b', 'a'], ordered=True)
In [200]: union_categoricals([a, b], ignore_order=True)
Out[200]:
[a, b, c, c, b, a]
Categories (3, object): [a, b, c]
```

`union_categoricals()` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`:

```python
In [201]: a = pd.Series(['b', 'c'], dtype='category')
In [202]: b = pd.Series(['a', 'b'], dtype='category')
In [203]: union_categoricals([a, b])
Out[203]:
[b, c, a, b]
Categories (3, object): [b, c, a]
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

**Note:** `union_categoricals` may recode the integer codes for categories when combining categoricals. This is likely what you want, but if you are relying on the exact numbering of the categories, be aware.

```
In [204]: c1 = pd.Categorical(['b', 'c'])

In [205]: c2 = pd.Categorical(['a', 'b'])

In [206]: c1
Out[206]:
[b, c]
Categories (2, object): [b, c]
# "b" is coded to 0
In [207]: c1.codes
Out[207]: array([0, 1], dtype=int8)

In [208]: c2
Out[208]:
[a, b]
Categories (2, object): [a, b]
# "b" is coded to 1
In [209]: c2.codes
Out[209]: array([0, 1], dtype=int8)

In [210]: c = union_categoricals([c1, c2])

In [211]: c
Out[211]:
[b, c, a, b]
Categories (3, object): [b, c, a]
# "b" is coded to 0 throughout, same as c1, different from c2
In [212]: c.codes
Out[212]: array([0, 1, 2, 0], dtype=int8)
```

### 21.8.6 Concatenation

This section describes concatenations specific to category dtype. See *Concatenating objects* for general description.

By default, `Series` or `DataFrame` concatenation which contains the same categories results in category dtype, otherwise results in object dtype. Use `.astype` or `union_categoricals` to get category result.

```
# same categories
In [213]: s1 = pd.Series(['a', 'b'], dtype='category')

In [214]: s2 = pd.Series(['a', 'b', 'a'], dtype='category')

In [215]: pd.concat([s1, s2])
Out[215]:
0  a
```

(continues on next page)
1 b
0 a
1 b
dtype: category
Categories (2, object): [a, b]

# different categories
In [216]: s3 = pd.Series(['b', 'c'], dtype='category')

In [217]: pd.concat([s1, s3])
Out[217]:
0 a
1 b
0 b
1 c
dtype: object

In [218]: pd.concat([s1, s3]).astype('category')
Out[218]:
0 a
1 b
0 b
1 c
dtype: category
Categories (3, object): [a, b, c]

In [219]: union_categoricals([s1.values, s3.values])
→
[a, b, b, c]
Categories (3, object): [a, b, c]

Following table summarizes the results of Categoricals related concatenations.

<table>
<thead>
<tr>
<th>arg1</th>
<th>arg2</th>
<th>result</th>
</tr>
</thead>
<tbody>
<tr>
<td>category</td>
<td>category (identical categories)</td>
<td>category</td>
</tr>
<tr>
<td>category</td>
<td>category (different categories, both not ordered)</td>
<td>object (dtype is inferred)</td>
</tr>
<tr>
<td>category</td>
<td>category (different categories, either one is ordered)</td>
<td>object (dtype is inferred)</td>
</tr>
<tr>
<td>category</td>
<td>not category</td>
<td>object (dtype is inferred)</td>
</tr>
</tbody>
</table>

### 21.9 Getting Data In/Out

You can write data that contains category dtypes to a HDFStore. See here for an example and caveats.

It is also possible to write data to and reading data from Stata format files. See here for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to category and assign the right categories and categories ordering.

In [220]: s = pd.Series(pd.Categorical(['a', 'b', 'b', 'a', 'a', 'd']))

# rename the categories

(continues on next page)
In [221]: s.cat.categories = ["very good", "good", "bad"]

# reorder the categories and add missing categories
In [222]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [223]: df = pd.DataFrame( {"cats":s, "vals" :[1,2,3,4,5,6]})

In [224]: csv = StringIO()

In [225]: df.to_csv(csv)

In [226]: df2 = pd.read_csv(StringIO(csv.getvalue()))

In [227]: df2.dtypes
Out[227]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Unnamed: 0</td>
<td>int64</td>
</tr>
<tr>
<td>cats</td>
<td>object</td>
</tr>
<tr>
<td>vals</td>
<td>int64</td>
</tr>
<tr>
<td>dtype:</td>
<td>object</td>
</tr>
</tbody>
</table>

In [228]: df2["cats"]

→

0  very good
1  good
2  good
3  very good
4  very good
5  bad
Name: cats, dtype: object

# Redo the category
In [229]: df2["cats"] = df2["cats"].astype("category")

In [230]: df2["cats"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"], inplace=True)

In [231]: df2.dtypes
Out[231]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Unnamed: 0</td>
<td>int64</td>
</tr>
<tr>
<td>cats</td>
<td>category</td>
</tr>
<tr>
<td>vals</td>
<td>int64</td>
</tr>
<tr>
<td>dtype:</td>
<td>object</td>
</tr>
</tbody>
</table>

In [232]: df2["cats"]

→

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`.

## 21.10 Missing Data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the Missing Data section.

Missing values should **not** be included in the Categorical’s `categories`, only in the `values`. Instead, it is understood that NaN is different, and is always a possibility. When working with the Categorical’s `codes`, missing values will always have a code of `-1`.

```python
In [233]: s = pd.Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [234]: s
Out[234]:
0    a
1    b
2   NaN
3    a
dtype: category
Categories (2, object): [a, b]

In [235]: s.cat.codes
Out[235]:
0    0
1    1
2   -1
3    0
dtype: int8
```

Methods for working with missing data, e.g. `isna()`, `fillna()`, `dropna()`, all work normally:

```python
In [236]: s = pd.Series(["a", "b", np.nan], dtype="category")

In [237]: s
Out[237]:
0    a
1    b
2   NaN
dtype: category
Categories (2, object): [a, b]

In [238]: pd.isna(s)
Out[238]:
0   False
1   False
2    True
dtype: bool

In [239]: s.fillna("a")
Out[239]:
0    a
```

(continues on next page)
21.11 Differences to R’s `factor`

The following differences to R’s factor functions can be observed:

- R’s `levels` are named `categories`.
- R’s `levels` are always of type string, while `categories` in pandas can be of any dtype.
- It’s not possible to specify labels at creation time. Use `s.cat.rename_categories(new_labels)` afterwards.
- In contrast to R’s `factor` function, using categorical data as the sole input to create a new categorical series will not remove unused categories but create a new categorical series which is equal to the passed in one!
- R allows for missing values to be included in its `levels` (pandas’ `categories`). Pandas does not allow `NaN` categories, but missing values can still be in the `values`.

21.12 Gotchas

21.12.1 Memory Usage

The memory usage of a `Categorical` is proportional to the number of categories plus the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [240]: s = pd.Series(['foo','bar'] * 1000)

# object dtype
In [241]: s.nbytes
Out[241]: 16000

# category dtype
In [242]: s.astype('category').nbytes
Out[242]: 2016
```

Note: If the number of categories approaches the length of the data, the `Categorical` will use nearly the same or more memory than an equivalent `object` dtype representation.

```
In [243]: s = pd.Series(['foo%d' % i for i in range(2000)])

# object dtype
In [244]: s.nbytes
Out[244]: 16000

# category dtype
In [245]: s.astype('category').nbytes
Out[245]: 20000
```
21.12.2 *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 [246]: try:
    ....:     np.dtype("category")
    ....: except TypeError as e:
    ....:     print("TypeError: " + str(e))
    ....:
TypeError: data type "category" not understood
```

```python
In [247]: dtype = pd.Categorical(["a"]).dtype
```

```python
In [248]: try:
    ....:     np.dtype(dtype)
    ....: except TypeError as e:
    ....:     print("TypeError: " + str(e))
    ....:
TypeError: data type not understood
```

Dtype comparisons work:

```python
In [249]: dtype == np.str_
Out[249]: False

In [250]: np.str_ == dtype
```

To check if a Series contains Categorical data, use `hasattr(s, 'cat')`:

```python
In [251]: hasattr(pd.Series(["a"], dtype='category'), 'cat')
Out[251]: True

In [252]: hasattr(pd.Series(['a']), 'cat')
```

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 [253]: s = pd.Series(pd.Categorical([1,2,3,4]))
```

```python
In [254]: try:
    ....:     np.sum(s)
    ....: except TypeError as e:
    ....:     print("TypeError: " + str(e))
    ....:
TypeError: Categorical cannot perform the operation sum
```

**Note:** If such a function works, please file a bug at [https://github.com/pandas-dev/pandas!](https://github.com/pandas-dev/pandas!)
21.12.3 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 [255]: df = pd.DataFrame({"a": [1,2,3,4],
                      .....:
                      "b": ["a","b","c","d"],
                      .....:
                      "cats": pd.Categorical([1,2,3,2])})

In [256]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[256]:
0  <class 'int'>
1  <class 'int'>
2  <class 'int'>
3  <class 'int'>
dtype: object
```

```
In [257]: df.apply(lambda col: col.dtype, axis=0)
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
Out[257]:
\rightarrow
a  int64
b  object
cats  category
dtype: object
```

21.12.4 Categorical Index

CategoricalIndex is a type of index that is useful for supporting indexing with duplicates. This is a container around a Categorical and allows efficient indexing and storage of an index with a large number of duplicated elements. See the advanced indexing docs for a more detailed explanation.

Setting the index will create a CategoricalIndex:

```
In [258]: cats = pd.Categorical([1,2,3,4], categories=[4,2,3,1])

In [259]: strings = ["a","b","c","d"]

In [260]: values = [4,2,3,1]

In [261]: df = pd.DataFrame({"strings":strings, "values":values}, index=cats)

In [262]: df.index
Out[262]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False,
\rightarrow dtype='category')

# This now sorts by the categories order
In [263]: df.sort_index()
\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
Out[263]:
\rightarrow
   strings  values
4       d      1
2       b      2
3       c      3
1       a      4
```

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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:

```python
In [264]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [265]: s = pd.Series(cat, name="cat")

In [266]: cat
Out[266]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [267]: s.iloc[0:2] = 10

In [268]: cat
Out[268]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [269]: df = pd.DataFrame(s)

In [270]: df["cat"].cat.categories = [1,2,3,4,5]

In [271]: cat
Out[271]:
[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:

```python
In [272]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [273]: s = pd.Series(cat, name="cat", copy=True)

In [274]: cat
Out[274]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [275]: s.iloc[0:2] = 10

In [276]: cat
Out[276]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

Note: This also happens in some cases when you supply a NumPy array instead of a Categorical: using an int array (e.g. np.array([1,2,3,4])) will exhibit the same behavior, while using a string array (e.g. np.array(["a","b","c","a"])) will not.
Chapter 21. Categorical Data
We use the standard convention for referencing the matplotlib API:

```python
In [1]: import matplotlib.pyplot as plt
```

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.

## 22.1 Basic Plotting: `plot`

We will demonstrate the basics, see the `cookbook` for some advanced strategies.

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```python
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 0x1c2e7e3c50>
```
If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```python
In [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 `x` and `y` keywords in `plot()`:

```python
In [8]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()
In [9]: df3['A'] = pd.Series(list(range(len(df))))
In [10]: df3.plot(x='A', y='B')
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2fd3f550>
```
22.2 Other Plots

Plotting methods allow for a handful of plot styles other than the default line plot. These methods can be provided as the `kind` keyword argument to `plot()`, and include:

- `'bar'` or `'barh'` for bar plots
- `'hist'` for histogram
- `'box'` for boxplot
- `'kde'` or `'density'` for density plots
- `'area'` for area plots
- `'scatter'` for scatter plots
- `'hexbin'` for hexagonal bin plots
- `'pie'` for pie plots

For example, a bar plot can be created the following way:
In [11]: plt.figure();
In [12]: df.iloc[5].plot(kind='bar');

You can also create these other plots using the methods `DataFrame.plot.<kind>` instead of providing the `kind` keyword argument. This makes it easier to discover plot methods and the specific arguments they use:

In [13]: df = pd.DataFrame()
In [14]: 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

In addition to these `kind`s, there are the `DataFrame.hist()` and `DataFrame.boxplot()` methods, which use a separate interface.

Finally, there are several `plotting functions` in `pandas.plotting` that take a `Series` or `DataFrame` as an argument. These include:

- Scatter Matrix
- Andrews Curves
- Parallel Coordinates
- Lag Plot

22.2. Other Plots
• Autocorrelation Plot
• Bootstrap Plot
• RadViz

Plots may also be adorned with errorbars or tables.

### 22.2.1 Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```python
In [15]: plt.figure();
In [16]: df.iloc[5].plot.bar(); plt.axhline(0, color='k')
Out[16]: <matplotlib.lines.Line2D at 0x1c31253b38>
```

Calling a DataFrame's `plot.bar()` method produces a multiple bar plot:

```python
In [17]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
In [18]: df2.plot.bar();
```
To produce a stacked bar plot, pass `stacked=True`:

```
In [19]: df2.plot.bar(stacked=True);
```
To get horizontal bar plots, use the `barh` method:

```python
In [20]: df2.plot.barh(stacked=True);
```
22.2.2 Histograms

Histograms can be drawn by using the `DataFrame.plot.hist()` and `Series.plot.hist()` methods.

```
In [21]: 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 [22]: plt.figure();

In [23]: df4.plot.hist(alpha=0.5)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2f7804a8>
```
A histogram can be stacked using \texttt{stacked=True}. Bin size can be changed using the \texttt{bins} keyword.

\begin{Verbatim}
In [24]: plt.figure();
In [25]: df4.plot.hist(stacked=True, bins=20)
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2fe3f0b8>
\end{Verbatim}
You can pass other keywords supported by matplotlib `hist`. For example, horizontal and cumulative histograms can be drawn by `orientation='horizontal'` and `cumulative=True`.

```
In [26]: plt.figure();
In [27]: df4['a'].plot.hist(orientation='horizontal', cumulative=True)
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1c30a000b8>
```
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 [28]: plt.figure();

In [29]: df['A'].diff().hist()
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2c154630>
```
`DataFrame.hist()` plots the histograms of the columns on multiple subplots:

```
In [30]: plt.figure()
Out[30]: <Figure size 640x480 with 0 Axes>

In [31]: df.diff().hist(color='k', alpha=0.5, bins=50)
```

```
Out[31]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1c39866198>],
          [<matplotlib.axes._subplots.AxesSubplot object at 0x1c39883f98>],
          [<matplotlib.axes._subplots.AxesSubplot object at 0x1c399d42e8>],
          [<matplotlib.axes._subplots.AxesSubplot object at 0x1c2f90a5f8>]],
         dtype=object)
```
The `by` keyword can be specified to plot grouped histograms:

```python
In [32]: data = pd.Series(np.random.randn(1000))
In [33]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
Out[33]:
```

---

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22.2.3 Box Plots

Boxplot can be drawn calling `Series.plot.box()` and `DataFrame.plot.box()`, or `DataFrame.boxplot()` to visualize the distribution of values within each column.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

In [34]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
In [35]: df.plot.box()
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1c30f426d8>
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 [36]: color = dict(boxes='DarkGreen', whiskers='DarkOrange',
                   ....:       medians='DarkBlue', caps='Gray')

In [37]: df.plot.box(color=color, sym='r+)
```

```
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1c310e5ef0>
```
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.

```
In [38]: df.plot.box(vert=False, positions=[1, 4, 5, 6, 8])
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3458e780>
```
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 [39]: df = pd.DataFrame(np.random.rand(10,5))
In [40]: plt.figure();
In [41]: bp = df.boxplot()
```
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [42]: df = pd.DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'])
In [43]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])
In [44]: plt.figure();
In [45]: bp = df.boxplot(by='X')
```
You can also pass a subset of columns to plot, as well as group by multiple columns:

```python
In [46]: df = pd.DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])
In [47]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])
In [48]: df['Y'] = pd.Series(['A','B','A','B','A','B','A','B','A','B'])
In [49]: plt.figure();
In [50]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```
Warning: The default changed from 'dict' to 'axes' in version 0.19.0.

In `boxplot`, the return type can be controlled by the `return_type` keyword. The valid choices are {"axes", "dict", "both", None}. Faceting, created by `DataFrame.boxplot` with the by keyword, will affect the output type as well:

<table>
<thead>
<tr>
<th><code>return_type</code></th>
<th>Faceted</th>
<th>Output type</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>No</td>
<td>axes</td>
</tr>
<tr>
<td>None</td>
<td>Yes</td>
<td>2-D ndarray of axes</td>
</tr>
<tr>
<td>'axes'</td>
<td>No</td>
<td>axes</td>
</tr>
<tr>
<td>'axes'</td>
<td>Yes</td>
<td>Series of axes</td>
</tr>
<tr>
<td>'dict'</td>
<td>No</td>
<td>dict of artists</td>
</tr>
<tr>
<td>'dict'</td>
<td>Yes</td>
<td>Series of dicts of artists</td>
</tr>
<tr>
<td>'both'</td>
<td>No</td>
<td>namedtuple</td>
</tr>
<tr>
<td>'both'</td>
<td>Yes</td>
<td>Series of namedtuples</td>
</tr>
</tbody>
</table>

`Groupby.boxplot` always returns a Series of `return_type`.

```python
In [51]: np.random.seed(1234)

In [52]: df_box = pd.DataFrame(np.random.randn(50, 2))
```
```python
In [53]: df_box['g'] = np.random.choice(['A', 'B'], size=50)
In [54]: df_box.loc[df_box['g'] == 'B', 1] += 3
In [55]: bp = df_box.boxplot(by='g')
```

The subplots above are split by the numeric columns first, then the value of the `g` column. Below the subplots are first split by the value of `g`, then by the numeric columns.

```python
In [56]: bp = df_box.groupby('g').boxplot()
```
22.2.4 Area Plot

You can create area plots with `Series.plot.area()` and `DataFrame.plot.area()`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains `NaN`, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling `plot`.

```python
In [57]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
In [58]: df.plot.area();
```
To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```python
In [59]: df.plot.area(stacked=False);
```
22.2.5 Scatter Plot

Scatter plot can be drawn by using the `DataFrame.plot.scatter()` method. Scatter plot requires numeric columns for the x and y axes. These can be specified by the x and y keywords.

```
In [60]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])
In [61]: df.plot.scatter(x='a', y='b');
```
To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

```
In [62]: ax = df.plot.scatter(x='a', y='b', color='DarkBlue', label='Group 1');
In [63]: df.plot.scatter(x='c', y='d', color='DarkGreen', label='Group 2', ax=ax);
```
The keyword `c` may be given as the name of a column to provide colors for each point:

```python
In [64]: df.plot.scatter(x='a', y='b', c='c', s=50);
```
You can pass other keywords supported by matplotlib `scatter`. The example below shows a bubble chart using a column of the DataFrame as the bubble size.

```python
In [65]: df.plot.scatter(x='a', y='b', s=df['c']*200);
```
See the `scatter` method and the matplotlib `scatter` documentation for more.

### 22.2.6 Hexagonal Bin Plot

You can create hexagonal bin plots with `DataFrame.plot.hexbin()`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [66]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
In [67]: df['b'] = df['b'] + np.arange(1000)
In [68]: df.plot.hexbin(x='a', y='b', gridsize=25)
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3bd78198>
```
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.

```python
In [69]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
In [70]: df['b'] = df['b'] = df['b'] + np.arange(1000)
In [71]: df['z'] = np.random.uniform(0, 3, 1000)
In [72]: df.plot.hexbin(x='a', y='b', C='z', reduce_C_function=np.max, gridsize=25)
....:
```

Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3c0515c0>
22.2.7 Pie plot

You can create a pie plot with `DataFrame.plot.pie()` or `Series.plot.pie()`. If your data includes any NaN, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

```python
In [73]: series = pd.Series(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], name='series')
In [74]: series.plot.pie(figsize=(6, 6))
Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3f2e2a20>
```

See the `hexbin` method and the matplotlib hexbin documentation for more.
For pie plots it’s best to use square figures, i.e. a figure aspect ratio 1. You can create the figure with equal width and height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned axes object.

Note that pie plot with `DataFrame` requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```python
In [75]: df = pd.DataFrame(3 * np.random.rand(4, 2), index=['a', 'b', 'c', 'd'],
                     columns=['x', 'y'])

In [76]: df.plot.pie(subplots=True, figsize=(8, 4))
Out[76]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0x1c3f484128>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1c3f64a518>], 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 [77]: series.plot.pie(labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
   ....:     autopct='%.2f', fontsize=20, figsize=(6, 6))
   ....: Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x1c33123ef0>
```
If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [78]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')
In [79]: series.plot.pie(figsize=(6, 6))
Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3bd3f438>
```
See the matplotlib pie documentation for more.

22.3 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.
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 \texttt{fillna()} or \texttt{dropna()} before plotting.

### 22.4 Plotting Tools

These functions can be imported from \texttt{pandas.plotting} and take a \texttt{Series} or \texttt{DataFrame} as an argument.

#### 22.4.1 Scatter Matrix Plot

You can create a scatter plot matrix using the \texttt{scatter_matrix} method in \texttt{pandas.plotting}:

```python
In [80]: from pandas.plotting import scatter_matrix

In [81]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

In [82]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')

Out[82]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1c3146fa20>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c2fb1b8d0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c312f15f8>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c3100e940>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1c2de35128>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c2de354e0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c3413d3c8>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c2f0f2630>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1c3022d5f8>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c313c04e0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c39af4a20>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c217e898>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1c33f6f160>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c2f7d7f0>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c2fbc0c50>,
<matplotlib.axes._subplots.AxesSubplot object at 0x1c308384a8>]],
... dtype=object)
```
22.4.2 Density Plot

You can create density plots using the `Series.plot.kde()` and `DataFrame.plot.kde()` methods.

In [83]: ser = pd.Series(np.random.randn(1000))

In [84]: ser.plot.kde()

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2e7db9e8>
Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series, see the Wikipedia entry for more information. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

Note: The “Iris” dataset is available here.
22.4.4 Parallel Coordinates

Parallel coordinates is a plotting technique for plotting multivariate data, see the Wikipedia entry for an introduction. Parallel coordinates allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```
In [89]: from pandas.plotting import parallel_coordinates

In [90]: data = pd.read_csv('data/iris.data')

In [91]: plt.figure()
Out[91]: <Figure size 640x480 with 0 Axes>

In [92]: parallel_coordinates(data, 'Name')
```

---

22.4. Plotting Tools
22.4.5 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. The `lag` argument may be passed, and when `lag=1` the plot is essentially `data[:-1]` vs. `data[1:]`.

```
In [93]: from pandas.plotting import lag_plot
In [94]: plt.figure()
Out[94]: <Figure size 640x480 with 0 Axes>
In [95]: data = pd.Series(0.1 * np.random.rand(1000) +
                      0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))
In [96]: lag_plot(data)
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x10e180ef0>
```
22.4.6 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. See the Wikipedia entry for more about autocorrelation plots.

In [97]: from pandas.plotting import autocorrelation_plot

In [98]: plt.figure()
Out[98]: <Figure size 640x480 with 0 Axes>

In [99]: data = pd.Series(0.7 * np.random.rand(1000) +
      ....: 0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
      ....:

In [100]: autocorrelation_plot(data)
Out[100]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2e6ed630>

22.4. Plotting Tools
22.4.7 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 [101]: from pandas.plotting import bootstrap_plot

In [102]: data = pd.Series(np.random.rand(1000))

In [103]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[103]: <Figure size 640x480 with 6 Axes>
```
22.4.8 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. See the R package Radviz for more information.

Note: The “Iris” dataset is available here.

In [104]: from pandas.plotting import radviz

In [105]: data = pd.read_csv('data/iris.data')

In [106]: plt.figure()
Out[106]: <Figure size 640x480 with 0 Axes>

In [107]: radviz(data, 'Name')

---

22.4. Plotting Tools

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22.5 Plot Formatting

22.5.1 Setting the plot style

From version 1.5 and up, matplotlib offers a range of preconfigured plotting styles. Setting the style can be used to easily give plots the general look that you want. Setting the style is as easy as calling `matplotlib.style.use(my_plot_style)` before creating your plot. For example you could write `matplotlib.style.use('ggplot')` for ggplot-style plots.

You can see the various available style names at `matplotlib.style.available` and it’s very easy to try them out.

22.5.2 General plot style arguments

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [108]: 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.

### 22.5.3 Controlling the Legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```python
In [109]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))
In [110]: df = df.cumsum()
In [111]: df.plot(legend=False)
Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0x1c302e4be0>
```
22.5.4 Scales

You may pass `logy` to get a log-scale Y axis.

```python
In [112]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
In [113]: ts = np.exp(ts.cumsum())
In [114]: ts.plot(logy=True)
Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3027f780>
```


22.5.5 Plotting on a Secondary Y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [115]: df.A.plot()
Out[115]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2ee28b00>

In [116]: df.B.plot(secondary_y=True, style='g')
```

See also the `logx` and `loglog` keyword arguments.

---

22.5. Plot Formatting
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```python
In [117]: plt.figure()
Out[117]: <Figure size 640x480 with 0 Axes>

In [118]: ax = df.plot(secondary_y=['A', 'B'])

In [119]: ax.set_ylabel('CD scale')
Out[119]: Text(0,0.5,'CD scale')

In [120]: ax.right_ax.set_ylabel('AB scale')
```

---

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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 [121]: plt.figure()
Out[121]: <Figure size 640x480 with 0 Axes>

In [122]: df.plot(secondary_y=['A', 'B'], mark_right=False)
```

```
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x1a28452b00>
```
22.5.6 Suppressing Tick Resolution Adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labeling is performed:

```
In [123]: plt.figure()
Out[123]: <Figure size 640x480 with 0 Axes>

In [124]: df.A.plot()
```

```
Using the `x_compat` parameter, you can suppress this behavior:

```python
In [125]: plt.figure()
Out[125]: <Figure size 640x480 with 0 Axes>

In [126]: df.A.plot(x_compat=True)
```

Using the `x_compat` parameter, you can suppress this behavior:

```python
In [125]: plt.figure()
Out[125]: <Figure size 640x480 with 0 Axes>

In [126]: df.A.plot(x_compat=True)
```
If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plotting.plot_params` can be used in a `with statement`:

```python
In [127]: plt.figure()
Out[127]: <Figure size 640x480 with 0 Axes>

In [128]: with pd.plotting.plot_params.use('x_compat', True):
   ....:     df.A.plot(color='r')
   ....:     df.B.plot(color='g')
   ....:     df.C.plot(color='b')
   ....:
```
22.5.7 Automatic Date Tick Adjustment

New in version 0.20.0.

TimedeltaIndex now uses the native matplotlib tick locator methods, it is useful to call the automatic date tick adjustment from matplotlib for figures whose ticklabels overlap.

See the `autofmt_xdate` method and the matplotlib documentation for more.

22.5.8 Subplots

Each `Series` in a `DataFrame` can be plotted on a different axis with the `subplots` keyword:

```python
In [129]: df.plot(subplots=True, figsize=(6, 6));
```
22.5.9 Using Layout and Targeting Multiple Axes

The layout of subplots can be specified by the `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If the input is invalid, a `ValueError` will be raised.

The number of axes which can be contained by rows x columns specified by `layout` must be larger than the number of required subplots. If layout can contain more axes than required, blank axes are not drawn. Similar to a NumPy array’s `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [130]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```
The above example is identical to using:

```
In [131]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

You can pass multiple axes created beforehand as list-like via `ax` keyword. This allows more complicated layouts. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via the `ax` keyword, `layout`, `sharex` and `sharey` keywords don’t affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

```
In [132]: fig, axes = plt.subplots(4, 4, figsize=(6, 6));

In [133]: plt.subplots_adjust(wspace=0.5, hspace=0.5);

In [134]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]
```
Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

```python
In [138]: fig, axes = plt.subplots(nrows=2, ncols=2)
In [139]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A');
In [140]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B');
```

(continues on next page)
In [141]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C');
In [142]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D');

22.5.10 Plotting With Error Bars

Plotting with error bars is supported in DataFrame.plot() and Series.plot().

Horizontal and vertical error bars can be supplied to the xerr and yerr keyword arguments to plot(). The error values can be specified using a variety of formats:

- As a DataFrame or dict of errors with column names matching the columns attribute of the plotting DataFrame or matching the name attribute of the Series.

- As a str indicating which of the columns of plotting DataFrame contain the error values.

- As raw values (list, tuple, or np.ndarray). Must be the same length as the plotting DataFrame/Series.

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For 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 [143]: ix3 = pd.MultiIndex.from_arrays([['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'], ['foo', 'foo', 'bar', 'bar', 'foo', 'foo', 'bar', 'bar']], names=['letter', 'word'])

In [144]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2], 'data2': [6, 5, 7, 5, 4, 5, 6, 5]}, index=ix3)

# Group by index labels and take the means and standard deviations for each group
In [145]: gp3 = df3.groupby(level=('letter', 'word'))

In [146]: means = gp3.mean()

In [147]: errors = gp3.std()

In [148]: means
Out[148]:
    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 [149]: errors

# Plot
In [150]: fig, ax = plt.subplots()

In [151]: means.plot.bar(yerr=errors, ax=ax)
Out[151]: <matplotlib.axes._subplots.AxesSubplot at 0x1c3fc889b0>
22.5.11 Plotting Tables

Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

```
In [152]: fig, ax = plt.subplots(1, 1)
In [153]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])
In [154]: ax.get_xaxis().set_visible(False)  # Hide Ticks
In [155]: df.plot(table=True, ax=ax)
```

Out[155]: `<matplotlib.axes._subplots.AxesSubplot at 0x1c33c056d8>`
Also, you can pass a different `DataFrame` or `Series` to the `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as seen in the example below.

In [156]: fig, ax = plt.subplots(1, 1)

In [157]: ax.get_xaxis().set_visible(False)  # Hide Ticks

In [158]: df.plot(table=np.round(df.T, 2), ax=ax)

Out[158]: <matplotlib.axes._subplots.AxesSubplot at 0x1c31198c88>
There also exists a helper function `pandas.plotting.table`, which creates a table from `DataFrame` or `Series`, and adds it to a `matplotlib.Axes` instance. This function can accept keywords which the `matplotlib` table has.

```
In [159]: from pandas.plotting import table

In [160]: fig, ax = plt.subplots(1, 1)

In [161]: table(ax, np.round(df.describe(), 2),
          loc='upper right', colWidths=[0.2, 0.2, 0.2])

Out[161]: <matplotlib.table.Table at 0x1c41018240>

In [162]: df.plot(ax=ax, ylim=(0, 2), legend=None)
```

```
\|
```

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.13</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>1</td>
<td>0.97</td>
<td>0.38</td>
<td>0.84</td>
</tr>
</tbody>
</table>
```

22.5. Plot Formatting
Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the matplotlib table documentation for more.

### 22.5.12 Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, DataFrame plotting supports the use of the `colormap` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available here.

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the DataFrame. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

To use the cubehelix colormap, we can pass `colormap='cubehelix'`.

```python
In [163]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
In [164]: df = df.cumsum()
In [165]: plt.figure()
Out[165]: <Figure size 640x480 with 0 Axes>
In [166]: df.plot(colormap='cubehelix')
```

(continues on next page)
Alternatively, we can pass the colormap itself:

```python
In [167]: from matplotlib import cm
In [168]: plt.figure()
Out[168]: <Figure size 640x480 with 0 Axes>
In [169]: df.plot(colormap=cm.cubehelix)
```

Out[169]: `<matplotlib.axes._subplots.AxesSubplot at 0x1c40502550>`
Colormaps can also be used other plot types, like bar charts:

```python
In [170]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)
In [171]: dd = dd.cumsum()
In [172]: plt.figure()
Out[172]: <Figure size 640x480 with 0 Axes>
In [173]: dd.plot.bar(colormap='Greens')
```

Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0x1c400d5f98>
Parallel coordinates charts:

```python
In [174]: plt.figure()
Out[174]: <Figure size 640x480 with 0 Axes>

In [175]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
```

---

22.5. Plot Formatting
Andrews curves charts:

```python
In [176]: plt.figure()
Out[176]: <Figure size 640x480 with 0 Axes>

In [177]: andrews_curves(data, 'Name', colormap='winter')
```

![Andrews curves chart](chart.png)
22.6 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.

\[\text{In [178]: } \text{price} = \text{pd.Series(np.random.randn(150).cumsum(),}
\]
\[\text{index=pd.date_range('2000-1-1', periods=150, freq='B'))}
\]
\[\text{.....:}
\]
\[\text{In [179]: } \text{ma} = \text{price.rolling(20).mean()}
\]
\[\text{In [180]: } \text{mstd} = \text{price.rolling(20).std()}
\]
\[\text{In [181]: } \text{plt.figure()}
\]
\[\text{Out[181]: } <\text{Figure size 640x480 with 0 Axes}>
\]
\[\text{In [182]: } \text{plt.plot(price.index, price, 'k')}
\]
\[\text{Out[182]: } [\text{<matplotlib.lines.Line2D at 0x1c4187db70>}]\]
22.7 Trellis plotting interface

**Warning:** The rplot trellis plotting interface has been removed. Please use external packages like seaborn for similar but more refined functionality and refer to our 0.18.1 documentation here for how to convert to using it.
New in version 0.17.1

Provisional: This is a new feature and still under development. We’ll be adding features and possibly making breaking changes in future releases. We’d love to hear your feedback.

This document is written as a Jupyter Notebook, and can be viewed or downloaded here.

You can apply **conditional formatting**, the visual styling of a DataFrame depending on the data within, by using the `DataFrame.style` property. This is a property that returns a `Styler` object, which has useful methods for formatting and displaying DataFrames.

The styling is accomplished using CSS. You write “style functions” that take scalars, DataFrames or Series, and return *like-indexed* DataFrames or Series with CSS "attribute: value" pairs for the values. These functions can be incrementally passed to the `Styler` which collects the styles before rendering.

### 23.1 Building Styles

Pass your style functions into one of the following methods:

- `Styler.applymap`: elementwise
- `Styler.apply`: column-/row-/table-wise

Both of those methods take a function (and some other keyword arguments) and applies your function to the DataFrame in a certain way. `Styler.applymap` works through the DataFrame elementwise. `Styler.apply` passes each column or row into your DataFrame one-at-a-time or the entire table at once, depending on the `axis` keyword argument. For columnwise use `axis=0`, rowwise use `axis=1`, and for the entire table at once use `axis=None`.

For `Styler.applymap` your function should take a scalar and return a single string with the CSS attribute-value pair.

For `Styler.apply` your function should take a Series or DataFrame (depending on the `axis` parameter), and return a Series or DataFrame with an identical shape where each value is a string with a CSS attribute-value pair.

Let’s see some examples.

```
In [2]: import pandas as pd
   ...: import numpy as np
   ...: np.random.seed(24)
   ...: df = pd.DataFrame({'A': np.linspace(1, 10, 10)})
   ...: df = pd.concat([df, pd.DataFrame(np.random.randn(10, 4), columns=list('BCDE'))],
   ...:                axis=1)
   ...: df.iloc[0, 2] = np.nan
```

Here’s a boring example of rendering a DataFrame, without any (visible) styles:
In [3]: df.style

Out[3]: <pandas.io.formats.style.Styler at 0x113752cc0>

Note: The DataFrame.style attribute is a property that returns a Styler object. Styler has a _repr_html_ method defined on it so they are rendered automatically. If you want the actual HTML back for further processing or for writing to file call the .render() method which returns a string.

The above output looks very similar to the standard DataFrame HTML representation. But we’ve done some work behind the scenes to attach CSS classes to each cell. We can view these by calling the .render method.

In [4]: df.style.highlight_null().render().split('n')[:10]

Out[4]: ['<style type="text/css" >', ' #T_dcfc3b68_6e73_11e8_bf21_6a0003025570row0_col2 {', ' background-color: red;', ' }<style> ', '</thead>', '<tr>', '<th class="blank level0"></th>', '<th class="col_heading level0 col0" >A</th>', '<th class="col_heading level0 col1" >B</th>', '<th class="col_heading level0 col2" >C</th>']

The row0_col2 is the identifier for that particular cell. We’ve also prepended each row/column identifier with a UUID unique to each DataFrame so that the style from one doesn’t collide with the styling from another within the same notebook or page (you can set the uuid if you’d like to tie together the styling of two DataFrames).

When writing style functions, you take care of producing the CSS attribute / value pairs you want. Pandas matches those up with the CSS classes that identify each cell.

Let’s write a simple style function that will color negative numbers red and positive numbers black.

In [5]: def color_negative_red(val):
    """
    Takes a scalar and returns a string with the css property 'color: red' for negative strings, black otherwise.
    """
    color = 'red' if val < 0 else 'black'
    return 'color: %s' % color

In this case, the cell’s style depends only on it’s own value. That means we should use the Styler.applymap method which works elementwise.

In [6]: s = df.style.applymap(color_negative_red)

Out[6]: <pandas.io.formats.style.Styler at 0x111766d68>

Notice the similarity with the standard df.applymap, which operates on DataFrames elementwise. We want you to be able to reuse your existing knowledge of how to interact with DataFrames.

Notice also that our function returned a string containing the CSS attribute and value, separated by a colon just like in a <style> tag. This will be a common theme.

Finally, the input shapes matched. Styler.applymap calls the function on each scalar input, and the function returns a scalar output.

Now suppose you wanted to highlight the maximum value in each column. We can’t use .applymap anymore since that operated elementwise. Instead, we’ll turn to .apply which operates columnwise (or rowwise using the axis keyword). Later on we’ll see that something like highlight_max is already defined on Styler so you wouldn’t need to write this yourself.
In [7]: def highlight_max(s):
   ...:     
   ...:     '''
   ...:     highlight the maximum in a Series yellow.
   ...:     '''
   ...:     is_max = s == s.max()
   ...:     return ['background-color: yellow' if v else '' for v in is_max]
In [8]: df.style.apply(highlight_max)
Out[8]: <pandas.io.formats.style.Styler at 0x115a64b70>

In this case the input is a Series, one column at a time. Notice that the output shape of highlight_max matches the input shape, an array with \text{len(s)} items.

We encourage you to use method chains to build up a style piecewise, before finally rendering at the end of the chain.

In [9]: df.style.
   ...:     applymap(color_negative_red).
   ...:     apply(highlight_max)
Out[9]: <pandas.io.formats.style.Styler at 0x113752d68>

Above we used Styler.apply to pass in each column one at a time.

\textit{Debugging Tip}: If you’re having trouble writing your style function, try just passing it into DataFrame.apply. Internally, Styler.apply uses DataFrame.apply so the result should be the same.

What if you wanted to highlight just the maximum value in the entire table? Use \texttt{.apply(function, axis=None)} to indicate that your function wants the entire table, not one column or row at a time. Let’s try that next.

We’ll rewrite our highlight-max to handle either Series (from \texttt{.apply(axis=0 or 1)}) or DataFrames (from \texttt{.apply(axis=None)}). We’ll also allow the color to be adjustable, to demonstrate that \texttt{.apply} and \texttt{.applymap} pass along keyword arguments.

In [10]: def highlight_max(data, color='yellow'):
   ...:     
   ...:     '''
   ...:     highlight the maximum in a Series or DataFrame
   ...:     '''
   ...:     attr = 'background-color: {}'.format(color)
   ...:     if data.ndim == 1: # Series from \texttt{.apply(axis=0)} or \texttt{axis=1}
   ...:         is_max = data == data.max()
   ...:         return [attr if v else '' for v in is_max]
   ...:     else: # from \texttt{.apply(axis=None)}
   ...:         is_max = data == data.max().max()
   ...:         return pd.DataFrame(np.where(is_max, attr, ''),
   ...:               index=data.index, columns=data.columns)

When using Styler.apply\texttt{(func, axis=None)}, the function must return a DataFrame with the same index and column labels.

In [11]: df.style.apply(highlight_max, color='darkorange', axis=None)
Out[11]: <pandas.io.formats.style.Styler at 0x115ab1860>

\textbf{23.1. Building Styles Summary}

Style functions should return strings with one or more CSS \texttt{attribute: value} delimited by semicolons. Use

\begin{itemize}
\item \texttt{Styler.applymap(func)} for elementwise styles
\item \texttt{Styler.apply(func, axis=0)} for columnwise styles
\item \texttt{Styler.apply(func, axis=1)} for rowwise styles
\end{itemize}
• Styler.apply(func, axis=None) for tablewise styles

And crucially the input and output shapes of func must match. If x is the input then func(x).shape == x.shape.

23.2 Finer Control: Slicing

Both Styler.apply, and Styler.applymap accept a subset keyword. This allows you to apply styles to specific rows or columns, without having to code that logic into your style function.

The value passed to subset behaves similar to slicing a DataFrame.

• A scalar is treated as a column label
• A list (or series or numpy array)
• A tuple is treated as (row_indexer, column_indexer)

Consider using pd.IndexSlice to construct the tuple for the last one.

In [12]: df.style.apply(highlight_max, subset=[’B’, ’C’, ’D’])
Out[12]: <pandas.io.formats.style.Styler at 0x115ab1dd8>

For row and column slicing, any valid indexer to .loc will work.

In [13]: df.style.applymap(color_negative_red, subset=pd.IndexSlice[2:5, [’B’, ’D’]])
Out[13]: <pandas.io.formats.style.Styler at 0x115ab1f28>

Only label-based slicing is supported right now, not positional.

If your style function uses a subset or axis keyword argument, consider wrapping your function in a functools.partial, partialing out that keyword.

my_func2 = functools.partial(my_func, subset=42)

23.3 Finer Control: Display Values

We distinguish the display value from the actual value in Styler. To control the display value, the text is printed in each cell, use Styler.format. Cells can be formatted according to a format spec string or a callable that takes a single value and returns a string.

In [14]: df.style.format("{:.2%}")
Out[14]: <pandas.io.formats.style.Styler at 0x115ab1a90>

Use a dictionary to format specific columns.

In [15]: df.style.format({’B’: "{:0<4.0f}"’, ’D’: ”:+.2f”})
Out[15]: <pandas.io.formats.style.Styler at 0x115ab16d8>

Or pass in a callable (or dictionary of callables) for more flexible handling.

In [16]: df.style.format({”B”: lambda x: “±{:2f}””.format(abs(x))})
Out[16]: <pandas.io.formats.style.Styler at 0x115ab1a20>
23.4 Builtin Styles

Finally, we expect certain styling functions to be common enough that we’ve included a few “built-in” to the Styler, so you don’t have to write them yourself.

In [17]: df.style.highlight_null(null_color='red')
Out[17]: <pandas.io.formats.style.Styler at 0x115ab1898>

You can create “heatmaps” with the background_gradient method. These require matplotlib, and we’ll use Seaborn to get a nice colormap.

In [18]: import seaborn as sns
cm = sns.light_palette("green", as_cmap=True)
s = df.style.background_gradient(cmap=cm)
s
xa[xa < 0] = -1
Out[18]: <pandas.io.formats.style.Styler at 0x115b5f3c8>

Styler.background_gradient takes the keyword arguments low and high. Roughly speaking these extend the range of your data by low and high percent so that when we convert the colors, the colormap’s entire range isn’t used. This is useful so that you can actually read the text still.

In [19]: # Uses the full color range
df.loc[:4].style.background_gradient(cmap='viridis')
xa[xa < 0] = -1
Out[19]: <pandas.io.formats.style.Styler at 0x115b5f4a8>

In [20]: # Compress the color range
   (df.loc[:4]
   .style
   .background_gradient(cmap='viridis', low=.5, high=0)
   .highlight_null('red'))
xa[xa < 0] = -1
Out[20]: <pandas.io.formats.style.Styler at 0x11a178d1438>

There’s also .highlight_min and .highlight_max.

In [21]: df.style.highlight_max(axis=0)
Out[21]: <pandas.io.formats.style.Styler at 0x115a734a8>

Use Styler.set_properties when the style doesn’t actually depend on the values.

In [22]: df.style.set_properties(**{'background-color': 'black',
                              'color': 'lawngreen',
                              'border-color': 'white'})
Out[22]: <pandas.io.formats.style.Styler at 0x11a178d17f0>

23.4.1 Bar charts

You can include “bar charts” in your DataFrame.
In [23]: df.style.bar(subset=['A', 'B'], color='#d65f5f')
Out[23]: <pandas.io.formats.style.Styler at 0x1a178d1ac8>

New in version 0.20.0 is the ability to customize further the bar chart: You can now have the `df.style.bar` be centered on zero or midpoint value (in addition to the already existing way of having the min value at the left side of the cell), and you can pass a list of `[color_negative, color_positive]`.

Here's how you can change the above with the new `align='mid'` option:

In [24]: df.style.bar(subset=['A', 'B'], align='mid', color=['#d65f5f', '#5fba7d'])
Out[24]: <pandas.io.formats.style.Styler at 0x1a179db2e8>

The following example aims to give a highlight of the behavior of the new align options:

In [25]: import pandas as pd
            from IPython.display import HTML

            # Test series
            test1 = pd.Series([-100, -60, -30, -20], name='All Negative')
            test2 = pd.Series([10, 20, 50, 100], name='All Positive')
            test3 = pd.Series([-10, -5, 0, 90], name='Both Pos and Neg')

            head = ""
            <table>
                <thead>
                    <th>Align</th>
                    <th>All Negative</th>
                    <th>All Positive</th>
                    <th>Both Neg and Pos</th>
                </thead>
                </tbody>
            ""
            aligns = ['left', 'zero', 'mid']
            for align in aligns:
                row = "<tr><th>{}</th>".format(align)
                for serie in [test1, test2, test3]:
                    s = serie.copy()
                    s.name=''
                    row += "<td>{}</td>".format(s.to_frame().style.bar(align=align,
                        color=['#d65f5f', '#5fba7d'],
                        width=100).render())
                row += '</tr>'
                head += row
            ""
            HTML(head)
Out[25]: <IPython.core.display.HTML object>
23.5 Sharing Styles

Say you have a lovely style built up for a DataFrame, and now you want to apply the same style to a second DataFrame. Export the style with `df1.style.export`, and import it on the second DataFrame with `df1.style.set`.

```
In [26]: df2 = -df
    style1 = df.style.applymap(color_negative_red)
    style1
Out[26]: <pandas.io.formats.style.Styler at 0x1a179e1c18>
In [27]: style2 = df2.style
    style2.use(style1.export())
    style2
Out[27]: <pandas.io.formats.style.Styler at 0x1a179e1da0>
```

Notice that you’re able share the styles even though they’re data aware. The styles are re-evaluated on the new DataFrame they’ve been used upon.

23.6 Other Options

You’ve seen a few methods for data-driven styling. Styler also provides a few other options for styles that don’t depend on the data.

- precision
- captions
- table-wide styles
- hiding the index or columns

Each of these can be specified in two ways:

- A keyword argument to Styler.__init__
- A call to one of the .set_ or .hide_ methods, e.g. .set_caption or .hide_columns

The best method to use depends on the context. Use the Styler constructor when building many styled DataFrames that should all share the same properties. For interactive use, the .set_ and .hide_ methods are more convenient.

23.6.1 Precision

You can control the precision of floats using pandas’ regular display.precision option.

```
In [28]: with pd.option_context('display.precision', 2):
    html = (df.style
        .applymap(color_negative_red)
        .apply(highlight_max))
    html
Out[28]: <pandas.io.formats.style.Styler at 0x1a179e1cf8>
```

Or through a set_precision method.

```
In [29]: df.style
    .applymap(color_negative_red)
    .apply(highlight_max)
    .set_precision(2)
```
Setting the precision only affects the printed number; the full-precision values are always passed to your style functions. You can always use `df.round(2).style` if you’d prefer to round from the start.

### 23.6.2 Captions

Regular table captions can be added in a few ways.

```python
In [30]: df.style.set_caption('Colormaps, with a caption.')
   .background_gradient(cmap=cm)
```

Out[30]: <pandas.io.formats.style.Styler at 0x1a17921390>

### 23.6.3 Table Styles

The next option you have are “table styles”. These are styles that apply to the table as a whole, but don’t look at the data. Certain sytlings, including pseudo-selectors like `:hover` can only be used this way.

```python
In [31]: from IPython.display import HTML
def hover(hover_color="#ffff99"):
    return dict(selector="tr:hover",
                props=[("background-color", "$s" % hover_color)])
styles = [
    hover(),
    dict(selector="th", props=[("font-size", "150%"),
                              ("text-align", "center")]),
    dict(selector="caption", props=[("caption-side", "bottom")])
]
html = (df.style.set_table_styles(styles)
        .set_caption("Hover to highlight."))
```

Out[31]: <pandas.io.formats.style.Styler at 0x1a179ff518>

table_styles should be a list of dictionaries. Each dictionary should have the selector and props keys. The value for selector should be a valid CSS selector. Recall that all the styles are already attached to an id, unique to each Styler. This selector is in addition to that id. The value for props should be a list of tuples of ('attribute', 'value').

table_styles are extremely flexible, but not as fun to type out by hand. We hope to collect some useful ones either in pandas, or preferable in a new package that builds on top the tools here.

### 23.6.4 Hiding the Index or Columns

The index can be hidden from rendering by calling `Styler.hide_index`. Columns can be hidden from rendering by calling `Styler.hide_columns` and passing in the name of a column, or a slice of columns.

```python
In [32]: df.style.hide_index()
```

Out[32]: <pandas.io.formats.style.Styler at 0x1a1799f518>

```python
In [33]: df.style.hide_columns(['C','D'])
```
23.6.5 CSS Classes

Certain CSS classes are attached to cells.

- Index and Column names include `index_name` and `level<k>` where `k` is its level in a MultiIndex
- Index label cells include `row_heading`
- `row<n>` where `n` is the numeric position of the row
- `level<k>` where `k` is the level in a MultiIndex
- Column label cells include `col_heading`
- `col<n>` where `n` is the numeric position of the column
- `level<k>` where `k` is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

23.6.6 Limitations

- DataFrame only (use `Series.to_frame().style`)
- The index and columns must be unique
- No large repr, and performance isn’t great; this is intended for summary DataFrames
- You can only style the `values`, not the index or columns
- You can only apply styles, you can’t insert new HTML entities

Some of these will be addressed in the future.

23.6.7 Terms

- Style function: a function that’s passed into `Styler.apply` or `Styler.applymap` and returns values like `css attribute: value`
- Builtin style functions: style functions that are methods on `Styler`
- `table style`: a dictionary with the two keys `selector` and `props. selector` is the CSS selector that `props` will apply to. `props` is a list of `(attribute, value)` tuples. A list of table styles passed into `Styler`.

23.7 Fun stuff

Here are a few interesting examples.

`Styler` interacts pretty well with widgets. If you’re viewing this online instead of running the notebook yourself, you’re missing out on interactively adjusting the color palette.
In [34]: from IPython.html import widgets
   @widgets.interact
   def f(h_neg=(0, 359, 1), h_pos=(0, 359), s=(0., 99.9), l=(0., 99.9)):
       return df.style.background_gradient(
           cmap=sns.palettes.diverging_palette(h_neg=h_neg, h_pos=h_pos, s=s, l=l, as_cmap=True)
       )

   xa[xa < 0] = -1
<pandas.io.formats.style.Styler at 0x1a179ff278>
In [35]: def magnify():
   return [dict(selector="th",
        props=[("font-size", "4pt")]),
        dict(selector="td",
            props=[('padding', "0em 0em")],
        dict(selector="th:hover",
            props=[("font-size", "12pt")]),
        dict(selector="tr:hover td:hover",
            props=[("max-width", '200px'),
            ('font-size', '12pt')])
    ]

In [36]: np.random.seed(25)
   cmap = cmap=sns.diverging_palette(5, 250, as_cmap=True)
   bigdf = pd.DataFrame(np.random.randn(20, 25)).cumsum()
   bigdf.style.background_gradient(cmap, axis=1)
       .set_properties(**{'max-width': '80px', 'font-size': '1pt'})
       .set_caption("Hover to magnify")
       .set_precision(2)
       .set_table_styles(magnify())

Out[36]: <pandas.io.formats.style.Styler at 0x1a17a0e4a8>

23.8 Export to Excel

New in version 0.20.0

Experimental: This is a new feature and still under development. We’ll be adding features and possibly making breaking changes in future releases. We’d love to hear your feedback.

Some support is available for exporting styled DataFrames to Excel worksheets using the OpenPyXL or XlsxWriter engines. CSS2.2 properties handled include:

- background-color
- border-style, border-width, border-color and their {top, right, bottom, left} variants
- color
- font-family
- font-style
- font-weight
- text-align
- text-decoration
Only CSS2 named colors and hex colors of the form \texttt{#rgb} or \texttt{#rrggbb} are currently supported.

\begin{verbatim}
In [37]: df.style.\n   applymap(color_negative_red).\n   apply(highlight_max).\n   to_excel('styled.xlsx', engine='openpyxl')
\end{verbatim}

A screenshot of the output:

\begin{figure}
\centering
\includegraphics[width=\textwidth]{styled.xlsx}
\caption{Excel spreadsheet with styled DataFrame}
\end{figure}

23.9 Extensibility

The core of pandas is, and will remain, its “high-performance, easy-to-use data structures”. With that in mind, we hope that \texttt{DataFrame.style} accomplishes two goals

- Provide an API that is pleasing to use interactively and is “good enough” for many tasks
- Provide the foundations for dedicated libraries to build on

If you build a great library on top of this, let us know and we’ll link to it.

23.9.1 Subclassing

If the default template doesn’t quite suit your needs, you can subclass \texttt{Styler} and extend or override the template. We’ll show an example of extending the default template to insert a custom header before each table.

\begin{verbatim}
In [38]: from jinja2 import Environment, ChoiceLoader, FileSystemLoader
   from IPython.display import HTML
   from pandas.io.formats.style import Styler
\end{verbatim}
In [39]: %mkdir templates
mkdir: templates: File exists
This next cell writes the custom template. We extend the template html.tpl, which comes with pandas.
In [40]: %
   \[
   \text{mkdir templates/myhtml.tpl}
   \]
   \[
   \text{{% extends "html.tpl" %}}
   \]
   \[
   \text{{% block table %}}
   \]
   \[
   \text{\begin{center}\{\text{table_title}default("My Table")\}\end{center}}
   \]
   \[
   \text{{ super() }}
   \]
   \[
   \text{% endblock table %}
   \]
Overwriting templates/myhtml.tpl
Now that we’ve created a template, we need to set up a subclass of Styler that knows about it.
In [41]: class MyStyler(Styler):
   \[
   \text{\texttt{env = \texttt{Environment(}}
   \]
   \[
   \text{\texttt{loader=ChoiceLoader([}}
   \]
   \[
   \text{\texttt{FileSystemLoader("templates"),}}
   \]
   \[
   \text{\texttt{Styler.loader, \# the default}}
   \]
   \[
   \text{\texttt{])}}
   \]
   \[
   \text{\texttt{)}}
   \]
   \[
   \text{\texttt{template = env.get_template("myhtml.tpl")}}
   \]
Notice that we include the original loader in our environment’s loader. That’s because we extend the original template, so the Jinja environment needs to be able to find it.
Now we can use that custom styler. It’s __init__ takes a DataFrame.
In [42]: MyStyler(df)
Out[42]: <__main__.MyStyler at 0x1a179e1a20>
Our custom template accepts a table_title keyword. We can provide the value in the .render method.
In [43]: HTML(MyStyler(df).render(table_title="Extending Example"))
Out[43]: <IPython.core.display.HTML object>
For convenience, we provide the Styler.from_custom_template method that does the same as the custom subclass.
In [44]: EasyStyler = Styler.from_custom_template("templates", "myhtml.tpl")
EasyStyler(df)
Out[44]: <pandas.io.formats.style.Styler.from_custom_template.<locals>.MyStyler at 0x1a21b93da0>
Here’s the template structure:
In [45]: with open("template_structure.html") as f:
   \[
   \text{structure = f.read()}
   \]
   \[
   \text{HTML(structure)}
   \]
Out[45]: <IPython.core.display.HTML object>
See the template in the GitHub repo for more details.
IO TOOLS (TEXT, CSV, HDF5, ...) 

The pandas I/O API is a set of top level reader functions accessed like `pandas.read_csv()` that generally return a pandas object. The corresponding writer functions are object methods that are accessed like `DataFrame.to_csv()`. Below is a table containing available readers and writers.

<table>
<thead>
<tr>
<th>Format Type</th>
<th>Data Description</th>
<th>Reader</th>
<th>Writer</th>
</tr>
</thead>
<tbody>
<tr>
<td>text</td>
<td>CSV</td>
<td><code>read_csv</code></td>
<td><code>to_csv</code></td>
</tr>
<tr>
<td>text</td>
<td>JSON</td>
<td><code>read_json</code></td>
<td><code>to_json</code></td>
</tr>
<tr>
<td>text</td>
<td>HTML</td>
<td><code>read_html</code></td>
<td><code>to_html</code></td>
</tr>
<tr>
<td>text</td>
<td>Local clipboard</td>
<td><code>read_clipboard</code></td>
<td><code>to_clipboard</code></td>
</tr>
<tr>
<td>binary</td>
<td>MS Excel</td>
<td><code>read_excel</code></td>
<td><code>to_excel</code></td>
</tr>
<tr>
<td>binary</td>
<td>HDF5 Format</td>
<td><code>read_hdf</code></td>
<td><code>to_hdf</code></td>
</tr>
<tr>
<td>binary</td>
<td>Feather Format</td>
<td><code>read_feather</code></td>
<td><code>to_feather</code></td>
</tr>
<tr>
<td>binary</td>
<td>Parquet Format</td>
<td><code>read_parquet</code></td>
<td><code>to_parquet</code></td>
</tr>
<tr>
<td>binary</td>
<td>Msgpack</td>
<td><code>read_msgpack</code></td>
<td><code>to_msgpack</code></td>
</tr>
<tr>
<td>binary</td>
<td>Stata</td>
<td><code>read_stata</code></td>
<td><code>to_stata</code></td>
</tr>
<tr>
<td>binary</td>
<td>SAS</td>
<td><code>read_sas</code></td>
<td></td>
</tr>
<tr>
<td>binary</td>
<td>Python Pickle Format</td>
<td><code>read_pickle</code></td>
<td><code>to_pickle</code></td>
</tr>
<tr>
<td>SQL</td>
<td>SQL</td>
<td><code>read_sql</code></td>
<td><code>to_sql</code></td>
</tr>
<tr>
<td>SQL</td>
<td>Google Big Query</td>
<td><code>read_gbq</code></td>
<td><code>to_gbq</code></td>
</tr>
</tbody>
</table>

*Here* is an informal performance comparison for some of these IO methods.

**Note:** For examples that use the `StringIO` class, make sure you import it 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.

24.1.1 Parsing options

The functions `read_csv()` and `read_table()` accept the following common arguments:
24.1.1.1 Basic

**filepath_or_buffer** [various] Either a path to a file (a `str`, `pathlib.Path`, or `py._path.local.LocalPath`), URL (including http, ftp, and S3 locations), or any object with a `read()` method (such as an open file or `StringIO`).

**sep** [str, defaults to ',' for `read_csv()`, \t for `read_table()`] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s built-in sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from \s+ will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\r\t'.

**delimiter** [str, default None] Alternative argument name for sep.

**delim_whitespace** [boolean, default False] Specifies whether or not whitespace (e.g. ' ' or '\t') will be used as the delimiter. Equivalent to setting `sep='\s+'`. If this option is set to True, nothing should be passed in for the delimiter parameter.

New in version 0.18.1: support for the Python parser.

24.1.1.2 Column and Index Locations and Names

**header** [int or list of ints, default 'infer'] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names.

The header can be a list of ints that specify row locations for a multi-index on the columns e.g. 

The intervention can be a list of ints that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

**names** [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass `header=None`. Duplicates in this list will cause a `UserWarning` to be issued.

**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).

**usecols** [list-like or callable, default None] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like `usecols` parameter would be [0, 1, 2] or ['foo', 'bar', 'baz'].

Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from data with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in ['foo', 'bar'] order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']...]` for ['bar', 'foo'] order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True:

```
In [1]: data = 'col1,col2,col3\na,b,1\na,b,2\nc,d,3'
In [2]: pd.read_csv(StringIO(data))
Out[2]:
   col1  col2  col3
0     a     b     1
1     a     b     2
2     c     d     3
(continues on next page)
```
In [3]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ['COL1', 'COL3'])

Out[3]:
  col1  col3
0    a    1
1    a    2
2    c    3

Using this parameter results in much faster parsing time and lower memory usage.

squeeze [boolean, default False] If the parsed data only contains one column then return a Series.

prefix [str, default None] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1,...

mangle_dupe_cols [boolean, default True] Duplicate columns will be specified as ‘X’, ‘X.1’...’X.N’, rather than ‘X’...’X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

24.1.1.3 General Parsing Configuration

dtype [Type name or dict of column -> type, default None] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (unsupported with engine='python'). Use str or object together with suitable na_values settings to preserve and not interpret dtype.

New in version 0.20.0: support for the Python parser.

engine [{'c', 'python'}] Parser engine to use. The C engine is faster while the Python engine is currently more feature-complete.

converters [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

true_values [list, default None] Values to consider as True.

false_values [list, default None] Values to consider as False.

skipinitialspace [boolean, default False] Skip spaces after delimiter.

skiprows [list-like or integer, default None] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise:

In [4]: data = 'col1, col2, col3
0 a b 1
1 a b 2
2 c d 3'

In [5]: pd.read_csv(StringIO(data))

Out[5]:
  col1  col2  col3
0    a    b    1
1    a    b    2
2    c    d    3

In [6]: pd.read_csv(StringIO(data), skiprows=lambda x: x % 2 != 0)

(continues on next page)
skipfooter [int, default 0] Number of lines at bottom of file to skip (unsupported with engine=’c’).
nrows [int, default None] Number of rows of file to read. Useful for reading pieces of large files.
low_memory [boolean, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the dtype parameter. Note that the entire file is read into a single DataFrame regardless, use the chunksize or iterator parameter to return the data in chunks. (Only valid with C parser)
memory_map [boolean, default False] If a filepath is provided for filepath_or_buffer, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

24.1.1.4 NA and Missing Data Handling

na_values [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. See na values const below for a list of the values interpreted as NaN by default.

keep_default_na [boolean, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether na_values is passed in, the behavior is as follows:

• If keep_default_na is True, and na_values are specified, na_values is appended to the default NaN values used for parsing.
• If keep_default_na is True, and na_values are not specified, only the default NaN values are used for parsing.
• If keep_default_na is False, and na_values are specified, only the NaN values specified na_values are used for parsing.
• If keep_default_na is False, and na_values are not specified, no strings will be parsed as NaN.

Note that if na_filter is passed in as False, the keep_default_na and na_values parameters will be ignored.

na_filter [boolean, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.

verbose [boolean, default False] Indicate number of NA values placed in non-numeric columns.

skip_blank_lines [boolean, default True] If False, skip over blank lines rather than interpreting as NaN values.

24.1.1.5 Datetime Handling

parse_dates [boolean or list of ints or names or list of lists or dict, default False.]

• If True -> try parsing the index.
• If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
• If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
• If {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’. A fast-path exists for iso8601-formatted dates.

infer_datetime_format [boolean, default False] If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing.
**keep_date_col** [boolean, default False] If True and parse_dates specifies combining multiple columns then keep the original columns.

**date_parser** [function, default None] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. Pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

**dayfirst** [boolean, default False] DD/MM format dates, international and European format.

### 24.1.1.6 Iteration

**iterator** [boolean, default False] Return TextFileReader object for iteration or getting chunks with get_chunk().

**chunksize** [int, default None] Return TextFileReader object for iteration. See iterating and chunking below.

### 24.1.1.7 Quoting, Compression, and File Format

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip, bz2, zip, or xz if filepath_or_buffer is a string ending in ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’, respectively, and no decompression otherwise. If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.18.1: support for ‘zip’ and ‘xz’ compression.

**thousands** [str, default None] Thousands separator.

**decimal** [str, default ‘.’] Character to recognize as decimal point. E.g. use ‘,’ for European data.

**float_precision** [string, default None] Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, high for the high-precision converter, and round_trip for the round-trip converter.

**lineterminator** [str (length 1), default None] Character to break file into lines. Only valid with C parser.

**quotechar** [str (length 1)] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

**quoting** [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

**doublequote** [boolean, default True] When quotechar is specified and quoting is not QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements inside a field as a single quotechar element.

**escapechar** [str (length 1), default None] One-character string used to escape delimiter when quoting is QUOTE_NONE.

**comment** [str, default None] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as skip_blank_lines=True), fully commented lines are ignored by the parameter header but not by skiprows. For example, if comment='#', parsing '#empty
a,b,c
1,2,3' with header=0 will result in ‘a,b,c’ being treated as the header.

**encoding** [str, default None] Encoding to use for UTF when reading/writing (e.g. ‘utf-8’). List of Python standard encodings.
dialect [str or csv.Dialect instance, default None] If provided, this parameter will override values (default or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace, quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

tupleize_cols [boolean, default False]

Deprecated since version 0.21.0.

This argument will be removed and will always convert to MultiIndex

Leave a list of tuples on columns as is (default is to convert to a MultiIndex on the columns).

24.1.1.8 Error Handling

error_bad_lines [boolean, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will dropped from the DataFrame that is returned. See bad lines below.

warn_bad_lines [boolean, default True] If error_bad_lines is False, and warn_bad_lines is True, a warning for each “bad line” will be output.

24.1.2 Specifying column data types

You can indicate the data type for the whole DataFrame or individual columns:

```python
In [7]: data = 'a,b,c
1,2,3
4,5,6
7,8,9'

In [8]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [9]: df = pd.read_csv(StringIO(data), dtype=object)

In [10]: df
Out[10]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

In [11]: df['a'][0]
Out[11]: '1'

In [12]: df = pd.read_csv(StringIO(data), dtype={'b': object, 'c': np.float64})

In [13]: df.dtypes
Out[13]:
   a    int64
   b   object
   c  float64
dtype: object
```

Fortunately, pandas offers more than one way to ensure that your column(s) contain only one dtype. If you’re unfamiliar with these concepts, you can see here to learn more about dtypes, and here to learn more about object conversion in pandas.
For instance, you can use the converters argument of `read_csv()`:

```python
In [14]: data = "col_1\n1\n2\n'A'\n4.22"

In [15]: df = pd.read_csv(StringIO(data), converters={'col_1': str})

In [16]: df
Out[16]:
   col_1
0     1
1     2
2    'A'
3   4.22

In [17]: df['col_1'].apply(type).value_counts()
Out[17]:
<class 'str'>    4
Name: col_1, dtype: int64
```

Or you can use the `to_numeric()` function to coerce the dtypes after reading in the data,

```python
In [18]: df2 = pd.read_csv(StringIO(data))

In [19]: df2['col_1'] = pd.to_numeric(df2['col_1'], errors='coerce')

In [20]: df2
Out[20]:
   col_1
0     1.00
1     2.00
2      NaN
3    4.22

In [21]: df2['col_1'].apply(type).value_counts()
Out[21]:
<class 'float'>    4
Name: col_1, dtype: int64
```

which will convert all valid parsing to floats, leaving the invalid parsing as NaN.

Ultimately, how you deal with reading in columns containing mixed dtypes depends on your specific needs. In the case above, if you wanted to NaN out the data anomalies, then `to_numeric()` is probably your best option. However, if you wanted for all the data to be coerced, no matter the type, then using the converters argument of `read_csv()` would certainly be worth trying.

New in version 0.20.0: support for the Python parser.

The `dtype` option is supported by the ‘python’ engine.

**Note:** In some cases, reading in abnormal data with columns containing mixed dtypes will result in an inconsistent dataset. If you rely on pandas to infer the dtypes of your columns, the parsing engine will go and infer the dtypes for different chunks of the data, rather than the whole dataset at once. Consequently, you can end up with column(s) with mixed dtypes. For example,

```python
In [22]: df = pd.DataFrame({'col_1': list(range(500000)) + ['a', 'b'] + list(range(500000)))

In [23]: df.to_csv('foo.csv')
(continues on next page)```
In [24]: mixed_df = pd.read_csv('foo.csv')

In [25]: mixed_df['col_1'].apply(type).value_counts()
Out[25]:
<class 'int'> 737858
<class 'str'> 262144
Name: col_1, dtype: int64

In [26]: mixed_df['col_1'].dtype
Out[26]:
→ dtype('O')

will result with mixed_df containing an int dtype for certain chunks of the column, and str for others due to the mixed dtypes from the data that was read in. It is important to note that the overall column will be marked with a dtype of object, which is used for columns with mixed dtypes.

24.1.3 Specifying Categorical dtype

New in version 0.19.0.

Categorical columns can be parsed directly by specifying dtype='category' or dtype=CategoricalDtype(categories, ordered).

In [27]: data = 'col1,col2,col3
0 a,b,1
1 a,b,2
2 c,d,3'

In [28]: pd.read_csv(StringIO(data))
Out[28]:
col1  col2  col3
0    a    b    1
1    a    b    2
2    c    d    3

In [29]: pd.read_csv(StringIO(data)).dtypes
Out[29]:
→
col1  object
col2  object
col3  int64
dtype: object

In [30]: pd.read_csv(StringIO(data), dtype='category').dtypes

→
col1  category
col2  category
col3  category
dtype: object

Individual columns can be parsed as a Categorical using a dict specification:

In [31]: pd.read_csv(StringIO(data), dtype={'col1': 'category'}).dtypes
Out[31]:
col1  category
New in version 0.21.0.

Specifying `dtype='category'` will result in an unordered `Categorical` whose `categories` are the unique values observed in the data. For more control on the categories and order, create a `CategoricalDtype` ahead of time, and pass that for that column’s `dtype`.

```python
In [32]: from pandas.api.types import CategoricalDtype

In [33]: dtype = CategoricalDtype(['d', 'c', 'b', 'a'], ordered=True)

In [34]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).dtypes
Out[34]:
    col1 category
    col2 object
    col3 int64
name: dtypes, dtype: object
```

When using `dtype=CategoricalDtype`, “unexpected” values outside of `dtype.categories` are treated as missing values.

```python
In [35]: dtype = CategoricalDtype(['a', 'b', 'd'])  # No 'c'

In [36]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).col1
Out[36]:
0    a
1    a
2  NaN
Name: col1, dtype: category
Categories (3, object): [a, b, d]
```

This matches the behavior of `Categorical.set_categories()`.

**Note:** With `dtype='category'`, the resulting categories will always be parsed as strings (object `dtype`). If the categories are numeric they can be converted using the `to_numeric()` function, or as appropriate, another converter such as `to_datetime()`.

When `dtype` is a `CategoricalDtype` with homogenous categories (all numeric, all datetimes, etc.), the conversion is done automatically.

```python
In [37]: df = pd.read_csv(StringIO(data), dtype='category')

In [38]: df.dtypes
Out[38]:
    col1  category
    col2  category
    col3  category
dtype: object

In [39]: df['col3']
Out[39]:
0  1
1  2
```

(continues on next page)
2 3
Name: col3, dtype: category
Categories (3, object): [1, 2, 3]

In [40]: df['col3'].cat.categories = pd.to_numeric(df['col3'].cat.categories)

In [41]: df['col3']
Out[41]:
0 1
1 2
2 3
Name: col3, dtype: category
Categories (3, int64): [1, 2, 3]

24.1.4 Naming and Using Columns

24.1.4.1 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 [42]: data = 'a,b,c

1,2,3

4,5,6
7,8,9'

In [43]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [44]: pd.read_csv(StringIO(data))

Out[44]:
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 [45]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [46]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)

Out[46]:
foo bar baz
0 1 2 3
1 4 5 6
2 7 8 9

In [47]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)

...
If the header is in a row other than the first, pass the row number to `header`. This will skip the preceding rows:

```
In [48]: data = 'skip this skip it
   \na,b,c
   \n1,2,3
   4,5,6
   7,8,9'

In [49]: pd.read_csv(StringIO(data), header=1)
Out[49]:
   a  b  c
 0  1  2  3
 1  4  5  6
 2  7  8  9
```

**Note:** Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first nonblank line of the file, if column names are passed explicitly then the behavior is identical to `header=None`.

### 24.1.5 Duplicate names parsing

If the file or header contains duplicate names, pandas will by default distinguish between them so as to prevent overwriting data:

```
In [50]: data = 'a,b,a
   \n0,1,2
   3,4,5'

In [51]: pd.read_csv(StringIO(data))
Out[51]:
   a  b  a.1
 0  2  1  2
 1  5  4  5
```

There is no more duplicate data because `mangle_dupe_cols=True` by default, which modifies a series of duplicate columns ‘X’, ‘X’, ‘X’ to become ‘X’, ‘X.1’, ‘X’, ‘X’. If `mangle_dupe_cols=False`, duplicate data can arise:

```
In [2]: data = 'a,b,a
   \n0,1,2
   3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
Out[3]:
   a  b  a
 0  2  1  2
 1  5  4  5
```

To prevent users from encountering this problem with duplicate data, a `ValueError` exception is raised if `mangle_dupe_cols != True`:

```
In [2]: data = 'a,b,a
   \n0,1,2
   3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
...  
ValueError: Setting mangle_dupe_cols=False is not supported yet
```
24.1.5.1 Filtering columns (usecols)

The usecols argument allows you to select any subset of the columns in a file, either using the column names, position numbers or a callable:

New in version 0.20.0: support for callable usecols arguments

```
In [52]: data = 'a,b,c,d
  
1,2,3,foo
4,5,6,bar
7,8,9,baz'

In [53]: pd.read_csv(StringIO(data))
Out[53]:
   a  b  c  d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [54]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[54]:
   b  d
0  2  foo
1  5  bar
2  8  baz

In [55]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
   a  c  d
0  1  3  foo
1  4  6  bar
2  7  9  baz

In [56]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ['A', 'C'])
   a  c
0  1  3
1  4  6
2  7  9
```

The usecols argument can also be used to specify which columns not to use in the final result:

```
In [57]: pd.read_csv(StringIO(data), usecols=lambda x: x not in ['a', 'c'])
Out[57]:
   b  d
0  2  foo
1  5  bar
2  8  baz
```

In this case, the callable is specifying that we exclude the “a” and “c” columns from the output.

24.1.6 Comments and Empty Lines

24.1.6.1 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.
In [58]: data = '\na,b,c
   \n# commented line
   \n1,2,3
   
4,5,6

In [59]: print(data)
    a,b,c
    # commented line
    1,2,3
    4,5,6

In [60]: pd.read_csv(StringIO(data), comment='#')

   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 [61]: data = 'a,b,c
   
1,2,3
   
4,5,6'

In [62]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[62]:
   a  b  c
   0  NaN NaN NaN
   1  1.0 2.0 3.0
   2  NaN NaN NaN
   3  NaN NaN NaN
   4  4.0 5.0 6.0

Warning: The presence of ignored lines might create ambiguities involving line numbers; the parameter header uses row numbers (ignoring commented/empty lines), while skiprows uses line numbers (including commented/empty lines):

In [63]: data = '#comment
   a,b,c
   A,B,C
   1,2,3'

In [64]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[64]:
   A  B  C
   0  1  2  3

In [65]: data = 'A,B,C
   #comment
   a,b,c
   1,2,3'

In [66]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[66]:
   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:
24.1.6.2 Comments

Sometimes comments or meta data may be included in a file:

```
In [70]: 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 [71]: df = pd.read_csv('tmp.csv')
```

```
Out[71]:
   ID     level category
0  Patient1  123000      x  # really unpleasant
1  Patient2  23000      y  # wouldn't take his medicine
2  Patient3 1234018      z  # awesome
```

We can suppress the comments using the `comment` keyword:

```
In [73]: df = pd.read_csv('tmp.csv', comment='#')
```

```
In [74]: df
Out[74]:
   ID     level category
0  Patient1  123000      x
1  Patient2  23000      y
2  Patient3 1234018      z
```
24.1.7 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:

```python
In [75]: data = b'word,length\nTräumen,7
Grüße,5'.decode('utf8').encode('latin-1')
In [76]: df = pd.read_csv(BytesIO(data), encoding='latin-1')
In [77]: df
Out[77]:
word  length
0  Träumen  7
1  Grüße  5
In [78]: df['word'][1]
```

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.

24.1.8 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:

```python
In [79]: data = 'a,b,c
4,apple,bat,5.7
8,orange,cow,10'
In [80]: pd.read_csv(StringIO(data))
Out[80]:
a  b  c
4  apple  bat  5.7
8  orange  cow  10.0
In [81]: data = 'index,a,b,c
4,apple,bat,5.7
8,orange,cow,10'
In [82]: pd.read_csv(StringIO(data), index_col=0)
Out[82]:
index
4  apple  bat  5.7
8  orange  cow  10.0
```

Ordinarily, you can achieve this behavior using the index_col option.

There are some exception cases when a file has been prepared with delimiters at the end of each data line, confusing the parser. To explicitly disable the index column inference and discard the last column, pass `index_col=False`:

```python
In [83]: data = 'a,b,c
4,apple,bat,
8,orange,cow,'
In [84]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,
```

(continues on next page)
In [85]: pd.read_csv(StringIO(data))
   a b c
4 apple bat NaN
8 orange cow NaN

In [86]: pd.read_csv(StringIO(data), index_col=False)
   a b c
0 4 apple bat
1 8 orange cow

If a subset of data is being parsed using the usecols option, the index_col specification is based on that subset, not the original data.

In [87]: data = 'a,b,c
4,apple,bat,
8,orange,cow,'

In [88]: print(data)
 a,b,c
4,apple,bat,
8,orange,cow,

In [89]: pd.read_csv(StringIO(data), usecols=['b', 'c'])
   b c
4 bat NaN
8 cow NaN

In [90]: pd.read_csv(StringIO(data), usecols=['b', 'c'], index_col=0)
   b c
4 bat NaN
8 cow NaN

24.1.9 Date Handling

24.1.9.1 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:

# Use a column as an index, and parse it as dates.
In [91]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)

In [92]: df
Out[92]:
     A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5

(continues on next page)
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:

```python
In [94]: 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 [95]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [96]: df
Out[96]:
   1_2       1_3        0
0 1999-01-27 19:00:00 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 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:

```python
In [97]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
                      keep_date_col=True)

In [98]: df
Out[98]:
   1_2       1_3       0 1 2 3 4
0 1999-01-27 19:00:00 18:56:00 KORD 19990127 19:00:00 18:56:00 0.81
1 1999-01-27 20:00:00 19:56:00 KORD 19990127 20:00:00 19:56:00 0.01
2 1999-01-27 21:00:00 20:56:00 KORD 19990127 21:00:00 20:56:00 -0.59
3 1999-01-27 21:00:00 21:18:00 KORD 19990127 21:00:00 21:18:00 -0.99
4 1999-01-27 22:00:00 21:56:00 KORD 19990127 22:00:00 21:56:00 -0.59
5 1999-01-27 23:00:00 22:56:00 KORD 19990127 23:00:00 22:56:00 -0.59
```

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other words, `parse_dates=[[1, 2]]` indicates that the second and third columns should each be parsed as separate date columns while `parse_dates=[[1, 2]]` means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:
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 [102]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}
In [103]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
                   index_col=0)  # index is the nominal column
```

```
Out[104]:
    nominal      actual  0  4
0 1999-01-27 19:00:00 1999-01-27 18:56:00 KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00 KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00 KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00 KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00 KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00 KORD -0.59
```

**Note:** If a column or index contains an unparsable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `to_datetime()` after `pd.read_csv`.

**Note:** `read_csv` has a fast_path for parsing datetime strings in iso8601 format, e.g “2000-01-01T00:01:02+00:00” and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

**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.
24.1.9.2 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 [105]: import pandas.io.date_converters as conv

In [106]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
               ......:                   date_parser=conv.parse_date_time)
       ......:

In [107]: df
```

<table>
<thead>
<tr>
<th></th>
<th>nominal</th>
<th>actual</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1999-01-27 19:00:00</td>
<td>1999-01-27 18:56:00</td>
<td>KORD</td>
<td>0.81</td>
</tr>
<tr>
<td>1</td>
<td>1999-01-27 20:00:00</td>
<td>1999-01-27 19:56:00</td>
<td>KORD</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>1999-01-27 21:00:00</td>
<td>1999-01-27 20:56:00</td>
<td>KORD</td>
<td>-0.59</td>
</tr>
<tr>
<td>3</td>
<td>1999-01-27 21:00:00</td>
<td>1999-01-27 21:18:00</td>
<td>KORD</td>
<td>-0.99</td>
</tr>
<tr>
<td>4</td>
<td>1999-01-27 22:00:00</td>
<td>1999-01-27 21:56:00</td>
<td>KORD</td>
<td>-0.59</td>
</tr>
<tr>
<td>5</td>
<td>1999-01-27 23:00:00</td>
<td>1999-01-27 22:56:00</td>
<td>KORD</td>
<td>-0.59</td>
</tr>
</tbody>
</table>

Pandas will try to call the date_parser function in three different ways. If an exception is raised, the next one is tried:

1. date_parser is first called with one or more arrays as arguments, as defined using parse_dates (e.g., date_parser(["2013", "2013"], ["1", "2"]).
2. If #1 fails, date_parser is called with all the columns concatenated row-wise into a single array (e.g., date_parser(["2013 1", "2013 2"]).
3. If #2 fails, date_parser is called once for every row with one or more string arguments from the columns indicated with parse_dates (e.g., date_parser("2013", "1") for the first row, date_parser("2013", "2") for the second, etc.).

Note that performance-wise, you should try these methods of parsing dates in order:

1. Try to infer the format using infer_datetime_format=True (see section below).
2. If you know the format, use pd.to_datetime(): date_parser=lambda x: pd.to_datetime(x, format=...).
3. If you have a really non-standard format, use a custom date_parser function. For optimal performance, this should be vectorized, i.e., it should accept arrays as arguments.

You can explore the date parsing functionality in date_converters.py and add your own. We would love to turn this module into a community supported set of date/time parsers. To get you started, date_converters.py contains functions to parse dual date and time columns, year/month/day columns, and year/month/day/hour/minute/second columns. It also contains a generic_parser function so you can curry it with a function that deals with a single date rather than the entire array.

24.1.9.3 Inferring Datetime Format

If you have parse_dates enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting infer_datetime_format=True. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, infer_datetime_format should not have any negative consequences if enabled.
Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00):

- “20111230”
- “2011/12/30”
- “20111230 00:00:00”
- “12/30/2011 00:00:00”
- “30/Dec/2011 00:00:00”
- “30/December/2011 00:00:00”

Note that `infer_datetime_format` is sensitive to `dayfirst`. With `dayfirst=True`, it will guess “01/12/2011” to be December 1st. With `dayfirst=False` (default) it will guess “01/12/2011” to be January 12th.

```python
# Try to infer the format for the index column
In [108]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
                     :     infer_datetime_format=True)

In [109]: df
```

```
Out[109]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td>2009-01-01</td>
<td>a</td>
<td>1</td>
</tr>
<tr>
<td>date</td>
<td>2009-01-02</td>
<td>b</td>
<td>3</td>
</tr>
<tr>
<td>date</td>
<td>2009-01-03</td>
<td>c</td>
<td>4</td>
</tr>
</tbody>
</table>
```

### 24.1.9.4 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.

```python
In [110]: print(open('tmp.csv').read())

out[110]:
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [111]: pd.read_csv('tmp.csv', parse_dates=[0])
```

```
Out[111]:

<table>
<thead>
<tr>
<th></th>
<th>date</th>
<th>value</th>
<th>cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td>2000-01-06</td>
<td>5</td>
<td>a</td>
</tr>
<tr>
<td>date</td>
<td>2000-02-06</td>
<td>10</td>
<td>b</td>
</tr>
<tr>
<td>date</td>
<td>2000-03-06</td>
<td>15</td>
<td>c</td>
</tr>
</tbody>
</table>

In [112]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
```

```
Out[112]:

<table>
<thead>
<tr>
<th></th>
<th>date</th>
<th>value</th>
<th>cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td>2000-06-01</td>
<td>5</td>
<td>a</td>
</tr>
<tr>
<td>date</td>
<td>2000-06-02</td>
<td>10</td>
<td>b</td>
</tr>
<tr>
<td>date</td>
<td>2000-06-03</td>
<td>15</td>
<td>c</td>
</tr>
</tbody>
</table>
```
24.1.10 Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```python
In [113]: val = '0.3066101993807095471566981359501369297504425048828125'
In [114]: data = 'a,b,c
1,2,{' + val + '}'.format(val)
In [115]: abs(pd.read_csv(StringIO(data), engine='c', float_precision=None)['c'][0] - float(val))
Out[115]: 1.1102230246251565e-16
In [116]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='high')['c'][0] - float(val))
Out[116]: 5.5511151231257827e-17
In [117]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='round_trip')['c'][0] - float(val))
Out[117]: 0.0
```

24.1.11 Thousand Separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings:

```python
In [118]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
In [119]: df = pd.read_csv('tmp.csv', sep='|')
In [120]: df
Out[120]:
   ID    level  category
0 Patient1 123,000     x
1 Patient2  23,000     y
2 Patient3 1,234,018   z
In [121]: df.level.dtype
dtype('O')
```

The `thousands` keyword allows integers to be parsed correctly:

```python
In [122]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

(continues on next page)
24.1.12 NA Values

To control which values are parsed as missing values (which are signified by NaN), specify a string in na_values. If you specify a list of strings, then all values in it are considered to be missing values. If you specify a number (a float, like 5.0 or an integer like 5), the corresponding equivalent values will also imply a missing value (in this case effectively [5.0, 5] are recognized as NaN).

To completely override the default values that are recognized as missing, specify keep_default_na=False.

The default NaN recognized values are ['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A N/A', '#N/A', 'N/A', 'n/a', 'NA', '#NA', 'NULL', 'null', 'NaN', '-NaN', 'nan', '-nan', '']

Let us consider some examples:

```
read_csv(path, na_values=[5])
```

In the example above 5 and 5.0 will be recognized as NaN, in addition to the defaults. A string will first be interpreted as a numerical 5, then as a NaN.

```
read_csv(path, keep_default_na=False, na_values=[''])
```

Above, only an empty field will be recognized as NaN.

```
read_csv(path, keep_default_na=False, na_values=['NA', '0'])
```

Above, both 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.

24.1.13 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.

24.1.14 Returning Series

Using the squeeze keyword, the parser will return output with a single column as a Series:
24.1.15 Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Occasionally you might want to recognize other values as being boolean. To do this, use the `true_values` and `false_values` options as follows:

```
In [130]: data= 'a,b,c
a,b,c
1,Yes,2
3,No,4'

In [131]: pd.read_csv(StringIO(data))
Out[131]:
\ a b c
0 1 Yes 2
1 3 No 4

In [133]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[133]:
\ a b c
0 1 True 2
1 3 False 4
```

24.1.16 Handling “bad” lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many fields will raise an error by default:

```
In [27]: data = 'a,b,c\n1,2,3\n4,5,6,7\n8,9,10'

In [28]: pd.read_csv(StringIO(data))
ParserError
--------------------------
Traceback (most recent call last)
ParserError: Error tokenizing data. C error: Expected 3 fields in line 3, saw 4
```
You can elect to skip bad lines:

```python
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
Skipping line 3: expected 3 fields, saw 4
```

```plaintext
Out[29]:
    a  b  c
0  1  2  3
1  8  9 10
```

You can also use the `usecols` parameter to eliminate extraneous column data that appear in some lines but not others:

```python
In [30]: pd.read_csv(StringIO(data), usecols=[0, 1, 2])
```

```plaintext
Out[30]:
       a  b  c
0   1  2  3
1   4  5  6
2   8  9 10
```

### 24.1.17 Dialect

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```python
In [134]: 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`:

```python
In [135]: dia = csv.excel()
In [136]: dia.quoting = csv.QUOTE_NONE
In [137]: pd.read_csv(StringIO(data), dialect=dia)
```

```plaintext
Out[137]:
    label1  label2  label3
index1   a       c       e
index2   b       d       f
```

All of the dialect options can be specified separately by keyword arguments:

```python
In [138]: data = 'a,b,c~1,2,3~4,5,6'
In [139]: pd.read_csv(StringIO(data), lineterminator='~')
```

```plaintext
Out[139]:
    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 [140]: data = 'a, b, c\n1, 2, 3\n4, 5, 6'

In [141]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [142]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[142]:
a b c
0 1 2 3
1 4 5 6

The parsers make every attempt to “do the right thing” and not be fragile. Type inference is a pretty big deal. If a column can be coerced to integer dtype without altering the contents, the parser will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

24.1.18 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 [143]: data = 'a,b\n"hello, \"Bob\\", nice to see you",5'

In [144]: print(data)
a,b
"hello, "Bob", nice to see you",5

In [145]: pd.read_csv(StringIO(data), escapechar='\')
Out[145]:
a b
0 hello, "Bob", nice to see you 5

24.1.19 Files with Fixed Width Columns

While read_csv() reads delimited data, the read_fwf() function works with data files that have known and fixed column widths. The function parameters to read_fwf are largely the same as read_csv with two extra parameters, and a different usage of the delimiter parameter:

- colspecs: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to]). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behavior, if not specified, is to infer.

- widths: A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.

- delimiter: Characters to consider as filler characters in the fixed-width file. Can be used to specify the filler character of the fields if it is not spaces (e.g., ‘~’).

Consider a typical fixed-width data file:

In [146]: print(open('bar.csv').read())
id8141 360.242940 149.910199 11950.7
id1594 444.953632 166.985655 11788.4
id1849 364.136849 183.628767 11806.2
id1230 413.836124 184.375703 11916.8
id1948 502.953953 173.237159 12468.3
In order to parse this file into a DataFrame, we simply need to supply the column specifications to the `read_fwf` function along with the file name:

```python
# Column specifications are a list of half-intervals
In [147]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [148]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)

In [149]: df
```

```
Out[149]:
    1      2      3
0  id8141  360.242940  149.910199  11950.7
1  id1594  444.953632  166.985655  11788.4
2  id1849  364.136849  183.628767  11806.2
3  id1230  413.836124  184.375703  11916.8
4  id1948  502.953953  173.237159  12468.3
```

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```python
# Widths are a list of integers
In [150]: widths = [6, 14, 13, 10]

In [151]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [152]: df
```

```
Out[152]:
       1    2    3
0  id8141  360.242940  149.910199  11950.7
1  id1594  444.953632  166.985655  11788.4
2  id1849  364.136849  183.628767  11806.2
3  id1230  413.836124  184.375703  11916.8
4  id1948  502.953953  173.237159  12468.3
```

The parser will take care of extra white spaces around the columns so it’s ok to have extra separation between the columns in the file.

By default, `read_fwf` will try to infer the file’s `colspecs` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```python
In [153]: df = pd.read_fwf('bar.csv', header=None, index_col=0)

In [154]: df
```

```
Out[154]:
       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
```

New in version 0.20.0.

`read_fwf` supports the `dtype` parameter for specifying the types of parsed columns to be different from the inferred type.
24.1.20 Indexes

24.1.20.1 Files with an “implicit” index column

Consider a file with one less entry in the header than the number of data column:

```python
In [157]: print(open('foo.csv').read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the DataFrame:

```python
In [158]: pd.read_csv('foo.csv')
Out[158]:
   A    B  C
0  a  1.0  2
1  b  3.0  4
2  c  4.0  5
```

Note that the dates weren’t automatically parsed. In that case you would need to do as before:

```python
In [159]: df = pd.read_csv('foo.csv', parse_dates=True)
In [160]: df.index
Out[160]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', freq=None)
```

24.1.20.2 Reading an index with a MultiIndex

Suppose you have data indexed by two columns:

```python
In [161]: 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
```

(continues on next page)
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:

```python
In [162]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0,1])
```

```python
In [163]: df
Out[163]:
      zit  xit
year indiv  
1977 A  1.20 0.60
        B  1.50 0.50
        C  1.70 0.80
1978 A  0.20 0.06
        B  0.70 0.20
        C  0.80 0.30
        D  0.90 0.50
        E  1.40 0.90
1979 C  0.20 0.15
        D  0.14 0.05
        E  0.50 0.15
        F  1.20 0.50
        G  3.40 1.90
        H  5.40 2.70
        I  6.40 1.20
```

24.1.20.3 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.

```python
In [164]: df.loc[1978]
```

```python
→
      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
```

```python
In [165]: from pandas.util.testing import makeCustomDataframe as mkdf
```
In [166]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)

In [167]: df.to_csv('mi.csv')

In [168]:
   
   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 [169]:
   
   pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1])

   
   \rightarrow
   
   C0 C_l0_g0 C_l0_g1 C_l0_g2
   C1 C_l1_g0 C_l1_g1 C_l1_g2
   C2 C_l2_g0 C_l2_g1 C_l2_g2
   C3 C_l3_g0 C_l3_g1 C_l3_g2
   R0 R1
   R_l0_g0 R_l1_g0 R0C0 R0C1 R0C2
   R_l0_g1 R_l1_g1 R1C0 R1C1 R1C2
   R_l0_g2 R_l1_g2 R2C0 R2C1 R2C2
   R_l0_g3 R_l1_g3 R3C0 R3C1 R3C2
   R_l0_g4 R_l1_g4 R4C0 R4C1 R4C2

read_csv is also able to interpret a more common format of multi-columns indices.

In [170]:
   
   print(open('mi2.csv').read())

,a,a,a,b,c,c
,q,r,s,t,u,v
one,1,2,3,4,5,6
two,7,8,9,10,11,12

In [171]:
   
   pd.read_csv('mi2.csv', header=[0, 1], index_col=0)

   \rightarrow
   
   a b c
   q r s t u v
   one 1 2 3 4 5 6
two 7 8 9 10 11 12

Note: If an index_col is not specified (e.g. you don’t have an index, or wrote it with df.to_csv(..., index=False)), then any names on the columns index will be lost.

24.1.21 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.
24.1.22 Reading multiple files to create a single DataFrame

It’s best to use `concat()` to combine multiple files. See the cookbook for an example.

24.1.23 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:
By specifying a chunksize to read_csv or read_table, the return value will be an iterable object of type TextFileReader:

```python
In [177]: reader = pd.read_csv('tmp.csv', sep='|', chunksize=4)
In [178]: reader
Out[178]: <pandas.io.parsers.TextFileReader at 0x1c32977ef0>
In [179]: 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 -1.344312 0.844885
           4 4 -0.424972 0.567020 0.276232 -1.087401
           5 5 -0.673690 0.113648 -1.715002 -1.039268
           6 6 0.404705 0.577046 -1.157892 -1.344312
           7 7 -0.370647 -1.157892 -1.344312 0.844885
           8 8 1.075770 -0.109050 1.643563 -1.469388
           9 9 0.357021 -0.674600 -1.776904 -0.968914
```

Specifying `iterator=True` will also return the TextFileReader object:

```python
In [180]: reader = pd.read_csv('tmp.csv', sep='|', iterator=True)
In [181]: reader.get_chunk(5)
Out[181]:
                  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 -1.344312 0.844885
           4 4 -0.424972 0.567020 0.276232 -1.087401
```

24.1. CSV & Text files
24.1.24 Specifying the parser engine

Under the hood pandas uses a fast and efficient parser implemented in C as well as a Python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to Python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skipfooter`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

24.1.25 Reading remote files

You can pass in a URL to a CSV file:

```python
df = pd.read_csv('https://download.bls.gov/pub/time.series/cu/cu.item', sep='\t')
```

S3 URLs are handled as well:

```python
df = pd.read_csv('s3://pandas-test/tips.csv')
```

24.1.26 Writing out Data

24.1.26.1 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). Note that if you have set a `float_format` then floats are converted to strings and csv.QUOTE_NONNUMERIC will treat them as non-numeric
• **quotechar**: Character used to quote fields (default ‘”’)
• **doublequote**: Control quoting of quotechar in fields (default True)
• **escapechar**: Character used to escape sep and quotechar when appropriate (default None)
• **chunksize**: Number of rows to write at a time
• **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

### 24.1.26.2 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, table}

The format of the JSON string

<table>
<thead>
<tr>
<th>Split</th>
<th>Dict like {index -&gt; [index], columns -&gt; [columns], data -&gt; [values]}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Records</td>
<td>List like [{column -&gt; value}, . . . , {column -&gt; value}]</td>
</tr>
<tr>
<td>Index</td>
<td>Dict like {index -&gt; {column -&gt; value}}</td>
</tr>
<tr>
<td>Columns</td>
<td>Dict like {column -&gt; {index -&gt; value}}</td>
</tr>
<tr>
<td>Values</td>
<td>Just the values array</td>
</tr>
</tbody>
</table>

- `date_format`: string, type of date conversion, ‘epoch’ for timestamp, ‘iso’ for ISO8601.
- `double_precision`: The number of decimal places to use when encoding floating point values, default 10.
- `force_ascii`: force encoded string to be ASCII, default True.
- `date_unit`: The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’ or ‘ns’ for seconds, milliseconds, microseconds and nanoseconds respectively. Default ‘ms’.
- `default_handler`: The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.
- `lines`: If `records` orient, then will write each record per line as json.

Note NaN’s, NaT’s and None will be converted to `null` and datetime objects will be converted based on the `date_format` and `date_unit` parameters.

```
In [182]: dfj = pd.DataFrame(randn(5, 2), columns=list('AB'))
In [183]: json = dfj.to_json()
In [184]: json
Out[184]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.0061535699,"4":0.8957173022},"B":{"0":0.4137381054,"1":-0.472034511,"2":-0.3625429925,"3":-0.923060654,"4":0.8052440254}}'
```

### 24.2.1 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 [185]: dfjo = pd.DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),
                        columns=list('ABC'), index=list('xyz'))
In [186]: dfjo
Out[186]:
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>1</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>y</td>
<td>2</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>z</td>
<td>3</td>
<td>6</td>
<td>9</td>
</tr>
</tbody>
</table>
```

(continues on next page)
Column oriented (the default for DataFrame) serializes the data as nested JSON objects with column labels acting as the primary index:

```python
In [189]: dfjo.to_json(orient="columns")
Out[189]: '{"A":{"x":1,"y":2,"z":3},"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:

```python
In [190]: dfjo.to_json(orient="index")
In [191]: sjo.to_json(orient="index")
   →'{"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:

```python
In [192]: dfjo.to_json(orient="records")
In [193]: sjo.to_json(orient="records")
   →'[[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:

```python
In [194]: dfjo.to_json(orient="values")
Out[194]: '[[1,4,7],[2,5,8],[3,6,9]]'
```

# Not available for Series

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for Series:

```python
In [195]: dfjo.to_json(orient="split")
Out[195]: '{"columns":['"A","B","C"],"index":['"x","y","z"],"data":[[1,4,7],[2,5,8],[3,6,9]]}'
In [196]: sjo.to_json(orient="split")
   →'{"name":"D","index":['"x","y","z"],"data":[15,16,17]}'
```
Table oriented serializes to the JSON Table Schema, allowing for the preservation of metadata including but not limited to dtypes and index names.

Note: Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the split option as it uses ordered containers.

### 24.2.1.2 Date Handling

Writing in ISO date format:

```python
In [197]: dfd = pd.DataFrame(randn(5, 2), columns=list('AB'))
In [198]: dfd['date'] = pd.Timestamp('20130101')
In [199]: dfd = dfd.sort_index(1, ascending=False)
In [200]: json = dfd.to_json(date_format='iso')
In [201]: json
```

```
Out[201]:
{
    "date": {
        "0": "2013-01-01T00:00:00.000Z",
        "1": "2013-01-01T00:00:00.000Z",
        "2": "2013-01-01T00:00:00.000Z",
        "3": "2013-01-01T00:00:00.000Z",
        "4": "2013-01-01T00:00.000Z"
    },
    "B": {
        "0": 2.5656459463,
        "1": 1.3403088498,
        "2": -0.2261692849,
        "3": 0.8138502857,
        "4": -0.8273169356
    },
    "A": {
        "0": -1.2064117817,
        "1": 1.4312559863,
        "2": -1.1702987971,
        "3": 0.4108345112,
        "4": 0.1320031703
    }
}
```

Writing in ISO date format, with microseconds:

```python
In [202]: json = dfd.to_json(date_format='iso', date_unit='us')
In [203]: json
```

```
Out[203]:
{
    "date": {
        "0": "2013-01-01T00:00:00.000000Z",
        "1": "2013-01-01T00:00:00.000000Z",
        "2": "2013-01-01T00:00:00.000000Z",
        "3": "2013-01-01T00:00:00.000000Z",
        "4": "2013-01-01T00:00.000000Z"
    },
    "B": {
        "0": 2.5656459463,
        "1": 1.3403088498,
        "2": -0.2261692849,
        "3": 0.8138502857,
        "4": -0.8273169356
    },
    "A": {
        "0": -1.2064117817,
        "1": 1.4312559863,
        "2": -1.1702987971,
        "3": 0.4108345112,
        "4": 0.1320031703
    }
}
```

Epoch timestamps, in seconds:

```python
In [204]: json = dfd.to_json(date_format='epoch', date_unit='s')
In [205]: json
```

```
Out[205]:
{
    "date": {
        "0": 1356998400,
        "1": 1356998400,
        "2": 1356998400,
        "3": 1356998400,
        "4": 1356998400
    },
    "B": {
        "0": 2.5656459463,
        "1": 1.3403088498,
        "2": -0.2261692849,
        "3": 0.8138502857,
        "4": -0.8273169356
    },
    "A": {
        "0": -1.2064117817,
        "1": 1.4312559863,
        "2": -1.1702987971,
        "3": 0.4108345112,
        "4": 0.1320031703
    }
}
```

Writing to a file, with a date index and a date column:

```python
In [206]: dfj2 = dfj2.copy()
In [207]: dfj2['date'] = pd.Timestamp('20130101')
In [208]: dfj2['ints'] = list(range(5))
In [209]: dfj2['bools'] = True
(continues on next page)
24.2.1.3 Fallback Behavior

If the JSON serializer cannot handle the container contents directly it will fall back in the following manner:

- if the dtype is unsupported (e.g. np.complex) then the default_handler, if provided, will be called for each value, otherwise an exception is raised.
- if an object is unsupported it will attempt the following:
  - check if the object has defined a toDict method and call it. A toDict method should return a dict which will then be JSON serialized.
  - invoke the default_handler if one was provided.
  - convert the object to a dict by traversing its contents. However this will often fail with an OverflowError or give unexpected results.

In general the best approach for unsupported objects or dtypes is to provide a default_handler. For example:

```python
In [213]: pd.DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json(default_handler=str)
Out [213]: '{"0":"(1+0j)","1":"(2+0j)","2":(1+2j)"}'
```

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: 

24.2. JSON 1159
Series:
- default is index
- allowed values are {split, records, index}

DataFrame
- default is columns
- allowed values are {split, records, index, columns, values, table}

The format of the JSON string:

<table>
<thead>
<tr>
<th>Key</th>
<th>Format</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}, ...., {column -&gt; value}]</td>
</tr>
<tr>
<td>index</td>
<td>dict like {index -&gt; {column -&gt; value}}</td>
</tr>
<tr>
<td>columns</td>
<td>dict like {column -&gt; {index -&gt; value}}</td>
</tr>
<tr>
<td>values</td>
<td>just the values array</td>
</tr>
<tr>
<td>table</td>
<td>adhering to the JSON Table Schema</td>
</tr>
</tbody>
</table>

- **dtype**: if True, infer dtypes, if a dict of column to dtype, then use those, if False, then don’t infer dtypes at all, default is True, apply only to the data.
- **convert_axes**: boolean, try to convert the axes to the proper dtypes, default is True
- **convert_dates**: a list of columns to parse for dates; If True, then try to parse date-like columns, default is True.
- **keep_default_dates**: boolean, default True. If parsing dates, then parse the default date-like columns.
- **numpy**: direct decoding to NumPy arrays. default is False; Supports numeric data only, although labels may be non-numeric. Also note that the JSON ordering MUST be the same for each term if numpy=True.
- **precise_float**: boolean, default False. Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (False) is to use fast but less precise builtin functionality.
- **date_unit**: string, the timestamp unit to detect if converting dates. Default None. By default the timestamp precision will be detected, if this is not desired then pass one of ‘s’, ‘ms’, ‘us’ or ‘ns’ to force timestamp precision to seconds, milliseconds, microseconds or nanoseconds respectively.
- **lines**: reads file as one json object per line.
- **encoding**: The encoding to use to decode py3 bytes.
- **chunksize**: when used in combination with lines=True, return a JsonReader which reads in chunksize lines per iteration.

The parser will raise one of ValueError/TypeError/AssertionError if the JSON is not parseable.

If a non-default orient was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see Orient Options for an overview.

### 24.2.2.1 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 \texttt{convert\_dates=True} and the data and/or column labels appear ‘date-like’. The exact threshold depends on the \texttt{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 \texttt{dtype} keyword argument.

Reading from a JSON string:

```
In [214]: pd.read_json(json)
Out[214]:
   date     B     A
0 2013-01-01 2.565646 -1.206412
1 2013-01-01 1.340309  1.431256
2 2013-01-01  0.226169  1.170299
3 2013-01-01  0.813850  0.410835
4 2013-01-01 -0.827317  0.132003
```

Reading from a file:

```
In [215]: pd.read_json('test.json')
Out[215]:
      A     B      date     ints   bools
0  2013-01-01 -1.294524  0.413738  2013-01-01   0   True
1  2013-01-02  0.276662 -0.472035  2013-01-01   1   True
2  2013-01-03 -0.013960 -0.362543  2013-01-01   2   True
3  2013-01-04 -0.006154 -0.923061  2013-01-01   3   True
4  2013-01-05  0.895717  0.805244  2013-01-01   4   True
```

Don’t convert any data (but still convert axes and dates):

```
In [216]: pd.read_json('test.json', dtype=object).dtypes
Out[216]:
      A   B   date     ints   bools
dtype: object
```

24.2. JSON
Specify dtypes for conversion:

```
In [217]: pd.read_json('test.json', dtype={'A': 'float32', 'bools': 'int8'}).dtypes
Out[217]:
A    float32
B    float64
date  datetime64[ns]
ints  int64
bools int8
dtype: object
```

Preserve string indices:

```
In [218]: si = pd.DataFrame(np.zeros((4, 4)),
                      columns=list(range(4)),
                      index=[str(i) for i in range(4)])

In [219]: si
Out[219]:
    0  1  2  3
0  0.0 0.0 0.0 0.0
1  0.0 0.0 0.0 0.0
2  0.0 0.0 0.0 0.0
3  0.0 0.0 0.0 0.0

In [220]: si.index
Index(['0', '1', '2', '3'], dtype='object')

In [221]: si.columns
Int64Index([0, 1, 2, 3], dtype='int64')

In [222]: json = si.to_json()

In [223]: sij = pd.read_json(json, convert_axes=False)

In [224]: sij
Out[224]:
    0  1  2  3
0  0  0  0  0
1  0  0  0  0
2  0  0  0  0
3  0  0  0  0

In [225]: sij.index
Index(['0', '1', '2', '3'], dtype='object')

In [226]: sij.columns
Index(['0', '1', '2', '3'], dtype='object')
```

Dates written in nanoseconds need to be read back in nanoseconds:

```
In [227]: json = dfj2.to_json(date_unit='ns')
```
# Try to parse timestamps as milliseconds -> Won't Work

In [228]: dfju = pd.read_json(json, date_unit='ms')

In [229]: dfju

Out[229]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>date</th>
<th>ints</th>
<th>bools</th>
</tr>
</thead>
<tbody>
<tr>
<td>135699840000000000</td>
<td>-1.294524</td>
<td>135699840000000000000</td>
<td>0</td>
<td>True</td>
</tr>
<tr>
<td>135708480000000000</td>
<td>0.276662</td>
<td>135699840000000000000</td>
<td>1</td>
<td>True</td>
</tr>
<tr>
<td>135717120000000000</td>
<td>-0.013960</td>
<td>135699840000000000000</td>
<td>2</td>
<td>True</td>
</tr>
<tr>
<td>135725760000000000</td>
<td>-0.006154</td>
<td>135699840000000000000</td>
<td>3</td>
<td>True</td>
</tr>
<tr>
<td>135734400000000000</td>
<td>0.895717</td>
<td>135699840000000000000</td>
<td>4</td>
<td>True</td>
</tr>
</tbody>
</table>

# Let pandas detect the correct precision

In [230]: dfju = pd.read_json(json)

In [231]: dfju

Out[231]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>date</th>
<th>ints</th>
<th>bools</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>-1.294524</td>
<td>2013-01-01</td>
<td>0</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-02</td>
<td>0.276662</td>
<td>2013-01-01</td>
<td>1</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>-0.013960</td>
<td>2013-01-01</td>
<td>2</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>-0.006154</td>
<td>2013-01-01</td>
<td>3</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>0.895717</td>
<td>2013-01-01</td>
<td>4</td>
<td>True</td>
</tr>
</tbody>
</table>

# Or specify that all timestamps are in nanoseconds

In [232]: dfju = pd.read_json(json, date_unit='ns')

In [233]: dfju

Out[233]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>date</th>
<th>ints</th>
<th>bools</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>-1.294524</td>
<td>2013-01-01</td>
<td>0</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-02</td>
<td>0.276662</td>
<td>2013-01-01</td>
<td>1</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>-0.013960</td>
<td>2013-01-01</td>
<td>2</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>-0.006154</td>
<td>2013-01-01</td>
<td>3</td>
<td>True</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>0.895717</td>
<td>2013-01-01</td>
<td>4</td>
<td>True</td>
</tr>
</tbody>
</table>

### 24.2.2.2 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:

In [234]: randfloats = np.random.uniform(-100, 1000, 10000)

In [235]: randfloats.shape = (1000, 10)

In [236]: dffloats = pd.DataFrame(randfloats, columns=list('ABCDEFGHIJ'))

In [237]: jsonfloats = dffloats.to_json()
The speedup is less noticeable for smaller datasets:

```
In [240]: jsonfloats = dffloats.head(100).to_json()

In [241]: timeit pd.read_json(jsonfloats)
5.07 ms +- 64.2 us per loop (mean +- std. dev. of 7 runs, 100 loops each)

In [242]: timeit pd.read_json(jsonfloats, numpy=True)
4.39 ms +- 82.7 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

**Warning:** Direct NumPy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The dtype is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.

### 24.2.3 Normalization

pandas provides a utility function to take a dict or list of dicts and normalize this semi-structured data into a flat table.

```
In [243]: from pandas.io.json import json_normalize

In [244]: data = [{'id': 1, 'name': {'first': 'Coleen', 'last': 'Volk'}},
               ...
               {'name': {'given': 'Mose', 'family': 'Regner'}},
               ...
               {'id': 2, 'name': 'Faye Raker'}]

In [245]: json_normalize(data)
Out[245]:
   id     name.name.name.family name.first name.given name.last
0 1.0          NaN          NaN          NaN      Coleen          NaN     Volk
1  NaN          NaN          NaN          NaN     Regner          NaN          NaN
2  2.0      Faye Raker          NaN          NaN          NaN          NaN          NaN
```
24.2.4 Line delimited json

New in version 0.19.0.

pandas is able to read and write line-delimited json files that are common in data processing pipelines using Hadoop or Spark.

New in version 0.21.0.

For line-delimited json files, pandas can also return an iterator which reads in chunksize lines at a time. This can be useful for large files or to read from a stream.

```python
In [247]: json_normalize(data, 'counties', ['state', 'shortname', ['info', 'governor']])
Out[247]:
    name  population  state   shortname info.governor
0   Dade       12345  Florida  FL    Rick Scott
1  Broward      40000  Florida  FL    Rick Scott
2 Palm Beach     60000  Florida  FL    Rick Scott
3  Summit       1234   Ohio    OH  John Kasich
4 Cuyahoga      1337   Ohio    OH  John Kasich
```

# reader is an iterator that returns 'chunksize' lines each iteration
```
In [251]: reader = pd.read_json(StringIO(jsonl), lines=True, chunksize=1)
```

```
In [254]: for chunk in reader:
```
24.2.5 Table Schema

New in version 0.20.0.

Table Schema is a spec for describing tabular datasets as a JSON object. The JSON includes information on the field names, types, and other attributes. You can use the orient table to build a JSON string with two fields, schema and data.

```python
In [255]: df = pd.DataFrame(
      .....:   {'A': [1, 2, 3],
      .....:     'B': ['a', 'b', 'c'],
      .....:     'C': pd.date_range('2016-01-01', freq='d', periods=3),
      .....: ), index=pd.Index(range(3), name='idx'))
In [256]: df
Out[256]:
     A     B         C
idx  
0    1    a 2016-01-01
1    2    b 2016-01-02
2    3    c 2016-01-03
In [257]: df.to_json(orient='table', date_format="iso")
```

The schema field contains the fields key, which itself contains a list of column name to type pairs, including the Index or MultiIndex (see below for a list of types). The schema field also contains a primaryKey field if the (Multi)index is unique.

The second field, data, contains the serialized data with the records orient. The index is included, and any datetimes are ISO 8601 formatted, as required by the Table Schema spec.

The full list of types supported are described in the Table Schema spec. This table shows the mapping from pandas types:
<table>
<thead>
<tr>
<th>Pandas type</th>
<th>Table Schema type</th>
</tr>
</thead>
<tbody>
<tr>
<td>int64</td>
<td>integer</td>
</tr>
<tr>
<td>float64</td>
<td>number</td>
</tr>
<tr>
<td>bool</td>
<td>boolean</td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td>datetime</td>
</tr>
<tr>
<td>timedelta64[ns]</td>
<td>duration</td>
</tr>
<tr>
<td>categorical</td>
<td>any</td>
</tr>
<tr>
<td>object</td>
<td>str</td>
</tr>
</tbody>
</table>

A few notes on the generated table schema:

- The schema object contains a pandas_version field. This contains the version of pandas’ dialect of the schema, and will be incremented with each revision.

- All dates are converted to UTC when serializing. Even timezone naïve values, which are treated as UTC with an offset of 0.

```python
In [258]: from pandas.io.json import build_table_schema
In [259]: s = pd.Series(pd.date_range('2016', periods=4))
In [260]: build_table_schema(s)
Out[260]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'datetime'}],
     'primaryKey': ['index'],
     'pandas_version': '0.20.0'}
```

- Datetimes with a timezone (before serializing), include an additional field tz with the time zone name (e.g. 'US/Central').

```python
In [261]: s_tz = pd.Series(pd.date_range('2016', periods=12, 
                  ....:              tz='US/Central'))
                  ....:
In [262]: build_table_schema(s_tz)
Out[262]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'datetime', 'tz': 'US/Central'}],
     'primaryKey': ['index'],
     'pandas_version': '0.20.0'}
```

- Periods are converted to timestamps before serialization, and so have the same behavior of being converted to UTC. In addition, periods will contain additional field freq with the period’s frequency, e.g. 'A-DEC'.

```python
In [263]: s_per = pd.Series(1, index=pd.period_range('2016', freq='A-DEC',
                  ....:              periods=4))
                  ....:
In [264]: build_table_schema(s_per)
Out[264]:
{'fields': [{'name': 'index', 'type': 'datetime', 'freq': 'A-DEC'},
            {'name': 'values', 'type': 'integer'}],
     'primaryKey': ['index'],
     'pandas_version': '0.20.0'}
```
• Categoricals use the any type and an enum constraint listing the set of possible values. Additionally, an ordered field is included:

```python
In [265]: s_cat = pd.Series(pd.Categorical(['a', 'b', 'a']))
In [266]: build_table_schema(s_cat)
Out[266]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'any',
             'constraints': {'enum': ['a', 'b']},
             'ordered': False},
            'primaryKey': ['index'],
            'pandas_version': '0.20.0'}
```

• A primaryKey field, containing an array of labels, is included if the index is unique:

```python
In [267]: s_dupe = pd.Series([1, 2], index=[1, 1])
In [268]: build_table_schema(s_dupe)
Out[268]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'integer'}],
 'pandas_version': '0.20.0'}
```

• The primaryKey behavior is the same with MultiIndexes, but in this case the primaryKey is an array:

```python
In [269]: s_multi = pd.Series(1, index=pd.MultiIndex.from_product([('a', 'b'), (0, 1)]))
In [270]: build_table_schema(s_multi)
Out[270]:
{'fields': [{'name': 'level_0', 'type': 'string'},
            {'name': 'level_1', 'type': 'integer'},
            {'name': 'values', 'type': 'integer'}],
 'primaryKey': FrozenList(['level_0', 'level_1']),
 'pandas_version': '0.20.0'}
```

• The default naming roughly follows these rules:
  – For series, the object.name is used. If that’s none, then the name is values
  – For DataFrames, the stringified version of the column name is used
  – For Index (not MultiIndex), index.name is used, with a fallback to index if that is None.
  – For MultiIndex, mi.names is used. If any level has no name, then level_<i> is used.

New in version 0.23.0.

read_json also accepts orient='table' as an argument. This allows for the preservation of metadata such as dtypes and index names in a round-trippable manner.

```python
In [271]: df = pd.DataFrame({'foo': [1, 2, 3, 4],
                      'bar': ['a', 'b', 'c', 'd'],
                      'baz': pd.date_range('2018-01-01', freq='d', periods=4),
                      'qux': pd.Categorical(['a', 'b', 'c', 'c'])}, index=pd.Index(range(4), name='idx'))
```
.....:

In [272]: df
Out[272]:
   foo  bar  baz  qux
idx
0  a  2018-01-01  a
1  b  2018-01-02  b
2  c  2018-01-03  c
3  d  2018-01-04  c

In [273]: df.dtypes
   ...
foo   int64
bar   object
baz   datetime64[ns]
qux   category
dtype: object

In [274]: df.to_json('test.json', orient='table')

In [275]: new_df = pd.read_json('test.json', orient='table')

In [276]: new_df
   ...
   foo  bar  baz  qux
idx
0  a  2018-01-01  a
1  b  2018-01-02  b
2  c  2018-01-03  c
3  d  2018-01-04  c

In [277]: new_df.dtypes
   ...
foo   int64
bar   object
baz   datetime64[ns]
qux   category
dtype: object

Please note that the literal string 'index' as the name of an Index is not round-trippable, nor are any names beginning with 'level_' within a MultiIndex. These are used by default in DataFrame.to_json() to indicate missing values and the subsequent read cannot distinguish the intent.

In [278]: df.index.name = 'index'

In [279]: df.to_json('test.json', orient='table')

In [280]: new_df = pd.read_json('test.json', orient='table')

In [281]: print(new_df.index.name)
None

24.2. JSON 1169
## 24.3 HTML

### 24.3.1 Reading HTML Content

**Warning:** We highly encourage you to read the HTML Table Parsing gotchas below regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

The top-level `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas DataFrames. Let’s look at a few examples.

**Note:** `read_html` returns a list of DataFrame objects, even if there is only a single table contained in the HTML content.

Read a URL with no options:

```python
In [282]: url = 'http://www.fdic.gov/bank/individual/failed/banklist.html'

In [283]: dfs = pd.read_html(url)

In [284]: dfs
```

Output:

<table>
<thead>
<tr>
<th>Bank Name</th>
<th>City</th>
<th>Closing Date</th>
<th>Updated Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Washington Federal Bank for Savings</td>
<td>Chicago</td>
<td>December 15, 2017</td>
<td>February 21, 2018</td>
</tr>
<tr>
<td>The Farmers and Merchants State Bank of Argonia</td>
<td>Argonia</td>
<td>October 13, 2017</td>
<td>February 21, 2018</td>
</tr>
<tr>
<td>Fayette County Bank</td>
<td>Saint Elmo</td>
<td>May 26, 2017</td>
<td>July 26, 2017</td>
</tr>
<tr>
<td>Guaranty Bank, (d/b/a BestBank in Georgia &amp; Mi...</td>
<td>Milwaukee</td>
<td>May 5, 2017</td>
<td>March 22, 2018</td>
</tr>
<tr>
<td>First NBC Bank</td>
<td>New Orleans</td>
<td>April 28, 2017</td>
<td>December 5, 2017</td>
</tr>
<tr>
<td>Proficio Bank</td>
<td>Cottonwood Heights</td>
<td>March 3, 2017</td>
<td>March 7, 2018</td>
</tr>
<tr>
<td>Seaway Bank and Trust Company</td>
<td>Chicago</td>
<td>January 27, 2017</td>
<td>May 18, 2017</td>
</tr>
<tr>
<td>Hamilton Bank, NA</td>
<td>Miami</td>
<td>January 11, 2002</td>
<td>September 21, 2015</td>
</tr>
<tr>
<td>Sinclair National Bank</td>
<td>Gravette</td>
<td>September 7, 2001</td>
<td>October 6, 2017</td>
</tr>
<tr>
<td>Malta National Bank</td>
<td>Malta</td>
<td>May 3, 2001</td>
<td>November 18, 2002</td>
</tr>
<tr>
<td>First Alliance Bank &amp; Trust Co.</td>
<td>Manchester</td>
<td>February 2, 2001</td>
<td>February 18, 2003</td>
</tr>
<tr>
<td>National State Bank of Metropolis</td>
<td>Metropolis</td>
<td>December 14, 2000</td>
<td>March 17, 2005</td>
</tr>
<tr>
<td>Bank of Honolulu</td>
<td>Honolulu</td>
<td>October 13, 2000</td>
<td>March 17, 2005</td>
</tr>
</tbody>
</table>

(continues on next page)
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:

```python
In [285]: with open(file_path, 'r') as f:
    .....:
    dfs = pd.read_html(f.read())
    .....:

In [286]: dfs
```

```
  | Bank Name                  | City   | ST  |   |
---|---------------------------|--------|-----|---|
0  | Acquiring Institution     | Closing Date | Updated Date | ... |
1  | Banks of Wisconsin d/b/a Bank of Kenosha | Kenosha | WI  | ... |
2  | North Shore Bank, FSB     | May 31, 2013 | May 31, 2013 | ... |
3  | Central Arizona Bank      | Scottsdale | AZ  | ... |
4  | Western State Bank        | May 14, 2013 | May 20, 2013 | ... |
5  | Sunrise Bank              | Valdosta  | GA  | ... |
6  | Synovus Bank              | May 10, 2013 | May 21, 2013 | ... |
7  | Pisgah Community Bank     | Asheville | NC  | ... |
8  | Capital Bank, N.A.        | May 10, 2013 | May 14, 2013 | ... |
9  | Douglas County Bank       | Douglasville | GA  | ... |
10 | Hamilton State Bank       | April 26, 2013 | May 16, 2013 | ... |
11 | Parkway Bank              | Lenoir   | NC  | ... |
12 | CertusBank, National Association | April 26, 2013 | May 17, 2013 | ... |
13 | First Federal Bank of Florida | April 19, 2013 | May 16, 2013 | ... |
14 | ...                       | ...      | ... | ... |
```

You can even pass in an instance of `StringIO` if you so desire:

```python
In [287]: with open(file_path, 'r') as f:
    .....:
    sio = StringIO(f.read())
    .....:
```
In [288]: dfs = pd.read_html(sio)

In [289]: dfs

Out[289]:
[ Bank Name City ST ...  
 0 Banks of Wisconsin d/b/a Bank of Kenosha Kenosha WI ...  
 1 North Shore Bank, FSB May 31, 2013 May 31, 2013  
 2 Central Arizona Bank Scottsdale AZ ...  
 3 Western State Bank May 14, 2013 May 20, 2013  
 4 Sunrise Bank Valdosta GA ...  
 5 Synovus Bank May 10, 2013 May 21, 2013  
 6 Pisgah Community Bank Asheville NC ...  
 7 Capital Bank, N.A. May 10, 2013 May 14, 2013  
 8 Douglas County Bank Douglasville GA ...  
 9 Hamilton State Bank April 26, 2013 May 16, 2013  
 10 Parkway Bank Lenoir NC ...  
 11 CertusBank, National Association April 26, 2013 May 17, 2013  
 12 Chipola Community Bank Marianna FL ...  
 14 ... ... ... ...  
 498 Hamilton Bank, NAEn Espanol Miami FL ...  
 500 Sinclair National Bank Gravette AR ...  
 501 Delta Trust & Bank September 7, 2001 February 10, 2004  
 502 Superior Bank, FSB Hinsdale IL ...  
 504 Malta National Bank Malta OH ...  
 505 North Valley Bank May 3, 2001 November 18, 2002  
 506 First Alliance Bank & Trust Co. Manchester NH ...  
 507 Southern New Hampshire Bank & Trust February 2, 2001 February 18, 2003  
 508 National State Bank of Metropolis Metropolis IL ...  
 509 Banterra Bank of Marion December 14, 2000 March 17, 2005  
 510 Bank of Honolulu Honolulu HI ...  
 511 Bank of the Orient October 13, 2000 March 17, 2005  
[505 rows x 7 columns]]

Note: The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn’t run, please do not hesitate to report it over on pandas GitHub issues page.
dfs = pd.read_html(url, index_col=0)

Specify a number of rows to skip:

dfs = pd.read_html(url, skiprows=0)

Specify a number of rows to skip using a list (xrange (Python 2 only) works as well):

dfs = pd.read_html(url, skiprows=range(2))

Specify an HTML attribute:

dfs1 = pd.read_html(url, attrs={'id': 'table'})
dfs2 = pd.read_html(url, attrs={'class': 'sortable'})
print(np.array_equal(dfs1[0], dfs2[0]))  # Should be True

Specify values that should be converted to NaN:

dfs = pd.read_html(url, na_values=['No Acquirer'])

New in version 0.19.

Specify whether to keep the default set of NaN values:

dfs = pd.read_html(url, keep_default_na=False)

New in version 0.19.

Specify converters for columns. This is useful for numerical text data that has leading zeros. By default columns that are numerical are cast to numeric types and the leading zeros are lost. To avoid this, we can convert these columns to strings.

url_mcc = 'https://en.wikipedia.org/wiki/Mobile_country_code'
dfs = pd.read_html(url_mcc, match='Telekom Albania', header=0, converters={'MNC': str})

New in version 0.19.

Use some combination of the above:

dfs = pd.read_html(url, match='Metcalf Bank', index_col=0)

Read in pandas to_html output (with some loss of floating point precision):

df = pd.DataFrame(randn(2, 2))
s = df.to_html(float_format='{0:.40g}'.format)
dfin = pd.read_html(s, index_col=0)

The lxml backend will raise an error on a failed parse if that is the only parser you provide. If you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings. You may use:

dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml'])

Or you could pass flavor='lxml' without a list:

dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor='lxml')
However, if you have bs4 and html5lib installed and pass None or ['lxml', 'bs4'] then the parse will most likely succeed. Note that as soon as a parse succeeds, the function will return.

```python
dfs = pd.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.

```python
In [290]: df = pd.DataFrame(randn(2, 2))
In [291]: df
Out[291]:
       0      1
0  0.184744  0.496971
1  0.856240  1.857977
```

```python
In [292]: print(df.to_html())
# raw html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">  
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

**HTML:**

The `columns` argument will limit the columns shown:

```python
In [293]: 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>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

(continues on next page)
HTML:

`float_format` takes a Python callable to control the precision of floating point values:

```python
In [294]: print(df.to_html(float_format='{0:.10f}'.format))
```

```html
<table border="1" class="dataframe">
<thead>
  <tr style="text-align: right;">
    <th></th>
    <th>0</th>
    <th>1</th>
  </tr>
</thead>
<tbody>
  <tr>
    <td>-0.1847438576</td>
    <td>0.4969711327</td>
  </tr>
  <tr>
    <td>-0.8562396763</td>
    <td>1.8579766508</td>
  </tr>
</tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off:

```python
In [295]: print(df.to_html(bold_rows=False))
```

```html
<table border="1" class="dataframe">
<thead>
  <tr style="text-align: right;">
    <th></th>
    <th>0</th>
    <th>1</th>
  </tr>
</thead>
<tbody>
  <tr>
    <td>-0.1847438576</td>
    <td>0.4969711327</td>
  </tr>
  <tr>
    <td>-0.8562396763</td>
    <td>1.8579766508</td>
  </tr>
</tbody>
</table>
```
The **classes** argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are *appended* to the existing 'dataframe' class.

```
In [296]: 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 [297]: df = pd.DataFrame({'a': list('&<>'), 'b': randn(3)})
Escaped:
```

```
In [298]: 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:

```python
In [299]: print(df.to_html(escape=False))
<!DOCTYPE html>
<html>
<head>
</head>
<body>
<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>&amp;</td>
<td>-0.474063</td>
</tr>
<tr>
<th>1</th>
<td>&lt;</td>
<td>-0.230305</td>
</tr>
<tr>
<th>2</th>
<td>&gt;</td>
<td>-0.400654</td>
</tr>
</tbody>
</table>
</body>
</html>
```

**Note:** Some browsers may not show a difference in the rendering of the previous two HTML tables.

### 24.3.3 HTML Table Parsing Gotchas

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas io function `read_html`. 

---

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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.

### 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 `sheet_name` indicating which sheet to parse.

```python
# Returns a DataFrame
read_excel('path_to_file.xls', sheet_name='Sheet1')
```
To facilitate working with multiple sheets from the same file, the ExcelFile class can be used to wrap the file and can be passed into read_excel. There will be a performance benefit for reading multiple sheets as the file is read into memory only once.

```python
taxs = pd.ExcelFile('path_to_file.xls')
df = pd.read_excel(txs, '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=1)

# equivalent using the read_excel function
data = read_excel('path_to_file.xls', ['Sheet1', 'Sheet2'], index_col=None, na_values=['NA'])
```

### 24.4.1.2 Specifying Sheets

**Note:** The second argument is sheet_name, not to be confused with ExcelFile.sheet_names.

**Note:** An ExcelFile’s attribute sheet_names provides access to a list of sheets.

- The arguments sheet_name allows specifying the sheet or sheets to read.
- The default value for sheet_name is 0, indicating to read the first sheet.
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a None to return a dictionary of all available sheets.
# 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', sheet_name=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', sheet_name=['Sheet1', 3])
```

read_excel can read more than one sheet, by setting `sheet_name` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets. Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

### 24.4.1.3 Reading a MultiIndex

read_excel can read a MultiIndex index, by passing a list of columns to `index_col` and a MultiIndex column by passing a list of rows to `header`. If either the index or columns have serialized level names those will be read in as well by specifying the rows/columns that make up the levels.

For example, to read in a MultiIndex index without names:

```
In [300]: df = pd.DataFrame({'a':[1, 2, 3, 4], 'b':[5, 6, 7, 8]},
                    index=pd.MultiIndex.from_product([['a', 'b'], ['c', 'd']]))
```

```
In [301]: df.to_excel('path_to_file.xlsx')
```

```
In [302]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])
```

```
In [303]: df
Out[303]:
   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 [304]: df.index = df.index.set_names([lv1l, lv2l])
```

```
In [305]: df.to_excel('path_to_file.xlsx')
```
In [306]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])

In [307]: df
Out[307]:
     a   b
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 [308]: df.columns = pd.MultiIndex.from_product([['a'], ['b', 'd']], names=['c1', 'c2'])

In [309]: df.to_excel('path_to_file.xlsx')

In [310]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1], header=[0, 1])

In [311]: df
Out[311]:
     c1  a
     c2  b  d
lvl1 lvl2
a c  1  5
d  2  6
b c  3  7
d  4  8

### 24.4.1.4 Parsing Specific Columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. `read_excel` takes a `usecols` keyword to allow you to specify a subset of columns to parse.

If `usecols` is an integer, then it is assumed to indicate the last column to be parsed.

```python
read_excel('path_to_file.xls', 'Sheet1', usecols=2)
```

If `usecols` 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', usecols=[0, 2, 3])
```

Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`.

### 24.4.1.5 Parsing Dates

Datetime-like values are normally automatically converted to the appropriate dtype when reading the excel file. But if you have a column of strings that look like dates (but are not actually formatted as dates in excel), you can use the `parse_dates` keyword to parse those strings to datetimes:
24.4.1.6 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 option handles missing values and treats exceptions in the `converters` as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```python
cfun = lambda x: int(x) if x else -1
read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

24.4.1.7 `dtype` Specifications

New in version 0.20.

As an alternative to `converters`, the type for an entire column can be specified using the `dtype` keyword, which takes a dictionary mapping column names to types. To interpret data with no type inference, use the type `str` or `object`.

```python
read_excel('path_to_file.xls', dtype={'MyInts': 'int64', 'MyText': str})
```

24.4.2 Writing Excel Files

24.4.2.1 Writing Excel Files to Disk

To write a DataFrame object to a sheet of an Excel file, you can use the `to_excel` instance method. The arguments are largely the same as `to_csv` described above, the first argument being the name of the excel file, and the optional second argument the name of the sheet to which the DataFrame should be written. For example:

```python
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The DataFrame will be written in a way that tries to mimic the REPL output. The `index_label` will be placed in the second row instead of the first. You can place it in the first row by setting the `merge_cells` option in `to_excel()` to `False`:

```python
df.to_excel('path_to_file.xlsx', index_label='label', merge_cells=False)
```

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.

### 24.4.2.2 Writing Excel Files to Memory

Pandas supports writing Excel files to buffer-like objects such as StringIO or BytesIO using ExcelWriter.

```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

Pandas chooses an Excel writer via two methods:

1. the engine keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the XlsxWriter for .xlsx, openpyxl for .xlsm, and xlwt for .xls files. If you have multiple engines installed, you can set the default engine through 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: version 2.4 or higher is required
- xlsxwriter
- xlwt
24.4.4 Style and Formatting

The look and feel of Excel worksheets created from pandas can be modified using the following parameters on the DataFrame's `to_excel` method.

- **float_format**: Format string for floating point numbers (default `None`).
- **freeze_panes**: A tuple of two integers representing the bottommost row and rightmost column to freeze. Each of these parameters is one-based, so `(1, 1)` will freeze the first row and first column (default `None`).

### 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:

```
clipdf = pd.read_clipboard()
```

```
In [312]: clipdf
Out[312]:
   A  B  C
0  x  1  4  p
1  y  2  5  q
2  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 [313]: df = pd.DataFrame(randn(5, 3))
In [314]: df
Out[314]:
   0  1  2
0  0  1  2
```

(continues on next page)
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, PyQt5, PyQt4 or qtpy) 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 [315]: df.to_clipboard()

In [316]: pd.read_clipboard()
Out[316]:
   0    1    2
0 -0.2883 -0.0849  0.0048
1  1.3829  0.3436 -1.2539
2 -0.1249  0.2122  0.4967
3  0.5254  1.2386 -1.2105
4 -1.1757 -0.1724 -0.7341
```

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 [317]: df
Out[317]:
   0    1    2
0 -0.2883 -0.0849  0.0048
1  1.3829  0.3436 -1.2539
2 -0.1249  0.2122  0.4967
3  0.5254  1.2386 -1.2105
4 -1.1757 -0.1724 -0.7341

In [318]: df.to_pickle('foo.pkl')

In [319]: pd.read_pickle('foo.pkl')
Out[319]:
   0    1    2
0 -0.2883 -0.0849  0.0048
1  1.3829  0.3436 -1.2539
2 -0.1249  0.2122  0.4967
3  0.5254  1.2386 -1.2105
4 -1.1757 -0.1724 -0.7341
```

**Warning:** Loading pickled data received from untrusted sources can be unsafe.
Warning: Several internal refactorings have been done while still preserving compatibility with pickles created with older versions of pandas. However, for such cases, pickled DataFrames, Series etc, must be read with `pd.read_pickle`, rather than `pickle.load`.

See [here](https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html#io-tools) and [here](https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html#io-tools) for some examples of compatibility-breaking changes. See this question for a detailed explanation.

## 24.6.1 Compressed pickle files

New in version 0.20.0.

`read_pickle()`, `DataFrame.to_pickle()` and `Series.to_pickle()` can read and write compressed pickle files. The compression types of `gzip`, `bz2`, `xz` are supported for reading and writing. The `zip` file format only supports reading and must contain only one data file to be read.

The compression type can be an explicit parameter or be inferred from the file extension. If ‘infer’, then use `gzip`, `bz2`, `zip`, or `xz` if filename ends in `.gz`, `.bz2`, `.zip`, or `.xz`, respectively.

### Using an explicit compression type:

```python
In [322]: df = pd.DataFrame(
    ....:     {'A': np.random.randn(1000),
    ....:      'B': 'foo',
    ....:      'C': pd.date_range('20130101', periods=1000, freq='s')})

In [323]: df.to_pickle("data.pkl.compress", compression="gzip")

In [324]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")
```

(continues on next page)
Out[324]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.478412</td>
<td>foo</td>
<td>2013-01-01 00:00:00</td>
</tr>
<tr>
<td>1</td>
<td>-0.783748</td>
<td>foo</td>
<td>2013-01-01 00:00:01</td>
</tr>
<tr>
<td>2</td>
<td>1.403558</td>
<td>foo</td>
<td>2013-01-01 00:00:02</td>
</tr>
<tr>
<td>3</td>
<td>-0.539282</td>
<td>foo</td>
<td>2013-01-01 00:00:03</td>
</tr>
<tr>
<td>4</td>
<td>-1.651012</td>
<td>foo</td>
<td>2013-01-01 00:00:04</td>
</tr>
<tr>
<td>5</td>
<td>0.692072</td>
<td>foo</td>
<td>2013-01-01 00:00:05</td>
</tr>
<tr>
<td>6</td>
<td>1.022171</td>
<td>foo</td>
<td>2013-01-01 00:00:06</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>993</td>
<td>-1.613932</td>
<td>foo</td>
<td>2013-01-01 00:16:33</td>
</tr>
<tr>
<td>994</td>
<td>1.088104</td>
<td>foo</td>
<td>2013-01-01 00:16:34</td>
</tr>
<tr>
<td>995</td>
<td>-0.632963</td>
<td>foo</td>
<td>2013-01-01 00:16:35</td>
</tr>
<tr>
<td>996</td>
<td>-0.585314</td>
<td>foo</td>
<td>2013-01-01 00:16:36</td>
</tr>
<tr>
<td>997</td>
<td>-0.275038</td>
<td>foo</td>
<td>2013-01-01 00:16:37</td>
</tr>
<tr>
<td>998</td>
<td>-0.937512</td>
<td>foo</td>
<td>2013-01-01 00:16:38</td>
</tr>
<tr>
<td>999</td>
<td>0.632369</td>
<td>foo</td>
<td>2013-01-01 00:16:39</td>
</tr>
</tbody>
</table>

[1000 rows x 3 columns]

Inferring compression type from the extension:

In [325]: df.to_pickle("data.pkl.xz", compression="infer")

In [326]: rt = pd.read_pickle("data.pkl.xz", compression="infer")

In [327]: rt

Out[327]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.478412</td>
<td>foo</td>
<td>2013-01-01 00:00:00</td>
</tr>
<tr>
<td>1</td>
<td>-0.783748</td>
<td>foo</td>
<td>2013-01-01 00:00:01</td>
</tr>
<tr>
<td>2</td>
<td>1.403558</td>
<td>foo</td>
<td>2013-01-01 00:00:02</td>
</tr>
<tr>
<td>3</td>
<td>-0.539282</td>
<td>foo</td>
<td>2013-01-01 00:00:03</td>
</tr>
<tr>
<td>4</td>
<td>-1.651012</td>
<td>foo</td>
<td>2013-01-01 00:00:04</td>
</tr>
<tr>
<td>5</td>
<td>0.692072</td>
<td>foo</td>
<td>2013-01-01 00:00:05</td>
</tr>
<tr>
<td>6</td>
<td>1.022171</td>
<td>foo</td>
<td>2013-01-01 00:00:06</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>993</td>
<td>-1.613932</td>
<td>foo</td>
<td>2013-01-01 00:16:33</td>
</tr>
<tr>
<td>994</td>
<td>1.088104</td>
<td>foo</td>
<td>2013-01-01 00:16:34</td>
</tr>
<tr>
<td>995</td>
<td>-0.632963</td>
<td>foo</td>
<td>2013-01-01 00:16:35</td>
</tr>
<tr>
<td>996</td>
<td>-0.585314</td>
<td>foo</td>
<td>2013-01-01 00:16:36</td>
</tr>
<tr>
<td>997</td>
<td>-0.275038</td>
<td>foo</td>
<td>2013-01-01 00:16:37</td>
</tr>
<tr>
<td>998</td>
<td>-0.937512</td>
<td>foo</td>
<td>2013-01-01 00:16:38</td>
</tr>
<tr>
<td>999</td>
<td>0.632369</td>
<td>foo</td>
<td>2013-01-01 00:16:39</td>
</tr>
</tbody>
</table>

[1000 rows x 3 columns]

The default is to ‘infer’:

In [328]: df.to_pickle("data.pkl.gz")

In [329]: rt = pd.read_pickle("data.pkl.gz")

In [330]: rt

Out[330]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.478412</td>
<td>foo</td>
<td>2013-01-01 00:00:00</td>
</tr>
</tbody>
</table>

(continues on next page)
1 -0.783748 foo 2013-01-01 00:00:01
2 1.403558 foo 2013-01-01 00:00:02
3 -0.539282 foo 2013-01-01 00:00:03
4 -1.651012 foo 2013-01-01 00:00:04
5 0.692072 foo 2013-01-01 00:00:05
6 1.022171 foo 2013-01-01 00:00:06
...
993 -1.613932 foo 2013-01-01 00:16:33
994 1.088104 foo 2013-01-01 00:16:34
995 -0.632963 foo 2013-01-01 00:16:35
996 -0.585314 foo 2013-01-01 00:16:36
997 -0.275038 foo 2013-01-01 00:16:37
998 -0.937512 foo 2013-01-01 00:16:38
999 0.632369 foo 2013-01-01 00:16:39

[1000 rows x 3 columns]

In [331]: df[“A”].to_pickle(“s1.pkl.bz2”)

In [332]: rt = pd.read_pickle(“s1.pkl.bz2”)

In [333]: rt

Out[333]:
0 0.478412
1 -0.783748
2 1.403558
3 -0.539282
4 -1.651012
5 0.692072
6 1.022171
...
993 -1.613932
994 1.088104
995 -0.632963
996 -0.585314
997 -0.275038
998 -0.937512
999 0.632369
Name: A, Length: 1000, dtype: float64

24.7 msgpack

pandas supports 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.

In [334]: df = pd.DataFrame(np.random.rand(5, 2), columns=list(‘AB’))
In [335]: df.to_msgpack('foo.msg')

In [336]: pd.read_msgpack('foo.msg')
Out[336]:
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.170801</td>
</tr>
<tr>
<td>1</td>
<td>0.838238</td>
</tr>
<tr>
<td>2</td>
<td>0.664140</td>
</tr>
<tr>
<td>3</td>
<td>0.449593</td>
</tr>
<tr>
<td>4</td>
<td>0.983618</td>
</tr>
</tbody>
</table>

In [337]: s = pd.Series(np.random.rand(5), index=pd.date_range('20130101', periods=5))

You can pass a list of objects and you will receive them back on deserialization.

In [338]: pd.to_msgpack('foo.msg', df, 'foo', np.array([1, 2, 3]), s)

In [339]: pd.read_msgpack('foo.msg')
Out[339]:
```
[ A  B       
| 0  | 0.170801| 0.895366 |
| 1  | 0.838238| 0.052592 |
| 2  | 0.664140| 0.289750 |
| 3  | 0.449593| 0.872087 |
| 4  | 0.983618| 0.744359 |
foo
| 1  |
| 2  |
| 3  |
2013-01-01 0.548134
2013-01-02 0.503447
2013-01-03 0.348438
2013-01-04 0.707267
2013-01-05 0.261656
Freq: D, dtype: float64]
```

You can pass `iterator=True` to iterate over the unpacked results:

```
In [340]: for o in pd.read_msgpack('foo.msg', iterator=True):
    ....:     print(o)
    ....:
    A  | B  |
| 0  | 0.170801| 0.895366 |
| 1  | 0.838238| 0.052592 |
| 2  | 0.664140| 0.289750 |
| 3  | 0.449593| 0.872087 |
| 4  | 0.983618| 0.744359 |
foo
[1 2 3]
2013-01-01 0.548134
2013-01-02 0.503447
2013-01-03 0.348438
2013-01-04 0.707267
2013-01-05 0.261656
Freq: D, dtype: float64
```

You can pass `append=True` to the writer to append to an existing pack:

In [341]: df.to_msgpack('foo.msg', append=True)

In [342]: pd.read_msgpack('foo.msg')
Out[342]:
```
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 [343]: pd.to_msgpack('foo2.msg', {'dict': [{ 'df': df }, {'string': 'foo'},
                 .....:
                 .....:
                 
In [344]: pd.read_msgpack('foo2.msg')
Out[344]:
{ 'dict': ({'df': A B
    0 0.170801 0.895366
    1 0.838238 0.052592
    2 0.664140 0.289750
    3 0.449593 0.872087
    4 0.983618 0.744359},
             {'string': 'foo'},
             {'scalar': 1.0},
             {'s': 2013-01-01 0.548134
    2013-01-02 0.503447
    2013-01-03 0.348438
    2013-01-04 0.707267
    2013-01-05 0.261656
Freq: D, dtype: float64, A B
    0 0.170801 0.895366
    1 0.838238 0.052592
    2 0.664140 0.289750
    3 0.449593 0.872087
    4 0.983618 0.744359]}
```

24.7.1 Read/Write API

Msgpacks can also be read from and written to strings.

```python
In [345]: df.to_msgpack()
Out[345]:
```

Furthermore you can concatenate the strings to produce a list of the original objects.

```
In [345]: df.to_msgpack()
Out[345]:
```

Chapter 24. IO Tools (Text, CSV, HDF5, ...)

1190
24.8 HDF5 (PyTables)

HDFStore is a dict-like object which reads and writes pandas using the high performance HDF5 format using the excellent PyTables library. See the cookbook for some advanced strategies.

**Warning:** pandas requires PyTables >= 3.0.0. There is a indexing bug in PyTables < 3.2 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.

In [347]: store = pd.HDFStore('store.h5')

In [348]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

Objects can be written to the file just like adding key-value pairs to a dict:

In [349]: np.random.seed(1234)
In [350]: index = pd.date_range('1/1/2000', periods=8)
In [351]: s = pd.Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [352]: df = pd.DataFrame(randn(8, 3), index=index, columns=['A', 'B', 'C'])
.....:
In [353]: wp = pd.Panel(randn(2, 5, 4), items=['Item1', 'Item2'], major_axis=pd.date_range('1/1/2000', periods=5), minor_axis=['A', 'B', 'C', 'D'])
.....:

# store.put('s', s) is an equivalent method
In [354]: store['s'] = s
In [355]: store['df'] = df
In [356]: store['wp'] = wp

(continues on next page)
In [357]: store.root.wp._v_attrs.pandas_type
Out[357]: 'wide'

In [358]: store
Out[358]: <class 'pandas.io.pytables.HDFStore'>
 File path: store.h5

In a current or later Python session, you can retrieve stored objects:

In [359]: store['df']
Out[359]:
   A    B    C
0 2000-01-01  0.887163  0.859588 -0.636524
1 2000-01-02  0.015696 -2.242685  1.150036
2 2000-01-03  0.991946  0.953324 -2.021255
3 2000-01-04 -0.334077  0.002118  0.405453
4 2000-01-05  0.289092  1.321158 -1.546906
5 2000-01-06 -0.202646 -0.655969  0.193421
6 2000-01-07  0.553439  1.318152 -0.469305
7 2000-01-08  0.675554 -1.817027 -0.183109

# dotted (attribute) access provides get as well
In [360]: store.df
→
   A    B    C
0 2000-01-01  0.887163  0.859588 -0.636524
1 2000-01-02  0.015696 -2.242685  1.150036
2 2000-01-03  0.991946  0.953324 -2.021255
3 2000-01-04 -0.334077  0.002118  0.405453
4 2000-01-05  0.289092  1.321158 -1.546906
5 2000-01-06 -0.202646 -0.655969  0.193421
6 2000-01-07  0.553439  1.318152 -0.469305
7 2000-01-08  0.675554 -1.817027 -0.183109

Deletion of the object specified by the key:

In [361]: del store['wp']
In [362]: store
Out[362]: <class 'pandas.io.pytables.HDFStore'>
 File path: store.h5

Closing a Store and using a context manager:

In [363]: store.close()
In [364]: store
Out[364]: <class 'pandas.io.pytables.HDFStore'>
 File path: store.h5

(continues on next page)
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.

```python
In [367]: df_tl = pd.DataFrame(dict(A=list(range(5)), B=list(range(5))))
In [368]: df_tl.to_hdf('store_tl.h5', 'table', append=True)
In [369]: pd.read_hdf('store_tl.h5', 'table', where=['index>2'])
```

HDFStore will by default not drop rows that are all missing. This behavior can be changed by setting dropna=True.

```python
In [370]: df_with_missing = pd.DataFrame({'col1': [0, np.nan, 2],
                           'col2': [1, np.nan, np.nan]})
In [371]: df_with_missing.to_hdf('file.h5', 'df_with_missing',
                           format='table', mode='w')
In [373]: pd.read_hdf('file.h5', 'df_with_missing')
```

(continues on next page)
This is also true for the major axis of a Panel:

```python
In [376]: 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 [377]: panel_with_major_axis_all_missing = pd.Panel(matrix,
       items=['Item1', 'Item2', 'Item3'],
       major_axis=[1, 2],
       minor_axis=['A', 'B', 'C'])

In [378]: panel_with_major_axis_all_missing
Out[378]:
<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 [379]: panel_with_major_axis_all_missing.to_hdf('file.h5', 'panel',
       dropna=True,
       format='table',
       mode='w')

In [380]: reloaded = pd.read_hdf('file.h5', 'panel')

In [381]: reloaded
Out[381]:
<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

The examples above show storing using `put`, which write the HDF5 to PyTables in a fixed array format, called the fixed format. These types of stores are not appendable once written (though you can simply remove them and rewrite). Nor are they queryable; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The fixed format stores offer very fast writing and slightly faster reading than table stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`.

**Warning:** A fixed format will raise a `TypeError` if you try to retrieve using a `where`:

```python
pd.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 and query type operations are supported. This format is specified by format='table' or format='t' to append or put or to_hdf.

This format can be set as an option as well pd.set_option('io.hdf.default_format','table') to enable put/append/to_hdf to by default store in the table format.

```python
In [382]: store = pd.HDFStore('store.h5')

In [383]: df1 = df[0:4]

In [384]: df2 = df[4:]

# append data (creates a table automatically)
In [385]: store.append('df', df1)

In [386]: store.append('df', df2)

In [387]: store
```

```
Out[387]: <class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# select the entire object
In [388]: store.select('df')
```

```
\                          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

# the type of stored data
In [389]: store.root.df._v_attrs.pandas_type
```

```
˓→'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 with
out 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.

```python
In [390]: store.put('foo/bar/bah', df)
In [391]: store.append('food/orange', df)
In [392]: store.append('food/apple', df)
In [393]: store
Out[393]:<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
# a list of keys are returned
In [394]: store.keys()
Out[394]: ['/df', '/food/orange', '/food/apple', '/foo/bar/bah']

# remove all nodes under this level
In [395]: store.remove('food')
In [396]: store
Out[396]:<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

**Warning:** Hierarchical keys cannot be retrieved as dotted (attribute) access as described above for items stored
under the root node.

```python
In [8]: store.foo.bar.bah
AttributeError: 'HDFStore' object has no attribute 'foo'

# you can directly access the actual PyTables node but using the root node
In [9]: store.root.foo.bar.bah
Out[9]:
'/foo/bar/bah' (Group) ''
   children := ['block0_items' (Array), 'block0_values' (Array), 'axis0' (Array),
   'axis1' (Array)]
```

Instead, use explicit string based keys:

```python
In [397]: store['foo/bar/bah']
Out[397]:
   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
```
24.8.5 Storing Types

24.8.5.1 Storing Mixed Types in a Table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent attempts at appending longer strings will raise a ValueError.

Passing `min_itemsize={'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 [398]: df_mixed = pd.DataFrame({'A': randn(8),
.....: 'B': randn(8),
.....: 'C': np.array(randn(8), dtype='float32'),
.....: 'string':'string',
.....: 'int': 1,
.....: 'bool': True,
.....: 'datetime64': pd.Timestamp('20010102')},
.....: index=list(range(8))

In [399]: df_mixed.loc[df_mixed.index[3:5], ['A', 'B', 'string', 'datetime64']] = np.
   → nan

In [400]: store.append('df_mixed', df_mixed, min_itemsize = {'values': 50})

In [401]: df_mixed1 = store.select('df_mixed')

In [402]: df_mixed1
```
```
Out[402]:
   A      B      C        string  int   bool  datetime64
0  0.704721 -1.152659 -0.430096   string     1   True  2001-01-02
1 -0.785435  0.631979  0.767369   string     1   True  2001-01-02
2  0.462060  0.039513 -0.984920   string     1   True  2001-01-02
3  NaN      NaN  0.270836   NaN    1   True   NaT
4  NaN      NaN  1.391986   NaN    1   True   NaT
5 -0.926254  1.321106  0.079842   string     1   True  2001-01-02
6  2.007843  0.152631 -0.399965   string     1   True  2001-01-02
7  0.226963  0.164530 -1.027851   string     1   True  2001-01-02

In [403]: df_mixed1.get_dtype_counts()
```
```
# we have provided a minimum string column size
In [404]: store.root.df_mixed.table
```
```
```
```
```
(continues on next page)
24.8.5.2 Storing Multi-Index DataFrames

Storing multi-index DataFrames as tables is very similar to storing/selecting from homogeneous index DataFrames.

```python
In [405]: index = pd.MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'], ['one', 'two', 'three']],
                           labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
                                   [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
                           names=['foo', 'bar'])

In [406]: df_mi = pd.DataFrame(np.random.randn(10, 3), index=index,
                           columns=['A', 'B', 'C'])

In [407]: df_mi
Out[407]:
         A     B     C
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 [408]: store.append('df_mi', df_mi)

In [409]: store.select('df_mi')
Out[409]:
         A     B     C
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
```

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24.8.6 Querying

24.8.6.1 Querying a Table

select and delete operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the Term class under the hood, as a boolean expression.

- index and columns are supported indexers of 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']"
The indexers are on the left-hand side of the sub-expression:

columns, major_axis, ts

The right-hand side of the sub-expression (after a comparison operator) can be:

- functions that will be evaluated, e.g. Timestamp('2012-02-01')
- strings, e.g. 'bar'
- date-like, e.g. 20130101, or "20130101"
- lists, e.g. ['A', 'B']
- variables that are defined in the local names space, e.g. date

Note: Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this:

```python
string = "HolyMoly"
store.select('df', 'index == string')
```

instead of this:

```python
string = "HolyMoly"
store.select('df', '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:

```python
store.select('df', 'index == %r % string')
```

which will quote string.

Here are some examples:

```python
In [411]: dfq = pd.DataFrame(randn(10, 4), columns=list('ABCD'), index=pd.date_range('20130101', periods=10))
......:
......:
In [412]: store.append('dfq', dfq, format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.
In [413]: store.select('dfq', "index>pd.Timestamp('20130104') & columns=['A', 'B']")
Out[413]:
    A    B
  2013-01-05  1.210384  0.797435
  2013-01-06 -0.850346  1.176812
  2013-01-07  0.984188 -0.121728
  2013-01-08  0.796595 -0.474021
  2013-01-09 -0.804834 -2.123620
  2013-01-10  0.334198  0.536784

Use and inline column reference

In [414]: store.select('dfq', where="A>0 or C>0")
Out[414]:
    A    B    C    D
  2013-01-01  0.436258 -1.703013  0.393711 -0.479324
  2013-01-02 -0.299016  0.694103  0.678630  0.239556
  2013-01-03  0.151227  0.816127  1.893534  0.639633
  2013-01-04 -0.962029 -2.085266  1.930247 -1.735349
  2013-01-05  1.210384  0.797435 -0.379811  0.702562
  2013-01-07  0.984188 -0.121728  2.365769  0.496143
  2013-01-08  0.796595 -0.474021 -0.056696  1.357797
  2013-01-10  0.334198  0.536784 -0.743830 -0.320204

Works with a Panel as well.

In [415]: store.append('wp', wp)
In [416]: store
Out[416]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
In [417]: store.select('wp', "major_axis>pd.Timestamp('20000102') & minor_axis=['A', 'B']")

<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 [418]: store.select('df', "columns=['A', 'B']")
Out[418]:
    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  0.675554 -1.817027

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.

```python
# this is effectively what the storage of a Panel looks like
In [419]: wp.to_frame()
Out[419]:
    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 -2.074978 -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
```python
In [420]: store.select('wp', 'major_axis>20000102 & minor_axis=['A', 'B']", start=0, stop=10)
```

\<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 1 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to B

Note: select will raise a ValueError if the query expression has an unknown variable reference. Usually this means that you are trying to select on a column that is not a data_column.

select will raise a SyntaxError if the query expression is not valid.

---

### 24.8.6.2 Using timedelta64[ns]

You can store and query using the timedelta64[ns] type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be `D,s,ms,us,ns` for the timedelta. Here’s an example:

```python
In [421]: from datetime import timedelta
In [422]: dftd = pd.DataFrame(dict(A = pd.Timestamp('20130101'), B = [ pd.Timestamp('20130101') + timedelta(days=i, seconds=10) for i in range(10) ]))
In [423]: dftd['C'] = dftd['A'] - dftd['B']

(continues on next page)
In [424]: dftd
Out[424]:
<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2013-01-01</td>
<td>2013-01-01</td>
<td>00:00:10</td>
</tr>
<tr>
<td>1</td>
<td>2013-01-01</td>
<td>2013-01-02</td>
<td>00:00:10</td>
</tr>
<tr>
<td>2</td>
<td>2013-01-01</td>
<td>2013-01-03</td>
<td>00:00:10</td>
</tr>
<tr>
<td>3</td>
<td>2013-01-01</td>
<td>2013-01-04</td>
<td>00:00:10</td>
</tr>
<tr>
<td>4</td>
<td>2013-01-01</td>
<td>2013-01-05</td>
<td>00:00:10</td>
</tr>
<tr>
<td>5</td>
<td>2013-01-01</td>
<td>2013-01-06</td>
<td>00:00:10</td>
</tr>
<tr>
<td>6</td>
<td>2013-01-01</td>
<td>2013-01-07</td>
<td>00:00:10</td>
</tr>
<tr>
<td>7</td>
<td>2013-01-01</td>
<td>2013-01-08</td>
<td>00:00:10</td>
</tr>
<tr>
<td>8</td>
<td>2013-01-01</td>
<td>2013-01-09</td>
<td>00:00:10</td>
</tr>
<tr>
<td>9</td>
<td>2013-01-01</td>
<td>2013-01-10</td>
<td>00:00:10</td>
</tr>
</tbody>
</table>

In [425]: store.append('dftd', dftd, data_columns=True)

In [426]: store.select('dftd', "C<'-3.5D'")
Out[426]:
<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>2013-01-01</td>
<td>2013-01-05</td>
<td>00:00:10</td>
</tr>
<tr>
<td>5</td>
<td>2013-01-01</td>
<td>2013-01-06</td>
<td>00:00:10</td>
</tr>
<tr>
<td>6</td>
<td>2013-01-01</td>
<td>2013-01-07</td>
<td>00:00:10</td>
</tr>
<tr>
<td>7</td>
<td>2013-01-01</td>
<td>2013-01-08</td>
<td>00:00:10</td>
</tr>
<tr>
<td>8</td>
<td>2013-01-01</td>
<td>2013-01-09</td>
<td>00:00:10</td>
</tr>
<tr>
<td>9</td>
<td>2013-01-01</td>
<td>2013-01-10</td>
<td>00:00:10</td>
</tr>
</tbody>
</table>

24.8.6.3 Indexing

You can create/modify an index for a table with create_table_index after data is already in the table (after and append/put operation). Creating a table index is **highly** encouraged. This will speed your queries a great deal when you use a select with the indexed dimension as the where.

**Note:** Indexes are automagically created on the indexables and any data columns you specify. This behavior can be turned off by passing index=False to append.

```python
# we have automagically already created an index (in the first section)
In [427]: i = store.root.df.table.cols.index.index

In [428]: i.optlevel, i.kind
Out[428]: (6, 'medium')

# change an index by passing new parameters
In [429]: store.create_table_index('df', optlevel=9, kind='full')

In [430]: i = store.root.df.table.cols.index.index

In [431]: i.optlevel, i.kind
Out[431]: (9, 'full')
```

Oftentimes when appending large amounts of data to a store, it is useful to turn off index creation for each append, then recreate at the end.
In [432]: df_1 = pd.DataFrame(randn(10, 2), columns=list('AB'))
In [433]: df_2 = pd.DataFrame(randn(10, 2), columns=list('AB'))
In [434]: st = pd.HDFStore('appends.h5', mode='w')
In [435]: st.append('df', df_1, data_columns=['B'], index=False)
In [436]: st.append('df', df_2, data_columns=['B'], index=False)
In [437]: st.get_storer('df').table
Out[437]:
<table>
<thead>
<tr>
<th>/df/table (Table(20,))</th>
</tr>
</thead>
<tbody>
<tr>
<td>description := {</td>
</tr>
<tr>
<td>&quot;index&quot;: Int64Col(shape=(), dflt=0, pos=0),</td>
</tr>
<tr>
<td>&quot;values_block_0&quot;: Float64Col(shape=(1,), dflt=0.0, pos=1),</td>
</tr>
<tr>
<td>&quot;B&quot;: Float64Col(shape=(), dflt=0.0, pos=2)</td>
</tr>
<tr>
<td>byteorder := 'little'</td>
</tr>
<tr>
<td>chunkshape := (2730,)</td>
</tr>
</tbody>
</table>

Then create the index when finished appending.

In [438]: st.create_table_index('df', columns=['B'], optlevel=9, kind='full')
In [439]: st.get_storer('df').table
Out[439]:
<table>
<thead>
<tr>
<th>/df/table (Table(20,))</th>
</tr>
</thead>
<tbody>
<tr>
<td>description := {</td>
</tr>
<tr>
<td>&quot;index&quot;: Int64Col(shape=(), dflt=0, pos=0),</td>
</tr>
<tr>
<td>&quot;values_block_0&quot;: Float64Col(shape=(1,), dflt=0.0, pos=1),</td>
</tr>
<tr>
<td>&quot;B&quot;: Float64Col(shape=(), dflt=0.0, pos=2)</td>
</tr>
<tr>
<td>byteorder := 'little'</td>
</tr>
<tr>
<td>chunkshape := (2730,)</td>
</tr>
<tr>
<td>autoindex := True</td>
</tr>
<tr>
<td>colindexes := {</td>
</tr>
<tr>
<td>&quot;B&quot;: Index(9, full, shuffle, zlib(1)).is_csi=True</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
In [440]: st.close()

See here for how to create a completely-sorted-index (CSI) on an existing store.

### 24.8.6.4 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 [441]: df_dc = df.copy()
In [442]: df_dc['string'] = 'foo'
In [443]: df_dc.loc[df_dc.index[4: 6], 'string'] = np.nan
In [444]: df_dc.loc[df_dc.index[7: 9], 'string'] = 'bar'

(continues on next page)
In [445]: df_dc['string2'] = 'cool'

In [446]: df_dc.loc[df_dc.index[1:3], ['B', 'C']] = 1.0

In [447]: df_dc

Out[447]:
   A    B    C     string string2
0 2000-01-01  0.887163  0.859588  -0.636524    foo      cool
1 2000-01-02  0.015696    1.000000    1.000000    foo      cool
2 2000-01-03   0.991946    1.000000    1.000000    foo      cool
3 2000-01-04  -0.334077  0.002118    0.405453    foo      cool
4 2000-01-05   0.289092  1.321158  -1.546906  NaN      cool
5 2000-01-06  -0.202646 -0.655969    0.193421  NaN      cool
6 2000-01-07   0.553439  1.318152  -0.469305    foo      cool
7 2000-01-08   0.675554 -1.817027  -0.183109   bar      cool

# on-disk operations
In [448]: store.append('df_dc', df_dc, data_columns=['B', 'C', 'string', 'string2'])

In [449]: store.select('df_dc', where='B > 0')

Out[449]:
   A    B    C     string string2
0 2000-01-01  0.887163  0.859588  -0.636524    foo      cool
1 2000-01-02  0.015696    1.000000    1.000000    foo      cool
2 2000-01-03   0.991946    1.000000    1.000000    foo      cool
3 2000-01-04  -0.334077  0.002118    0.405453    foo      cool
4 2000-01-05   0.289092  1.321158  -1.546906  NaN      cool
5 2000-01-07   0.553439  1.318152  -0.469305    foo      cool
6 2000-01-08   0.675554 -1.817027  -0.183109   bar      cool

In [450]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')

Out[450]:
   A    B    C     string string2
0 2000-01-02  0.015696    1.000000    1.000000    foo      cool
1 2000-01-03   0.991946    1.000000    1.000000    foo      cool
2 2000-01-04  -0.334077  0.002118    0.405453    foo      cool

In [451]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]

Out[451]:
   A    B    C     string string2
0 2000-01-02  0.015696    1.000000    1.000000    foo      cool
1 2000-01-03   0.991946    1.000000    1.000000    foo      cool
2 2000-01-04  -0.334077  0.002118    0.405453    foo      cool

In [452]: store.root.df_dc.table

Out[452]:
   /df_dc/table (Table(8,)) ''
   description := {
   "index": Int64Col(shape=(), dflt=0, pos=0),
   "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
   "B": Float64Col(shape=(), dflt=0.0, pos=2),
   "C": Float64Col(shape=(), dflt=0.0, pos=3),
   "string": StringCol(shape=(), dflt=''),
   "string2": StringCol(shape=(), dflt=''),
   }
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!).

### 24.8.6.5 Iterator

You can pass `iterator=True` or `chunksize=number_in_a_chunk` to `select` and `select_as_multiple` to return an iterator on the results. The default is 50,000 rows returned in a chunk.

```
In [453]: for df in store.select('df', chunksize=3):
    print(df)

       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
    A    B    C
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
    A    B    C
2000-01-07  0.553439  1.318152 -0.469305
2000-01-08  0.675554 -1.817027 -0.183109
```

**Note:** You can also use the iterator with `read_hdf` which will open, then automatically close the store when finished iterating.

```
for df in pd.read_hdf('store.h5','df', chunksize=3):
    print(df)
```

Note, that the chunksize keyword applies to the *source* rows. So if you are doing a query, then the chunksize will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```
In [454]: dfeq = pd.DataFrame({'number': np.arange(1, 11)})
In [455]: dfeq
```

```
Out[455]:
   number
0     1
1     2
2     3
3     4
4     5
5     6
6     7
7     8
8     9
9    10
```

(continues on next page)
In [456]: store.append('df_eq', df_eq, data_columns=['number'])

In [457]: def chunks(l, n):
    .....:     return [l[i: i+n] for i in range(0, len(l), n)]
    .....:

In [458]: evens = [2, 4, 6, 8, 10]

In [459]: coordinates = store.select_as_coordinates('df_eq', 'number=evens')

In [460]: for c in chunks(coordinates, 2):
    .....:     print(store.select('df_eq', where=c))
    .....:     number
1  2
3  4
5  6
7  8
9 10

24.8.6.6 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 [461]: store.select_column('df_dc', 'index')
Out[461]:
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 [462]: store.select_column('df_dc', 'string')

(continues on next page)
Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```python
In [463]: df_coord = pd.DataFrame(np.random.randn(1000, 2),
                   index=pd.date_range('20000101', periods=1000))

In [464]: store.append('df_coord', df_coord)

In [465]: c = store.select_as_coordinates('df_coord', 'index > 20020101')

In [466]: c
Out[466]:
Int64Index([732, 733, 734, 735, 736, 737, 738, 739, 740, 741,
            ...
            990, 991, 992, 993, 994, 995, 996, 997, 998, 999],
           dtype='int64', length=268)

In [467]: store.select('df_coord', where=c)
```

```
**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 [468]: df_mask = pd.DataFrame(np.random.randn(1000, 2),
                           index=pd.date_range('20000101', periods=1000))

In [469]: store.append('df_mask', df_mask)

In [470]: c = store.select_column('df_mask', 'index')

In [471]: where = c[pd.DatetimeIndex(c).month == 5].index

In [472]: store.select('df_mask', where=where)
```

```
[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 [473]: store.get_storer('df_dc').nrows
```

```
Out[473]: 8
```

### 24.8.6.7 Multiple Table Queries

The methods `append_to_multiple` and `select_as_multiple` can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table’s index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of ‘columns’ you want in that table. If `None` is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which
table is the selector table (which you can make queries from). The argument dropna will drop rows from the input DataFrame to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely np.Nan, that row will be dropped from all tables.

If dropna is False, THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES. Remember that entirely np.Nan rows are not written to the HDFStore, so if you choose to call dropna=False, some tables may have more rows than others, and therefore select_as_multiple may not work or it may return unexpected results.

In [474]: df_mt = pd.DataFrame(randn(8, 6), index=pd.date_range('1/1/2000', periods=8), columns=['A', 'B', 'C', 'D', 'E', 'F'])

In [475]: df_mt['foo'] = 'bar'

In [476]: df_mt.loc[df_mt.index[1], ('A', 'B')] = np.nan

# you can also create the tables individually

In [477]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None }, df_mt, selector='df1_mt')

In [478]: store

Out[478]: <class 'pandas.io.pytables.HDFStore'>

File path: store.h5

# individual tables were created

In [479]: store.select('df1_mt')

Out[479]:

A  B
2000-01-01 0.714697 0.318215
2000-01-02 NaN NaN
2000-01-03 -0.086919 0.416905
2000-01-04 0.489131 -0.253340
2000-01-05 -0.382952 -0.397373
2000-01-06 0.538116 0.226388
2000-01-07 -2.073479 -0.115926
2000-01-08 -0.695400 0.402493

In [480]: store.select('df2_mt')

Out[480]:

C  D  E  F  foo
2000-01-01 0.607460 0.790907 0.852225 0.096696 bar
2000-01-02 0.811031 -0.356817 1.047085 0.664705 bar
2000-01-03 -0.764381 -0.287229 -0.089351 -1.035115 bar
2000-01-04 -1.948100 -0.116556 0.800597 -0.796154 bar
2000-01-05 -0.717627 0.156995 -0.344718 -0.171208 bar
2000-01-06 1.541729 0.205256 1.998065 0.953591 bar
2000-01-07 1.391070 0.303013 1.093347 -0.101000 bar
2000-01-08 -1.507639 0.089575 0.658822 -1.037627 bar

# as a multiple

In [481]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'], selector = 'df1_mt')

(continues on next page)
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.

```python
# returns the number of rows deleted
In [482]: store.remove('wp', 'major_axis > 20000102' )
Out[482]: 12

In [483]: store.select('wp')
```

```
<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 repack and clean the file, use `ptrepack`.

24.8.8 Notes & Caveats

24.8.8.1 Compression

PyTables allows the stored data to be compressed. This applies to all kinds of stores, not just tables. Two parameters are used to control compression: `complevel` and `complib`.

`complevel` specifies if and how hard data is to be compressed. `complevel=0` and `complevel=None` disables compression and `0<complevel<10` enables compression.
**complib specifies which compression library to use. If nothing is** specified the default library zlib is used. A compression library usually optimizes for either good compression rates or speed and the results will depend on the type of data. Which type of compression to choose depends on your specific needs and data. The list of supported compression libraries:

- **zlib**: The default compression library. A classic in terms of compression, achieves good compression rates but is somewhat slow.
- **lz4**: Fast compression and decompression.
- **bzip2**: Good compression rates.
- **blosc**: Fast compression and decompression.

New in version 0.20.2: Support for alternative blosc compressors:

- **blosc:blosclz** This is the default compressor for blosc
- **blosc: lz4**: A compact, very popular and fast compressor.
- **blosc: lz4hc**: A tweaked version of LZ4, produces better compression ratios at the expense of speed.
- **blosc: snappy**: A popular compressor used in many places.
- **blosc: zlib**: A classic; somewhat slower than the previous ones, but achieving better compression ratios.
- **blosc: zstd**: An extremely well balanced codec; it provides the best compression ratios among the others above, and at reasonably fast speed.

If compild is defined as something other than the listed libraries a `ValueError` exception is issued.

**Note:** If the library specified with the `complib` option is missing on your platform, compression defaults to zlib without further ado.

Enable compression for all objects within the file:

```python
store_compressed = pd.HDFStore('store_compressed.h5', complevel=9, 
complib='blosc:blosclz')
```

Or on-the-fly compression (this only applies to tables) in stores where compression is not enabled:

```python
store.append('df', df, complib='zlib', complevel=5)
```

### 24.8.8.2 ptrepack

PyTables offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied PyTables utility ptrepack. In addition, ptrepack can change compression levels after the fact.

```
ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5
```

Furthermore ptrepack in.h5 out.h5 will repack the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the copy method.
24.8.3 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

**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>floating: float64, float32, float16</td>
<td>np.nan</td>
</tr>
<tr>
<td>integer: int64, int32, int8, uint64, uint32, uint8</td>
<td></td>
</tr>
<tr>
<td>boolean</td>
<td></td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td>NaT</td>
</tr>
<tr>
<td>timedelta64[ns]</td>
<td>NaT</td>
</tr>
<tr>
<td>categorical: see the section below</td>
<td></td>
</tr>
<tr>
<td>object: strings</td>
<td>np.nan</td>
</tr>
</tbody>
</table>

Unicode columns are not supported, and WILL FAIL.

24.8.9.1 Categorical Data

You can write data that contains category dtypes to a HDFStore. Queries work the same as if it was an object array. However, the category dtyped data is stored in a more efficient manner.

```
In [484]: dfcat = pd.DataFrame({'A': pd.Series(list('aabbcdba')).astype('category'),
                           'B': np.random.randn(8)})
```

```
In [485]: dfcat
```
(continues on next page)
24.8.9.2 String Columns

\texttt{min\_itemsize}

The underlying implementation of \texttt{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 \texttt{HDFStore}, \texttt{in the first append}. Subsequent appends, may introduce a string for a column \texttt{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 \texttt{min\_itemsize} on the first table creation to a-priori specify the minimum length of a particular string column. \texttt{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 \texttt{indexables} or \texttt{data\_columns} to have this \texttt{min\_itemsize}.

Passing a \texttt{min\_itemsize} dict will cause all passed columns to be created as \texttt{data\_columns} automatically.

\textbf{Note:} If you are not passing any \texttt{data\_columns}, then the \texttt{min\_itemsize} will be the maximum of the length of
any string passed

```python
In [492]: dfs = pd.DataFrame(dict(A='foo', B='bar'), index=list(range(5)))
In [493]: dfs
Out[493]:
   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 [494]: store.append('dfs', dfs, min_itemsize=30)
In [495]: store.get_storer('dfs').table
Out[495]:
/dfs/table (Table(5,)) ''
  description := {
      "index": Int64Col(shape=(), dflt=0, pos=0),
      "values_block_0": StringCol(itemsize=30, shape=(2,), dflt=b'', pos=1)}
  byteorder := 'little'
  chunkshape := (963,)
  autoindex := True
  colindexes := {
      "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

# A is created as a data_column with a size of 30
# B is size is calculated
In [496]: store.append('dfs2', dfs, min_itemsize={'A': 30})
In [497]: store.get_storer('dfs2').table
Out[497]:
/dfs2/table (Table(5,)) ''
  description := {
      "index": Int64Col(shape=(), dflt=0, pos=0),
      "values_block_0": StringCol(itemsize=3, shape=(1,), dflt=b'', pos=1),
      "A": StringCol(itemsize=30, shape=(), dflt=b'', pos=2)}
  byteorder := 'little'
  chunkshape := (1598,)
  autoindex := True
  colindexes := {
      "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
      "A": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

**nan_rep**

String columns will serialize a `np.nan` (a missing value) with the `nan_rep` string representation. This defaults to the string value `nan`. You could inadvertently turn an actual `nan` value into a missing value.

```python
In [498]: dfss = pd.DataFrame(dict(A=['foo', 'bar', 'nan']))
In [499]: dfss
Out[499]:
   A
0 foo
```

(continues on next page)
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:

```python
In [504]: np.random.seed(1)
In [505]: 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 [506]: df_for_r.head()
Out[506]:
         first       second    class
0  0.417022  0.32664512  0
1  0.720324  0.52705812  0
2  0.000114  0.88594212  1
3  0.302333  0.35727012  1
4  0.146756  0.90853512  1
In [507]: store_export = pd.HDFStore('export.h5')
In [508]: store_export.append('df_for_r', df_for_r, data_columns=df_dc.columns)
In [509]: store_export
Out[509]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
```
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 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 0.4170220047 0.3266449  0
2 0.7203244934 0.5270581  0
3 0.0001143748 0.8859421  1
4 0.3023325726 0.3572698  1
5 0.1467558908 0.9085352  1
6 0.0923385948 0.6233601  1
```

**Note:** The R function lists the entire HDF5 file’s contents and assembles the `data.frame` object from all matching nodes, so use this only as a starting point if you have stored multiple `DataFrame` objects to a single HDF5 file.

### 24.8.11 Performance

- `tables` format come with a writing performance penalty as compared to `fixed` stores. The benefit is the ability to append/delete and query (potentially very large amounts of data). Write times are generally longer as compared with regular stores. Query times can be quite fast, especially on an indexed axis.
- You can pass `chunksize=<int>` to `append`, specifying the write chunksize (default is 50000). This will
significantly lower your memory usage on writing.

- You can pass `expectedrows=<int>` to the first `append` to set the TOTAL number of 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.

### 24.9 Feather

New in version 0.20.0.

Feather provides binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy.

Feather is designed to faithfully serialize and de-serialize DataFrames, supporting all of the pandas dtypes, including extension dtypes such as categorical and datetime with tz.

Several caveats.

- This is a newer library, and the format, though stable, is not guaranteed to be backward compatible to the earlier versions.
- The format will NOT write an `Index`, or `MultiIndex` for the DataFrame and will raise an error if a non-default one is provided. You can `.reset_index()` to store the index or `.reset_index(drop=True)` to ignore it.
- Duplicate column names and non-string columns names are not supported
- Non supported types include `Period` and actual Python object types. These will raise a helpful error message on an attempt at serialization.

See the Full Documentation.

```python
In [510]: df = pd.DataFrame({
    ...:     'a': list('abc'),
    ...:     'b': list(range(1, 4)),
    ...:     'c': np.arange(3, 6).astype('u1'),
    ...:     'd': np.arange(4.0, 7.0, dtype='float64'),
    ...:     'e': [True, False, True],
    ...:     'f': pd.Categorical(list('abc')),
    ...:     'g': pd.date_range('20130101', periods=3),
    ...:     'h': pd.date_range('20130101', periods=3, tz='US/Eastern'),
    ...:     'i': pd.date_range('20130101', periods=3, freq='ns')})

In [511]: df
Out[511]:
   a    b     c    d     e   f               g               h
0  a    1     3  4.0  True  a 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.
      →000000000  000000000
1  b    2     4  5.0 False  b 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.
      →000000001  000000000
2  c    3     5  6.0  True  c 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.
      →000000002  000000000
```

(continues on next page)
In [512]: df.dtypes

<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>int64</td>
</tr>
<tr>
<td>c</td>
<td>uint8</td>
</tr>
<tr>
<td>d</td>
<td>float64</td>
</tr>
<tr>
<td>e</td>
<td>bool</td>
</tr>
<tr>
<td>f</td>
<td>category</td>
</tr>
<tr>
<td>g</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>h</td>
<td>datetime64[ns, US/Eastern]</td>
</tr>
<tr>
<td>i</td>
<td>datetime64[ns]</td>
</tr>
</tbody>
</table>

dtype: object

Write to a feather file.

In [513]: df.to_feather('example.feather')

Read from a feather file.

In [514]: result = pd.read_feather('example.feather')

In [515]: result

Out[515]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
<th>g</th>
<th>h</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 a 1 3 4.0 True a 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.000000000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 b 2 4 5.0 False b 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.000000001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 c 3 5 6.0 True c 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.000000002</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

# we preserve dtypes
In [516]: result.dtypes

<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>int64</td>
</tr>
<tr>
<td>c</td>
<td>uint8</td>
</tr>
<tr>
<td>d</td>
<td>float64</td>
</tr>
<tr>
<td>e</td>
<td>bool</td>
</tr>
<tr>
<td>f</td>
<td>category</td>
</tr>
<tr>
<td>g</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>h</td>
<td>datetime64[ns, US/Eastern]</td>
</tr>
<tr>
<td>i</td>
<td>datetime64[ns]</td>
</tr>
</tbody>
</table>

dtype: object

### 24.10 Parquet

New in version 0.21.0.

Apache Parquet provides a partitioned binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy. Parquet can use a variety
of compression techniques to shrink the file size as much as possible while still maintaining good read performance.

Parquet is designed to faithfully serialize and de-serialize `DataFrame`s, supporting all of the pandas dtypes, including extension dtypes such as datetime with tz.

Several caveats.

- Duplicate column names and non-string columns names are not supported.
- Index level names, if specified, must be strings.
- Categorical dtypes can be serialized to parquet, but will de-serialize as `object` dtype.
- Non supported types include `Period` and actual Python object types. These will raise a helpful error message on an attempt at serialization.

You can specify an engine to direct the serialization. This can be one of `pyarrow`, or `fastparquet`, or `auto`. If the engine is NOT specified, then the `pd.options.io.parquet.engine` option is checked; if this is also auto, then `pyarrow` is tried, and falling back to `fastparquet`.

See the documentation for `pyarrow` and `fastparquet`.

**Note:** These engines are very similar and should read/write nearly identical parquet format files. Currently `pyarrow` does not support timedelta data. `fastparquet>=0.1.4` supports timezone aware datetimes. These libraries differ by having different underlying dependencies (`fastparquet` by using `numba`, while `pyarrow` uses a c-library).

In [517]: df = pd.DataFrame({'a': list('abc'), 'b': list(range(1, 4)),
    'c': np.arange(3, 6).astype('u1'), 'd': np.arange(4.0, 7.0, dtype='float64'),
    'e': [True, False, True], 'f': pd.date_range('20130101', periods=3),
    'g': pd.date_range('20130101', periods=3, tz='US/Eastern')})

In [518]: df
Out[518]:
     a  b  c  d  e         f                 g
0  a  1  3  4.0  True 2013-01-01 00:00:00-05:00
1  b  2  4  5.0  False 2013-01-02 00:00:00-05:00
2  c  3  5  6.0  True 2013-01-03 00:00:00-05:00

In [519]: df.dtypes
Out[519]:
     a  b  c  d  e  f         g
object  int64  uint8  float64  bool  datetime64[ns]
dtype: object

Write to a parquet file.
In [520]: df.to_parquet('example_pa.parquet', engine='pyarrow')
In [521]: df.to_parquet('example_fp.parquet', engine='fastparquet')

Read from a parquet file.

In [522]: result = pd.read_parquet('example_fp.parquet', engine='fastparquet')
In [523]: result = pd.read_parquet('example_pa.parquet', engine='pyarrow')
In [524]: result.dtypes
Out [524]:
  a     object
  b   int64
  c   uint8
  d  float64
  e    bool
  f  datet ime64[ns]
  g  datet ime64[ns, US/Eastern]
dtype: object

Read only certain columns of a parquet file.

In [525]: result = pd.read_parquet('example_fp.parquet',
                   engine='fastparquet', columns=['a', 'b'])
In [526]: result.dtypes
Out [526]:
  a     object
  b   int64
dtype: object

24.11 SQL Queries

The pandas.io.sql module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed. In addition you will need a driver library for your database. Examples of such drivers are psycopg2 for PostgreSQL or pymysql for MySQL. For SQLite this is included in Python’s standard library by default. You can find an overview of supported drivers for each SQL dialect in the SQLAlchemy docs.

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the Python DB-API.

See also some cookbook examples for some advanced strategies.

The key functions are:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>read_sql_table</td>
<td>Read SQL database table into a DataFrame.</td>
</tr>
<tr>
<td>read_sql_query</td>
<td>Read SQL query into a DataFrame.</td>
</tr>
<tr>
<td>read_sql</td>
<td>Read SQL query or database table into a DataFrame.</td>
</tr>
<tr>
<td>DataFrame.to_sql</td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
</tbody>
</table>
24.11.1 pandas.read_sql_table

```python
def 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 a 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
  Name of SQL schema in database to query (if database flavor supports this). Uses
default schema if None (default).

- **index_col** : string or list of strings, optional, default: None
  Column(s) to set as index(MultiIndex).

- **coerce_float** : boolean, default True
  Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal)
to floating point. Can result in loss of Precision.

- **parse_dates** : list or dict, default: None
  - List of column names to parse as dates.
  - Dict of {column_name: format string} where format string is strftime compat-
    ible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer
timestamps.
  - Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword
    arguments of pandas.to_datetime() Especially useful with databases without 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, returns 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**
24.11.2 pandas.read_sql_query

```python
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)
  SQL query to be executed.

- `con` : SQLAlchemy connectable(engine/connection), 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 or list of strings, optional, default: None
  Column(s) to set as index(MultiIndex).

- `coerce_float` : boolean, default True
  Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Useful for SQL result sets.

- `params` : list, tuple or dict, optional, default: None
  List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249’s paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}

- `parse_dates` : list or dict, default: None
  - List of column names to parse as dates.
  - Dict of {column_name: format string} where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
  - Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of pandas.to_datetime() Especially useful with databases without native Datetime support, such as SQLite.

- `chunksize` : int, default None
  If specified, return an iterator where chunksize is the number of rows to include in each chunk.

Returns

DataFrame

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.

**24.11.3 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.

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (for backward compatibility). It will delegate to the specific function depending on the provided input. A SQL query will be routed to `read_sql_query`, while a database table name will be routed to `read_sql_table`. Note that the delegated function might have more specific notes about their functionality not listed here.

**Parameters**

- `sql`: string or SQLAlchemy Selectable (select or text object)
  SQL query to be executed or a table name.

- `con`: SQLAlchemy connectable (engine/connection) or database string URI
  Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

- `index_col`: string or list of strings, optional, default: None
  Column(s) to set as index(MultiIndex).

- `coerce_float`: boolean, default True
  Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.

- `params`: list, tuple or dict, optional, default: None
  List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}

- `parse_dates`: list or dict, default: None
  - List of column names to parse as dates.
  - Dict of `{column_name: format string}` where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
  - Dict of `{column_name: arg dict}`, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite.

- `columns`: list, default: None
  List of column names to select from SQL table (only used when reading a table).

- `chunksize`: int, default None
If specified, return an iterator where chunksize is the number of rows to include in each chunk.

Returns
DataFrame

See also:

read_sql_table Read SQL database table into a DataFrame.
read_sql_query Read SQL query into a DataFrame.

24.11.4 pandas.DataFrame.to_sql

DataFrame.to_sql(name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [R16] are supported. Tables can be newly created, appended to, or overwritten.

Parameters name : string
Name of SQL table.

con : sqalchemy.engine.Engine or sqlite3.Connection
Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects.

schema : string, optional
Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'
How to behave if the table already exists.
• fail: Raise a ValueError.
• replace: Drop the table before inserting new values.
• append: Insert new values to the existing table.

index : boolean, default True
Write DataFrame index as a column. Uses index_label as the column name in the table.

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, optional
Rows will be written in batches of this size at a time. By default, all rows will be written at once.

dtype : dict, optional
Specifying the datatype for columns. The keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode.

Raises ValueError
When the table already exists and if_exists is ‘fail’ (the default).

See also:

pandas.read_sql  read a DataFrame from a table

References

[R16], [R17]

Examples

Create an in-memory SQLite database.

```python
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```python
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
  name
0  User 1
1  User 2
2  User 3

>>> df.to_sql('users', con=engine)
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]

>>> df1 = pd.DataFrame({'name' : ['User 4', 'User 5']})
>>>
```

Overwrite the table with just df1.

```python
>>> df1.to_sql('users', con=engine, if_exists='replace',
... index_label='id')
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```python
>>> df = pd.DataFrame({"A": [1, None, 2]})
>>> df
  A
0  1.0
1  NaN
2  2.0
```
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 characters.

In the following example, we use the SQLite SQL database engine. You can use a temporary SQLite database where data are stored in “memory”.

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For more information on `create_engine()` and the URI formatting, see the examples below and the SQLAlchemy documentation.

```python
In [527]: from sqlalchemy import create_engine
# Create your engine.
In [528]: engine = create_engine('sqlite:///:memory:)
```

If you want to manage your own connections you can pass one of those instead:

```python
with engine.connect() as conn, conn.begin():
    data = pd.read_sql_table('data', conn)
```

### 24.11.5 Writing DataFrames

Assuming the following data is in a DataFrame `data`, we can insert it into the database using `to_sql()`.

```python
<table>
<thead>
<tr>
<th>id</th>
<th>Date</th>
<th>Col_1</th>
<th>Col_2</th>
<th>Col_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>2012-10-18</td>
<td>X</td>
<td>25.7</td>
<td>True</td>
</tr>
<tr>
<td>42</td>
<td>2012-10-19</td>
<td>Y</td>
<td>-12.4</td>
<td>False</td>
</tr>
<tr>
<td>63</td>
<td>2012-10-20</td>
<td>Z</td>
<td>5.73</td>
<td>True</td>
</tr>
</tbody>
</table>
```

```python
In [529]: 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:

```python
In [530]: data.to_sql('data_chunked', engine, chunksize=1000)
```

to_sql() will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype `object`, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the
sqlite3 fallback mode). For example, specifying to use the sqlalchemy String type instead of the default Text type for string columns:

```python
In [531]: from sqlalchemy.types import String
In [532]: 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.

## 24.11.6 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.

```python
In [533]: pd.read_sql_table('data', engine)
Out[533]:
   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.

```python
In [534]: pd.read_sql_table('data', engine, index_col='id')
Out[534]:
   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
```

```python
In [535]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
```

And you can explicitly force columns to be parsed as dates:

```python
In [536]: pd.read_sql_table('data', engine, parse_dates=['Date'])
Out[536]:
   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()

### 24.11.7 Schema support

Reading from and writing to different schema’s is supported through the schema keyword in the read_sql_table() and to_sql() functions. Note however that this depends on the database flavor (sqlite does not have schema’s). For example:

```
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

### 24.11.8 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 [537]: pd.read_sql_query('SELECT * FROM data', engine)
Out[537]:
      index   id  Date       Col_1  Col_2  Col_3
0     0    0  2010-10-18    X   27.50   True
1     1    1  2010-10-19   Y  -12.50   False
2     2    2  2010-10-20   Z    5.73   True
```

Of course, you can specify a more “complex” query.

```
In [538]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)
Out[538]:
   id  Col_1  Col_2
0  42      Y  -12.5
```

The read_sql_query() function supports a chunksize argument. Specifying this will return an iterator through chunks of the query result:

```
In [539]: df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))
In [540]: df.to_sql('data_chunks', engine, index=False)
In [541]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine, chunksize=5):
            print(chunk)
```
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)])
```

### 24.11.9 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')
```
# Advanced SQLAlchemy queries

You can use SQLAlchemy constructs to describe your query.

Use `sqlalchemy.text()` to specify query parameters in a backend-neutral way:

```python
In [542]: import sqlalchemy as sa

In [543]: pd.read_sql(sa.text('SELECT * FROM data where Col_1=:col1'),
           engine, params={'col1': 'X'})
```

If you have an SQLAlchemy description of your database you can express where conditions using SQLAlchemy expressions:

```python
In [544]: metadata = sa.MetaData()

In [545]: 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 [546]: pd.read_sql(sa.select([data_table]).where(data_table.c.Col_3 == True),
               engine)
```

You can combine SQLAlchemy expressions with parameters passed to `read_sql()` using `sqlalchemy.bindparam()`:

```python
In [547]: import datetime as dt

In [548]: expr = sa.select([data_table]).where(data_table.c.Date > sa.bindparam('date'))

In [549]: pd.read_sql(expr, engine, params={'date': dt.datetime(2010, 10, 18)})
```
24.11.11 Sqlite fallback

The use of sqlite is supported without using SQLAlchemy. This mode requires a Python database adapter which respect the Python DB-API.

You can create connections like so:

```python
import sqlite3
con = sqlite3.connect(':memory:)
```

And then issue the following queries:

```
data.to_sql('data', cnx)
pd.read_sql_query("SELECT * FROM data", con)
```

24.12 Google BigQuery

**Warning:** Starting in 0.20.0, pandas has split off Google BigQuery support into the separate package pandas-gbq. You can pip install pandas-gbq to get it.

The pandas-gbq package provides functionality to read/write from Google BigQuery.

pandas integrates with this external package. if pandas-gbq is installed, you can use the pandas methods pd. read_gbq and DataFrame.to_gbq, which will call the respective functions from pandas-gbq.

Full documentation can be found here.

24.13 Stata Format

24.13.1 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 [550]: df = pd.DataFrame(randn(10, 2), columns=list('AB'))
In [551]: df.to_stata('stata.dta')
```

Stata data files have limited data type support; only strings with 244 or fewer characters, `int8`, `int16`, `int32`, `float32` and `float64` can be stored in .dta files. Additionally, Stata reserves certain values to represent missing data. Exporting a non-missing value that is outside of the permitted range in Stata for a particular data type will retype the variable to the next larger size. For example, `int8` values are restricted to lie between -127 and 100 in Stata, and so variables with values above 100 will trigger a conversion to `int16`. Nan values in floating points data types are stored as the basic missing data type (. in Stata).

**Note:** It is not possible to export missing data values for integer data types.

The Stata writer gracefully handles other data types including `int64`, bool, `uint8`, `uint16`, `uint32` by casting to the smallest supported type that can represent the data. For example, data with a type of `uint8` will be cast to
int8 if all values are less than 100 (the upper bound for non-missing int8 data in Stata), or, if values are outside of this range, the variable is cast to int16.

**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.

### 24.13.2 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 [552]: pd.read_stata('stata.dta')
Out[552]:
   A    B
0  1.810535 -1.305727
1 -0.344987 -0.230840
2 -2.793085  1.937529
3  0.366332 -1.044589
4  2.051173  0.585662
5  0.429526 -0.606998
6  0.134048  1.202055
7  0.284748  0.262467
8  0.106223 -1.525680
9  0.795026 -0.374438

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 [553]: reader = pd.read_stata('stata.dta', chunksize=3)

In [554]: 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 [555]: reader = pd.read_stata('stata.dta', iterator=True)
In [556]: chunk1 = reader.read(5)
In [557]: 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.

### 24.13.2.1 Categorical Data

Categorical data can be exported to Stata data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. Stata does not have an explicit equivalent to a `Categorical` and information about whether the variable is ordered is lost when exporting.

**Warning:** Stata only supports string value labels, and so `str` is called on the categories when exporting data. Exporting `Categorical` variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from Stata data files as `Categorical` variables using the keyword argument `convert_categoricals=True` by default). The keyword argument `order_categoricals=True` by default) determines whether imported `Categorical` variables are ordered.

**Note:** When importing categorical data, the values of the variables in the Stata data file are not preserved since `Categorical` variables always use integer data types between -1 and n-1 where n is the number of categories. If the original values in the Stata data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original Stata data values and the category codes of imported Categorical variables: missing values are assigned code -1, and the smallest original value is assigned 0, the second smallest is assigned 1 and so on until the largest original value is assigned the code n-1.

**Note:** Stata supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a `Categorical` with string categories for the values that are labeled and numeric categories for values with no label.

### 24.14 SAS Formats

The top-level function `read_sas()` can read (but not write) SAS xport (.XPT) and (since v0.18.0) SAS7BDAT (.sas7bdat) format files.
SAS files only contain two value types: ASCII text and floating point values (usually 8 bytes but sometimes truncated). For xport files, there is no automatic type conversion to integers, dates, or categoricals. For SAS7BDAT files, the format codes may allow date variables to be automatically converted to dates. By default the whole file is read and returned as a DataFrame.

Specify a chunksize or use iterator=True to obtain reader objects (XportReader or SAS7BDATReader) for incrementally reading the file. The reader objects also have attributes that contain additional information about the file and its variables.

Read a SAS7BDAT file:

```python
df = pd.read_sas('sas_data.sas7bdat')
```

Obtain an iterator and read an XPORT file 100,000 lines at a time:

```python
rdr = pd.read_sas('sas_xport.xpt', chunk=100000)
for chunk in rdr:
    do_something(chunk)
```

The specification for the xport file format is available from the SAS web site.

No official documentation is available for the SAS7BDAT format.

## 24.15 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.

### 24.15.1 netCDF

xarray provides data structures inspired by the pandas DataFrame for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

## 24.16 Performance Considerations

This is an informal comparison of various IO methods, using pandas 0.20.3. Timings are machine dependent and small differences should be ignored.

```python
In [1]: sz = 1000000
In [3]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A 1000000 non-null float64
B 1000000 non-null int64
dtypes: float64(1), int64(1)
memory usage: 15.3 MB
```

When writing, the top-three functions in terms of speed are are `test_pickle_write`, `test_feather_write` and `test_hdf_fixed_write_compress`.

24.15. Other file formats
In [14]: %timeit test_sql_write(df)
2.37 s ± 36.6 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [15]: %timeit test_hdf_fixed_write(df)
194 ms ± 65.9 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [26]: %timeit test_hdf_fixed_write_compress(df)
119 ms ± 2.15 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [16]: %timeit test_hdf_table_write(df)
623 ms ± 125 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [27]: %timeit test_hdf_table_write_compress(df)
563 ms ± 23.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [17]: %timeit test_csv_write(df)
3.13 s ± 49.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [30]: %timeit test_feather_write(df)
103 ms ± 5.88 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [31]: %timeit test_pickle_write(df)
109 ms ± 3.72 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [32]: %timeit test_pickle_write_compress(df)
3.33 s ± 55.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

When reading, the top three are test_feather_read, test_pickle_read and test_hdf_fixed_read.

In [18]: %timeit test_sql_read()
1.35 s ± 14.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [19]: %timeit test_hdf_fixed_read()
14.3 ms ± 438 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [28]: %timeit test_hdf_fixed_read_compress()
23.5 ms ± 672 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [20]: %timeit test_hdf_table_read()
35.4 ms ± 314 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [29]: %timeit test_hdf_table_read_compress()
42.6 ms ± 2.1 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [22]: %timeit test_csv_read()
516 ms ± 27.1 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [33]: %timeit test_feather_read()
4.06 ms ± 115 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [34]: %timeit test_pickle_read()
6.5 ms ± 172 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [35]: %timeit test_pickle_read_compress()
588 ms ± 3.57 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Space on disk (in bytes)
And here’s the code:

```python
import os
import pandas as pd
import sqlite3
from numpy.random import randn
from pandas.io import sql

sz = 1000000

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')

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')
```

(continues on next page)
def test_csv_write(df):
    df.to_csv('test.csv', mode='w')

def test_csv_read(
    pd.read_csv('test.csv', index_col=0)

def test_feather_write(df):
    df.to_feather('test.feather')

def test_feather_read():
    pd.read_feather('test.feather')

def test_pickle_write(df):
    df.to_pickle('test.pkl')

def test_pickle_read():
    pd.read_pickle('test.pkl')

def test_pickle_write_compress(df):
    df.to_pickle('test.pkl.compress', compression='xz')

def test_pickle_read_compress():
    pd.read_pickle('test.pkl.compress', compression='xz')
In this part of the tutorial, we will investigate how to speed up certain functions operating on pandas DataFrames using three different techniques: Cython, Numba and `pandas.eval()`. We will see a speed improvement of ~200 when we use Cython and Numba on a test function operating row-wise on the DataFrame. Using `pandas.eval()` we will speed up a sum by an order of ~2.

### 25.1 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 by trying to remove for-loops and making use of NumPy vectorization. It’s always worth optimising in Python first.

This tutorial walks through a “typical” process of cythonizing a slow computation. We use an example from the Cython documentation but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure Python solution.

#### 25.1.1 Pure python

We have a DataFrame to which we want to apply a function row-wise.

```python
In [1]: df = pd.DataFrame({'a': np.random.randn(1000),
                      ...: 'b': np.random.randn(1000),
                      ...: 'N': np.random.randint(100, 1000, (1000)),
                      ...: 'x': 'x'})
```

```output
Out[2]:
    a     b    N    x
0  0.469112 -0.218470 585  x
1 -0.282863 -0.061645 841  x
2 -1.509059 -0.723780 251  x
3 -1.135632  0.551225 972  x
4  1.212112 -0.497767 181  x
5  0.131892  0.290162 190  x
6  0.342097  0.215341 931  x
```

(continues on next page)
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)
```

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.

### 25.1.2 Plain Cython

First we’re going to need to import the Cython magic function to ipython:
In [6]: %load_ext Cython

Now, let’s simply copy our functions over to Cython as is (the suffix is here to distinguish between function versions):

```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.

```python
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.

### 25.1.3 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)
cdef double integrate_f_typed(double a, double b, int N):
   ...: cdef int i
   ...: cdef double s, dx
   ...: s = 0
   ...: dx = (b - a) / N
   ...: for i in range(N):
   ...:     s += f_typed(a + i * dx)
   ...: return s * dx
```

```python
In [4]: %timeit df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
```

10 loops, best of 3: 20.3 ms per loop

Now, we’re talking! It’s now over ten times faster than the original python implementation, and we haven’t really modified the code. Let’s have another look at what’s eating up time:

```python
In [9]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
```

119288 function calls (114268 primitive calls) in 0.052 seconds

Ordered by: internal time
List reduced from 211 to 4 due to restriction <4>

(continues on next page)
25.1.4 Using ndarray

It’s calling series... a lot! It’s creating a Series from each row, and get-ting from both the index and the series (three times for each row). Function calls are expensive in Python, so maybe we could minimize these by cythonizing the apply part.

Note: We are now passing ndarrays into the Cython function, fortunately Cython plays very nicely with NumPy.

```
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:** 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. The reason is that the Cython definition is specific to an ndarray and not the passed Series.

So, do not do this:

```
apply_integrate_f(df['a'], df['b'], df['N'])
```

But rather, 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)
215 function calls in 0.001 seconds
Ordered by: internal time
List reduced from 55 to 4 due to restriction <4>
ncalls  tottime  percall  cumtime  percall filename:lineno(function)
    1  0.001    0.001   0.001    0.001 {built-in method _cython_magic__039cb0af339d11610fbd07bd4033a1cf.apply_integrate_f}
     3  0.000    0.000    0.000    0.000 internals.py:4137(iget)
    1  0.000    0.000    0.001    0.001 {built-in method builtins.exec}
     3  0.000    0.000    0.000    0.000 frame.py:2664(__getitem__)
```

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.

### 25.1.5 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
cimport numpy as np
cdef double f_typed(double x) except? -2:
    return x * (x - 1)
cdef 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 int i, n = len(col_N)
    assert len(col_a) == len(col_b) == n
    cdef np.ndarray[double] res = np.empty(n)
    for i in range(n):
        res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
    return res
```
In [4]: %timeit apply_integrate_f_wrap(df['a'].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. For more about boundscheck and wraparound, see the Cython docs on compiler directives.

25.2 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 pyc compiler). 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.

25.2.1 Jit

We demonstrate how to use Numba to just-in-time compile our code. We simply take the plain Python code from above and annotate with the @jit decorator.

```python
import numba

@numba.jit
def f_plain(x):
    return x * (x - 1)

@numba.jit
def integrate_f_numba(a, b, N):
    s = 0
dx = (b - a) / N
    for i in range(N):
        s += f_plain(a + i * dx)
    return s * dx

@numba.jit
def apply_integrate_f_numba(col_a, col_b, col_N):
    n = len(col_N)
    result = np.empty(n, dtype='float64')
    assert len(col_a) == len(col_b) == n
    for i in range(n):
        # (continues on next page)
```
result[i] = integrate_f_numba(col_a[i], col_b[i], col_N[i])
return result

def compute_numba(df):
    result = apply_integrate_f_numba(df['a'].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

In this example, using Numba was faster than Cython.

### 25.2.2 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

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
```

### 25.2.3 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.

### 25.3 Expression Evaluation via `eval()`

The top-level function `pandas.eval()` implements expression evaluation of `Series` and `DataFrame` objects.

**Note:** To benefit from using `eval()` you need to install numexpr. See the recommended dependencies section for more details.

The point of using `eval()` for expression evaluation rather than plain Python is two-fold: 1) large `DataFrame` objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default numexpr is used for evaluation).

**Note:** You should not use `eval()` for simple expressions or for expressions involving small DataFrames. In fact, `eval()` is many orders of magnitude slower for smaller expressions/objects than plain ol’ Python. A good rule of thumb is to only use `eval()` when you have a `DataFrame` with more than 10,000 rows.

`eval()` supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

**Note:** The larger the frame and the larger the expression the more speedup you will see from using `eval()`.

#### 25.3.1 Supported Syntax

These operations are supported by `pandas.eval()`:

- Arithmetic operations except for the left shift (`<<`) and right shift (`>>`) operators, e.g., `df + 2 * pi / s ** 4 % 42 - the_golden_ratio`
- Comparison operations, including chained comparisons, e.g., `2 < df < df2`
- Boolean operations, e.g., `df < df2 and df3 < df4 or not df_bool`
- `list` and `tuple` literals, e.g., `[1, 2] or (1, 2)`
- Attribute access, e.g., `df.a`
- Subscript expressions, e.g., `df[0]`
- Simple variable evaluation, e.g., `pd.eval('df')` (this is not very useful)
- Math functions: `sin`, `cos`, `exp`, `log`, `expm1`, `log1p`, `sqrt`, `sinh`, `cosh`, `tanh`, `arcsin`, `arccos`, `arctan`, `arccosh`, `arseinh`, `arctanh`, `abs` and `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.

25.3.2 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
11.7 ms +- 1.34 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [16]: %timeit pd.eval('df1 + df2 + df3 + df4')
8 ms +- 543 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Now let’s do the same thing but with comparisons:

```
In [17]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
26.7 ms +- 295 us per loop (mean +- std. dev. of 7 runs, 10 loops each)
```

```
In [18]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
9.9 ms +- 489 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

*eval()* also works with unaligned pandas objects:

```
In [19]: s = pd.Series(np.random.randn(50))
```

```
In [20]: %timeit df1 + df2 + df3 + df4 + s
24.1 ms +- 2.13 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [21]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
9.75 ms +- 1.11 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Note: Operations such as
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.

### 25.3.3 The DataFrame.eval method

In addition to the top level pandas.eval() function you can also evaluate an expression in the “context” of a DataFrame.

```python
In [22]: df = pd.DataFrame(np.random.randn(5, 2), columns=['a', 'b'])
In [23]: df.eval('a + b')
Out[23]:
   0   1
0 -0.246747
1  0.867786
2 -1.626063
3 -1.134978
4 -1.027798
```

Any expression that is a valid pandas.eval() expression is also a valid DataFrame.eval() expression, with the added benefit that you don’t have to prefix the name of the DataFrame to the column(s) you’re interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for formulaic evaluation. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

New in version 0.18.0.

The inplace keyword determines whether this assignment will performed on the original DataFrame or return a copy with the new column.

```
Warning: For backwards compatibility, inplace defaults to True if not specified. This will change in a future version of pandas - if your code depends on an inplace assignment you should update to explicitly set inplace=True.
```

```python
In [24]: d = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
In [25]: d.eval('c = a + b', inplace=True)
In [26]: d.eval('d = a + b + c', inplace=True)
In [27]: d.eval('a = 1', inplace=True)
In [28]: d
Out[28]:
     a  b  c  d
0  0  5  5 10
1  1  6  7 14
```

(continues on next page)
When `inplace` is set to `False`, a copy of the DataFrame with the new or modified columns is returned and the original frame is unchanged.

```
In [29]: df
Out[29]:
      a  b  c  d
0     1  5  5 10
1     1  6  7 14
2     1  7  9 18
3     1  8 11 22
4     1  9 13 26

In [30]: df.eval('e = a - c', inplace=False)
Out[30]:
     a  b  c  d   e
0     1  5  5 10 -4
1     1  6  7 14 -6
2     1  7  9 18 -8
3     1  8 11 22 -10
4     1  9 13 26 -12

In [31]: df
Out[31]:
      a  b  c  d
0     1  5  5 10
1     1  6  7 14
2     1  7  9 18
3     1  8 11 22
4     1  9 13 26
```

New in version 0.18.0.

As a convenience, multiple assignments can be performed by using a multi-line string.

```
In [32]: df.eval(""
       ....: c = a + b
       ....: d = a + b + c
       ....: a = 1\"\", inplace=False)
       ....:
Out[32]:
      a  b  c  d
0     1  5  6 12
1     1  6  7 14
2     1  7  8 16
3     1  8  9 18
4     1  9 10 20
```

The equivalent in standard Python would be

```
In [33]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
```

(continues on next page)
In [34]: df['c'] = df.a + df.b
In [35]: df['d'] = df.a + df.b + df.c
In [36]: df['a'] = 1
In [37]: df
Out[37]:
<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>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>5</td>
<td>7</td>
<td>14</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>7</td>
<td>9</td>
<td>18</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>9</td>
<td>11</td>
<td>22</td>
</tr>
</tbody>
</table>

New in version 0.18.0.
The `query` method gained the `inplace` keyword which determines whether the query modifies the original frame.

In [38]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
In [39]: df.query('a > 2')
Out[39]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
</tr>
</tbody>
</table>
In [40]: df.query('a > 2', inplace=True)
In [41]: df
Out[41]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
</tr>
</tbody>
</table>

**Warning:** Unlike with `eval`, the default value for `inplace` for `query` is `False`. This is consistent with prior versions of pandas.

### 25.3.4 Local Variables

You must explicitly reference any local variable that you want to use in an expression by placing the `@` character in front of the name. For example,

In [42]: df = pd.DataFrame(np.random.randn(5, 2), columns=list('ab'))
In [43]: newcol = np.random.randn(len(df))
In [44]: df.eval('b + @newcol')
Out[44]:
<table>
<thead>
<tr>
<th>0</th>
<th>-0.173926</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.493083</td>
</tr>
<tr>
<td>2</td>
<td>-0.881831</td>
</tr>
<tr>
<td>3</td>
<td>-0.691045</td>
</tr>
</tbody>
</table>
If you don’t prefix the local variable with @, pandas will raise an exception telling you the variable is undefined.

When using `DataFrame.eval()` and `DataFrame.query()`, this allows you to have a local variable and a `DataFrame` column with the same name in an expression.

```
In [46]: a = np.random.randn()

In [47]: df.query('@a < a')
```

```
Out[47]:
        a     b
0  0.863987 -0.115998
```

```
In [48]: df.loc[a < df.a]  # same as the previous expression
```

```
Out[48]:
        a     b
0  0.863987 -0.115998
```

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 [49]: a, b = 1, 2

In [50]: pd.eval('@a + b')
```

```
Traceback (most recent call last):
    exec(code_obj, self.user_global_ns, self.user_ns)
  File "/Users/taugspurger/sandbox/pandas-release/pandas-docs/pandas/core/computation/eval.py", line 283, in eval
    _check_for_locals(expr, level, parser)
  File "/Users/taugspurger/sandbox/pandas-release/pandas-docs/pandas/core/computation/eval.py", line 150, in _check_for_locals
    raise SyntaxError(msg)
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.

---

25.3. Expression Evaluation via `eval()`
25.3.5 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 [52]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'
In [53]: x = pd.eval(expr, parser='python')
In [54]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'
In [55]: y = pd.eval(expr_no_parens, parser='pandas')
In [56]: np.all(x == y)
Out[56]: True
```

The same expression can be “anded” together with the word and as well:

```
In [57]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'
In [58]: x = pd.eval(expr, parser='python')
In [59]: expr_with_ands = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'
In [60]: y = pd.eval(expr_with_ands, parser='pandas')
In [61]: np.all(x == y)
Out[61]: True
```

The and and or operators here have the same precedence that they would in vanilla Python.

25.3.6 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.

```
In [62]: %timeit df1 + df2 + df3 + df4
12 ms +- 613 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Chapter 25. Enhancing Performance
25.3.7 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.

![DataFrame.eval() Performance](image)

**Note:** Operations with smallish objects (around 15k-20k rows) are faster using plain Python:

![DataFrame.eval() Performance](image)

This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.
25.3.8 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 [64]: df = pd.DataFrame({'strings': np.repeat(list('cba'), 3), 
                      'nums': np.repeat(range(3), 3)})
....: 

In [65]: df
Out[65]:
   strings  nums
0      c      0
1      c      0
2      c      0
3      b      1
4      b      1
5      b      1
6      a      2
7      a      2
8      a      2

In [66]: df.query('strings == "a" and nums == 1')
```

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.
Note: The SparsePanel class has been removed in 0.19.0

We have implemented “sparse” versions of Series and DataFrame. These are not sparse in the typical “mostly 0”. Rather, you can view these objects as being “compressed” where any data matching a specific value (NaN / missing value, though any value can be chosen) is omitted. A special SparseIndex object tracks where data has been “sparsified”. This will make much more sense with 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], dtype=int32)
Block lengths: array([2, 2], dtype=int32)
```

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
```

(continues on next page)
The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```python
In [6]: df = pd.DataFrame(randn(10000, 4))
In [7]: df.iloc[:9998] = np.nan
In [8]: sdf = df.to_sparse()
In [9]: sdf
```

```
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
6 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 0.509184 -0.774928 -1.369894 -0.382141
9999 0.280249 -1.648493 1.490865 -0.890819
```

```
[10000 rows x 4 columns]
```

```python
In [10]: sdf.density
```

```
˓→ 0.0002
```

As you can see, the density (% of values that have not been “compressed”) is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter. 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`:

```python
In [11]: sts.to_dense()
```

```
0 0.469112
1 -0.282863
2 NaN
3 NaN
4 NaN
5 NaN
6 NaN
```

(continues on next page)
26.1 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:

```python
In [12]: arr = np.random.randn(10)
In [14]: sparr = pd.SparseArray(arr)
In [15]: sparr
Out[15]:
[-1.9556635297215477, -1.6588664275960427, nan, nan, nan, 1.1589328886422277, 0.14529711373305043, nan, 0.6060271905134522, 1.3342113401317768]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

Like the indexed objects (SparseSeries, SparseDataFrame), a SparseArray can be converted back to a regular ndarray by calling to_dense:

```python
In [16]: sparr.to_dense()
Out[16]:
array([-1.9557, -1.6589, nan, nan, nan, 1.1589, 0.1453, nan, 0.606, 1.3342])
```

26.2 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 arrays 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.

26.3 Sparse Dtypes

Sparse data should have the same dtype as its dense representation. Currently, float64, int64 and bool dtypes are supported. Depending on the original dtype, fill_value default changes:

- float64: np.nan
- int64: 0
- bool: False
In [17]: s = pd.Series([1, np.nan, np.nan])

In [18]: s
Out[18]:
0   1.0
1   NaN
2   NaN
dtype: float64

In [19]: s.to_sparse()
Out[19]:
0   1.0
1   NaN
2   NaN
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([1], dtype=int32)

In [20]: s = pd.Series([1, 0, 0])

In [21]: s
Out[21]:
0   1
1   0
2   0
dtype: int64

In [22]: s.to_sparse()
Out[22]:
0   1
1   0
2   0
dtype: int64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([1], dtype=int32)

In [23]: s = pd.Series([True, False, True])

In [24]: s
Out[24]:
0   True
1   False
2   True
dtype: bool

In [25]: s.to_sparse()
Out[25]:
0   True
1   False
2   True
dtype: bool
BlockIndex
Block locations: array([0, 2], dtype=int32)
Block lengths: array([1, 1], dtype=int32)

You can change the dtype using \texttt{.astype()}, the result is also sparse. Note that \texttt{.astype()} also affects to the
fill_value to keep its dense representation.

```python
In [26]: s = pd.Series([1, 0, 0, 0, 0])
In [27]: s
Out[27]:
0    1
1     0
2     0
3     0
4     0
dtype: int64
In [28]: ss = s.to_sparse()
In [29]: ss
Out[29]:
0    1
1     0
2     0
3     0
4     0
dtype: int64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([1], dtype=int32)
In [30]: ss.astype(np.float64)
```

It raises if any value cannot be coerced to specified dtype.

```python
In [1]: ss = pd.Series([1, np.nan, np.nan]).to_sparse()
0    1.0
1   NaN
2   NaN
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([1], dtype=int32)
In [2]: ss.astype(np.int64)
ValueError: unable to coerce current fill_value nan to int64 dtype
```

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26.4 Sparse Calculation

You can apply NumPy ufuncs to SparseArray and get a SparseArray as a result.

```python
In [31]: arr = pd.SparseArray([1., np.nan, np.nan, -2., np.nan])
In [32]: np.abs(arr)
Out[32]:
[1.0, nan, nan, 2.0, nan]
Fill: nan
IntIndex
Indices: array([0, 3], dtype=int32)
```

The ufunc is also applied to fill_value. This is needed to get the correct dense result.

```python
In [33]: arr = pd.SparseArray([1., -1, -1, -2., -1], fill_value=-1)
In [34]: np.abs(arr)
Out[34]:
[1.0, 1.0, 1.0, 2.0, 1.0]
Fill: 1
IntIndex
Indices: array([0, 3], dtype=int32)
```

```python
In [35]: np.abs(arr).to_dense()
Out[35]:
array([ 1., 1., 1., 2., 1.])
```

26.5 Interaction with scipy.sparse

26.5.1 SparseDataFrame

New in version 0.20.0.

Pandas supports creating sparse dataframes directly from scipy.sparse matrices.

```python
In [36]: from scipy.sparse import csr_matrix
In [37]: arr = np.random.random(size=(1000, 5))
In [38]: arr[arr < .9] = 0
In [39]: sp_arr = csr_matrix(arr)
In [40]: sp_arr
Out[40]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
    with 517 stored elements in Compressed Sparse Row format>
In [41]: sdf = pd.SparseDataFrame(sp_arr)
In [42]: sdf
Out[42]:
     0  1  2  3  4
(continues on next page)```
All sparse formats are supported, but matrices that are not in `COOrdinate` format will be converted, copying data as needed. To convert a `SparseDataFrame` back to sparse SciPy matrix in COO format, you can use the `SparseDataFrame.to_coo()` method:

```
In [43]: sdf.to_coo()
Out[43]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
         with 517 stored elements in COOrdinate format>
```

### 26.5.2 SparseSeries

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 [44]: s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
In [45]: 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 [46]: s
Out[46]:
A  B  C  D
1 2  a  0  3.0
   1  NaN
1 1  b  0  1.0
   1  3.0
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 [49]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
    ....:     column_levels=['C', 'D'],
    ....:     sort_labels=True)

In [50]: A
Out[50]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [51]: A.todense()
    →
    matrix([[ 0., 0., 1., 3.],
             [ 3., 0., 0., 0.],
             [ 0., 0., 0., 0.]])

In [52]: rows
    →[(1, 1), (1, 2), (2, 1)]

In [53]: columns
    →[('a', 0), ('a', 1), ('b', 0), ('b', 1)]

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

In [54]: A, rows, columns = ss.to_coo(row_levels=['A', 'B', 'C'],
    ....:     column_levels=['D'],
    ....:     sort_labels=False)

In [55]: A
Out[55]:
A convenience method `SparseSeries.from_coo()` is implemented for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`.

```python
In [59]: from scipy import sparse
In [60]: A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])), shape=(3, 4))
In [61]: A
Out[61]: <3x4 sparse matrix of type '<class 'numpy.float64'>'
         with 3 stored elements in COOrdinate format>
In [62]: A.todense()
   →
          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 [63]: ss = pd.SparseSeries.from_coo(A)
In [64]: ss
Out[64]:
0  2  1.0
3  2.0
1  0  3.0
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([3], dtype=int32)
```

Specifying `dense_index=True` will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to `dense_index=False`) if the sparse matrix is large (and sparse) enough.
In [65]: ss_dense = pd.SparseSeries.from_coo(A, dense_index=True)

In [66]: ss_dense
Out[66]:
0 0 NaN
 1 NaN
 2 1.0
 3 2.0
1 0 3.0
 1 NaN
 2 NaN
 3 NaN
2 0 NaN
 1 NaN
 2 NaN
 3 NaN
dtype: float64
BlockIndex
Block locations: array([2], dtype=int32)
Block lengths: array([3], dtype=int32)
27.1 DataFrame memory usage

The memory usage of a DataFrame (including the index) is shown when calling the `info()`. A configuration option, `display.memory_usage` (see the list of options), specifies if the DataFrame’s memory usage will be displayed when invoking the `df.info()` method.

For example, the memory usage of the DataFrame below is shown when calling `info()`:

```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'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
   int64 5000 non-null int64
   float64 5000 non-null float64
   datetime64[ns] 5000 non-null datetime64[ns]
   timedelta64[ns] 5000 non-null timedelta64[ns]
   complex128 5000 non-null complex128
   object 5000 non-null object
   bool 5000 non-null bool
   categorical 5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),
   timedelta64[ns](1)
memory usage: 289.1+ 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`.

Passing `memory_usage='deep'` will enable a more accurate memory usage report, accounting for the full usage of the contained objects. This is optional as it can be expensive to do this deeper introspection.
In [7]: df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
int64     5000 non-null int64
float64   5000 non-null float64
datetime64[ns] 5000 non-null datetime64[ns]
timedelta64[ns] 5000 non-null timedelta64[ns]
complex128 5000 non-null complex128
object     5000 non-null object
bool       5000 non-null bool
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: 425.6 KB

By default the display option is set to True but can be explicitly overridden by passing the memory_usage argument when invoking df.info().

The memory usage of each column can be found by calling the memory_usage() method. This returns a Series with an index represented by column names and memory usage of each column shown in bytes. For the DataFrame above, the memory usage of each column and the total memory usage can be found with the memory_usage method:

In [8]: df.memory_usage()
Out[8]:

Index   80
int64  40000
float64  40000
datetime64[ns]  40000
timedelta64[ns]  40000
complex128  80000
object  40000
bool  5000
categorical  10920
dtype: int64

# total memory usage of dataframe
In [9]: df.memory_usage().sum()

˓→296000

By default the memory usage of the DataFrame's index is shown in the returned Series, the memory usage of the index can be suppressed by passing the index=False argument:

In [10]: df.memory_usage(index=False)
Out[10]:

int64  40000
float64  40000
datetime64[ns]  40000
timedelta64[ns]  40000
complex128  80000
object  40000
bool  5000
categorical  10920
dtype: int64

The memory usage displayed by the info() method utilizes the memory_usage() method to determine the memory usage of a DataFrame while also formatting the output in human-readable units (base-2 representation; i.e., 1KB
27.2 Using If/Truth Statements with pandas

pandas follows the NumPy convention of raising an error when you try to convert something to a bool. This happens in an if-statement or when using the boolean operations: and, or, and not. It is not clear what the result of the following code should be:

```python
>>> if pd.Series([False, True, False]):
... print("I was true")
>>> print("I was not None")
```

Should it be True because it’s not zero-length, or False because there are False values? It is unclear, so instead, pandas raises a ValueError:

```python
>>> if pd.Series([False, True, False]):
... print("I was true")
Traceback
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

You need to explicitly choose what you want to do with the DataFrame, e.g. use any(), all() or empty(). Alternatively, you might want to compare if the pandas object is None:

```python
>>> if pd.Series([False, True, False]) is not None:
... print("I was not None")
```

Below is how to check if any of the values are 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 [11]: pd.Series([True]).bool()
Out[11]: True
In [12]: pd.Series([False]).bool()
Out[12]: False
In [13]: pd.DataFrame([[True]]).bool()
Out[13]: True
In [14]: pd.DataFrame([[False]]).bool()
Out[14]: False
```

27.2.1 Bitwise boolean

Bitwise boolean operators like == and != return a boolean Series, which is almost always what you want anyways.
```
>>> 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.

### 27.2.2 Using the *in* operator

Using the Python *in* operator on a `Series` tests for membership in the index, not membership among the values.

```
In [15]: s = pd.Series(range(5), index=list('abcde'))

In [16]: 2 in s
Out[16]: False

In [17]: 'b' in s
Out[17]: True
```

If this behavior is surprising, keep in mind that using *in* on a Python dictionary tests keys, not values, and `Series` are dict-like. To test for membership in the values, use the method `isin()`:

```
In [18]: s.isin([2])
Out[18]:
a   False
b   False
c   True
d   False
e   False
dtype: bool

In [19]: s.isin([2]).any()
Out[19]: True
```

For `DataFrames`, likewise, *in* applies to the column axis, testing for membership in the list of column names.

### 27.3 NaN, Integer NA values and NA type promotions

#### 27.3.1 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 is there or is missing.
- Using a special sentinel value, bit pattern, or set of sentinel values to denote `NA` across the dtypes.

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value `NaN` (Not-A-Number) is used
everywhere as the NA value, and there are API functions `isna` and `notna` which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

### 27.3.2 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 [20]: s = pd.Series([1, 2, 3, 4, 5], index=list('abcde'))

In [21]: s
Out[21]:
   a  1
   b  2
   c  3
   d  4
   e  5
dtype: int64

In [22]: s.dtype
Out[22]: dtype('int64')

In [23]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])

In [24]: s2
Out[24]:
   a  1.0
   b  2.0
   c  3.0
   f  NaN
   u  NaN
dtype: float64

In [25]: s2.dtype
Out[25]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting `Series` continues to be “numeric”. One possibility is to use `dtype=object` arrays instead.

### 27.3.3 NA type promotions

When introducing NAs into an existing `Series` or `DataFrame` via `reindex()` or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. The promotions are summarized in this table:

<table>
<thead>
<tr>
<th>Typeclass</th>
<th>Promotion dtype for storing NAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>floating</td>
<td>no change</td>
</tr>
<tr>
<td>object</td>
<td>no change</td>
</tr>
<tr>
<td>integer</td>
<td>cast to float64</td>
</tr>
<tr>
<td>boolean</td>
<td>cast to object</td>
</tr>
</tbody>
</table>

---

27.3. NaN, Integer NA values and NA type promotions
While this may seem like a heavy trade-off, I have found very few cases where this is an issue in practice i.e. storing values greater than 2**53. Some explanation for the motivation is in the next section.

### 27.3.4 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 R. Part of the reason is the NumPy type hierarchy:

<table>
<thead>
<tr>
<th>Typeclass</th>
<th>Dtypes</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy.floating</td>
<td>float16, float32, float64, float128</td>
</tr>
<tr>
<td>numpy.integer</td>
<td>int8, int16, int32, int64</td>
</tr>
<tr>
<td>numpy.unsignedinteger</td>
<td>uint8, uint16, uint32, uint64</td>
</tr>
<tr>
<td>numpy.object_</td>
<td>object_</td>
</tr>
<tr>
<td>numpy.bool_</td>
<td>bool_</td>
</tr>
<tr>
<td>numpy.character</td>
<td>string_, unicode_</td>
</tr>
</tbody>
</table>

The R language, by contrast, only has a handful of built-in data types: integer, numeric (floating-point), character, and boolean. NA types are implemented by reserving special bit patterns for each type to be used as the missing value. While doing this with the full NumPy type hierarchy would be possible, it would be a more substantial trade-off (especially for the 8- and 16-bit data types) and implementation undertaking.

An alternate approach is that of using masked arrays. A masked array is an array of data with an associated boolean mask denoting whether each value should be considered NA or not. I am personally not in love with this approach as I feel that overall it places a fairly heavy burden on the user and the library implementer. Additionally, it exacts a fairly high performance cost when working with numerical data compared with the simple approach of using NaN. Thus, I have chosen the Pythonic “practicality beats purity” approach and traded integer NA capability for a much simpler approach of using a special value in float and object arrays to denote NA, and promoting integer arrays to floating when NAs must be introduced.

### 27.4 Differences with NumPy

For Series and DataFrame objects, \( \text{var}() \) normalizes by \( N-1 \) to produce unbiased estimates of the sample variance, while NumPy’s \( \text{var} \) normalizes by \( N \), which measures the variance of the sample. Note that \( \text{cov}() \) normalizes by \( N-1 \) in both pandas and NumPy.

### 27.5 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the \( \text{copy}() \) 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.

### 27.6 Byte-Ordering Issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like:
Traceback
...
ValueError: Big-endian buffer not supported on little-endian compiler

To deal with this issue you should convert the underlying NumPy array to the native system byte order before passing it to Series or DataFrame constructors using something similar to the following:

```
In [26]: x = np.array(list(range(10)), '>i4')  # big endian
In [27]: newx = x.byteswap().newbyteorder()  # force native byteorder
In [28]: s = pd.Series(newx)
```

See the NumPy documentation on byte order for more details.
rpy2 is an interface to R running embedded in a Python process, and also includes functionality to deal with pandas DataFrames. 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().

See also the documentation of the rpy2 project: https://rpy2.readthedocs.io.

In the remainder of this page, a few examples of explicit conversion is given. The pandas conversion of rpy2 needs first to be activated:

```python
In [1]: from rpy2.robjects import r, pandas2ri
In [2]: pandas2ri.activate()
```

### 28.1 Transferring R data sets into Python

Once the pandas conversion is activated (pandas2ri.activate()), many conversions of R to pandas objects will be done automatically. For example, to obtain the ‘iris’ dataset as a pandas DataFrame:

```python
In [3]: r.data('iris')
Out[3]:
R object with classes: {'character',} mapped to:
<StrVector : Python:0x1c3aa7a808 / R:0x7f83de5168e8>
['iris']

In [4]: r['iris'].head()
```

<table>
<thead>
<tr>
<th></th>
<th>Sepal.Length</th>
<th>Sepal.Width</th>
<th>Petal.Length</th>
<th>Petal.Width</th>
<th>Species</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>setosa</td>
</tr>
<tr>
<td>1</td>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>setosa</td>
</tr>
<tr>
<td>2</td>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>setosa</td>
</tr>
<tr>
<td>3</td>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>setosa</td>
</tr>
<tr>
<td>4</td>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>setosa</td>
</tr>
</tbody>
</table>
If the pandas conversion was not activated, the above could also be accomplished by explicitly converting it with the `pandas2ri.ri2py` function (`pandas2ri.ri2py(r['iris'])`).

### 28.2 Converting DataFrames into R objects

The `pandas2ri.py2ri` function supports the reverse operation to convert DataFrames into the equivalent R object (that is, `data.frame`):

```python
In [5]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C':[7,8,9]},
...:     index=['one', 'two', 'three'])
...:
In [6]: r_dataframe = pandas2ri.py2ri(df)

In [7]: print(type(r_dataframe))
<class 'rpy2.robjects.vectors.DataFrame'>

In [8]: 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.
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.

### 29.1 Statistics and Machine Learning

#### 29.1.1 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.

#### 29.1.2 sklearn-pandas

Use pandas DataFrames in your scikit-learn ML pipeline.

#### 29.1.3 Featuretools

Featuretools is a Python library for automated feature engineering built on top of pandas. It excels at transforming temporal and relational datasets into feature matrices for machine learning using reusable feature engineering “primitives”. Users can contribute their own primitives in Python and share them with the rest of the community.

### 29.2 Visualization

#### 29.2.1 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.
29.2.2 seaborn

Seaborn is a Python visualization library based on matplotlib. It provides a high-level, dataset-oriented interface for creating attractive statistical graphics. The plotting functions in seaborn understand pandas objects and leverage pandas grouping operations internally to support concise specification of complex visualizations. Seaborn also goes beyond matplotlib and pandas with the option to perform statistical estimation while plotting, aggregating across observations and visualizing the fit of statistical models to emphasize patterns in a dataset.

29.2.3 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.

29.2.4 Vincent

The Vincent project leverages Vega (that in turn, leverages d3) to create plots. Although functional, as of Summer 2016 the Vincent project has not been updated in over two years and is unlikely to receive further updates.

29.2.5 IPython Vega

Like Vincent, the IPython Vega project leverages Vega to create plots, but primarily targets the IPython Notebook environment.

29.2.6 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.

29.2.7 QtPandas

Spun off from the main pandas library, the qtpandas library enables DataFrame visualization and manipulation in PyQt4 and PySide applications.

29.3 IDE

29.3.1 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.)

### 29.3.2 quantopian/qgrid

qgrid is “an interactive grid for sorting and filtering DataFrames in IPython Notebook” built with SlickGrid.

### 29.3.3 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.”

### 29.4 API

#### 29.4.1 pandas-datareader

pandas-datareader is a remote data access library for pandas (PyPI: pandas-datareader). It is based on functionality that was located in pandas.io.data and pandas.io.wb but was split off in v0.19. See more in the pandas-datareader docs:

The following data feeds are available:

- Yahoo! Finance
- Google Finance
- FRED
- Fama/French
- World Bank
- OECD
- Eurostat
- EDGAR Index

#### 29.4.2 quandl/Python

Quandl API for Python wraps the Quandl REST API to return Pandas DataFrames with timeseries indexes.

#### 29.4.3 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).
29.4.4 pandaSDMX

pandaSDMX is a library to retrieve and acquire statistical data and metadata disseminated in SDMX 2.1, an ISO-standard widely used by institutions such as statistics offices, central banks, and international organisations. pandaSDMX can expose datasets and related structural metadata including dataflows, code-lists, and datastructure definitions as pandas Series or multi-indexed DataFrames.

29.4.5 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.

29.5 Domain Specific

29.5.1 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.

29.5.2 xarray

xarray 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.

29.6 Out-of-core

29.6.1 Dask

Dask is a flexible parallel computing library for analytics. Dask provides a familiar DataFrame interface for out-of-core, parallel and distributed computing.

29.6.2 Dask-ML

Dask-ML enables parallel and distributed machine learning using Dask alongside existing machine learning libraries like Scikit-Learn, XGBoost, and TensorFlow.

29.6.3 Blaze

Blaze provides a standard API for doing computations with various in-memory and on-disk backends: NumPy, Pandas, SQLAlchemy, MongoDB, PyTables, PySpark.
29.6.4 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.

29.7 Data validation

29.7.1 Engarde

Engarde is a lightweight library used to explicitly state your assumptions about your datasets and check that they’re actually true.

29.8 Extension Data Types

Pandas provides an interface for defining extension types to extend NumPy’s type system. The following libraries implement that interface to provide types not found in NumPy or pandas, which work well with pandas’ data containers.

29.8.1 cyberpandas

Cyberpandas provides an extension type for storing arrays of IP Addresses. These arrays can be stored inside pandas’ Series and DataFrame.

29.9 Accessors

A directory of projects providing extension accessors. This is for users to discover new accessors and for library authors to coordinate on the namespace.

<table>
<thead>
<tr>
<th>Library</th>
<th>Accessor</th>
<th>Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>cyberpandas</td>
<td>ip</td>
<td>Series</td>
</tr>
<tr>
<td>pdvega</td>
<td>vgplot</td>
<td>Series,DataFrame</td>
</tr>
</tbody>
</table>
CHAPTER
THIRTY

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.

### 30.1 Quick Reference

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

#### 30.1.1 Querying, Filtering, Sampling

<table>
<thead>
<tr>
<th>R</th>
<th>pandas</th>
</tr>
</thead>
<tbody>
<tr>
<td>dim(df)</td>
<td>df.shape</td>
</tr>
<tr>
<td>head(df)</td>
<td>df.head()</td>
</tr>
<tr>
<td>slice(df, 1:10)</td>
<td>df.iloc[:9]</td>
</tr>
<tr>
<td>filter(df, col1 == 1, col2 == 1)</td>
<td>df.query('col1 == 1 &amp; col2 == 1')</td>
</tr>
<tr>
<td>df[df$col1 == 1 &amp; df$col2 == 1,]</td>
<td>df[(df.col1 == 1) &amp; (df.col2 == 1)]</td>
</tr>
<tr>
<td>select(df, col1, col2)</td>
<td>df[['col1', 'col2']]</td>
</tr>
<tr>
<td>select(df, col1:col3)</td>
<td>df.loc[:, 'col1':'col3']</td>
</tr>
<tr>
<td>select(df, -(col1:col3))</td>
<td>df.drop(cols_to_drop, axis=1) but see¹</td>
</tr>
<tr>
<td>distinct(select(df, col1))</td>
<td>df[['col1']].drop_duplicates()</td>
</tr>
<tr>
<td>distinct(select(df, col1, col2))</td>
<td>df[['col1', 'col2']].drop_duplicates()</td>
</tr>
<tr>
<td>sample_n(df, 10)</td>
<td>df.sample(n=10)</td>
</tr>
<tr>
<td>sample_frac(df, 0.01)</td>
<td>df.sample(frac=0.01)</td>
</tr>
</tbody>
</table>

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

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

30.1.3 Transforming

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

30.1.4 Grouping and Summarizing

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

30.2 Base R

30.2.1 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

```python
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
```

(continues on next page)
### 30.2. Base R

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1.039575</td>
<td>-0.424972</td>
</tr>
<tr>
<td>1</td>
<td>0.567020</td>
<td>-1.087401</td>
</tr>
<tr>
<td>2</td>
<td>-0.673690</td>
<td>-1.478427</td>
</tr>
<tr>
<td>3</td>
<td>0.524988</td>
<td>0.577046</td>
</tr>
<tr>
<td>4</td>
<td>-1.715002</td>
<td>-0.370647</td>
</tr>
<tr>
<td>5</td>
<td>-1.157892</td>
<td>0.844885</td>
</tr>
<tr>
<td>6</td>
<td>1.075770</td>
<td>1.643563</td>
</tr>
<tr>
<td>7</td>
<td>-1.469388</td>
<td>-0.674600</td>
</tr>
<tr>
<td>8</td>
<td>-1.776904</td>
<td>-1.294524</td>
</tr>
<tr>
<td>9</td>
<td>0.413738</td>
<td>-0.472035</td>
</tr>
</tbody>
</table>

```python
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
```

**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]]

```python
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 -1.743161 -0.826591 -0.345352  1.314232  0.690579  0.995761  0.875906
 3  1.266143  0.299368 -0.863838  0.408204 -1.048089 -0.025747 -2.211372
 4 -0.988387  0.094055  1.262731  1.289997  0.082423 -0.055758  0.536580
 5  0.221471 -0.744471  0.758587  1.729689 -0.964980 -0.845696  0.875906
 6 -1.340896  1.846883 -1.328865  1.682706 -1.717693  0.887882  0.228440
 7  1.850396  0.650776 -1.461665 -1.137707 -0.891060 -0.693921  1.613616
 8  0.464000  0.227371 -0.496922  0.306389 -2.290613 -1.134623 -1.561819
 9 -0.523962 -0.008434  1.952541 -1.056652  0.533946 -1.226970  0.040403
```

(continues on next page)
24  2.071413  -1.364763  1.751987  0.419071  -1.118283  ...  -0.611561  -1.040389  -0.796211  0.241596  0.385922  -0.486078  0.433042
25   0.036609   0.359986  1.211905  0.850427  1.554957  -0.888463  -1.508808  ...  0.01402   0.150664  -3.060395  0.040268  0.066091  -0.192862  1.979055
26   -1.179240   0.238923  1.756671  -0.747571  0.543625  -0.159609  -0.051458  ...  -1.179240  0.238923  1.756671  -0.747571  0.543625  -0.159609  -0.051458
27   0.439086   0.812684  -0.128932  -0.142506  -1.137207  0.462001  -0.159466  ...  0.439086  0.812684  -0.128932  -0.142506  -1.137207  0.462001  -0.159466
28   -0.909806   -0.312006  0.383630  -0.631606  1.321415  -0.004799  -2.008210  ...  -0.909806  -0.312006  0.383630  -0.631606  1.321415  -0.004799  -2.008210

[30 rows x 16 columns]

### 30.2.2 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 by `by1` and `by2`:

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

The `groupby()` method is similar to base R `aggregate` function.

```python
In [9]: df = pd.DataFrame({
    ...:     'v1': [1,3,5,7,8,3,5,NA,4,5,7,9],
    ...:     'v2': [11,33,55,77,88,33,55,NA,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]
    ...:     })
    ...

In [10]: g = df.groupby(['by1','by2'])
In [11]: g[['v1','v2']].mean()
Out[11]:
   by1  by2
v1    v2
1     95  5.0  55.0
     99  5.0  55.0
2     95  7.0  77.0
     99  NaN  NaN
big  damp  3.0  33.0
blue  dry  3.0  33.0
red  green  4.0  44.0
wet    1.0  11.0
```

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

---

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30.2.3 match / %in%

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

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

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

```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))
```

For more details and examples see the reshaping documentation.

30.2.4 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`:

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

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

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

(continues on next page)
For more details and examples see the reshaping documentation.

### 30.2.5 subset

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

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

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

```python
In [18]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
In [19]: df.query('a <= b')
Out[19]:
   a    b
0 -2.6320  0.5574
1 -0.5518 -1.4989
2 -1.0258  0.9271
3  0.7997  0.6290
4  0.4735  1.1394
5 -1.3730  0.2537
6 -0.5486  0.1694
7 -0.8230 -0.2500
8  1.1991  0.5272
9 -1.0058  0.7280
```

In [20]: df[df.a <= df.b]
```
In [21]: df.loc[df.a <= df.b]
```

For more details and examples see the query documentation.

### 30.2.6 with

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:

```python
In [22]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
In [23]: df.eval('a + b')
Out[23]:
    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
dtype: float64
```

```python
In [24]: df.a + df.b  # same as the previous expression
Out[24]:
    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
dtype: float64
```

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

### 30.3 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><code>data.frame</code></td>
<td>dataframe</td>
</tr>
</tbody>
</table>
30.3.1 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 [25]: df = pd.DataFrame({
    ....:     'x': np.random.uniform(1., 168., 120),
    ....:     'y': np.random.uniform(7., 334., 120),
    ....:     'z': np.random.uniform(1.7, 20.7, 120),
    ....:     'month': [5, 6, 7, 8]*30,
    ....:     'week': np.random.randint(1,4, 120)
    ....: })

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

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

<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>97.730877</td>
<td>52.442172</td>
<td></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>59.255715</td>
<td>43.422336</td>
<td></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>104.787666</td>
<td>31.745437</td>
<td></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.

30.4 reshape / reshape2

30.4.1 melt.array

An expression using a 3 dimensional array called a in R where you want to melt it into a data.frame:
In Python, since `a` is a list, you can simply use list comprehension.

```python
In [28]: a = np.array(list(range(1,24))+[np.NAN]).reshape(2,3,4)
In [29]: pd.DataFrame([tuple(list(x)+[val]) for x, val in np.ndenumerate(a)])
Out[29]:
   0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
0  0  0  0  0  1  0  2  0  2  3  0  0  3  4  0  0  1  0  3  4  0  5  6  0
1  0  0  1  2  0  0  2  3  0  1  0  3  4  0  0  1  1  6  0  5  1  2  7  0
2  0  0  1  2  0  0  2  3  0  1  1  3  2  0  0  1  2  1  2  0  3  3  4  0
3  0  1  0  2  0  0  1  2  0  2  1  2  2  0  0  1  2  2  0  3  3  4  0
4  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
5  1  1  2  1  2  1  3  1  2  2  3  2  1  2  3  2  1  2  3  2  1  2  3  2
6  1  1  3  2  1  2  3  2  1  2  4  2  1  2  5  2  1  2  6  2  1  2  7  2
7  1  2  0  3  2  1  2  3  2  1  2  4  2  1  2  5  2  1  2  6  2  1  2  7
8  1  2  1  0  3  2  1  2  3  2  1  2  4  2  1  2  5  2  1  2  6  2  1  2
9  1  2  2  1  0  3  2  1  2  3  2  1  2  4  2  1  2  5  2  1  2  6  2  1
10 1  2  3  1  0  3  2  1  2  3  2  1  2  4  2  1  2  5  2  1  2  6  2  1
[24 rows x 4 columns]
```

### 30.4.2 melt.list

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

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

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

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

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

### 30.4.3 melt.data.frame

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

```r
30.4. reshape / reshape2
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

```
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 [32]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
                      ....:  'last' : ['Doe', 'Bo'],
                      ....:  'height' : [5.5, 6.0],
                      ....:  'weight' : [130, 150]})

In [33]: pd.melt(cheese, id_vars=['first', 'last'])
```

```
   first  last  variable value
0  John  Doe     height   5.5
1  Mary  Bo     height   6.0
2  John  Doe    weight  130.0
3  Mary  Bo    weight  150.0
```

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

```
   | first  last  value  
0  | John  Doe  height  5.5
    |         | weight  130.0
1  | Mary  Bo  height  6.0
    |         | weight  150.0
```

For more details and examples see the reshaping documentation.

### 30.4.4 cast

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

```
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()`:

```
In [35]: df = pd.DataFrame({
                      ....:  'x': np.random.uniform(1., 168., 12),
                      ....:  'y': np.random.uniform(7., 334., 12),
                      ....:  'z': np.random.uniform(1.7, 20.7),
                      ....:  'month': np.random.randint(5, 8),
                      ....:  'week': np.random.randint(1, 7)}
```

(continues on next page)
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 [38]: df = pd.DataFrame({
       ....:     'FeedType': ['A', 'B', 'A', 'A', 'B', 'B', 'A'],
       ....:     'Amount': [10, 7, 4, 2, 5, 6, 2],
       ....:   })

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

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

```python
```

30.4. reshape / reshape2 1291
In [40]: df.groupby(['Animal','FeedType'])['Amount'].sum()
Out[40]:
Animal  FeedType
Animal1 A  10
       B  5
Animal2 A  2
       B 13
Animal3 A  6
Name: Amount, dtype: int64

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

30.4.5 factor

pandas has a data type for categorical data.

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

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

In [41]: pd.cut(pd.Series([1,2,3,4,5,6]), 3)
Out[41]:
0 (0.995, 2.667]
1 (0.995, 2.667]
2 (2.667, 4.333]
3 (2.667, 4.333]
4 (4.333, 6.0]
5 (4.333, 6.0]
dtype: category
Categories (3, interval[float64]): [(0.995, 2.667] < (2.667, 4.333] < (4.333, 6.0]]

In [42]: pd.Series([1,2,3,2,2,3]).astype("category")
Out[42]:
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.
Since many potential pandas users have some familiarity with SQL, this page is meant to provide some examples of how various SQL operations would be performed using pandas.

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

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

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

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

```python
In [3]: url = 'https://raw.github.com/pandas-dev/pandas/master/pandas/tests/data/tips.csv'
In [4]: tips = pd.read_csv(url)
In [5]: tips.head()
```

![CSV file](https://raw.github.com/pandas-dev/pandas/master/pandas/tests/data/tips.csv)

### 31.1 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:

```python
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
Out[6]:
       total_bill  tip  smoker  time
0  16.990000  1.010 Female  Dinner
1  10.340000  1.660  Male  Dinner
2  21.010000  3.500  Male  Dinner
3  23.680000  3.310  Male  Dinner
4  24.590000  3.610 Female  Dinner
```
Calling the DataFrame without the list of column names would display all columns (akin to SQL’s *).

### 31.2 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     16.99  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
```

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]:
       True    176
      False     68
Name: time, dtype: int64
```

```python
In [10]: tips[is_dinner].head(5)
Out[10]:
     total_bill  tip    sex  smoker   day   time size
0     16.99  1.01  Female   No  Sun  Dinner   2
1     10.34  1.66    Male   No  Sun  Dinner   3
2     21.01  3.50    Male   No  Sun  Dinner   3
3     23.68  3.31    Male   No  Sun  Dinner   2
4     24.59  3.61  Female   No  Sun  Dinner   4
```

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

```sql
-- tips of more than $5.00 at Dinner meals
SELECT * 
FROM tips 
WHERE time = 'Dinner' AND tip > 5.00;
```
In [11]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
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>23</td>
<td>39.42</td>
<td>7.58</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>Dinner 4</td>
</tr>
<tr>
<td>44</td>
<td>30.40</td>
<td>5.60</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</td>
</tr>
<tr>
<td>47</td>
<td>32.40</td>
<td>6.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</td>
</tr>
<tr>
<td>52</td>
<td>34.81</td>
<td>5.20</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</td>
</tr>
<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>116</td>
<td>29.93</td>
<td>5.07</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</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>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>172</td>
<td>7.25</td>
<td>5.15</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner 2</td>
</tr>
<tr>
<td>181</td>
<td>23.33</td>
<td>5.65</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner 2</td>
</tr>
<tr>
<td>183</td>
<td>23.17</td>
<td>6.50</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner 4</td>
</tr>
<tr>
<td>211</td>
<td>25.89</td>
<td>5.16</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner 4</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>214</td>
<td>28.17</td>
<td>6.50</td>
<td>Female</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner 3</td>
</tr>
<tr>
<td>239</td>
<td>29.03</td>
<td>5.92</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>Dinner 3</td>
</tr>
</tbody>
</table>

-- tips by parties of at least 5 diners OR bill total was more than $45

SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;

In [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 5</td>
</tr>
</tbody>
</table>

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

                        'col2': ['F', np.NaN, 'G', 'H', 'I']})

In [14]: frame
Out[14]:
<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>F</td>
</tr>
<tr>
<td>B</td>
<td>NaN</td>
</tr>
<tr>
<td>NaN</td>
<td>G</td>
</tr>
<tr>
<td>C</td>
<td>H</td>
</tr>
<tr>
<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 \texttt{col2} IS NULL with the following query:

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

In [15]: frame[frame['col2'].isna()]
Out[15]:
<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Getting items where \texttt{col1} IS NOT NULL can be done with \texttt{notna()}.

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

In [16]: frame[frame['col1'].notna()]
Out[16]:
<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>F</td>
</tr>
<tr>
<td>1</td>
<td>NaN</td>
</tr>
<tr>
<td>3</td>
<td>C</td>
</tr>
<tr>
<td>4</td>
<td>D</td>
</tr>
</tbody>
</table>

### 31.3 GROUP BY

In pandas, SQL's GROUP BY operations are performed using the similarly named \texttt{groupby()} method. \texttt{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]:
<table>
<thead>
<tr>
<th>sex</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>87</td>
</tr>
<tr>
<td>Male</td>
<td>157</td>
</tr>
</tbody>
</table>
dtype: int64
```

Notice that in the pandas code we used \texttt{size()} and not \texttt{count()}. This is because \texttt{count()} applies the function to each column, returning the number of not null records within each.
Alternatively, we could have applied the `count()` method to an individual column:

```
In [19]: tips.groupby('sex')['total_bill'].count()
Out[19]:
sex    
Female 87   
Male   157  
Name: total_bill, dtype: int64
```

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

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

```
In [20]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
Out[20]:
         tip  day
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.

```
SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker day       
No   Fri   4 2.812500
         Sat 45 3.102889
         Sun 57 3.167895
         Thur 45 2.673778
Yes  Fri 15 2.714000
         Sat 42 2.875476
         Sun 19 3.516842
         Thur 17 3.030000
*/
```
In [21]: tips.groupby(['smoker', 'day']).agg({'tip': [np.size, np.mean]})
Out[21]:

<table>
<thead>
<tr>
<th>smoker</th>
<th>day</th>
<th>tip</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>size</td>
</tr>
<tr>
<td>No</td>
<td>Fri</td>
<td>4.0</td>
</tr>
<tr>
<td></td>
<td>Sat</td>
<td>45.0</td>
</tr>
<tr>
<td></td>
<td>Sun</td>
<td>57.0</td>
</tr>
<tr>
<td></td>
<td>Thur</td>
<td>45.0</td>
</tr>
<tr>
<td>Yes</td>
<td>Fri</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>Sat</td>
<td>42.0</td>
</tr>
<tr>
<td></td>
<td>Sun</td>
<td>19.0</td>
</tr>
<tr>
<td></td>
<td>Thur</td>
<td>17.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>mean</td>
</tr>
<tr>
<td>No</td>
<td>Fri</td>
<td>2.8125</td>
</tr>
<tr>
<td></td>
<td>Sat</td>
<td>3.1029</td>
</tr>
<tr>
<td></td>
<td>Sun</td>
<td>3.1679</td>
</tr>
<tr>
<td></td>
<td>Thur</td>
<td>2.6738</td>
</tr>
<tr>
<td>Yes</td>
<td>Fri</td>
<td>2.7140</td>
</tr>
<tr>
<td></td>
<td>Sat</td>
<td>2.8755</td>
</tr>
<tr>
<td></td>
<td>Sun</td>
<td>3.5168</td>
</tr>
<tr>
<td></td>
<td>Thur</td>
<td>3.0300</td>
</tr>
</tbody>
</table>

31.4 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).

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.

31.4.1 INNER JOIN

```
SELECT *
FROM df1
INNER JOIN df2
  ON df1.key = df2.key;
```

# merge performs an INNER JOIN by default
In [24]: pd.merge(df1, df2, on='key')
Out[24]:

<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-0.3182</td>
<td>0.5436</td>
</tr>
<tr>
<td>1</td>
<td>2.1699</td>
<td>-0.4261</td>
</tr>
<tr>
<td>2</td>
<td>2.1699</td>
<td>1.1381</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.

In [25]: indexed_df2 = df2.set_index('key')

In [26]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)

(continues on next page)
31.4.2 LEFT OUTER JOIN

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

```python
# 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
```

31.4.3 RIGHT JOIN

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

```python
# 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
```

31.4.4 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).

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

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

```python
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]})
    ....:
    ....:
```

```sql
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
*/
```

```python
In [32]: pd.concat([df1, df2])
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.

```sql
SELECT city, rank
FROM df1
UNION
SELECT city, rank
```
(continues on next page)
FROM df2;
-- notice that there is only one Chicago record this time
/*
<table>
<thead>
<tr>
<th>city</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>1</td>
</tr>
<tr>
<td>San Francisco</td>
<td>2</td>
</tr>
<tr>
<td>New York City</td>
<td>3</td>
</tr>
<tr>
<td>Boston</td>
<td>4</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>5</td>
</tr>
</tbody>
</table>
*/

In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

```python
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
2  Los Angeles    5
```

### 31.6 Pandas equivalents for some SQL analytic and aggregate functions

#### 31.6.1 Top N rows with offset

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

```python
In [34]: tips.nlargest(10+5, columns='tip').tail(10)
Out[34]:
     total_bill  tip    sex  smoker day      time  size
183     23.17  6.50  Male    Yes  Sun  Dinner    4
214     28.17  6.50 Female    Yes  Sat  Dinner    3
 47     32.40  6.00  Male     No  Sun  Dinner    4
239     29.03  5.92  Male     No  Sat  Dinner    3
  8     24.71  5.60  Male     No  Thur  Lunch    2
181     23.33  5.65  Male    Yes  Sun  Dinner    2
  4     30.40  5.60  Male     No  Sun  Dinner    4
  8     34.81  5.20 Female    No  Sun  Dinner    4
211     25.89  5.17  Male    Yes  Sat  Dinner    4
```

#### 31.6.2 Top N rows per group

```sql
-- Oracle's ROW_NUMBER() analytic function
SELECT * FROM
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 0.23.1

SELECT
t.*,  
ROW_NUMBER() OVER(PARTITION BY day ORDER BY total_bill DESC) AS rn  
FROM tips t  
WHERE rn < 3  
ORDER BY day, rn;

In [35]: (tips.assign(rn=tips.sort_values(["total_bill"], ascending=False)
        .groupby(["day"])
        .cumcount() + 1)
        .query('rn < 3')
        .sort_values(["day","rn"])

Out[35]:  total_bill  tip  sex  smoker  day  time  size  rn
    95  40.17  4.73  Male  Yes  Fri  Dinner  4  1
    90  28.97  3.00  Male  Yes  Fri  Dinner  2  2
   170  50.81  10.00  Male  Yes  Sat  Dinner  3  1
   212  48.33  9.00  Male  No  Sat  Dinner  4  2
   156  48.17  5.00  Male  No  Sun  Dinner  6  1
   182  45.35  3.50  Male  Yes  Sun  Dinner  3  2
   197  43.11  5.00  Female  Yes  Thur  Lunch  4  1
   142  41.19  5.00  Male  No  Thur  Lunch  5  2

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

In [36]: (tips.assign(rnk=tips.groupby(["day"])["total_bill"]
        .rank(method='first', ascending=False))
        .query('rnk < 3')
        .sort_values(["day","rnk"])

Out[36]:  total_bill  tip  sex  smoker  day  time  size  rnk
    95  40.17  4.73  Male  Yes  Fri  Dinner  4  1.0
    90  28.97  3.00  Male  Yes  Fri  Dinner  2  2.0
   170  50.81  10.00  Male  Yes  Sat  Dinner  3  1.0
   212  48.33  9.00  Male  No  Sat  Dinner  4  2.0
   156  48.17  5.00  Male  No  Sun  Dinner  6  1.0
   182  45.35  3.50  Male  Yes  Sun  Dinner  3  2.0
   197  43.11  5.00  Female  Yes  Thur  Lunch  4  1.0
   142  41.19  5.00  Male  No  Thur  Lunch  5  2.0

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

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

\begin{verbatim}
In [37]: (tips[tips['tip'] < 2]  
....: .assign(rnk_min=tips.groupby(['sex'])['tip']  
....: .rank(method='min'))  
....: .query('rnk_min < 3')  
....: .sort_values(['sex','rnk_min'])  
....: )

Out[37]:
   total_bill  tip  sex  smoker  day  time  size  rnk_min
 0     67.00  3.07 Female   Yes  Sat  Dinner   1   1.0
 1     92.00  5.75 Female   Yes  Fri  Dinner   2   1.0
 2    111.00  7.25 Female      No  Sat  Dinner   1   1.0
 3    236.00 12.60   Male   Yes  Sat  Dinner   2   1.0
 4    237.00 32.83   Male   Yes  Sat  Dinner   2   2.0
\end{verbatim}

### 31.7 UPDATE

\texttt{UPDATE tips}  
\texttt{SET tip = tip*2}  
\texttt{WHERE tip < 2;}

\begin{verbatim}
In [38]: tips.loc[tips['tip'] < 2, 'tip'] *= 2
\end{verbatim}

### 31.8 DELETE

\texttt{DELETE FROM tips}  
\texttt{WHERE tip > 9;}

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

\begin{verbatim}
In [39]: tips = tips.loc[tips['tip'] <= 9]
\end{verbatim}
COMPARISON WITH SAS

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

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

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

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

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

```
proc print data=df(obs=5);
run;
```

### 32.1 Data Structures

#### 32.1.1 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>

#### 32.1.2 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.

### 32.1.3 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 rows are essentially unlabeled, other than an implicit integer index that can be accessed during the `DATA` step (`_N_`).

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

### 32.2 Data Input / Output

#### 32.2.1 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]})
```

```text
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```

#### 32.2.2 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.
The pandas method is `read_csv()`, which works similarly.

```
In [5]: url = 'https://raw.githubusercontent.com/pandas-dev/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     16.990  1.010 Female     No  Sun    Dinner  2
   1     10.340  1.660  Male     No  Sun    Dinner  3
   2     21.000  3.500  Male     No  Sun    Dinner  3
   3     23.680  3.310  Male     No  Sun    Dinner  2
   4     24.590  3.610 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.

### 32.2.3 Exporting Data

The inverse of PROC IMPORT in SAS is PROC EXPORT

```
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.

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

### 32.3 Data Operations

#### 32.3.1 Operations on Columns

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

```
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.

In [8]: tips['total_bill'] = tips['total_bill'] - 2

In [9]: tips['new_bill'] = tips['total_bill'] / 2.0

In [10]: tips.head()

Out[10]:
   total_bill  tip    sex  smoker  day     time  size  new_bill
0       14.99  1.01 Female No  Sun  Dinner     2  7.495
1        8.34  1.66  Male  No  Sun  Dinner     3  4.170
2       19.01  3.50  Male  No  Sun  Dinner     3  9.505
3       21.68  3.31  Male  No  Sun  Dinner     2 10.840
4       22.59  3.61 Female  No  Sun  Dinner     4 11.295

32.3.2 Filtering

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

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

data tips;
   set tips;
   where total_bill > 10;
   /* equivalent in this case - where happens before the
   DATA step begins and can also be used in PROC statements */
run;

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

In [11]: tips[tips['total_bill'] > 10].head()

Out[11]:
   total_bill  tip    sex  smoker  day     time  size
0       14.99  1.01 Female No  Sun  Dinner     2
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

32.3.3 If/Then Logic

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

data tips;
   set tips;
   format bucket $4.;
   if total_bill < 10 then bucket = 'low';
   else bucket = 'high';
run;
The same operation in pandas can be accomplished using the `where` method from `numpy`.

```
In [12]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')

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

### 32.3.4 Date Functionality

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

```
data tips;
   set tips;
   format date1 date2 date1_plusmonth mmdy1y10.;
   date1 = mdy(1, 15, 2013);
   date2 = mdy(2, 15, 2015);
   date1_year = year(date1);
   date2_month = month(date2);
   * shift date to beginning of next interval;
   date1_next = intnx('MONTH', date1, 1);
   * count intervals between dates;
   months_between = intck('MONTH', date1, date2);
run;

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

```
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()
```

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32.3.5 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   14.9900  1.01
1   Male     8.3400  1.66
2   Male    19.0100  3.50
3   Male    21.6800  3.31
4  Female    22.5900  3.61

# drop
In [22]: tips.drop('sex', axis=1).head()
  →
       total_bill  tip smoker  day  time  size
0  14.9900  1.01   No  Sun  Dinner  2
1   8.3400  1.66   No  Sun  Dinner  3
2  19.0100  3.50   No  Sun  Dinner  3
3  21.6800  3.31   No  Sun  Dinner  2
4  22.5900  3.61   No  Sun  Dinner  4

# rename
In [23]: tips.rename(columns={'total_bill':'total_bill_2'}).head()
  →
       total_bill_2  tip  sex  smoker  day  time  size
0  14.9900  1.01   Female   No  Sun  Dinner  2
1   8.3400  1.66    Male   No  Sun  Dinner  3
2  19.0100  3.50    Male   No  Sun  Dinner  3
3  21.6800  3.31    Male   No  Sun  Dinner  2
4  22.5900  3.61   Female   No  Sun  Dinner  4
```
32.3.6 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.

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

```
In [25]: tips.head()
Out[25]:
```

<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>67</td>
<td>1.07</td>
<td>Female</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</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>
</tr>
<tr>
<td>111</td>
<td>5.25</td>
<td>Female</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</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>
</tr>
<tr>
<td>135</td>
<td>6.51</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
</tr>
</tbody>
</table>

32.4 String Processing

32.4.1 Length

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

```sas
data _null_;  
set tips;  
put (LENGTHN(time));  
put (LENGTHC(time));  
run;
```

Python determines the length of a character string with the `len` function. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [26]: tips['time'].str.len().head()
Out[26]:
```

```
67 6
92 6
111 6
145 5
135 5
Name: time, dtype: int64
```

```
In [27]: tips['time'].str.rstrip().str.len().head()
```

```
67 6
92 6
111 6
145 5
135 5
Name: time, dtype: int64
```
32.4.2 Find

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

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

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

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

32.4.3 Substring

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

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

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

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

32.4.4 Scan

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

```plaintext
data firstlast;  
input String $60.;  
First_Name = scan(string, 1);  
Last_Name = scan(string, -1);  
datalines2;
```
Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [30]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})
In [31]: firstlast['First_Name'] = firstlast['String'].str.split(" ", expand=True)[0]
In [32]: firstlast['Last_Name'] = firstlast['String'].str.rsplit(" ", expand=True)[0]
In [33]: firstlast
Out[33]:
<table>
<thead>
<tr>
<th>String</th>
<th>First_Name</th>
<th>Last_Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>John Smith</td>
<td>John</td>
<td>John</td>
</tr>
<tr>
<td>Jane Cook</td>
<td>Jane</td>
<td>Jane</td>
</tr>
</tbody>
</table>
```

### 32.4.5 Upcase, Lowcase, and Propcase

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

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

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

```
In [34]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})
In [35]: firstlast['string_up'] = firstlast['String'].str.upper()
In [36]: firstlast['string_low'] = firstlast['String'].str.lower()
In [37]: firstlast['string_prop'] = firstlast['String'].str.title()
In [38]: firstlast
Out[38]:
<table>
<thead>
<tr>
<th>String</th>
<th>string_up</th>
<th>string_low</th>
<th>string_prop</th>
</tr>
</thead>
<tbody>
<tr>
<td>John Smith</td>
<td>JOHN SMITH</td>
<td>john smith</td>
<td>John Smith</td>
</tr>
<tr>
<td>Jane Cook</td>
<td>JANE COOK</td>
<td>jane cook</td>
<td>Jane Cook</td>
</tr>
</tbody>
</table>
```

32.4. String Processing
32.5 Merging

The following tables will be used in the merge examples

```
In [39]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                         'value': np.random.randn(4)})

In [40]: df1
Out[40]:
   key   value
0   A  -0.857326
1   B   1.075416
2   C   0.371727
3   D   1.065735

In [41]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                         'value': np.random.randn(4)})

In [42]: df2
Out[42]:
   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.

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

In [44]: inner_join
Out[44]:
   key   value_x  value_y
0   B   1.075416 -0.227314
```
1  D  1.065735  2.102726
2  D  1.065735 -0.092796

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

In [46]: left_join
Out[46]:
    key  value_x  value_y
0    A    -0.857326  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 [47]: right_join = df1.merge(df2, on=['key'], how='right')

In [48]: right_join
Out[48]:
    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 [49]: outer_join = df1.merge(df2, on=['key'], how='outer')

In [50]: outer_join
Out[50]:
    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

32.6 Missing Data

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

In [51]: outer_join
Out[51]:
    key  value_x  value_y
0    A    -0.857326  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 [52]: outer_join['value_x'] + outer_join['value_y']
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.

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

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

Which doesn't work in pandas. Instead, the `pd.isna` or `pd.notna` functions should be used for comparisons.

```python
In [54]: outer_join[pd.isna(outer_join['value_x'])]
Out[54]:
   key  value_x  value_y
5    E        NaN   0.094694

In [55]: outer_join[pd.notna(outer_join['value_x'])]
   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
```

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.

```python
In [56]: outer_join.dropna()
Out[56]:
   key  value_x  value_y
1    B   1.075416 -0.227314
3    D  1.065735  2.102726
4    D  1.065735 -0.092796

In [57]: outer_join.fillna(method='ffill')
   key  value_x  value_y
    →
```

(continues on next page)
In [58]: outer_join['value_x'].fillna(outer_join['value_x'].mean())

0 -0.857326
1  1.075416
2  0.371727
3  1.065735
4  1.065735
5  0.544257
Name: value_x, dtype: float64

32.7 GroupBy

32.7.1 Aggregation

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

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

32.7.2 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.
pandas: powerful Python data analysis toolkit, Release 0.23.1

```plaintext
proc summary data=tips missing nway;
   class smoker;
   var total_bill;
   output out=smoker_means mean(total_bill)=group_bill;
run;

proc sort data=tips;
   by smoker;
run;

data tips;
   merge tips(in=a) smoker_means(in=b);
   by smoker;
   adj_total_bill = total_bill - group_bill;
   if a and b;
run;
```

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

In [61]: gb = tips.groupby('smoker')['total_bill']

In [62]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')

In [63]: tips.head()
Out[63]:
<table>
<thead>
<tr>
<th></th>
<th></th>
<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>67</td>
<td>1.07</td>
<td>Female</td>
<td>Yes</td>
<td>1.00</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-17.686344</td>
<td></td>
</tr>
<tr>
<td>92</td>
<td>3.75</td>
<td>Female</td>
<td>Yes</td>
<td>1.00</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
<td>-15.006344</td>
<td></td>
</tr>
<tr>
<td>111</td>
<td>5.25</td>
<td>Female</td>
<td>No</td>
<td>1.00</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-11.938278</td>
<td></td>
</tr>
<tr>
<td>145</td>
<td>6.35</td>
<td>Female</td>
<td>No</td>
<td>1.50</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
<td>-10.838278</td>
<td></td>
</tr>
<tr>
<td>135</td>
<td>6.51</td>
<td>Female</td>
<td>No</td>
<td>1.25</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
<td>-10.678278</td>
<td></td>
</tr>
</tbody>
</table>
```

32.7.3 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.

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

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

In pandas this would be written as:

In [64]: tips.groupby(['sex','smoker']).first()
Out[64]:
<table>
<thead>
<tr>
<th></th>
<th></th>
<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></td>
<td></td>
<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>
</tbody>
</table>
```

(continues on next page)
32.8 Other Considerations

32.8.1 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

32.8.2 Data Interop

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

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

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

```python
df = pd.read_sas('transport-file.xpt', format='xport')
df = pd.read_sas('binary-file.sas7bdat', format='sas7bdat')
```

XPORT is a relatively limited format and the parsing of it is not as optimized as some of the other pandas readers. An alternative way to interop data between SAS and pandas is to serialize to csv.

```python
# 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
```
COMPARISON WITH STATA

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

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

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

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

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

```stata
list in 1/5
```

### 33.1 Data Structures

#### 33.1.1 General Terminology Translation

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

#### 33.1.2 DataFrame / Series

A DataFrame in pandas is analogous to a Stata data set – a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set in Stata can also be accomplished in pandas.
A Series is the data structure that represents one column of a DataFrame. Stata doesn’t have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column of a data set in Stata.

### 33.1.3 Index

Every DataFrame and Series has an Index – labels on the rows of the data. Stata does not have an exactly analogous concept. In Stata, a data set’s rows are essentially unlabeled, other than an implicit integer index that can be accessed with _n.

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

### 33.2 Data Input / Output

#### 33.2.1 Constructing a DataFrame from Values

A Stata data set can be built from specified values by placing the data after an input statement and specifying the column names.

```plaintext
input x y
1 2
3 4
5 6
end
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```python
In [3]: df = pd.DataFrame({
    ...:     'x': [1, 3, 5],
    ...:     'y': [2, 4, 6])
```

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

#### 33.2.2 Reading External Data

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

Stata provides import delimited to read csv data into a data set in memory. If the tips.csv file is in the current working directory, we can import it as follows.

```python
import delimited tips.csv
```
The pandas method is `read_csv()`, which works similarly. Additionally, it will automatically download the data set if presented with a url.

```python
In [5]: url = 'https://raw.github.com/pandas-dev/pandas/master/pandas/tests/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 `import delimited`, `read_csv()` can take a number of parameters to specify how the data should be parsed. For example, if the data were instead tab delimited, did not have column names, and existed in the current working directory, the pandas command would be:

```python
tips = pd.read_csv('tips.csv', sep='\t', header=None)
# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)
```

Pandas can also read Stata data sets in .dta format with the `read_stata()` function.

```python
df = pd.read_stata('data.dta')
```

In addition to text/csv and Stata files, pandas supports a variety of other data formats such as Excel, SAS, HDF5, Parquet, and SQL databases. These are all read via a `pd.read_*` function. See the IO documentation for more details.

### 33.2.3 Exporting Data

The inverse of `import delimited` in Stata is `export delimited`

```python
export delimited tips2.csv
```

Similarly in pandas, the opposite of `read_csv` is `DataFrame.to_csv()`.

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

Pandas can also export to Stata file format with the `DataFrame.to_stata()` method.

```python
tips.to_stata('tips2.dta')
```

### 33.3 Data Operations

#### 33.3.1 Operations on Columns

In Stata, arbitrary math expressions can be used with the `generate` and `replace` commands on new or existing columns. The `drop` command drops the column from the data set.
replace total_bill = total_bill - 2
generate new_bill = total_bill / 2
drop new_bill

pandas provides similar vectorized operations by specifying the individual Series in the DataFrame. New columns can be assigned in the same way. The DataFrame.drop() method drops a column from the DataFrame.

```python
In [8]: tips['total_bill'] = tips['total_bill'] - 2
In [9]: tips['new_bill'] = tips['total_bill'] / 2
In [10]: tips.head()
Out[10]:
   total_bill  tip     sex  smoker  day     time  size  new_bill
0       14.99  1.01  Female    No  Sun   Dinner    2   7.495
1       8.34  1.66    Male    No  Sun   Dinner    3   4.170
2      19.01  3.50    Male    No  Sun   Dinner    3   9.505
3      21.68  3.31    Male    No  Sun   Dinner    2  10.840
4      22.59  3.61  Female    No  Sun   Dinner    4  11.295
```

### 33.3.2 Filtering

Filtering in Stata is done with an if clause on one or more columns.

```stata
list if total_bill > 10
```

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

```python
In [12]: tips[tips['total_bill'] > 10].head()
Out[12]:
   total_bill  tip     sex  smoker  day     time  size
0       14.99  1.01  Female    No  Sun   Dinner    2
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
```

### 33.3.3 If/Then Logic

In Stata, an if clause can also be used to create new columns.

```bash
generate bucket = "low" if total_bill < 10
replace bucket = "high" if total_bill >= 10
```

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

```python
In [13]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')
In [14]: tips.head()
Out[14]:
   total_bill  tip     sex  smoker  day     time  size  bucket
0       14.99  1.01  Female    No  Sun   Dinner    2   high
```

(continues on next page)
### 33.3.4 Date Functionality

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

```stata
generate date1 = mdy(1, 15, 2013)
generate date2 = date("Feb152015", "MDY")
generate date1_year = year(date1)
generate date2_month = month(date2)

* shift date to beginning of next month
generate date1_next = mdy(month(date1) + 1, 1, year(date1)) if month(date1) != 12
replace date1_next = mdy(1, 1, year(date1) + 1) if month(date1) == 12
generate months_between = mofd(date2) - mofd(date1)
```

The equivalent pandas operations are shown below. In addition to these functions, pandas supports other Time Series features not available in Stata (such as time zone handling and custom offsets) – see the timeseries documentation for more details.

```python
In [15]: tips['date1'] = pd.Timestamp('2013-01-15')
In [16]: tips['date2'] = pd.Timestamp('2015-02-15')
In [17]: tips['date1_year'] = tips['date1'].dt.year
In [18]: tips['date2_month'] = tips['date2'].dt.month
In [19]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()
In [20]: tips['months_between'] = (tips['date2'].dt.to_period('M') -
                          tips['date1'].dt.to_period('M'))
In [21]: tips[['date1','date2','date1_year','date2_month',
                      'date1_next','months_between']].head()
```

### 33.3.5 Selection of Columns

Stata provides keywords to select, drop, and rename columns.
The same operations are expressed in pandas below. Note that in contrast to Stata, these operations do not happen in place. To make these changes persist, assign the operation back to a variable.

```python
# keep
In [22]: tips[['sex', 'total_bill', 'tip']].head()
Out[22]:
   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 [23]: tips.drop('sex', axis=1).head()
   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 [24]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
   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 Stata is accomplished via `sort`:

```stata
sort sex total_bill
```

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

```python
In [25]: tips = tips.sort_values(['sex', 'total_bill'])
In [26]: tips.head()
Out[26]:
   total_bill  tip  sex  smoker  day  time  size
0      1.07  1.00 Female    Yes   Sat  Dinner  1
... (continues on next page)
33.4 String Processing

33.4.1 Finding Length of String

Stata determines the length of a character string with the `strlen()` and `ustrlen()` functions for ASCII and Unicode strings, respectively.

```
generate strlen_time = strlen(time)
generate ustrlen_time = ustrlen(time)
```

Python determines the length of a character string with the `len` function. In Python 3, all strings are Unicode strings. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

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

In [28]: tips['time'].str.rstrip().str.len().head()
...
       67   6
       92   6
      111  6
      145  5
      135  5
Name: time, dtype: int64
```

33.4.2 Finding Position of Substring

Stata determines the position of a character in a string with the `strpos()` function. This takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
generate str_position = strpos(sex, "ale")
```

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

```
In [29]: tips['sex'].str.find("ale").head()
Out[29]:
       67   3
```
33.4.3 Extracting Substring by Position

Stata extracts a substring from a string based on its position with the `substr()` function.

```
generate short_sex = substr(sex, 1, 1)
```

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

```
In [30]: tips['sex'].str[:1].head()
Out[30]:
   67   F
   92   F
  111   F
  145   F
  135   F
Name: sex, dtype: object
```

33.4.4 Extracting nth Word

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

```
clear
input str20 string
"John Smith"
"Jane Cook"
end
generate first_name = word(name, 1)
generate last_name = word(name, -1)
```

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

```
In [31]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})
In [32]: firstlast['First_Name'] = firstlast['string'].str.split(' ', expand=True)[0]
In [33]: firstlast['Last_Name'] = firstlast['string'].str.rsplit(' ', expand=True)[0]
In [34]: firstlast
Out[34]:
     string  First_Name  Last_Name
   0  John Smith       John      John
   1   Jane Cook       Jane      Jane
```
### 33.4.5 Changing Case

The Stata `strupper()`, `strlower()`, `strproper()`, `ustrupper()`, `ustrlower()`, and `ustrtitle()` functions change the case of ASCII and Unicode strings, respectively.

```stata
clear
input str20 string
"John Smith"
"Jane Cook"
end
generate upper = strupper(string)
generate lower = strlower(string)
generate title = strproper(string)
list
```

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

```python
In [35]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})
In [36]: firstlast['upper'] = firstlast['string'].str.upper()
In [37]: firstlast['lower'] = firstlast['string'].str.lower()
In [38]: firstlast['title'] = firstlast['string'].str.title()
In [39]: firstlast
Out[39]:
    string   upper      lower      title
   0 John Smith  JOHN SMITH  john smith  John Smith
   1 Jane Cook   JANE COOK  jane cook   Jane Cook
```

### 33.5 Merging

The following tables will be used in the merge examples

```python
In [40]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                         'value': np.random.randn(4)})
In [41]: df1
Out[41]:
    key    value
   0   A  0.885906
   1   B  0.794848
   2   C -0.943848
   3   D  0.328609
In [42]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                         'value': np.random.randn(4)})
In [43]: df2
Out[43]:
    key    value
   0   B -0.943848
   1   D  0.328609
   2   D  0.328609
   3   E  1.142475
```

(continues on next page)
In Stata, to perform a merge, one data set must be in memory and the other must be referenced as a file name on disk. In contrast, Python must have both DataFrames already in memory.

By default, Stata performs an outer join, where all observations from both data sets are left in memory after the merge. One can keep only observations from the initial data set, the merged data set, or the intersection of the two by using the values created in the _merge variable.

```stata
* First create df2 and save to disk
clear
input str1 key
B
D
D
E
derend
generate value = rnormal()
save df2.dta

* Now create df1 in memory
clear
input str1 key
A
B
C
D
derend
generate value = rnormal()

preserve
  * Left join
  merge 1:n key using df2.dta
  keep if _merge == 1
  * Right join
  restore, preserve
  merge 1:n key using df2.dta
  keep if _merge == 2
  * Inner join
  restore, preserve
  merge 1:n key using df2.dta
  keep if _merge == 3
  * Outer join
  restore
  merge 1:n key using df2.dta
```

pandas DataFrames have a `DataFrame.merge()` method, which provides similar functionality. Note that different join types are accomplished via the `how` keyword.
33.6 Missing Data

Like Stata, pandas has a representation for missing data – the special float value NaN (not a number). Many of the semantics are the same; for example missing data propagates through numeric operations, and is ignored by default for aggregations.
One difference is that missing data cannot be compared to its sentinel value. For example, in Stata you could do this to filter missing values.

```python
* Keep missing values
list if value_x == .
* Keep non-missing values
list if value_x != .
```

This doesn’t work in pandas. Instead, the `pd.isna()` or `pd.notna()` functions should be used for comparisons.

```python
In [55]: outer_join[pd.isna(outer_join['value_x'])]
Out[55]:
   key  value_x  value_y
5  E          NaN  0.283297

In [56]: outer_join[pd.notna(outer_join['value_x'])]
Out[56]:
   key  value_x  value_y
0  A   0.885906      NaN
1  B   0.794848 -1.634931
2  C -0.943848      NaN
3  D   0.328609  2.197567
4  D   0.328609  0.054695
```

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

```python
# Drop rows with any missing value
In [57]: outer_join.dropna()
Out[57]:
   key  value_x  value_y
1  B   0.794848 -1.634931
3  D   0.328609  2.197567
4  D   0.328609  0.054695

# Fill forwards
In [58]: outer_join.fillna(method='ffill')
```

(continues on next page)
Out[58]:

<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.885906</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>0.794848</td>
<td>-1.634931</td>
</tr>
<tr>
<td>2</td>
<td>-0.943848</td>
<td>-1.634931</td>
</tr>
<tr>
<td>3</td>
<td>0.328609</td>
<td>2.197567</td>
</tr>
<tr>
<td>4</td>
<td>0.328609</td>
<td>0.054695</td>
</tr>
<tr>
<td>5</td>
<td>0.328609</td>
<td>0.283297</td>
</tr>
</tbody>
</table>

# Impute missing values with the mean

In [59]: outer_join['value_x'].fillna(outer_join['value_x'].mean())

Out[59]:

<table>
<thead>
<tr>
<th></th>
<th>value_x</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.885906</td>
</tr>
<tr>
<td>1</td>
<td>0.794848</td>
</tr>
<tr>
<td>2</td>
<td>-0.943848</td>
</tr>
<tr>
<td>3</td>
<td>0.328609</td>
</tr>
<tr>
<td>4</td>
<td>0.328609</td>
</tr>
<tr>
<td>5</td>
<td>0.278825</td>
</tr>
</tbody>
</table>

Name: value_x, dtype: float64

33.7 GroupBy

33.7.1 Aggregation

Stata’s `collapse` can be used to group by one or more key variables and compute aggregations on numeric columns.

```
collapse (sum) total_bill tip, by(sex smoker)
```

pandas provides a flexible `groupby` mechanism that allows similar aggregations. See the `groupby documentation` for more details and examples.

In [60]: tips_summed = tips.groupby(['sex', 'smoker'])['total_bill', 'tip'].sum()

In [61]: tips_summed.head()

Out[61]:

<table>
<thead>
<tr>
<th>sex</th>
<th>smoker</th>
<th>total_bill</th>
<th>tip</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>No</td>
<td>869.68</td>
<td>149.77</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>527.27</td>
<td>96.74</td>
</tr>
<tr>
<td>Male</td>
<td>No</td>
<td>1725.75</td>
<td>302.00</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1217.07</td>
<td>183.07</td>
</tr>
</tbody>
</table>

33.7.2 Transformation

In Stata, if the group aggregations need to be used with the original data set, one would usually use `bysort` with `egen()`. For example, to subtract the mean for each observation by smoker group.

```
bysort sex smoker: egen group_bill = mean(total_bill) 
generate adj_total_bill = total_bill - group_bill
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

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

```
In [62]: gb = tips.groupby('smoker')['total_bill']

In [63]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')

In [64]: tips.head()
Out[64]:
   total_bill  tip   sex   smoker  day   time   size  adj_total_bill
67     1.07   1.00  Female   Yes  Sat  Dinner  1   -17.686344
92     3.75   1.00  Female   Yes  Fri  Dinner  2   -15.006344
111    5.25   1.00  Female   No  Sat  Dinner  1   -11.938278
145    6.35   1.50  Female   No  Thur  Lunch  2   -10.838278
135    6.51   1.25  Female   No  Thur  Lunch  2   -10.678278
```

33.7.3 By Group Processing

In addition to aggregation, pandas groupby can be used to replicate most other bysort processing from Stata. For example, the following example lists the first observation in the current sort order by sex/smoker group.

```
bysort sex smoker: list if _n == 1
```

In pandas this would be written as:

```
In [65]: tips.groupby(['sex','smoker']).first()
Out[65]:
       total_bill  tip   sex   smoker  day   time   size  adj_total_bill
sex  smoker     
Female   No      5.25   1.00  Sat  Dinner  1   -11.938278
        Yes     1.07   1.00  Sat  Dinner  1   -17.686344
Male   No       5.51   2.00  Thur  Lunch  2   -11.678278
        Yes     5.25   1.15  Sun  Dinner  2   -13.506344
```

33.8 Other Considerations

33.8.1 Disk vs Memory

Pandas and Stata both operate exclusively in memory. This means that the size of data able to be loaded in pandas is limited by your machine’s memory. If out of core processing is needed, one possibility is the dask.dataframe library, which provides a subset of pandas functionality for an on-disk DataFrame.
This page gives an overview of all public pandas objects, functions and methods. All classes and functions exposed in pandas.* namespace are public.

Some subpackages are public which include pandas.errors, pandas.plotting, and pandas.testing. Public functions in pandas.io and pandas.tseries submodules are mentioned in the documentation. pandas.api.types subpackage holds some public functions related to data types in pandas.

**Warning:** The pandas.core, pandas.compat, and pandas.util top-level modules are PRIVATE. Stable functionality in such modules is not guaranteed.

### 34.1 Input/Output

#### 34.1.1 Pickling

**read_pickle**(path[, compression])

Load pickled pandas object (or any object) from file.

**34.1.1.1 pandas.read_pickle**

pandas.read_pickle *(path, compression='infer')*

Load pickled pandas object (or any object) from file.

**Warning:** Loading pickled data received from untrusted sources can be unsafe. See here.

**Parameters**

- **path** : str
  
  File path where the pickled object will be loaded.

- **compression** : {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default ‘infer’
  
  For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip, bz2, xz or zip if path ends in `.gz`, `.bz2`, `.xz`, or `.zip` respectively, and no decompression otherwise. Set to None for no decompression.

  New in version 0.20.0.

**Returns**

- **unpickled** [type of object stored in file]
See also:

**DataFrame.to_pickle**  Pickle (serialize) DataFrame object to file.

**Series.to_pickle**  Pickle (serialize) Series object to file.

**read_hdf**  Read HDF5 file into a DataFrame.

**read_sql**  Read SQL query or database table into a DataFrame.

**read_parquet**  Load a parquet object, returning a DataFrame.

Examples

```python
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9
```

```python
>>> pd.to_pickle(original_df, ".\dummy.pkl")
```

```python
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9
```

```python
>>> import os
>>> os.remove("./dummy.pkl")
```

34.1.2 Flat File

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>read_table(filepath_or_buffer[, sep,...])</code></td>
<td>Read general delimited file into DataFrame</td>
</tr>
<tr>
<td><code>read_csv(filepath_or_buffer[, sep,...])</code></td>
<td>Read CSV (comma-separated) file into DataFrame</td>
</tr>
<tr>
<td><code>read_fwf(filepath_or_buffer[, colspecs, widths])</code></td>
<td>Read a table of fixed-width formatted lines into DataFrame</td>
</tr>
<tr>
<td><code>read_msgpack(path_or_buf[, encoding, iterator])</code></td>
<td>Load msgpack pandas object from the specified file path</td>
</tr>
</tbody>
</table>
34.1.2.1 pandas.read_table

```python
pandas.read_table(filepath_or_buffer, sep='\t', delimiter=None, header='infer', names=None, index_col=None, usecols=None, squeeze=False, prefix=None, mangle_dupe_cols=True, dtype=None, engine=None, converters=None, true_values=None, false_values=None, skipinitialspace=False, skiprows=None, nrows=None, na_values=None, keep_default_na=True, na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=False, infer_datetime_format=False, keep_date_col=False, date_parser=None, dayfirst=False, iterator=False, chunksize=None, compression='infer', thousands=None, decimal='.', lineterminator=None, quoting=0, escapechar=None, comment=None, encoding=None, dialect=None, tupleize_cols=None, error_bad_lines=True, warn_bad_lines=True, skipfooter=0, doublequote=True, delim_whitespace=False, low_memory=True, memory_map=False, float_precision=None)
```

Read general delimited file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

**Parameters**

- `filepath_or_buffer` [str, pathlib.Path, py._path.local.LocalPath or any \]
  - object with a read() method (such as a file handle or 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` : str, default t (tab-stop)
  - Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from `\s+` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `'\t\t'`

- `delimiter` : str, default None
  - Alternative argument name for sep

- `delim_whitespace` : boolean, default False

  Specifies whether or not whitespace (e.g. `' '` or `'\t'`) will be used as the sep. Equivalent to setting `sep='\s+'`. If this option is set to True, nothing should be passed in for the delimiter parameter.

  New in version 0.18.1: support for the Python parser.

- `header` : int or list of ints, default ‘infer’

  Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. `[0,1,3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if
skip_blank_lines=True, so header=0 denotes the first line of data rather than
the first line of the file.

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly
pass header=None. Duplicates in this list will cause a UserWarning to be issued.

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)

usecols : list-like or callable, default None

Return a subset of the columns. If list-like, all elements must either be positional
(i.e. integer indices into the document columns) or strings that correspond to col-
umn names provided either by the user in names or inferred from the document
header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2]
or ['foo', 'bar', 'baz']. Element order is ignored, so usecols=[0, 1] is the
same as [1, 0]. To instantiate a DataFrame from data with element order pre-
served use pd.read_csv(data, usecols=['foo', 'bar'])[['foo',
'bar']] for columns in ['foo', 'bar'] order or pd.read_csv(data,
usecols=['foo', 'bar'])[['bar', 'foo']] for ['bar', 'foo'] or-
der.

If callable, the callable function will be evaluated against the column names, returning
names where the callable function evaluates to True. An example of a valid callable ar-
gument would be lambda x: x.upper() in ['AAA', 'BBB', 'DDD'].
Using this parameter results in much faster parsing time and lower memory usage.

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

prefix : str, default None

Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, …

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as ‘X’, ‘X.1’, … ‘X.N’, rather than ‘X’… ‘X’. Pass-
ing in False will cause data to be overwritten if there are duplicate names in the columns.

dtype : Type name or dict of column -> type, default None

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} Use str or object to-
gether with suitable na_values settings to preserve and not interpret dtype. If converters
are specified, they will be applied INSTEAD of dtype conversion.

engine : {'c', 'python'}, optional

Parser engine to use. The C engine is faster while the python engine is currently more
feature-complete.

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers
or column labels

true_values : list, default None
Values to consider as True

**false_values** : list, default None

Values to consider as False

**skipinitialspace** : boolean, default False

Skip spaces after delimiter.

**skiprows** : list-like or integer or callable, default None

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

**skipfooter** : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

**nrows** : int, default None

Number of rows of file to read. Useful for reading pieces of large files

**na_values** : scalar, str, list-like, or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep_default_na** : bool, default True

Whether or not to include the default NaN values when parsing the data. Depending on whether na_values is passed in, the behavior is as follows:

- If keep_default_na is True, and na_values are specified, na_values is appended to the default NaN values used for parsing.
- If keep_default_na is True, and na_values are not specified, only the default NaN values are used for parsing.
- If keep_default_na is False, and na_values are specified, only the NaN values specified na_values are used for parsing.
- If keep_default_na is False, and na_values are not specified, no strings will be parsed as NaN.

Note that if na_filter is passed in as False, the keep_default_na and na_values parameters will be ignored.

**na_filter** : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**skip_blank_lines** : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values
**parse_dates**: boolean or list of ints or names or list of lists or dict, default False

- boolean. If True -> try parsing the index.
- list of ints or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`.

Note: A fast-path exists for iso8601-formatted dates.

**infer_datetime_format**: boolean, default False

If True and `parse_dates` is enabled, pandas will attempt to infer the format of the date-time strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

**keep_date_col**: 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

**iterator**: boolean, default False

Return `TextFileReader` object for iteration or getting chunks with `get_chunk()`.

**chunksize**: int, default None

Return `TextFileReader` object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

**compression**: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default ‘infer’

For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.18.1: support for ‘zip’ and ‘xz’ compression.

**thousands**: str, default None

Thousands separator

**decimal**: str, default ‘.’
Character to recognize as decimal point (e.g. use ',' for European data).

float_precision : string, default None

Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, high for the high-precision converter, and round_trip for the round-trip converter.

lineterminator : str (length 1), default None

Character to break file into lines. Only valid with C parser.

quotechar : str (length 1), optional

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default 0

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote : boolean, default True

When quotechar is specified and quoting is not QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

escapechar : str (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

calendar : 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 calendar='#', parsing #empty
a,b,c
1,2,3 with header=0 will result in 'a,b,c' being treated as the header.

encoding : str, default None

Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings

dialect : str or csv.Dialect instance, default None

If provided, this parameter will override values (default or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace, quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

tupleize_cols : boolean, default False

Deprecated since version 0.21.0: This argument will be removed and will always convert to MultiIndex

Leave a list of tuples on columns as is (default is to convert to a MultiIndex 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.

**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.

**low_memory**: boolean, default True

Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the `dtype` parameter. Note that the entire file is read into a single DataFrame regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser)

**memory_map**: boolean, default False

If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

**Returns**

result [DataFrame or TextParser]

### 34.1.2.2 pandas.read_csv

`pandas.read_csv` *(filepath_or_buffer, sep=', ', delimiter=None, header='infer', names=None, index_col=None, usecols=None, squeeze=False, prefix=None, mangle_dupe_cols=True, skipinitialspace=False, skiprows=None, nrows=None, na_values=None, keep_default_na=True, na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=False, infer_datetime_format=False, keep_date_col=False, date_parser=None, dayfirst=False, iterator=False, chunksize=None, compression='infer', thousands=None, decimal=’, ‘, lineterminator=None, quotechar=None, quoting=0, escapechar=None, comment=None, encoding=None, dialect=None, tupleize_cols=None, error_bad_lines=True, warn_bad_lines=True, skipfooter=0, doublequote=True, delim_whitespace=False, low_memory=True, memory_map=False, float_precision=None)*

Read CSV (comma-separated) file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the [online docs for IO Tools](https://pandas.pydata.org/pandas-docs/stable/io.html).

**Parameters**

- **filepath_or_buffer** [str, pathlib.Path, py._path.local.LocalPath or any \]

  object with a `read()` method (such as a file handle or 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**: str, default ‘,’

  Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically
detect the separator by Python’s builtin sniffer tool, csv.Sniffer. In addition, separators longer than 1 character and different from '\s+' will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\r\t'

delimiter : str, default None

Alternative argument name for sep.

delim_whitespace : boolean, default False

Specifies whether or not whitespace (e.g. ' ' or '\t') will be used as the sep. Equivalent to setting sep='\s+'. If this option is set to True, nothing should be passed in for the delimiter parameter.

New in version 0.18.1: support for the Python parser.

header : int or list of ints, default 'infer'

Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly pass header=None. Duplicates in this list will cause a UserWarning to be issued.

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)

usecols : list-like or callable, default None

Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2] or ['foo', 'bar', 'baz']. Element order is ignored, so usecols=[0, 1] is the same as [1, 0]. To instantiate a DataFrame from data with element order preserved use pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']] for columns in ['foo', 'bar'] order or pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']] for ['bar', 'foo'] order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be lambda x: x.upper() in ['AAA', 'BBB', 'DDD']. Using this parameter results in much faster parsing time and lower memory usage.

squeeze : boolean, default False
If the parsed data only contains one column then return a Series

**prefix** : str, default None
Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, …

**mangle_dupe_cols** : boolean, default True
Duplicate columns will be specified as ‘X’, ‘X.1’, … ‘X.N’, rather than ‘X’ … ‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

**dtype** : Type name or dict of column -> type, default None
Data type for data or columns. E.g. {‘a’: np.float64, ‘b’: np.int32} Use str or object together with suitable *na_values* settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

**engine** : {‘c’, ‘python’}, optional
Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

**converters** : dict, default None
Dict of functions for converting values in certain columns. Keys can either be integers or column labels

**true_values** : list, default None
Values to consider as True

**false_values** : list, default None
Values to consider as False

**skipinitialspace** : boolean, default False
Skip spaces after delimiter.

**skiprows** : list-like or integer or callable, default None
Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.
If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be lambda x: x in [0, 2].

**skipfooter** : int, default 0
Number of lines at bottom of file to skip (Unsupported with engine=’c’)

**nrows** : int, default None
Number of rows of file to read. Useful for reading pieces of large files

**na_values** : scalar, str, list-like, or dict, default None
Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep_default_na** : bool, default True
Whether or not to include the default NaN values when parsing the data. Depending on whether *na_values* is passed in, the behavior is as follows:
• If `keep_default_na` is True, and `na_values` are specified, `na_values` is appended to the default NaN values used for parsing.

• If `keep_default_na` is True, and `na_values` are not specified, only the default NaN values are used for parsing.

• If `keep_default_na` is False, and `na_values` are specified, only the NaN values specified `na_values` are used for parsing.

• If `keep_default_na` is False, and `na_values` are not specified, no strings will be parsed as NaN.

Note that if `na_filter` is passed in as False, the `keep_default_na` and `na_values` parameters will be ignored.

**na_filter**: boolean, default True

Detect missing value markers (empty strings and the value of `na_values`). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file.

**verbose**: boolean, default False

Indicate number of NA values placed in non-numeric columns.

**skip_blank_lines**: boolean, default True

If True, skip over blank lines rather than interpreting as NaN values.

**parse_dates**: boolean or list of ints or names or list of lists or dict, default False

• boolean. If True -> try parsing the index.

• list of ints or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.

• list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.

• dict, e.g. {'foo': [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`.

Note: A fast-path exists for iso8601-formatted dates.

**infer_datetime_format**: boolean, default False

If True and `parse_dates` is enabled, pandas will attempt to infer the format of the date-time strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

**keep_date_col**: 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

iterator : boolean, default False

Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

chunksize : int, default None

Return TextFileReader object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

compression : {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default ‘infer’

For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: `.gz`, `.bz2`, `.zip`, or `.xz` (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.18.1: support for ‘zip’ and ‘xz’ compression.

thousands : str, default None

Thousands separator

decimal : str, default ‘.’

Character to recognize as decimal point (e.g. use ‘,’ for European data).

float_precision : string, default None

Specifies which converter the C engine should use for floating-point values. The options are `None` for the ordinary converter, `high` for the high-precision converter, and `round_trip` for the round-trip converter.

lineterminator : str (length 1), default None

Character to break file into lines. Only valid with C parser.

quotechar : str (length 1), optional

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default 0

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote : boolean, default True

When quotechar is specified and quoting is not QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

escapechar : str (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

comment : str, default None
Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as skip_blank_lines=True), fully commented lines are ignored by the parameter header but not by skiprows. For example, if comment='#', parsing #empty\na,b,c\n1,2,3 with header=0 will result in 'a,b,c' being treated as the header.

encoding : str, default None

   Encoding to use for UTF when reading/writing (ex. ‘utf-8’). See List of Python standard encodings

dialect : str or csv.Dialect instance, default None

   If provided, this parameter will override values (default or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace, quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

tupleize_cols : boolean, default False

   Deprecated since version 0.21.0: This argument will be removed and will always convert to MultiIndex

   Leave a list of tuples on columns as is (default is to convert to a MultiIndex 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.

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.

low_memory : boolean, default True

   Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the dtype parameter. Note that the entire file is read into a single DataFrame regardless, use the chunksizer or iterator parameter to return the data in chunks. (Only valid with C parser)

memory_map : boolean, default False

   If a filepath is provided for filepath_or_buffer, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

Returns

   result  [DataFrame or TextParser]

34.1.2.3 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.
Additional help can be found in the online docs for IO Tools.

Parameters

filepath_or_buffer : [str, pathlib.Path, py._path.local.LocalPath or any \]

object with a read() method (such as a file handle or 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 which are not being skipped via skiprows (default='infer').

widths : list of ints. optional

A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.

delim_whitespace : boolean, default False

Specifies whether or not whitespace (e.g. ' ' or '\t') will be used as the sep. Equivalent to setting sep='\s+'. If this option is set to True, nothing should be passed in for the delimiter parameter.

New in version 0.18.1: support for the Python parser.

header : int or list of ints, default ‘infer’

Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly pass header=None. Duplicates in this list will cause a UserWarning to be issued.

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)

usecols : list-like or callable, default None
Return a subset of the columns. If list-like, all elements must either be positional (i.e., integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2] or ['foo', 'bar', 'baz']. Element order is ignored, so usecols=[0, 1] is the same as [1, 0]. To instantiate a DataFrame from data with element order preserved use 
\[
pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]\]
for columns in ['foo', 'bar'] order or 
\[
pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]\]
for ['bar', 'foo'] order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be 
\[
\lambda x: x.upper() \in ['AAA', 'BBB', 'DDD']\]
Using this parameter results in much faster parsing time and lower memory usage.

**squeeze**: boolean, default False

If the parsed data only contains one column then return a Series

**prefix**: str, default None

Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, …

**mangle_dupe_cols**: boolean, default True

Duplicate columns will be specified as ‘X’, ‘X.1’, ‘X.2’, … ‘X.N’, rather than ‘X’… ‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

**dtype**: Type name or dict of column -> type, default None

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} Use str or object together with suitable na_values settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

**converters**: dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true_values**: list, default None

Values to consider as True

**false_values**: list, default None

Values to consider as False

**skipinitialspace**: boolean, default False

Skip spaces after delimiter.

**skiprows**: list-like or integer or callable, default None

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be 
\[
\lambda x: x \in [0, 2]\]

**skipfooter**: int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

**nrows**: int, default None
Number of rows of file to read. Useful for reading pieces of large files

**na_values** : scalar, str, list-like, or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep_default_na** : bool, default True

Whether or not to include the default NaN values when parsing the data. Depending on whether **na_values** is passed in, the behavior is as follows:

- If **keep_default_na** is True, and **na_values** are specified, **na_values** is appended to the default NaN values used for parsing.
- If **keep_default_na** is True, and **na_values** are not specified, only the default NaN values are used for parsing.
- If **keep_default_na** is False, and **na_values** are specified, only the NaN values specified **na_values** are used for parsing.
- If **keep_default_na** is False, and **na_values** are not specified, no strings will be parsed as NaN.

Note that if **na_filter** is passed in as False, the **keep_default_na** and **na_values** parameters will be ignored.

**na_filter** : boolean, default True

Detect missing value markers (empty strings and the value of **na_values**). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**skip_blank_lines** : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

**parse_dates** : boolean or list of ints or names or list of lists or dict, default False

- boolean. If True -> try parsing the index.
- list of ints or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1], [3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`

Note: A fast-path exists for iso8601-formatted dates.

**infer_datetime_format** : boolean, default False

If True and **parse_dates** is enabled, pandas will attempt to infer the format of the date-time strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.
**keep_date_col**: 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

**iterator**: boolean, default False

Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

**chunksize**: int, default None

Return TextFileReader object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

**compression**: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default ‘infer’

For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: `.gz`, `.bz2`, `.zip`, or `.xz` (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.18.1: support for ‘zip’ and ‘xz’ compression.

**thousands**: str, default None

Thousands separator

**decimal**: str, default ‘.’

Character to recognize as decimal point (e.g. use ‘,’ for European data).

**float_precision**: string, default None

Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, high for the high-precision converter, and round_trip for the round-trip converter.

**lineterminator**: str (length 1), default None

Character to break file into lines. Only valid with C parser.

**quotechar**: str (length 1), optional

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

**quoting**: int or csv.QUOTE_* instance, default 0

Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).
**doublequote**: boolean, default `True`

When quotechar is specified and quoting is not `QUOTE_NONE`, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

**escapechar**: str (length 1), default None

One-character string used to escape delimiter when quoting is `QUOTE_NONE`.

**comment**: str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment=' #'`, parsing `#empty
a,b,c
1,2,3` with `header=0` will result in ‘a,b,c’ being treated as the header.

**encoding**: str, default None

Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings

**dialect**: str or csv.Dialect instance, default None

If provided, this parameter will override values (default or not) for the following parameters: `delimiter`, `doublequote`, `escapechar`, `skipinitialspace`, `quotechar`, and `quoting`. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

**tupleize_cols**: boolean, default False

Deprecated since version 0.21.0: This argument will be removed and will always convert to MultiIndex

Leave a list of tuples on columns as is (default is to convert to a MultiIndex 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.

**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.

**low_memory**: boolean, default True

Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the `dtype` parameter. Note that the entire file is read into a single DataFrame regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser)

**memory_map**: boolean, default False

If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.
34.1.2.4 pandas.read_msgpack

**pandas.read_msgpack** *(path_or_buf, encoding='utf-8', iterator=False, **kwargs)*

Load msgpack pandas object from the specified file path

**Parameters**
- `path_or_buf [string File path, BytesIO like or string]`
- `encoding: Encoding for decoding msgpack str type`
- `iterator`: boolean, if True, return an iterator to the unpacker
  (default is False)

**Returns**
- `obj [type of object stored in file]`

34.1.3 Clipboard

**read_clipboard**(sep)

Read text from clipboard and pass to read_table.

34.1.3.1 pandas.read_clipboard

**pandas.read_clipboard**(sep='\s+', **kwargs)

Read text from clipboard and pass to read_table. See read_table for the full argument list

**Parameters**
- `sep`: str, default 's+'.
  A string or regex delimiter. The default of 's+' denotes one or more whitespace characters.

**Returns**
- `parsed [DataFrame]`

34.1.4 Excel

**read_excel**(io, sheet_name, header, names, ...)

Read an Excel table into a pandas DataFrame

**ExcelFile.parse**(sheet_name, header, names, ...)

Parse specified sheet(s) into a DataFrame
34.1.4.1 pandas.read_excel

```python
pandas.read_excel(io, sheet_name=0, header=0, names=None, index_col=None, usecols=None, squeeze=False, dtype=None, engine=None, converters=None, true_values=None, false_values=None, skiprows=None, nrows=None, na_values=None, parse_dates=False, date_parser=None, thousands=None, comment=None, skipfooter=0, convert_float=True, **kwds)
```

Read an Excel table into a pandas DataFrame

**Parameters**

- **io**: string, path object (pathlib.Path or py._path.local.LocalPath), 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

- **sheet_name**: string, int, mixed list of strings/ints, 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

- **sheetname**: string, int, mixed list of strings/int, or None, default 0
  
  Deprecated since version 0.21.0: Use sheet_name instead

- **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. Use None if there is no header.

- **names**: array-like, default None
  
  List of column names to use. If file contains no header row, then you should explicitly pass header=None

- **index_col**: int, list of 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. If a subset of data is selected with usecols, index_col is based on the subset.

- **parse_cols**: int or list, default None
  
  Deprecated since version 0.21.0: Pass in usecols instead.

- **usecols**: 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 Excel column letters and column ranges (e.g. “A:E” or “A,C,E:F”). Ranges are inclusive of both sides.

**squeeze** : boolean, default False

If the parsed data only contains one column then return a Series

**dtype** : Type name or dict of column -> type, default None

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} Use object to preserve data as stored in Excel and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

New in version 0.20.0.

**engine** : string, default None

If io is not a buffer or path, this must be set to identify io. Acceptable values are None or xlrd

**converters** : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the Excel cell content, and return the transformed content.

**true_values** : list, default None

Values to consider as True

New in version 0.19.0.

**false_values** : list, default None

Values to consider as False

New in version 0.19.0.

**skiprows** : list-like

Rows to skip at the beginning (0-indexed)

**nrows** : int, default None

Number of rows to parse

New in version 0.23.0.

**na_values** : scalar, str, list-like, or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**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
thousands : str, default None

Thousands separator for parsing string columns to numeric. Note that this parameter
is only necessary for columns stored as TEXT in Excel, any numeric columns will
automatically be parsed, regardless of display format.

comment : str, default None

Comments out remainder of line. Pass a character or characters to this argument to
indicate comments in the input file. Any data between the comment string and the end
of the current line is ignored.

skip_footer : int, default 0

Deprecated since version 0.23.0: Pass in skipfooter instead.

skipfooter : int, default 0

Rows at the end to skip (0-indexed)

convert_float : boolean, default True

cconvert 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

Returns parsed : DataFrame or Dict of DataFrames

DataFrame from the passed in Excel file. See notes in sheet_name argument for more
information on when a Dict of Dataframes is returned.

Examples

An example DataFrame written to a local file

```python
>>> df_out = pd.DataFrame([('string1', 1),
... ('string2', 2),
... ('string3', 3)],
... columns=['Name', 'Value'])
>>> df_out
       Name  Value
0   string1    1
1   string2    2
2   string3    3
>>> df_out.to_excel('tmp.xlsx')
```

The file can be read using the file name as string or an open file object:

```python
>>> pd.read_excel('tmp.xlsx')
       Name  Value
0   string1    1
1   string2    2
2   string3    3
```

```python
>>> pd.read_excel(open('tmp.xlsx','rb'))
       Name  Value
0   string1    1
1   string2    2
2   string3    3
```

Index and header can be specified via the index_col and header arguments
>>> pd.read_excel('tmp.xlsx', index_col=None, header=None)
   0  1  2
0 NaN Name Value
1  0.0 string1 1
2  1.0 string2 2
3  2.0 string3 3

Column types are inferred but can be explicitly specified

>>> pd.read_excel('tmp.xlsx', dtype={'Name':str, 'Value':float})
   Name Value
0  string1 1.0
1  string2 2.0
2  string3 3.0

True, False, and NA values, and thousands separators have defaults, but can be explicitly specified, too. Supply the values you would like as strings or lists of strings!

>>> pd.read_excel('tmp.xlsx', na_values=['string1', 'string2'])
   Name Value
0  NaN 1
1  NaN 2
2  string3 3

Comment lines in the excel input file can be skipped using the comment kwarg

>>> df = pd.DataFrame({'a': [1, '#2'], 'b': [2, 3]})
>>> df.to_excel('tmp.xlsx', index=False)
>>> pd.read_excel('tmp.xlsx')
   a  b
0  1  2
1 #2 3

>>> pd.read_excel('tmp.xlsx', comment='#')
   a  b
0  1  2

34.1.4.2 pandas.ExcelFile.parse

ExcelFile.parse(sheet_name=0, header=0, names=None, index_col=None, usecols=None, squeeze=False, converters=None, true_values=None, false_values=None, skiprows=None, nrows=None, na_values=None, parse_dates=False, date_parser=None, thousands=None, comment=None, skipfooter=0, convert_float=True, **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

 read_json([path_or_buf, orient, typ, dtype, ...]) Convert a JSON string to pandas object
34.1.5.1 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, encoding=None, lines=False, chunksize=None, compression='infer')

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 : string

Indication of expected JSON string format. Compatible JSON strings can be produced by to_json() with a corresponding orient value. The set of possible orients is:

- 'split': dict like {index -> [index], columns -> [columns], data -> [values]}
- 'records': list like [{column -> value}, ... , {column -> value}]
- 'index': dict like {index -> {column -> value}}
- 'columns': dict like {column -> {index -> value}}
- 'values': just the values array

The allowed and default values depend on the value of the typ parameter.

- when typ == 'series',
  - allowed orients are {'split','records','index'}
  - default is 'index'
  - The Series index must be unique for orient 'index'.
- when typ == 'frame',
  - allowed orients are {'split','records','index', 'columns', 'values', 'table'}
  - default is 'columns'
  - The DataFrame index must be unique for orients 'index' and 'columns'.
  - The DataFrame columns must be unique for orients 'index', 'columns', and 'records'.

New in version 0.23.0: ‘table’ as an allowed value for the orient argument

typ [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 detect the correct precision, but if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force parsing only seconds, milliseconds, microseconds or nanoseconds respectively.

lines : boolean, default False

Read the file as a json object per line.

New in version 0.19.0.

encoding : str, default is 'utf-8'

The encoding to use to decode py3 bytes.

New in version 0.19.0.

chunksize: integer, default None

Return JsonReader object for iteration. See the line-delimited json docs for more information on chunksize. This can only be passed if lines=True. If this is None, the file will be read into memory all at once.

New in version 0.21.0.

compression : {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer', then use gzip, bz2, zip or xz if path_or_buf is a string ending in '.gz', '.bz2', '.zip', or 'xz', respectively, and no decompression otherwise. If using 'zip', the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.21.0.

Returns

result [Series or DataFrame, depending on the value of typ.]
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See also:
DataFrame.to_json
Notes
Specific to orient='table', if a DataFrame with a literal Index name of index gets written with
to_json(), the subsequent read operation will incorrectly set the Index name to None. This is because
index is also used by DataFrame.to_json() to denote a missing Index name, and the subsequent
read_json() operation cannot distinguish between the two. The same limitation is encountered with a
MultiIndex and any names beginning with 'level_'.
Examples
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...
index=['row 1', 'row 2'],
...
columns=['col 1', 'col 2'])

Encoding/decoding a Dataframe using 'split' formatted JSON:
>>> df.to_json(orient='split')
'{"columns":["col 1","col 2"],
"index":["row 1","row 2"],
"data":[["a","b"],["c","d"]]}'
>>> pd.read_json(_, orient='split')
col 1 col 2
row 1
a
b
row 2
c
d

Encoding/decoding a Dataframe using 'index' formatted JSON:
>>> df.to_json(orient='index')
'{"row 1":{"col 1":"a","col 2":"b"},"row 2":{"col 1":"c","col 2":"d"}}'
>>> pd.read_json(_, orient='index')
col 1 col 2
row 1
a
b
row 2
c
d

Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved
with this encoding.
>>> df.to_json(orient='records')
'[{"col 1":"a","col 2":"b"},{"col 1":"c","col 2":"d"}]'
>>> pd.read_json(_, orient='records')
col 1 col 2
0
a
b
1
c
d

Encoding with Table Schema
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"},
{"name": "col 1", "type": "string"},
{"name": "col 2", "type": "string"}],
(continues on next page)

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"primaryKey": "index",
"pandas_version": "0.20.0"},
"data": [{"index": "row 1", "col 1": "a", "col 2": "b"},
{"index": "row 2", "col 1": "c", "col 2": "d"}]}'

json_normalize(data[, record_path, meta, . . . ])
build_table_schema(data[, index, . . . ])

“Normalize” semi-structured JSON data into a flat table
Create a Table schema from data.

34.1.5.2 pandas.io.json.json_normalize
pandas.io.json.json_normalize(data, record_path=None, meta=None, meta_prefix=None,
record_prefix=None, errors=’raise’, sep=’.’)
“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]
errors : {‘raise’, ‘ignore’}, default ‘raise’
• ‘ignore’ : will ignore KeyError if keys listed in meta are not always present
• ‘raise’ : will raise KeyError if keys listed in meta are not always present
New in version 0.20.0.
sep : string, default ‘.’
Nested records will generate names separated by sep, e.g., for sep=’.’, { ‘foo’ : { ‘bar’ :
0 } } -> foo.bar
New in version 0.20.0.
Returns
frame [DataFrame]
Examples

34.1. Input/Output

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>>> from pandas.io.json import json_normalize
>>> data = [{"id": 1, 'name': {'first': 'Coleen', 'last': 'Volk'}},
...     {"name": {'given': 'Mose', 'family': 'Regner'}},
...     {"id": 2, 'name': 'Faye Raker'}]
>>> json_normalize(data)
      id   name  name.family  name.first  name.given  name.last
0  1.0      NaN         NaN           Coleen           NaN          Volk
1  NaN   Nan            Regner           NaN           Mose          NaN
2  2.0   Faye Raker            NaN           NaN           NaN            NaN

>>> 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}]]

>>> result = json_normalize(data, 'counties', ['state', 'shortname',
...     ['info', 'governor']])

34.1.5.3 pandas.io.json.build_table_schema

pandas.io.json.build_table_schema(data, index=True, primary_key=None, version=True)

Create a Table schema from data.

Parameters

- **data** [Series, DataFrame]
- **index** : bool, default True
  Whether to include data.index in the schema.
- **primary_key** : bool or None, default True
  column names to designate as the primary key. The default None will set ‘primaryKey’
to the index level or levels if the index is unique.
- **version** : bool, default True
  Whether to include a field pandas_version with the version of pandas that generated the
  schema.

Returns
schema [dict]

Notes

See _as_json_table_type for conversion types. Timedeltas as converted to ISO8601 duration format with 9 decimal places after the seconds field for nanosecond precision.

Categoricals are converted to the any dtype, and use the enum field constraint to list the allowed values. The ordered attribute is included in an ordered field.

Examples

```python
>>> df = pd.DataFrame(
...     {'A': [1, 2, 3],
...     'B': ['a', 'b', 'c'],
...     'C': pd.date_range('2016-01-01', freq='d', periods=3),
... }, index=pd.Index(range(3), name='idx'))
>>> build_table_schema(df)
{'fields': [{'name': 'idx', 'type': 'integer'},
            {'name': 'A', 'type': 'integer'},
            {'name': 'B', 'type': 'string'},
            {'name': 'C', 'type': 'datetime'}],
'pandas_version': '0.20.0',
'primaryKey': ['idx']}
```

34.1.6 HTML

**read_html**(io[, match, flavor, header, ...])  Read HTML tables into a list of DataFrame objects.

34.1.6.1 pandas.read_html

pandas.read_html(io, match='.+', flavor=None, header=None, index_col=None, skiprows=None, attrs=None, parse_dates=False, tupleize_cols=None, thousands='.', encoding=None, converters=None, na_values=None, keep_default_na=True, displayed_only=True)  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.

Deprecated since version 0.21.0: This argument will be removed and will always convert to MultiIndex

**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).

**decimal** : str, default ‘.’

Character to recognize as decimal point (e.g. use ‘,’ for European data).

New in version 0.19.0.
converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the cell (not column) content, and return the transformed content.

New in version 0.19.0.

na_values : iterable, default None

Custom NA values

New in version 0.19.0.

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are over-ridden, otherwise they’re appended to

New in version 0.19.0.

display_only : bool, default True

Whether elements with “display: none” should be parsed

New in version 0.23.0.

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)

read_hdf(path_or_buf[, key, mode]) Read from the store, close it if we opened it.

HDFStore.put(key, value[, format, append]) Store object in HDFStore

Continued on next page
### Table 8 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>HDFStore.append</code></td>
<td>Append to Table in file</td>
</tr>
<tr>
<td><code>HDFStore.get</code></td>
<td>Retrieve pandas object stored in file</td>
</tr>
<tr>
<td><code>HDFStore.select</code></td>
<td>Retrieve pandas object stored in file, optionally based on where criteria</td>
</tr>
<tr>
<td><code>HDFStore.info</code></td>
<td>Print detailed information on the store</td>
</tr>
<tr>
<td><code>HDFStore.keys</code></td>
<td>Return a (potentially unordered) list of the keys corresponding to the objects stored in the HDFStore.</td>
</tr>
</tbody>
</table>

#### 34.1.7.1 pandas.read_hdf

```python
pandas.read_hdf(path_or_buf, key=None, mode='r', **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`: string, buffer or path object
  - Path to the file to open, or an open `pandas.HDFStore` object. Supports any object implementing the `__fspath__` protocol. This includes `pathlib.Path` and `py._path.local.LocalPath` objects.
  - New in version 0.19.0: support for `pathlib`, `py.path`.
  - New in version 0.21.0: support for `__fspath__` protocol.

- `key`: object, optional
  - The group identifier in the store. Can be omitted if the HDF file contains a single pandas object.

- `mode`: `{‘r’, ‘r+’, ‘a’}`, optional
  - Mode to use when opening the file. Ignored if `path_or_buf` is a `pandas.HDFStore`. Default is ‘r’.

- `where`: list, optional
  - A list of Term (or convertible) objects.

- `start`: int, optional
  - Row number to start selection.

- `stop`: int, optional
  - Row number to stop selection.

- `columns`: list, optional
  - A list of columns names to return.

- `iterator`: bool, optional
  - Return an iterator object.

- `chunksize`: int, optional
  - Number of rows to include in an iteration when using an iterator.

- `errors`: str, default ‘strict’
  - Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

**kwargs
Additional keyword arguments passed to HDFStore.

Returns item : object
The selected object. Return type depends on the object stored.

See also:

pandas.DataFrame.to_hdf write a HDF file from a DataFrame
pandas.HDFStore low-level access to HDF files

Examples

```python
>>> df = pd.DataFrame([[1, 1.0, 'a']], columns=['x', 'y', 'z'])
>>> df.to_hdf('./store.h5', 'data')
>>> reread = pd.read_hdf('./store.h5')
```

34.1.7.2 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.
data_columns : list of columns to create as data columns, or True to
  use all columns. See here # noqa
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’

34.1.7.3 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}]
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, or True, default None

  List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See here.

- **min_itemsize**: [dict of columns that specify minimum 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

### 34.1.7.4 pandas.HDFStore.get

**HDFStore.get**(key)

Retrieve pandas object stored in file

**Parameters**

- **key**: [object]

**Returns**

- **obj**: [type of object stored in file]

### 34.1.7.5 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 convertible) 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

### 34.1.7.6 pandas.HDFStore.info

HDFStore.info()

print detailed information on the store

New in version 0.21.0.

### 34.1.7.7 pandas.HDFStore.keys

HDFStore.keys()

Return a (potentially unordered) list of the keys corresponding to the objects stored in the HDFStore. These are ABSOLUTE path-names (e.g. have the leading ‘/’)

### 34.1.8 Feather

| read_feather(path[, nthreads]) | Load a feather-format object from the file path |

#### 34.1.8.1 pandas.read_feather

pandas.read_feather(path, nthreads=1)

Load a feather-format object from the file path

**Parameters**

path [string file path, or file-like object]

nthreads : int, default 1

Number of CPU threads to use when reading to pandas.DataFrame

**Returns**

type of object stored in file

### 34.1.9 Parquet

| read_parquet(path[, engine, columns]) | Load a parquet object from the file path, returning a DataFrame. |

---

**34.1. Input/Output 1369**
34.1.9.1 pandas.read_parquet

```python
pandas.read_parquet(path, engine='auto', columns=None, **kwargs)
```

Load a parquet object from the file path, returning a DataFrame.

**Parameters**
- `path` : string
  - File path
- `columns` : list, default=None
  - If not None, only these columns will be read from the file.
- `engine` : {'auto', 'pyarrow', 'fastparquet'}, default 'auto'
  - Parquet library to use. If 'auto', then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try 'pyarrow', falling back to 'fastparquet' if 'pyarrow' is unavailable.

**Returns**
- `DataFrame`

**kwargs** are passed to the engine

34.1.10 SAS

```python
read_sas(filepath_or_buffer[, format, . . . ])
```

Read SAS files stored as either XPORT or SAS7BDAT format files.

**Parameters**
- `filepath_or_buffer` : string or file-like object
  - Path to the SAS file.
- `format` : string {'xport', 'sas7bdat'} or None
  - If None, file format is inferred. If 'xport' or 'sas7bdat', uses the corresponding format.
- `index` : identifier of index column, defaults to None
  - Identifier of column that should be used as index of the DataFrame.
- `encoding` : string, default is None
  - Encoding for text data. If None, text data are stored as raw bytes.
- `chunksize` : int
  - Read file `chunksize` lines at a time, returns iterator.
- `iterator` : bool, defaults to False
  - If True, returns an iterator for reading the file incrementally.

**Returns**
- `DataFrame` if `iterator=False` and `chunksize=None`, else SAS7BDATReader
### 34.1.11 SQL

<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>
</tbody>
</table>

### 34.1.12 Google BigQuery

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>read_gbq</code></td>
<td>Load data from Google BigQuery.</td>
</tr>
</tbody>
</table>

#### 34.1.12.1 pandas.read_gbq

```python
pandas.read_gbq(query, project_id=None, index_col=None, col_order=None, reauth=False, verbose=None, private_key=None, dialect='legacy', **kwargs)
```

Load data from Google BigQuery.

This function requires the pandas-gbq package.

Authentication to the Google BigQuery service is via OAuth 2.0.

- If “private_key” is not provided:
  - By default “application default credentials” are used.
  - If default application credentials are not found or are restrictive, user account credentials are used. In this case, you will be asked to grant permissions for product name ‘pandas GBQ’.

- If “private_key” is provided:
  - Service account credentials will be used to authenticate.

**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.

- **private_key** : str, optional
  - Service account private key in JSON format. Can be file path or string contents. This is useful for remote server authentication (eg. Jupyter/IPython notebook on remote host).

- **dialect** : str, default ‘legacy’
SQL syntax dialect to use. Value can be one of:

- `'legacy'` Use BigQuery’s legacy SQL dialect. For more information see BigQuery Legacy SQL Reference.
- `'standard'` Use BigQuery’s standard SQL, which is compliant with the SQL 2011 standard. For more information see BigQuery Standard SQL Reference.

`verbose` : boolean, deprecated

*Deprecated in Pandas-GBQ 0.4.0.* Use the logging module to adjust verbosity instead.

`kwargs` : dict

Arbitrary keyword arguments. configuration (dict): query config parameters for job processing. For example:

```python
configuration = {'query': {'useQueryCache': False}}
```

For more information see BigQuery SQL Reference

Returns **df**: DataFrame

DataFrame representing results of query.

See also:

- `pandas_gbq.read_gbq` This function in the pandas-gbq library.
- `pandas.DataFrame.to_gbq` Write a DataFrame to Google BigQuery.

### 34.1.13 STATA

**read_stata** *(filepath_or_buffer[, ...])*  
Read Stata file into DataFrame.

#### 34.1.13.1 pandas.read_stata

`pandas.read_stata` *(filepath_or_buffer, convert_dates=True, convert_categoricals=True, encoding=None, index_col=None, convert_missing=False, preserve_dtypes=True, columns=None, order_categoricals=True, chunksize=None, iterator=False)*

Read Stata file into DataFrame.

**Parameters** **filepath_or_buffer** : 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. None defaults to latin-1.

**index_col** : string, optional, default: None

Column to set as index.

**convert_missing** : boolean, defaults to False
Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nan. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissingValue objects.

**preserve_dtypes** : 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.

**Returns**

DataFrame or StataReader

See also:

**pandas.io.stata.StataReader** low-level reader for Stata data files

**pandas.DataFrame.to_stata** export Stata data files

**Examples**

Read a Stata dta file:

```python
>>> import pandas as pd
>>> df = pd.read_stata('filename.dta')
```

Read a Stata dta file in 10,000 line chunks:

```python
>>> itr = pd.read_stata('filename.dta', chunksize=10000)
>>> for chunk in itr:
...   do_something(chunk)
```
34.1.13.2 pandas.io.stata.StataReader.data

StataReader.data(**kwargs)
Reads observations from Stata file, converting them into a dataframe

Depreciated since version: 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_col**: string, optional, default: None
  Column to set as index.
- **convert_missing**: boolean, defaults to False
  Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nan. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissingValue objects.
- **preserve_dtypes**: 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

34.1.13.3 pandas.io.stata.StataReader.data_label

StataReader.data_label()
Returns data label of Stata file

34.1.13.4 pandas.io.stata.StataReader.value_labels

StataReader.value_labels()
Returns a dict, associating each variable name with a dict, associating each value its corresponding label

34.1.13.5 pandas.io.stata.StataReader.variable_labels

StataReader.variable_labels()
Returns variable labels as a dict, associating each variable name with corresponding label
34.1.13.6 pandas.io.stata.StataWriter.write_file

StataWriter.write_file()

34.2 General functions

34.2.1 Data manipulations

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td>melt(frame[, id_vars, value_vars, var_name, ...])</td>
<td>“Unpivots” a DataFrame from wide format to long format, optionally leaving identifier variables set.</td>
</tr>
<tr>
<td>pivot(index, columns, values)</td>
<td>Produce ‘pivot’ table based on 3 columns of this DataFrame.</td>
</tr>
<tr>
<td>pivot_table(data[, values, index, columns, ...])</td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td>crosstab(index, columns[, values, rownames, ...])</td>
<td>Compute a simple cross-tabulation of two (or more) factors.</td>
</tr>
<tr>
<td>cut(x, bins[, right, labels, retbins, ...])</td>
<td>Bin values into discrete intervals.</td>
</tr>
<tr>
<td>qcut(x, q[, labels, retbins, precision, ...])</td>
<td>Quantile-based discretization function.</td>
</tr>
<tr>
<td>merge(left, right[, how, on, left_on, ...])</td>
<td>Merge DataFrame objects by performing a database-style join operation by columns or indexes.</td>
</tr>
<tr>
<td>merge_ordered(left, right[, on, left_on, ...])</td>
<td>Perform merge with optional filling/interpolation designed for ordered data like time series data.</td>
</tr>
<tr>
<td>merge_asof(left, right[, on, left_on, ...])</td>
<td>Perform an asof merge.</td>
</tr>
<tr>
<td>concat(objs[, axis, join, join_axes, ...])</td>
<td>Concatenate pandas objects along a particular axis with optional set logic along the other axes.</td>
</tr>
<tr>
<td>get_dummies(data[, prefix, prefix_sep, ...])</td>
<td>Convert categorical variable into dummy/indicator variables.</td>
</tr>
<tr>
<td>factorize(values[, sort, order, ...])</td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td>unique(values)</td>
<td>Hash table-based unique.</td>
</tr>
<tr>
<td>wide_to_long(df, stubnames, i, j[, sep, suffix])</td>
<td>Wide panel to long format.</td>
</tr>
</tbody>
</table>

34.2.1.1 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:

Dataframe.melt, 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
```

```python
>>> pd.melt(df, 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'], value_vars=['B', 'C'])
   A     variable  value
0  a       B       1
1  b       B       3
2  c       B       5
3  a       C       2
4  b       C       4
5  c       C       6
```

The names of ‘variable’ and ‘value’ columns can be customized:

```python
>>> pd.melt(df, id_vars=['A'], value_vars=['B'],
...          var_name='myVarname', value_name='myValname')
   A  myVarname  myValname
0  a      B       1
1  b      B       3
2  c      B       5
```

If you have multi-index columns:

```python
>>> df.columns = ['ABC', 'DEF']
>>> df
   A  B  C  D  E  F
0  a  1  2  3  4  5
```

(continues on next page)
```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
```

### 34.2.1.2 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

**See also:**

*DataFrame.pivot_table* generalization of pivot that can handle duplicate values for one index/column pair

**Notes**

Obviously, all 3 of the input arguments must have the same length

### 34.2.1.3 pandas.pivot_table

**pandas.pivot_table** *(data, values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True, margins_name='All')*

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 : column, Grouper, array, or list of the previous

If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : column, Grouper, array, or list of the previous

If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, list of functions, dict, default numpy.mean

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions

fill_value : scalar, default None

Value to replace missing values with

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

margins_name : string, default ‘All’

Name of the row / column that will contain the totals when margins is True.

Returns

table [DataFrame]

See also:

Dataframe.pivot  pivot without aggregation that can handle non-numeric data

Examples

```python
>>> df = pd.DataFrame({
    "A": ["foo", "foo", "foo", "foo", "foo", "bar", "bar", "bar", "bar"],
    "B": ["one", "one", "one", "two", "two", "one", "one", "two", "two"],
    "C": ["small", "large", "large", "small", "small", "large", "small", "small", "large"],
    "D": [1, 2, 2, 3, 3, 4, 5, 6, 7]})
```

```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
```

(continues on next page)
```python
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

   C large  small
  A B
bar one  4.0  5.0
   two  7.0  6.0
foo one  4.0  1.0
   two  NaN  6.0

>>> table = pivot_table(df, values='D', index=['A', 'B'],
                      columns=['C'], aggfunc=np.sum)
>>> table

   C large  small
  A B
bar one  4.0  5.0
   two  7.0  6.0
foo one  4.0  1.0
   two  NaN  6.0

>>> table = pivot_table(df, values=['D', 'E'], index=['A', 'C'],
                      aggfunc={'D': np.mean,
                               'E': [min, max, np.mean]})
>>> table

     D     E
     mean max  median  min
  A C
bar large  5.500000  16  14.5  13
   small  5.500000  15  14.5  14
foo large  2.000000  10  9.5  9
   small  2.333333  12 11.0  8
```

34.2.1.4 pandas.crosstab

**pandas.crosstab**

```python
pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name='All', dropna=True, normalize=False)
```

Compute a simple cross-tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed.

**Parameters**

- **index**: array-like, Series, or list of arrays/Series
  Values to group by in the rows

- **columns**: array-like, Series, or list of arrays/Series
  Values to group by in the columns

- **values**: array-like, optional
  Array of values to aggregate according to the factors. Requires *aggfunc* to be specified.
aggfunc : function, optional
    If specified, requires values be specified as well
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)
margins_name : string, default ‘All’
    Name of the row / column that will contain the totals when margins is True.
    New in version 0.21.0.
dropna : boolean, default True
    Do not include columns whose entries are all NaN
normalize : boolean, {'all', 'index', 'columns'}, or {0,1}, default False
    Normalize by dividing all values by the sum of values.
    • If passed ‘all’ or True, will normalize over all values.
    • If passed ‘index’ will normalize over each row.
    • If passed ‘columns’ will normalize over each column.
    • If margins is True, will also normalize margin values.
    New in version 0.18.1.

Returns
crosstab [DataFrame]

Notes
Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.
Any input passed containing Categorical data will have all of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.
In the event that there aren’t overlapping indexes an empty DataFrame will be returned.

Examples

```python
>>> a = np.array(["foo", "foo", "foo", "foo", "bar", "bar",
    ...                "bar", "bar", "foo", "foo"], dtype=object)
>>> b = np.array(["one", "one", "one", "two", "one", "one",
    ...                "one", "two", "two", "one"], dtype=object)
>>> c = np.array(["dull", "dull", "shiny", "dull", "dull", "shiny",
    ...                "shiny", "dull", "shiny", "shiny", "shiny"],
    ...                dtype=object)
```
>>> pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
...  
<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>two</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>dull</td>
<td>shiny</td>
</tr>
<tr>
<td>a</td>
<td>bar</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>foo</td>
<td>2</td>
</tr>
</tbody>
</table>

>>> foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])
>>> bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])
>>> crosstab(foo, bar)  # 'c' and 'f' are not represented in the data,  
...  
# but they still will be counted in the output
...  
<table>
<thead>
<tr>
<th></th>
<th>col_0</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>row_0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>b</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>c</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### 34.2.1.5 pandas.cut

**pandas.cut** *(x, bins, right=True, labels=None, retbins=False, precision=3, include_lowest=False, duplicates='raise')*

Bin values into discrete intervals.

Use `cut` when you need to segment and sort data values into bins. This function is also useful for going from a continuous variable to a categorical variable. For example, `cut` could convert ages to groups of age ranges.

**Supports binning into an equal number of bins, or a pre-specified array of bins.**

**Parameters**

- **x**: array-like
  
  The input array to be binned. Must be 1-dimensional.

- **bins**: int, sequence of scalars, or pandas.IntervalIndex
  
  The criteria to bin by.

  - int: Defines the number of equal-width bins in the range of x. The range of x is extended by .1% on each side to include the minimum and maximum values of x.

  - sequence of scalars: Defines the bin edges allowing for non-uniform width. No extension of the range of x is done.

  - IntervalIndex: Defines the exact bins to be used.

- **right**: bool, default True
  
  Indicates whether `bins` includes the rightmost edge or not. If `right == True` (the default), then the `bins` [1, 2, 3, 4] indicate (1,2], (2,3], (3,4]. This argument is ignored when `bins` is an IntervalIndex.

- **labels**: array or bool, optional
  
  Specifies the labels for the returned bins. Must be the same length as the resulting bins. If False, returns only integer indicators of the bins. This affects the type of the output container (see below). This argument is ignored when `bins` is an IntervalIndex.

- **retbins**: bool, default False
  
  Whether to return the bins or not. Useful when bins is provided as a scalar.
**precision** : int, default 3

The precision at which to store and display the bins labels.

**include_lowest** : bool, default False

Whether the first interval should be left-inclusive or not.

**duplicates** : {default ‘raise’, ‘drop’}, optional

If bin edges are not unique, raise ValueError or drop non-uniques.

New in version 0.23.0.

**Returns** : out

pandas.Categorical, Series, or ndarray

An array-like object representing the respective bin for each value of \( x \). The type depends on the value of \( labels \).

- True (default) : returns a Series for Series \( x \) or a pandas.Categorical for all other inputs. The values stored within are Interval dtype.
- sequence of scalars : returns a Series for Series \( x \) or a pandas.Categorical for all other inputs. The values stored within are whatever the type in the sequence is.
- False : returns an ndarray of integers.

**bins** : numpy.ndarray or IntervalIndex.

The computed or specified bins. Only returned when \( retbins=True \). For scalar or sequence \( bins \), this is an ndarray with the computed bins. If set \( duplicates=drop \), \( bins \) will drop non-unique bin. For an IntervalIndex \( bins \), this is equal to \( bins \).

See also:

- **qcut** : Discretize variable into equal-sized buckets based on rank or based on sample quantiles.
- **pandas.Categorical** : Array type for storing data that come from a fixed set of values.
- **Series** : One-dimensional array with axis labels (including time series).
- **pandas.IntervalIndex** : Immutable Index implementing an ordered, sliceable set.

**Notes**

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Series or pandas.Categorical object.

**Examples**

Discretize into three equal-sized bins.

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3)
...[(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0] < (3.0, 5.0] ...
```
Discovered the same bins, but assign them specific labels. Notice that the returned Categorical’s categories are *labels* and are ordered.

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, labels=['bad', 'medium', 'good'])
[bad, good, medium, medium, good, bad]
Categories (3, object): [bad < medium < good]
```

labels=False implies you just want the bins back.

```python
>>> pd.cut([0, 1, 1, 2], bins=4, labels=False)
array([0, 1, 1, 3])
```

Passing a Series as an input returns a Series with categorical dtype:

```python
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
                 index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, 3)
```

```python
   a  (1.992, 4.667]
   b  (1.992, 4.667]
   c  (4.667, 7.333]
   d  (7.333, 10.0]
   e  (7.333, 10.0]
Name: , dtype: category
Categories (3, interval[float64]): [(1.992, 4.667] < (4.667, ...
```

Passing a Series as an input returns a Series with mapping value. It is used to map numerically to intervals based on bins.

```python
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
                 index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, [0, 2, 4, 6, 10, 10], labels=False, retbins=True, right=False)
```

```python
   a  0.0
   b  1.0
   c  2.0
   d  3.0
   e  4.0
dtype: float64, array([0, 2, 4, 6, 8])
```

Use *drop* optional when bins is not unique

```
>>> pd.cut(s, [0, 2, 4, 6, 10, 10], labels=False, retbins=True,
         right=False, duplicates='drop')
```

```
   a  0.0
   b  1.0
   c  2.0
   d  3.0
```

(continues on next page)
Pandas: powerful Python data analysis toolkit, Release 0.23.1

```
e 3.0
dtype: float64, array([0, 2, 4, 6, 8]))
```

Passing an IntervalIndex for `bins` results in those categories exactly. Notice that values not covered by the IntervalIndex are set to NaN. 0 is to the left of the first bin (which is closed on the right), and 1.5 falls between two bins.

```
>>> bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
>>> pd.cut([0, 0.5, 1.5, 2.5, 4.5], bins)
[NaN, (0, 1], NaN, (2, 3], (4, 5]
```

Categories (3, interval[int64]): [(0, 1] < (2, 3] < (4, 5]]

34.2.1.6 pandas.qcut

`pandas.qcut(x, q, labels=None, retbins=False, precision=3, duplicates='raise')`

Quantile-based discretization function. Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

**Parameters**

- `x` [1d ndarray or Series]
- `q` : integer or array of quantiles
  Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles
- `labels` : array or 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, labels) or not. Can be useful if bins is given as a scalar.
- `precision` : int, optional
  The precision at which to store and display the bins labels
- `duplicates` : {default ‘raise’, ‘drop’}, optional
  If bin edges are not unique, raise ValueError or drop non-uniques.
  New in version 0.20.0.

**Returns**

- **out** : Categorical or Series or array of integers if labels is False
  The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.
- **bins** : ndarray of floats
  Returned only if `retbins` is True.

**Notes**

Out of bounds values will be NA in the resulting Categorical object
Examples

```python
>>> pd.qcut(range(5), 4)
...([-0.001, 1.0], [-0.001, 1.0], [1.0, 2.0], [2.0, 3.0], [3.0, 4.0])
Categories (4, interval[float64]): [(-0.001, 1.0] < (1.0, 2.0] ...

>>> 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)
aarray([0, 0, 1, 2, 3])
```

### 34.2.1.7 pandas.merge

pandas.merge(left, right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('x', '_y'), copy=True, indicator=False, validate=None)

Merge DataFrame 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, similar to a SQL left outer join; preserve key order
  - right: use only keys from right frame, similar to a SQL right outer join; preserve key order
  - outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically
  - inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys
- `on` : label or list
  Column or index level names to join on. These must be found in both DataFrames. If `on` is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.
- `left_on` : label or list, or array-like
  Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.
- `right_on` : label or list, or array-like
  Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.
left_index : 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. If False, the order of the join keys depends on the join type (how keyword).

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.

validate : string, default None
If specified, checks if merge is of specified type.
- “one_to_one” or “1:1”: check if merge keys are unique in both left and right datasets.
- “one_to_many” or “1:m”: check if merge keys are unique in left dataset.
- “many_to_one” or “m:1”: check if merge keys are unique in right dataset.
- “many_to_many” or “m:m”: allowed, but does not result in checks.

New in version 0.21.0.

Returns merged : DataFrame
The output type will the be same as ‘left’, if it is a subclass of DataFrame.

See also:
merge_ordered, merge_asof, DataFrame.join

Notes
Support for specifying index levels as the on, left_on, and right_on parameters was added in version 0.23.0.
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
  3   bar   8

>>> A.merge(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
```

34.2.1.8 pandas.merge_ordered

`pandas.merge_ordered(left, right, on=None, left_on=None, right_on=None, left_by=None, right_by=None, fill_method=None, suffixes=('_x', '_y'), how='outer')`

Perform merge with optional filling/interpolation designed for ordered data like time series data. Optionally perform group-wise merge (see examples)

Parameters

- `left` [DataFrame]
- `right` [DataFrame]
- `on` : label or list
  Field names to join on. Must be found in both DataFrames.
- `left_on` : label or list, or array-like
  Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns
- `right_on` : label or list, or array-like
  Field names to join on in right DataFrame or vector/list of vectors per left_on docs
- `left_by` : column name or list of column names
  Group left DataFrame by group columns and merge piece by piece with right DataFrame
- `right_by` : column name or list of column names
  Group right DataFrame by group columns and merge piece by piece with left DataFrame
- `fill_method` : {'ffill', None}, default None
  Interpolation method for data
- `suffixes` : 2-length sequence (tuple, list, ...)
  Suffix to apply to overlapping column names in the left and right side, respectively
- `how` : {'left', 'right', 'outer', 'inner'}, default 'outer'
  - left: use only keys from left frame (SQL: left outer join)
• right: use only keys from right frame (SQL: right outer join)
• outer: use union of keys from both frames (SQL: full outer join)
• inner: use intersection of keys from both frames (SQL: inner join)

New in version 0.19.0.

**Returns** `merged`: DataFrame

The output type will the be same as ‘left’, if it is a subclass of DataFrame.

**See also:**

`merge`, `merge_asof`

### Examples

```python
>>> A
 key  lvalue  group
0 a    1      a
1 c    2      a
2 e    3      a
3 a    1      b
4 c    2      b
5 e    3      b

>>> merge_ordered(A, B, fill_method='ffill', left_by='group')
 group  key  lvalue
0 a    a    a
1 a    b    1
2 a    c    2
3 a    d    3
4 a    e    3
5 b    a    1
6 b    b    1
7 b    c    2
8 b    d    2
9 b    e    3

34.2.1.9 pandas.merge_asof

pandas.merge_asof(left, right, on=None, left_on=None, right_on=None, left_index=False, right_index=False, by=None, left_by=None, right_by=None, suffixes=('_x', '_y'), tolerance=None, allow_exact_matches=True, direction='backward')

Perform an asof merge. This is similar to a left-join except that we match on nearest key rather than equal keys.

Both DataFrames must be sorted by the key.

For each row in the left DataFrame:

• A “backward” search selects the last row in the right DataFrame whose ‘on’ key is less than or equal to the left’s key.
• A “forward” search selects the first row in the right DataFrame whose ‘on’ key is greater than or equal to the left’s key.
• A “nearest” search selects the row in the right DataFrame whose ‘on’ key is closest in absolute distance to the left’s key.
The default is “backward” and is compatible in versions below 0.20.0. The direction parameter was added in version 0.20.0 and introduces “forward” and “nearest”.

Optionally match on equivalent keys with ‘by’ before searching with ‘on’.
New in version 0.19.0.

**Parameters**

- **left** [DataFrame]
- **right** [DataFrame]
- **on** : label
  
  Field name to join on. Must be found in both DataFrames. The data MUST be ordered. Furthermore this must be a numeric column, such as datetimelike, integer, or float. On or left_on/right_on must be given.

- **left_on** : label
  
  Field name to join on in left DataFrame.

- **right_on** : label
  
  Field name to join on in right DataFrame.

- **left_index** : boolean
  
  Use the index of the left DataFrame as the join key.
New in version 0.19.2.

- **right_index** : boolean
  
  Use the index of the right DataFrame as the join key.
New in version 0.19.2.

- **by** : column name or list of column names
  
  Match on these columns before performing merge operation.

- **left_by** : column name
  
  Field names to match on in the left DataFrame.
New in version 0.19.2.

- **right_by** : column name
  
  Field names to match on in the right DataFrame.
New in version 0.19.2.

- **suffixes** : 2-length sequence (tuple, list, . . .)
  
  Suffix to apply to overlapping column names in the left and right side, respectively.

- **tolerance** : integer or Timedelta, optional, default None
  
  Select asof tolerance within this range; must be compatible with the merge index.

- **allow_exact_matches** : boolean, default True

  - If True, allow matching with the same ‘on’ value (i.e. less-than-or-equal-to / greater-than-or-equal-to)
  
  - If False, don’t match the same ‘on’ value (i.e., strictly less-than / strictly greater-than)
direction : ‘backward’ (default), ‘forward’, or ‘nearest’

Whether to search for prior, subsequent, or closest matches.

New in version 0.20.0.

Returns
merged [DataFrame]

See also:
merge, merge_ordered

Examples

```python
def main():
    left = pd.DataFrame({'a': [1, 5, 10], 'left_val': ['a', 'b', 'c']})
    right = pd.DataFrame({'a': [1, 2, 3, 6, 7], 'right_val': [1, 2, 3, 6, 7]})

    pd.merge_asof(left, right, on='a')
    pd.merge_asof(left, right, on='a', allow_exact_matches=False)
    pd.merge_asof(left, right, on='a', direction='forward')
    pd.merge_asof(left, right, on='a', direction='nearest')

if __name__ == '__main__':
    main()
```
```
We can use indexed DataFrames as well.

```python
>>> left = pd.DataFrame({'left_val': ['a', 'b', 'c']}, index=[1, 5, 10])
>>> left
     left_val
1       a
5       b
10      c

>>> right = pd.DataFrame({'right_val': [1, 2, 3, 6, 7]}, index=[1, 2, 3, 6, 7])
>>> right
     right_val
1       1
2       2
3       3
6       6
7       7

>>> pd.merge_asof(left, right, left_index=True, right_index=True)
     left_val  right_val
1       a       1
5       b       3
10      c       7
```

Here is a real-world times-series example

```python
>>> quotes
     time  ticker  bid   ask
0 2016-05-25 13:30:00.023  GOOG  720.50  720.93
1 2016-05-25 13:30:00.023  MSFT  51.95   51.96
2 2016-05-25 13:30:00.030  MSFT  51.97   51.98
3 2016-05-25 13:30:00.041  MSFT  51.99   52.00
4 2016-05-25 13:30:00.048  GOOG  720.50  720.93
5 2016-05-25 13:30:00.049  AAPL  97.99   98.01
6 2016-05-25 13:30:00.072  GOOG  720.50  720.88
7 2016-05-25 13:30:00.075  MSFT  52.01   52.03
```

```python
>>> trades
     time  ticker  price  quantity
0 2016-05-25 13:30:00.023  MSFT   51.95     75
1 2016-05-25 13:30:00.038  MSFT   51.95   155
2 2016-05-25 13:30:00.048  GOOG   720.77    100
3 2016-05-25 13:30:00.048  GOOG   720.92    100
4 2016-05-25 13:30:00.048  AAPL   98.00    100
```

By default we are taking the asof of the quotes

```python
>>> pd.merge_asof(trades, quotes, on='time', by='ticker')
     time  ticker  price  quantity   bid   ask
0 2016-05-25 13:30:00.023  MSFT   51.95     75  51.95  51.96
1 2016-05-25 13:30:00.038  MSFT   51.95   155  51.97  51.98
2 2016-05-25 13:30:00.048  GOOG   720.77    100 720.77 720.93
3 2016-05-25 13:30:00.048  GOOG   720.92    100 720.50 720.93
4 2016-05-25 13:30:00.048  AAPL   98.00    100  NaN  NaN
```
We only asof within 2ms between the quote time and the trade time

```python
>>> pd.merge_asof(trades, quotes,
...     on='time',
...     by='ticker',
...     tolerance=pd.Timedelta('2ms'))
```

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25 13:30:00.023</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>51.95</td>
<td>51.96</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.038</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. However prior data will propagate forward

```python
>>> pd.merge_asof(trades, quotes,
...     on='time',
...     by='ticker',
...     tolerance=pd.Timedelta('10ms'),
...     allow_exact_matches=False)
```

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25 13:30:00.023</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.038</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2016-05-25 13:30:00.048</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

34.2.1.10 pandas.concat

`pandas.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, sort=None, 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/`index`, 1/`columns`}, default 0
    - The axis to concatenate along

  - `join`: {'inner', 'outer'}, default ‘outer’
    - How to handle indexes on other 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

  - `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 index values on the other axes are still respected in the join.

**keys** : sequence, default None

If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level

**levels** : list of sequences, default None

Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys

**names** : list, default None

Names for the levels in the resulting hierarchical index

**verify_integrity** : boolean, default False

Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation

**sort** : boolean, default None

Sort non-concatenation axis if it is not already aligned when `join` is ‘outer’. The current default of sorting is deprecated and will change to not-sorting in a future version of pandas.

Explicitly pass `sort=True` to silence the warning and sort. Explicitly pass `sort=False` to silence the warning and not sort.

This has no effect when `join='inner'`, which already preserves the order of the non-concatenation axis.

New in version 0.23.0.

**copy** : boolean, default True

If False, do not copy data unnecessarily

**Returns** **concatenated** : object, type of `objs`

When concatenating all `Series` along the index (axis=0), a `Series` is returned. When `objs` contains at least one `DataFrame`, a `DataFrame` is returned. When concatenating along the columns (axis=1), a `DataFrame` is returned.

See also:

`Series.append`, `DataFrame.append`, `DataFrame.join`, `DataFrame.merge`

**Notes**

The keys, levels, and names arguments are all optional.

A walkthrough of how this method fits in with other tools for combining pandas objects can be found [here](#).

**Examples**

Combine two `Series`.
>>> s1 = pd.Series(['a', 'b'])
>>> s2 = pd.Series(['c', 'd'])
>>> pd.concat([s1, s2])
0  a  
1  b  
0  c  
1  d  
dtype: object

Clear the existing index and reset it in the result by setting the `ignore_index` option to True.

>>> pd.concat([s1, s2], ignore_index=True)
0  a  
1  b  
2  c  
3  d  
dtype: object

Add a hierarchical index at the outermost level of the data with the `keys` option.

>>> pd.concat([s1, s2], keys=['s1', 's2'])
s1  0  a  
   1  b  
s2  0  c  
   1  d  
dtype: object

Label the index keys you create with the `names` option.

>>> pd.concat([s1, s2], keys=['s1', 's2'],
            ... names=['Series name', 'Row ID'])
Series name Row ID
s1  0  a  
   1  b  
s2  0  c  
   1  d  
dtype: object

Combine two `DataFrame` objects with identical columns.

>>> df1 = pd.DataFrame([['a', 1], ['b', 2]],
                     ... columns=['letter', 'number'])
>>> df1
   letter  number
0      a       1
1      b       2

>>> df2 = pd.DataFrame([['c', 3], ['d', 4]],
                     ... columns=['letter', 'number'])
>>> df2
   letter  number
0      c       3
1      d       4

>>> pd.concat([df1, df2])
   letter  number
0      a       1
1      b       2
0      c       3
1      d       4
Combine DataFrame objects with overlapping columns and return everything. Columns outside the intersection will be filled with NaN values.

```python
>>> df3 = pd.DataFrame([['c', 3, 'cat'], ['d', 4, 'dog']],
                        columns=['letter', 'number', 'animal'])
>>> df3
   letter number animal
0    c      3    cat
1    d      4    dog
>>> pd.concat([df1, df3])
   animal letter number
0       NaN    a      1
1       NaN    b      2
0       cat    c      3
1       dog    d      4
```

Combine DataFrame objects with overlapping columns and return only those that are shared by passing inner to the join keyword argument.

```python
>>> pd.concat([df1, df3], join="inner")
   letter number
0    a      1
1    b      2
0    c      3
1    d      4
```

Combine DataFrame objects horizontally along the x axis by passing in axis=1.

```python
>>> df4 = pd.DataFrame([['bird', 'polly'], ['monkey', 'george']],
                        columns=['animal', 'name'])
>>> pd.concat([df1, df4], axis=1)
   letter number animal  name
0    a      1   bird  polly
1    b      2  monkey  george
```

Prevent the result from including duplicate index values with the verify_integrity option.

```python
>>> df5 = pd.DataFrame([1], index=['a'])
>>> df5
0  a
   1
>>> df6 = pd.DataFrame([2], index=['a'])
>>> df6
0  a
   2
>>> pd.concat([df5, df6], verify_integrity=True)
Traceback (most recent call last):
  ...
ValueError: Indexes have overlapping values: ['a']
```

### 34.2.11 pandas.get_dummies

`pandas.get_dummies(data, prefix=None, prefix_sep='\_', dummy_na=False, columns=None, sparse=False, drop_first=False, dtype=None)`

Convert categorical variable into dummy/indicator variables

Parameters
**pandas: powerful Python data analysis toolkit, Release 0.23.1**

- **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. Alternatively, `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.
  - **drop_first**: bool, default False
    - Whether to get k-1 dummies out of k categorical levels by removing the first level.
    - New in version 0.18.0.
  - **dtype**: dtype, default np.uint8
    - Data type for new columns. Only a single dtype is allowed.
    - New in version 0.23.0.

**Returns**

- **dummies**: [DataFrame or SparseDataFrame]

**See also**

- `Series.str.get_dummies`

**Examples**

```python
>>> import pandas as pd
>>> s = pd.Series(list('abca'))
```

```bash
>>> pd.get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
```

```bash
>>> sl = ['a', 'b', np.nan]
```
```python
>>> pd.get_dummies(sl)
a  b
0  1  0
1  0  1
2  0  0
```

```python
>>> pd.get_dummies(sl, dummy_na=True)
a  b  NaN
0  1  0  0
1  0  1  0
2  0  0  1
```

```python
df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'], 'C': [1, 2, 3]})
```

```python
>>> pd.get_dummies(df, prefix=['col1', 'col2'])
C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1  1  0  0  1  0
1  2  0  1  1  0  0
2  3  1  0  0  0  1
```

```python
>>> pd.get_dummies(pd.Series(list('abcaa')))
a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
4  1  0  0
```

```python
>>> pd.get_dummies(pd.Series(list('abcaa')), drop_first=True)
b  c
0  0  0
1  1  0
2  0  1
3  0  0
4  0  0
```

```python
>>> pd.get_dummies(pd.Series(list('abc')), dtype=float)
a  b  c
0  1.0  0.0  0.0
1  0.0  1.0  0.0
2  0.0  0.0  1.0
```

## 34.2.1.12 pandas.factorize

`pandas.factorize(values, sort=False, order=None, na_sentinel=-1, size_hint=None)`

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

*Parameters*

- `values` : sequence
A 1-D sequence. Sequences that aren’t pandas objects are coerced to ndarrays before factorization.

**sort**: bool, default False

Sort *uniques* and shuffle *labels* to maintain the relationship.

**order**

Deprecated since version 0.23.0: This parameter has no effect and is deprecated.

**na_sentinel**: int, default -1

Value to mark “not found”.

**size_hint**: int, optional

Hint to the hashtable sizer.

Returns **labels**: ndarray

An integer ndarray that’s an indexer into *uniques*. *uniques.take(labels)* will have the same values as *values*.

**uniques**: ndarray, Index, or Categorical

The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

**Note**: Even if there’s a missing value in *values*, *uniques* will not contain an entry for it.

See also:

**pandas.cut** Discretize continuous-valued array.

**pandas.unique** Find the unique value in an array.

**Examples**

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> labels
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *labels* will be shuffled so that the relationship is maintained.

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> labels
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```
Missing values are indicated in `labels` with `na_sentinel` (−1 by default). Note that missing values are never included in `uniques`.

```python
>>> labels, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> labels
array([ 0, -1,  1,  2,  0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we’ve only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of `uniques` will differ. For Categoricals, a `Categorical` is returned.

```python
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]
```

Notice that 'b' is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```python
>>> cat = pd.Series(['a', 'a', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
array([0, 0, 1])
>>> uniques
Index(['a', 'c'], dtype='object')
```

### 34.2.1.13 pandas.unique

`pandas.unique(values)`

Hash table-based unique. Uniques are returned in order of appearance. This does NOT sort.

Significantly faster than `numpy.unique`. Includes NA values.

**Parameters**

- `values` [1d array-like]

**Returns unique values.**

- If the input is an Index, the return is an Index
- If the input is a Categorical dtype, the return is a Categorical
- If the input is a Series/ndarray, the return will be an ndarray

**See also:**

- `pandas.Index.unique`, `pandas.Series.unique`

**Examples**

```python
>>> pd.unique(pd.Series([2, 1, 3, 3]))
array([2, 1, 3])
```
```python
>>> pd.unique(pd.Series([2] + [1] * 5))
array([2, 1])

>>> pd.unique(pd.Series([pd.Timestamp('20160101'),
...                       pd.Timestamp('20160101')]))
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')

>>> pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
...                        pd.Timestamp('20160101', tz='US/Eastern')]))
datetimeindex(['2016-01-01 00:00:00-05:00'],
...               dtype='datetime64[ns, US/Eastern]', freq=None)

>>> pd.unique(list('baabc'))
array(['b', 'a', 'c'], dtype=object)

An unordered Categorical will return categories in the order of appearance.

``` python
>>> pd.unique(Series(pd.Categorical(list('baabc'))))
[b, a, c]
Categories (3, object): [b, a, c]

``` python
>>> pd.unique(Series(pd.Categorical(list('baabc'),
...                       categories=list('abc'))))
[b, a, c]
Categories (3, object): [b, a, c]

An ordered Categorical preserves the category ordering.

``` python
>>> pd.unique(Series(pd.Categorical(list('baabc'),
...                       categories=list('abc'),
...                       ordered=True)))
[b, a, c]
Categories (3, object): [a < b < c]

An array of tuples

``` python
>>> pd.unique([('a', 'b'), ('b', 'a'), ('a', 'c'), ('b', 'a'))]
array([('a', 'b'), ('b', 'a'), ('a', 'c')], dtype=object)

34.2.1.14 pandas.wide_to_long

pandas.wide_to_long(df, stubnames, i, j, sep='", suffix='\d+')
Wide panel to long format. Less flexible but more user-friendly than melt.

With stubnames ['A', 'B'], this function expects to find one or more group of columns with format Asuffix1, Asuffix2,..., Bsuffix1, Bsuffix2,... You specify what you want to call this suffix in the resulting long format with j (for example j='year')

Each row of these wide variables are assumed to be uniquely identified by i (can be a single column name or a list of column names)
All remaining variables in the data frame are left intact.

**Parameters**

- **df**: DataFrame
  The wide-format DataFrame
- **stubnames**: str or list-like
  The stub name(s). The wide format variables are assumed to start with the stub names.
- **i**: str or list-like
  Column(s) to use as id variable(s)
- **j**: str
  The name of the subobservation variable. What you wish to name your suffix in the long format.
- **sep**: str, default ""
  A character indicating the separation of the variable names in the wide format, to be stripped from the names in the long format. For example, if your column names are A-suffix1, A-suffix2, you can strip the hyphen by specifying `sep='-'`.
  New in version 0.20.0.
- **suffix**: str, default `\d+`
  A regular expression capturing the wanted suffixes. `\d+` captures numeric suffixes. Suffixes with no numbers could be specified with the negated character class `\D+`. You can also further disambiguate suffixes, for example, if your wide variables are of the form Aone, Btwo, ..., and you have an unrelated column Arating, you can ignore the last one by specifying `suffix='(!?one|two)'`.
  New in version 0.20.0.
  Changed in version 0.23.0: When all suffixes are numeric, they are cast to int64/float64.

**Returns**

DataFrame

A DataFrame that contains each stub name as a variable, with new index (i, j)

**Notes**

All extra variables are left untouched. This simply uses `pandas.melt` under the hood, but is hard-coded to “do the right thing” in a typical case.

**Examples**

```python
>>> import pandas as pd
>>> import numpy as np
gerand.seed(123)
>>> df = pd.DataFrame({"A1970": {0: "a", 1: "b", 2: "c"},
...                     "A1980": {0: "d", 1: "e", 2: "f"},
...                     "B1970": {0: 2.5, 1: 1.2, 2: .7},
...                     "B1980": {0: 3.2, 1: 1.3, 2: .1},
...                     "X": dict(zip(range(3), np.random.randn(3)))
...                     })
>>> df["id"] = df.index
```

(continues on next page)
>>> df
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
>>> pd.wide_to_long(df, ["A", "B"], i="id", j="year")

...     X   A   B
id year
0  1970  -1.085631  a  2.5
1  1970   0.997345  b  1.2
2  1970   0.282978  c  0.7
0  1980  -1.085631  d  3.2
1  1980   0.997345  e  1.3
2  1980   0.282978  f  0.1

With multiple id columns

```python
>>> df = pd.DataFrame(
...     {'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht1': [2.8, 2.9, 2.2, 1.8, 1.9, 2.2, 2.3, 2.1],
...     'ht2': [3.4, 3.8, 2.9, 3.2, 3.1, 2.8, 2.4, 3.3, 2.9]
... )
``` 

```python
>>> df
   birth  famid  ht1  ht2
0      1     1    2.8    3.4
1      2     1    2.9    3.8
2      3     1    2.2    2.9
3      1     2    2.0    3.2
4      2     2    1.8    2.8
5      3     2    1.9    2.4
6      1     3    2.2    3.3
7      2     3    2.3    3.4
8      3     3    2.1    2.9
``` 

```python
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age')
``` 

```python
>>> l
...     ht
famid birth  age
1     1     1    2.8
2     1     1    3.4
2     2     1    2.9
2     2     1    3.8
3     1     2    2.2
2     2     2    2.9
2     2     1    2.0
2     2     2    3.2
2     2     1    1.8
2     2     2    2.8
3     1     1    1.9
2     2     2    2.4
3     1     1    2.2
2     2     2    3.3
2     1     2    2.3
2     2     2    3.4
3     1     2    2.1
```
Going from long back to wide just takes some creative use of `unstack`

```python
g = l.unstack()
g.columns = g.columns.map('{0[0]}{0[1]}'.format)
g.reset_index()
```

<table>
<thead>
<tr>
<th>famid</th>
<th>birth</th>
<th>h1</th>
<th>h2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2.8</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2.9</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>3</td>
<td>2.2</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>1</td>
<td>2.0</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1.8</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>3</td>
<td>1.9</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>1</td>
<td>2.2</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td>8</td>
<td>3</td>
<td>3</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Less wieldy column names are also handled

```python
np.random.seed(0)

df = pd.DataFrame({'A(quarterly)-2010': np.random.rand(3),
    ...
'B(quarterly)-2010': np.random.rand(3),
    ...
'B(quarterly)-2011': np.random.rand(3),
    ...
'X': np.random.randint(3, size=3)})

df['id'] = df.index

df
```

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.548814</td>
<td>0.544883</td>
<td>0.437587</td>
<td>0.383442</td>
</tr>
<tr>
<td>1</td>
<td>0.715189</td>
<td>0.423655</td>
<td>0.891773</td>
<td>0.791725</td>
</tr>
<tr>
<td>2</td>
<td>0.602763</td>
<td>0.645894</td>
<td>0.963663</td>
<td>0.528895</td>
</tr>
</tbody>
</table>

If we have many columns, we could also use a regex to find our stubnames and pass that list on to `wide_to_long`

```python
stubnames = sorted(
    ...
    set([match[0] for match in df.columns.str.findall(r'[A-B]\\(.*\\)'].values if match != []])
    ...
)

list(stubnames)
```

```
['A(quarterly)', 'B(quarterly)']
```

34.2. General functions

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All of the above examples have integers as suffixes. It is possible to have non-integers as suffixes.

```python
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht_one': [2.8, 2.9, 2.2, 1.8, 1.9, 2.2, 1.8, 2.3, 2.1],
...     'ht_two': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })
```

```python
>>> df
```

```
   birth  famid  ht_one  ht_two
0      1     1     2.8     3.4
1      2     1     2.9     3.8
2      3     1     2.2     2.9
3      1     2     2.0     3.2
4      2     2     1.8     2.8
5      3     2     1.9     2.4
6      1     3     2.2     3.3
7      2     3     2.3     3.4
8      3     3     2.1     2.9
```

```python
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age', sep='_', suffix='\w')
```

```python
>>> l
```

```
   famid  birth  age  ht
0     1     1   one  2.8
     1     1   two  3.4
     2     1   one  2.9
     2     1   two  3.8
     3     1   one  2.2
     3     1   two  2.9
     2     1   one  2.0
     2     1   two  3.2
     2     2   one  1.8
     2     2   two  2.8
     3     1   one  1.9
     3     1   two  2.4
     3     1   one  2.2
     3     1   two  3.3
     2     2   one  2.3
     2     2   two  3.4
     3     1   one  2.1
     3     1   two  2.9
```

### 34.2.2 Top-level missing data

- **isna**(obj) - Detect missing values for an array-like object.
- **isnull**(obj) - Detect missing values for an array-like object.
- **notna**(obj) - Detect non-missing values for an array-like object.
- **notnull**(obj) - Detect non-missing values for an array-like object.
34.2.2.1 pandas.isna

pandas.isna(obj)

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters obj : scalar or array-like

Object to check for null or missing values.

Returns bool or array-like of bool

For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

See also:

notna boolean inverse of pandas.isna.

Series.isna Detect missing values in a Series.

DataFrame.isna Detect missing values in a DataFrame.

Index.isna Detect missing values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```python
>>> pd.isna('dog')
False
```

```python
>>> pd.isna(np.nan)
True
```

Ndarrays result in an ndarray of booleans.

```python
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
>>> pd.isna(array)
array([[False, True, False],
       [False, False, True]])
```

For indexes, an ndarray of booleans is returned.

```python
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', None, ...
       '2017-07-08'])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([[False, False, True],
       [False, False, True]])
```

For Series and DataFrame, the same type is returned, containing booleans.
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
    0  1  2
0  ant bee cat
1  dog None fly

>>> pd.isna(df)
    0   1   2
0  False False False
1  False  True False

>>> pd.isna(df[1])
    0   1
0  False
1  True
Name: 1, dtype: bool

3.4.2.2 pandas.isnull

pandas.isnull(obj)

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters obj : scalar or array-like

Object to check for null or missing values.

Returns bool or array-like of bool

For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

See also:

notna boolean inverse of pandas.isna.

Series.isna Detecet missing values in a Series.

DataFrame.isna Detecet missing values in a DataFrame.

Index.isna Detecet missing values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

>>> pd.isna('dog')
False

>>> pd.isna(np.nan)
True

darrays result in an ndarray of booleans.
```python
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
>>> pd.isna(array)
array([[False, True, False],
       [False, False, True]])

For indexes, an ndarray of booleans is returned.
```}

```python
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None, 
... "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
               dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([False, False, True, False])

For Series and DataFrame, the same type is returned, containing booleans.
```}

```python
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0   1   2
0  ant  bee  cat
1   dog    None  fly
>>> pd.isna(df)
   0  1  2
0  False False False
1  False    True False

>>> pd.isna(df[1])
0  False
1  True
Name: 1, dtype: bool
```

### 34.2.2.3 pandas.notna

**pandas.notna**(obj)

Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

**Parameters**

*obj* : array-like or object value

Object to check for *not* null or *non*-missing values.

**Returns**

*bool* or *array-like of bool*

For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

**See also:**

*isna* : boolean inverse of pandas.notna.

*Series.notna* : Detect valid values in a Series.

*DataFrame.notna* : Detect valid values in a DataFrame.
Index.notna Detect valid values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```python
>>> pd.notna('dog')
True

>>> pd.notna(np.nan)
False
```

ndarrays result in an ndarray of booleans.

```python
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
>>> pd.notna(array)
array([[ True, False, True],
       [ True, True, False]])
```

For indexes, an ndarray of booleans is returned.

```python
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True, True, False, True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```python
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0  1  2
0 ant bee cat
1 dog None fly
>>> pd.notna(df)
   0   1   2
0  True True True
1  True False True
```

```python
>>> pd.notna(df[1])
0   True
1  False
Name: 1, dtype: bool
```

34.2.2.4 pandas.notnull

pandas.notnull(obj)

Detect non-missing values for an array-like object.
This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

**Parameters**

`obj` : array-like or object value

Object to check for not null or non-missing values.

**Returns**

`bool or array-like of bool`

For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

See also:

- `isna` boolean inverse of pandas.notna.
- `Series.notna` Detect valid values in a Series.
- `DataFrame.notna` Detect valid values in a DataFrame.
- `Index.notna` Detect valid values in an Index.

**Examples**

Scalar arguments (including strings) result in a scalar boolean.

```python
>>> pd.notna('dog')
True
```

```python
>>> pd.notna(np.nan)
False
```

Ndarrays result in an ndarray of booleans.

```python
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
>>> pd.notna(array)
array([[ True, False, True],
       [ True, True, False]])
```

For indexes, an ndarray of booleans is returned.

```python
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', None, ... '2017-07-08'])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
            dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True, True, False, True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```python
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0   1   2
0  ant  bee  cat
```

(continues on next page)
```
1   dog  None  fly
>>> pd.notna(df)
   0  1  2
0  True  True  True
1  True  False  True

>>> pd.notna(df[1])
0  True
1  False
Name: 1, dtype: bool
```

### 34.2.3 Top-level conversions

**to_numeric(arg[, errors, downcast])**

Convert argument to a numeric type.

#### 34.2.3.1 pandas.to_numeric

**pandas.to_numeric(arg, errors=’raise’, downcast=None)**

Convert argument to a numeric type.

**Parameters**

- **arg** [list, tuple, 1-d array, 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
- **downcast** : {‘integer’, ‘signed’, ‘unsigned’, ‘float’}, default None
  - If not None, and if the data has been successfully cast to a numerical dtype (or if the data was numeric to begin with), downcast that resulting data to the smallest numerical dtype possible according to the following rules:
    - ‘integer’ or ‘signed’: smallest signed int dtype (min.: np.int8)
    - ‘unsigned’: smallest unsigned int dtype (min.: np.uint8)
    - ‘float’: smallest float dtype (min.: np.float32)
  - As this behaviour is separate from the core conversion to numeric values, any errors raised during the downcasting will be surfaced regardless of the value of the ‘errors’ input.
  - In addition, downcasting will only occur if the size of the resulting data’s dtype is strictly larger than the dtype it is to be cast to, so if none of the dtypes checked satisfy that specification, no downcasting will be performed on the data.
  - New in version 0.19.0.

**Returns** **ret** : numeric if parsing succeeded.

- Return type depends on input. Series if Series, otherwise ndarray

**See also:**

...
**pandas.DataFrame.astype** Cast argument to a specified dtype.

**pandas.to_datetime** Convert argument to datetime.

**pandas.to_timedelta** Convert argument to timedelta.

**numpy.ndarray.astype** Cast a numpy array to a specified type.

### 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)
0 1.0
1 2.0
2 -3.0
dtype: float64
>>> pd.to_numeric(s, downcast='float')
0 1.0
1 2.0
2 -3.0
dtype: float32
>>> pd.to_numeric(s, downcast='signed')
0 1
1 2
2 -3
dtype: int8
>>> s = pd.Series(['apple', '1.0', '2', -3])
>>> pd.to_numeric(s, errors='ignore')
0 apple
1 1.0
2 2
3 -3
dtype: object
>>> pd.to_numeric(s, errors='coerce')
0 NaN
1 1.0
2 2.0
3 -3.0
dtype: float64
```

### 34.2.4 Top-level dealing with datetimelike

- **to_datetime**(arg[, errors, dayfirst, ...]) Convert argument to datetime.
- **to_timedelta**(arg[, unit, box, errors]) Convert argument to timedelta.
- **date_range**(start, end, periods, freq[, tz, ...]) Return a fixed frequency DatetimeIndex.
- **bdate_range**(start, end, periods, freq, tz[, ...]) Return a fixed frequency DatetimeIndex, with business day as the default frequency.
- **period_range**(start, end, periods, freq, name) Return a fixed frequency PeriodIndex, with day (calendar) as the default frequency.
- **timedelta_range**(start, end, periods, freq[, ...]) Return a fixed frequency TimedeltaIndex, with day as the default frequency.

Continued on next page
Infer the most likely frequency given the input index.

### 34.2.4.1 pandas.to_datetime

```python
pandas.to_datetime(arg, errors='raise', dayfirst=False, yearfirst=False, utc=None, box=True, format=None, exact=True, unit=None, infer_datetime_format=False, origin='unix', cache=False)
```

Convert argument to datetime.

**Parameters**

- **arg**: integer, float, string, datetime, list, tuple, 1-d array, Series
  - New in version 0.18.1: or DataFrame/dict-like
- **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).
  - New in version 0.16.1.
- **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**: string, default ‘ns’
unit of the arg (D,s,ms,us,ns) denote the unit, which is an integer or float number. This will be based off the origin. Example, with unit='ms' and origin='unix' (the default), this would calculate the number of milliseconds to the unix epoch start.

**infer_datetime_format**: boolean, default False

If True and no *format* is given, attempt to infer the format of the datetime strings, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

**origin**: scalar, default is ‘unix’

Define the reference date. The numeric values would be parsed as number of units (defined by *unit*) since this reference date.

- If ‘unix’ (or POSIX) time; origin is set to 1970-01-01.
- If ‘julian’, unit must be ‘D’, and origin is set to beginning of Julian Calendar. Julian day number 0 is assigned to the day starting at noon on January 1, 4713 BC.
- If Timestamp convertible, origin is set to Timestamp identified by origin.

New in version 0.20.0.

**cache**: boolean, default False

If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.23.0.

**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 corresponding array/Series).

See also:

- **pandas.DataFrame.astype** Cast argument to a specified dtype.
- **pandas.to_timedelta** Convert argument to timedelta.

**Examples**

Assembling a datetime from multiple columns of a DataFrame. The keys can be common abbreviations like ['year', 'month', 'day', 'minute', 'second', 'ms', 'us', 'ns']) or plurals of the same.

```python
>>> df = pd.DataFrame({'year': [2015, 2016],
                      'month': [2, 3],
                      'day': [4, 5])
>>> pd.to_datetime(df)
0   2015-02-04
```

(continues on next page)
If a date does not meet the timestamp limitations, passing errors='ignore' will return the original input instead of raising any exception.

Passing errors='coerce' will force an out-of-bounds date to NaT, in addition to forcing non-dates (or non-parseable dates) to NaT.

```python
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='ignore')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='coerce')
NaT
```

Passing infer_datetime_format=True can often-times speedup a parsing if its not an ISO8601 format exactly, but in a regular format.

```python
>>> s.head()
0 3/11/2000
1 3/12/2000
2 3/13/2000
3 3/11/2000
4 3/12/2000
dtype: object
```

```python
>>> %timeit pd.to_datetime(s,infer_datetime_format=True)
100 loops, best of 3: 10.4 ms per loop
>>> %timeit pd.to_datetime(s,infer_datetime_format=False)
1 loop, best of 3: 471 ms per loop
```

Using a unix epoch time

```python
>>> pd.to_datetime(1490195805, unit='s')
Timestamp('2017-03-22 15:16:45')
>>> pd.to_datetime(1490195805433502912, unit='ns')
Timestamp('2017-03-22 15:16:45.433502912')
```

**Warning:** For float arg, precision rounding might happen. To prevent unexpected behavior use a fixed-width exact type.

Using a non-unix epoch origin

```python
>>> pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
0 1960-01-02
1 1960-01-03
2 1960-01-04
```
34.2.4.2 pandas.to_timedelta

pandas.to_timedelta(arg, unit='ns', box=True, errors='raise')

Convert argument to timedelta

Parameters

arg [string, timedelta, list, tuple, 1-d array, or Series]

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]

See also:

pandas.DataFrame.astype Cast argument to a specified dtype.
pandas.to_datetime Convert argument to datetime.

Examples

Parsing a single string to a Timedelta:

```python
>>> pd.to_timedelta('1 days 06:05:01.00003')
Timedelta('1 days 06:05:01.000030')
>>> pd.to_timedelta('15.5us')
Timedelta('0 days 00:00:00.000015')
```

Parsing a list or array of strings:

```python
>>> pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT],
               dtype='timedelta64[ns]', freq=None)
```

Converting numbers by specifying the unit keyword argument:

```python
>>> pd.to_timedelta(np.arange(5), unit='s')
TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02',
                '00:00:03', '00:00:04'],
               dtype='timedelta64[ns]', freq=None)
>>> pd.to_timedelta(np.arange(5), unit='d')
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)
```
34.2.4.3 pandas.date_range

pandas.date_range (start=None, end=None, periods=None, freq=None, tz=None, normalize=False, name=None, closed=None, **kwargs)

Return a fixed frequency DatetimeIndex.

**Parameters**

start : str or datetime-like, optional
    Left bound for generating dates.

end : str or datetime-like, optional
    Right bound for generating dates.

periods : integer, optional
    Number of periods to generate.

datetime: str or DateOffset, default ‘D’ (calendar daily)
    Frequency strings can have multiples, e.g. ‘5H’. See here for a list of frequency aliases.

tz : str or tzinfo, optional
    Time zone name for returning localized DatetimeIndex, for example ‘Asia/Hong_Kong’. By default, the resulting DatetimeIndex is timezone-naive.

normalize : bool, default False
    Normalize start/end dates to midnight before generating date range.

name : str, default None
    Name of the resulting DatetimeIndex.

closed : {None, ‘left’, ‘right’}, optional
    Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None, the default).

**kwargs
    For compatibility. Has no effect on the result.

**Returns**

rng [DatetimeIndex]

See also:

pandas.DatetimeIndex  An immutable container for datetimes.
pandas.timedelta_range  Return a fixed frequency TimedeltaIndex.
pandas.period_range  Return a fixed frequency PeriodIndex.
pandas.interval_range  Return a fixed frequency IntervalIndex.

Notes

Of the four parameters start, end, periods, and freq, exactly three must be specified. If freq is omitted, the resulting DatetimeIndex will have periods linearly spaced elements between start and end (closed on both sides).

To learn more about the frequency strings, please see this link.
Examples

Specifying the values

The next four examples generate the same DatetimeIndex, but vary the combination of start, end and periods.

Specify start and end, with the default daily frequency.

```python
>>> pd.date_range(start='1/1/2018', end='1/08/2018')
              dtype='datetime64[ns]', freq='D')
```

Specify start and periods, the number of periods (days).

```python
>>> pd.date_range(start='1/1/2018', periods=8)
              dtype='datetime64[ns]', freq='D')
```

Specify end and periods, the number of periods (days).

```python
>>> pd.date_range(end='1/1/2018', periods=8)
DatetimeIndex(['2017-12-25', '2017-12-26', '2017-12-27', '2017-12-28',
              '2017-12-29', '2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

Specify start, end, and periods; the frequency is generated automatically (linearly spaced).

```python
>>> pd.date_range(start='2018-04-24', end='2018-04-27', periods=3)
DatetimeIndex(['2018-04-24 00:00:00', '2018-04-25 12:00:00',
              '2018-04-27 00:00:00'], freq=None)
```

Other Parameters

Changed the freq (frequency) to 'M' (month end frequency).

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq='M')
              '2018-05-31'], dtype='datetime64[ns]', freq='M')
```

Multiples are allowed

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq='3M')
              '2019-01-31'], dtype='datetime64[ns]', freq='3M')
```

freq can also be specified as an Offset object.

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq=pd.offsets.MonthEnd(3))
              '2019-01-31'], dtype='datetime64[ns]', freq='3M')
```

Specify tz to set the timezone.
```python
>>> pd.date_range(start='1/1/2018', periods=5, tz='Asia/Tokyo')
DatetimeIndex(['2018-01-01 00:00:00+09:00', '2018-01-02 00:00:00+09:00',
              '2018-01-03 00:00:00+09:00', '2018-01-04 00:00:00+09:00',
              '2018-01-05 00:00:00+09:00'],
              dtype='datetime64[ns, Asia/Tokyo]', freq='D')
```

closed controls whether to include start and end that are on the boundary. The default includes boundary points on either end.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed=None)
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```
Use closed='left' to exclude end if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='left')
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03'],
              dtype='datetime64[ns]', freq='D')
```
Use closed='right' to exclude start if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='right')
DatetimeIndex(['2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```

### 34.2.4.4 pandas.bdate_range

**pandas.bdate_range**

```
pandas.bdate_range(start=None, end=None, periods=None, freq='B', tz=None, normalize=True, name=None, weekmask=None, holidays=None, closed=None, **kwargs)
```

Return a fixed frequency DatetimeIndex, 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, default None
  - Number of periods to generate
- **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**: string, default None
  - Name of the resulting DatetimeIndex
- **weekmask**: string or None, default None
  - Mask of the weekdays that are a business day, e.g. ‘M,T’
Weekmask of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed. The default value None is equivalent to ‘Mon Tue Wed Thu Fri’

New in version 0.21.0.

**holidays** : list-like or None, default None

Dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed

New in version 0.21.0.

**closed** : string, default None

Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

Returns

`rng` [DatetimeIndex]

Notes

Of the four parameters: start, end, periods, and freq, exactly three must be specified. Specifying freq is a requirement for `bdate_range`. Use `date_range` if specifying freq is not desired.

To learn more about the frequency strings, please see this link.

### 34.2.4.5 pandas.period_range

`pandas.period_range(start=None, end=None, periods=None, freq='D', name=None)`

Return a fixed frequency PeriodIndex, with day (calendar) as the default frequency

**Parameters**

**start** : string or period-like, default None

Left bound for generating periods

**end** : string or period-like, default None

Right bound for generating periods

**periods** : integer, default None

Number of periods to generate

**freq** : string or DateOffset, default ‘D’ (calendar daily)

Frequency alias

**name** : string, default None

Name of the resulting PeriodIndex

Returns

`prng` [PeriodIndex]
Notes

Of the three parameters: start, end, and periods, exactly two must be specified.
To learn more about the frequency strings, please see this link.

Examples

```python
>>> pd.period_range(start='2017-01-01', end='2018-01-01', freq='M')
```
If start or end are Period objects, they will be used as anchor endpoints for a PeriodIndex with frequency matching that of the period_range constructor.

```python
>>> pd.period_range(start=pd.Period('2017Q1', freq='Q'), ...
end=pd.Period('2017Q2', freq='Q'), freq='M')
PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'], dtype='period[M]', freq='M')
```

34.2.4.6 pandas.timedelta_range

```python
datetime_range(start=None, end=None, periods=None, freq=None, name=None, closed=None)
```
Return a fixed frequency TimedeltaIndex, with day as the default frequency

**Parameters**

- **start**: string or timedelta-like, default None
  Left bound for generating timedeltas
- **end**: string or timedelta-like, default None
  Right bound for generating timedeltas
- **periods**: integer, default None
  Number of periods to generate
- **freq**: string or DateOffset, default ‘D’ (calendar daily)
  Frequency strings can have multiples, e.g. ‘5H’
- **name**: string, default None
  Name of the resulting TimedeltaIndex
- **closed**: string, default None
  Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

**Returns**

- **rng** [TimedeltaIndex]
Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `TimedeltaIndex` will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see this link.

Examples

```python
>>> pd.timedelta_range(start='1 day', periods=4)
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `closed` parameter specifies which endpoint is included. The default behavior is to include both endpoints.

```python
>>> pd.timedelta_range(start='1 day', periods=4, closed='right')
TimedeltaIndex(['2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `freq` parameter specifies the frequency of the `TimedeltaIndex`. Only fixed frequencies can be passed, non-fixed frequencies such as 'M' (month end) will raise.

```python
>>> pd.timedelta_range(start='1 day', end='2 days', freq='6H')
TimedeltaIndex(['1 days 00:00:00', '1 days 06:00:00', '1 days 12:00:00',
                 '1 days 18:00:00', '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='6H')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```python
>>> pd.timedelta_range(start='1 day', end='5 days', periods=4)
TimedeltaIndex(['1 days 00:00:00', '2 days 08:00:00', '3 days 16:00:00',
                 '5 days 00:00:00'],
               dtype='timedelta64[ns]', freq=None)
```

34.2.4.7 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 dealing with intervals
interval_range([start, end, periods, freq, ...])  Return a fixed frequency IntervalIndex

34.2.5.1 pandas.interval_range

pandas.interval_range(start=None, end=None, periods=None, freq=None, name=None, closed='right')

Return a fixed frequency IntervalIndex

Parameters

start : numeric or datetime-like, default None
  Left bound for generating intervals

date : numeric or datetime-like, default None
  Right bound for generating intervals

periods : integer, default None
  Number of periods to generate

freq : numeric, string, or DateOffset, default None
  The length of each interval. Must be consistent with the type of start and end, e.g. 2 for numeric, or ‘5H’ for datetime-like. Default is 1 for numeric and ‘D’ (calendar daily) for datetime-like.

name : string, default None
  Name of the resulting IntervalIndex

closed : {'left', 'right', 'both', 'neither'}, default 'right'
  Whether the intervals are closed on the left-side, right-side, both or neither.

Returns

rng [IntervalIndex]

See also:

IntervalIndex  an Index of intervals that are all closed on the same side.

Notes

Of the four parameters start, end, periods, and freq, exactly three must be specified. If freq is omitted, the resulting IntervalIndex will have periods linearly spaced elements between start and end, inclusively.

To learn more about datetime-like frequency strings, please see this link.

Examples

Numeric start and end is supported.

```python
>>> pd.interval_range(start=0, end=5)
IntervalIndex([0, 1], (1, 2], (2, 3], (3, 4], (4, 5]
  closed='right', dtype='interval[int64]')
```

Additionally, datetime-like input is also supported.
```python
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
                    end=pd.Timestamp('2017-01-04'))
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03],
              (2017-01-03, 2017-01-04]
closed='right', dtype='interval[datetime64[ns]]')
```

The `freq` parameter specifies the frequency between the left and right endpoints of the individual intervals within the `IntervalIndex`. For numeric `start` and `end`, the frequency must also be numeric.

```python
>>> pd.interval_range(start=0, periods=4, freq=1.5)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]
closed='right', dtype='interval[float64]')
```

Similarly, for datetime-like `start` and `end`, the frequency must be convertible to a DateOffset.

```python
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
                    periods=3, freq='MS')
IntervalIndex([(2017-01-01, 2017-02-01], (2017-02-01, 2017-03-01],
              (2017-03-01, 2017-04-01]
closed='right', dtype='interval[datetime64[ns]]')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```python
>>> pd.interval_range(start=0, end=6, periods=4)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]
closed='right',
            dtype='interval[float64]')
```

The `closed` parameter specifies which endpoints of the individual intervals within the `IntervalIndex` are closed.

```python
>>> pd.interval_range(end=5, periods=4, closed='both')
IntervalIndex([[1, 2], [2, 3], [3, 4], [4, 5]
closed='both', dtype='interval[int64]')
```

### 34.2.6 Top-level evaluation

**eval**(*expr[, parser, engine, truediv, ...]*)  
Evaluate a Python expression as a string using various backends.

#### 34.2.6.1 pandas.eval

```python
pandas.eval (expr, parser='pandas', engine=None, truediv=True, local_dict=None, global_dict=None, resolvers=(), level=0, target=None, inplace=False)
```

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: `+`, `-`, `*`, `**`, `%`, `/` (python engine only) along with the following boolean operations: `|` (or), `&` (and), and `~` (not). Additionally, the 'pandas' parser allows the use of `and`, `or`, and `not` with the same semantics as the corresponding bitwise operators. `Series` and `DataFrame` objects are supported and behave as they would with plain ol' Python evaluation.

**Parameters**  
*expr* : str 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 or None, default ‘numexpr’, {'python', 'numexpr'}

The engine used to evaluate the expression. Supported engines are

- None : tries to use numexpr, falls back to python
- 'numexpr' : **This default engine evaluates pandas objects using** numexpr for large speed ups in complex expressions with large frames.
- 'python' : Performs operations as if you had `eval`'d in top level python. This engine is generally not that useful.

More backends may be available in the future.

**truediv** : bool, optional

Whether to use true division, like in Python >= 3

**local_dict** : dict or None, optional

A dictionary of local variables, taken from locals() by default.

**global_dict** : dict or None, optional

A dictionary of global variables, taken from globals() by default.

**resolvers** : list of dict-like or None, optional

A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the `query()` method to inject the `DataFrame.index` and `DataFrame.columns` variables that refer to their respective `DataFrame` instance attributes.

**level** : int, optional

The number of prior stack frames to traverse and add to the current scope. Most users will not need to change this parameter.

**target** : object, optional, default None

This is the target object for assignment. It is used when there is variable assignment in the expression. If so, then `target` must support item assignment with string keys, and if a copy is being returned, it must also support `.copy()`.

**inplace** : bool, default False

If `target` is provided, and the expression mutates `target`, whether to modify `target` inplace. Otherwise, return a copy of `target` with the mutation.

**Returns**

ndarray, numeric scalar, DataFrame, Series

**Raises** ValueError

There are many instances where such an error can be raised:

- `target=None`, but the expression is multiline.
• The expression is multiline, but not all them have item assignment. An example of such an arrangement is this:

\[ a = b + 1 \ a + 2 \]

Here, there are expressions on different lines, making it multiline, but the last line has no variable assigned to the output of \( a + 2 \).

• inplace=True, but the expression is missing item assignment.

• Item assignment is provided, but the target does not support string item assignment.

• Item assignment is provided and inplace=False, but the target does not support the .copy() method.

See also:
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.

34.2.7 Testing

test([extra_args])

34.2.7.1 pandas.test

def test(extra_args=None)

34.3 Series

34.3.1 Constructor

Series([data, index, dtype, name, copy, ...]) One-dimensional ndarray with axis labels (including time series).

34.3.1.1 pandas.Series

def Series(data=None, index=None, dtype=None, name=None, copy=False, fastpath=False)

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 a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN).

Operations between Series (+, -, /, *) align values based on their associated index values—they need not be the same length. The result index will be the sorted union of the two indexes.
pandas: powerful Python data analysis toolkit, Release 0.23.1

**Parameters**

- `data`: array-like, dict, or scalar value
  - Contains data stored in Series
  - Changed in version 0.23.0: If data is a dict, argument order is maintained for Python 3.6 and later.

- `index`: array-like or Index (1d)
  - Values must be hashable and have the same length as `data`. Non-unique index values are allowed. Will default to RangeIndex (0, 1, 2, ..., n) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

- `dtype`: 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
- `asobject`: Return object Series which contains boxed values.
- `at`: Access a single value for a row/column label pair.
- `axes`: Return a list of the row axis labels
- `base`: return the base object if the memory of the underlying data is shared
- `blocks`: (DEPRECATED) 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 dtype object of the underlying data
- `flags`: return if the data is sparseldense
- `ftypes`: return if the data is sparseldense
- `hasnans`: return if I have any nans; enables various perf speedups
- `iat`: Access a single value for a row/column pair by integer position.
- `iloc`: Purely integer-location based indexing for selection by position.
- `index`: The index (axis labels) of the Series.
- `is_monotonic`: Return boolean if values in the object are monotonic_increasing
- `is_monotonic_decreasing`: Return boolean if values in the object are monotonic_decreasing
- `is_monotonic_increasing`: Return boolean if values in the object are monotonic_increasing
- `is_unique`: Return boolean if values in the object are unique
- `itemsize`: return the size of the dtype of the item of the underlying data

Continued on next page
Table 24 – continued from previous page

<table>
<thead>
<tr>
<th>ix</th>
<th>A primarily label-location based indexer, with integer position fallback.</th>
</tr>
</thead>
<tbody>
<tr>
<td>loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</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>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 depending on the dtype</td>
</tr>
</tbody>
</table>

**pandas.Series.T**

Series.T

return the transpose, which is by definition self

**pandas.Series.asobject**

Series.asobject

Return object Series which contains boxed values.

Deprecation since version 0.23.0: Use `astype(object)` instead.

this is an internal non-public method

**pandas.Series.at**

Series.at

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

Raises **KeyError**

When label does not exist in DataFrame

See also:

- `DataFrame.iat` Access a single value for a row/column pair by integer position
- `DataFrame.loc` Access a group of rows and columns by label(s)
- `Series.at` Access a single value using a label

**Examples**

```python
goldenrule
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                     index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
```

(continues on next page)
Get value at specified row/column pair

```python
>>> df.at[4, 'B']
2
```

Set value at specified row/column pair

```python
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```python
>>> df.loc[5].at['B']
4
```

**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()
  - Deprecated since version 0.21.0.

**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.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
    return if I have any nans; enables various perf speedups

pandas.Series.iat

Series.iat
    Access a single value for a row/column pair by integer position.
    Similar to iloc, in that both provide integer-based lookups. Use iat if you only need to get or set a single value in a DataFrame or Series.
    
    Raises IndexError
    When integer position is out of bounds
    
    See also:
    
    DataFrame.at Access a single value for a row/column label pair
    DataFrame.loc Access a group of rows and columns by label(s)
    DataFrame.iloc Access a group of rows and columns by integer position(s)

    Examples
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
... columns=['A', 'B', 'C'])
>>> df
   A  B  C
0  0  2  3
1  0  4  1
2 10 20 30

Get value at specified row/column pair

>>> df.iat[1, 2]
1

Set value at specified row/column pair

>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10

Get value within a series

>>> df.loc[0].iat[1]
2

**pandas.Series.iloc**

Series.iloc
Purely integer-location based indexing for selection by position.

.iloc[] is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

.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.index**

Series.index
The index (axis labels) of the Series.
pandas.Series.is_monotonic

Series.is_monotonic
Return boolean if values in the object are monotonic_increasing
New in version 0.19.0.
Returns
is_monotonic [boolean]

pandas.Series.is_monotonic_decreasing

Series.is_monotonic_decreasing
Return boolean if values in the object are monotonic_decreasing
New in version 0.19.0.
Returns
is_monotonic_decreasing [boolean]

pandas.Series.is_monotonic_increasing

Series.is_monotonic_increasing
Return boolean if values in the object are monotonic_increasing
New in version 0.19.0.
Returns
is_monotonic [boolean]

pandas.Series.is_unique

Series.is_unique
Return boolean if values in the object are unique
Returns
is_unique [boolean]

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.
Warning: Starting in 0.20.0, the .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers.
.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
Access a group of rows and columns by label(s) or a boolean array.

.loc[] is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

• A single label, e.g. 5 or 'a', (note that 5 is interpreted as a label of the index, and never as an integer position along the index).

• A list or array of labels, e.g. ['a', 'b', 'c'].

• A slice object with labels, e.g. 'a':'f'.

Warning: Note that contrary to usual python slices, both the start and the stop are included

• A boolean array of the same length as the axis being sliced, e.g. [True, False, True].

• A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

See more at Selection by Label

Raises KeyError:
when any items are not found

See also:

DataFrame.at Access a single value for a row/column label pair
DataFrame.iloc Access group of rows and columns by integer position(s)
DataFrame.xs Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
Series.loc Access group of values using labels

Examples

Getting values
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> df = pd.DataFrame([[[1, 2], [4, 5], [7, 8]],
...                     index=['cobra', 'viper', 'sidewinder'],
...                     columns=['max_speed', 'shield'])
```

```
max_speed shield
cobra 1 2
viper 4 5
sidewinder 7 8
```

Single label. Note this returns the row as a Series.

```python
>>> df.loc['viper']
max_speed 4
shield 5
Name: viper, dtype: int64
```

List of labels. Note using [[]] returns a DataFrame.

```python
>>> df.loc[['viper', 'sidewinder']]
max_speed shield
viper 4 5
sidewinder 7 8
```

Single label for row and column

```python
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```python
>>> df.loc['cobra':'viper', 'max_speed']
cobra 1
viper 4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```python
>>> df.loc[[False, False, True]]
sidewinder 7 8
```

Conditional that returns a boolean Series

```python
>>> df.loc[df['shield'] > 6]
sidewinder 7 8
```

Conditional that returns a boolean Series with column labels specified

```python
>>> df.loc[df['shield'] > 6, ['max_speed']]
sidewinder 7
```

Callable that returns a boolean Series
Setting values

Set value for all items matching the list of labels

```python
>>> df.loc[[lambda df: df['shield'] == 8]
   max_speed shield
sidewinder 7 8
```

Set value for an entire row

```python
>>> df.loc['cobra'] = 10
>>> df
    max_speed   shield
cobra      10       10
viper       4        50
sidewinder  7        50
```

Set value for an entire column

```python
>>> df.loc[:, 'max_speed'] = 30
>>> df
    max_speed   shield
cobra      30       10
viper       30       50
sidewinder  30       50
```

Set value for rows matching callable condition

```python
>>> df.loc[df['shield'] > 35] = 0
>>> df
    max_speed   shield
cobra      30       10
viper       0        0
sidewinder  0        0
```

Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
    max_speed   shield
   7        1       2
   8        4        5
   9        7        8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.
Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```python
>>> tuples = [
    ... ('cobra', 'mark i'), ('cobra', 'mark ii'),
    ... ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
    ... ('viper', 'mark ii'), ('viper', 'mark iii')
    ... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [
    ... [12, 2], [0, 4], [10, 20],
    ... [1, 4], [7, 1], [16, 36]
    ... ]
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
   max_speed  shield
cobra mark i     12     2
    mark ii      0     4
sidewinder mark i  10    20
     mark ii     1     4
   viper mark ii     7     1
     mark iii    16    36
```

Single label. Note this returns a DataFrame with a single index.

```python
>>> df.loc['cobra']
   max_speed  shield
    mark i     12     2
    mark ii      0     4
```

Single index tuple. Note this returns a Series.

```python
>>> df.loc[('cobra', 'mark ii')]
   max_speed  shield
cobra mark ii      0     4
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```python
>>> df.loc['cobra', 'mark i']
   max_speed  shield
cobra mark i     12     2
```

Single tuple. Note using [[]] returns a DataFrame.

```python
>>> df.loc[['cobra', 'mark ii']]
   max_speed  shield
cobra mark ii      0     4
```

Single tuple for the index with a single label for the column
>>> df.loc[('cobra', 'mark i'), 'shield']
2

Slice from index tuple to single label

>>> df.loc[('cobra', 'mark i'):'viper']

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra mark i</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>mark ii</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>sidewinder mark i</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>mark ii</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>viper mark ii</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>mark iii</td>
<td>16</td>
<td>36</td>
</tr>
</tbody>
</table>

Slice from index tuple to index tuple

>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra mark i</td>
<td>12</td>
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</tr>
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<td>0</td>
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</tr>
<tr>
<td>sidewinder mark i</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>mark ii</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>viper mark ii</td>
<td>7</td>
<td>1</td>
</tr>
</tbody>
</table>

**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.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**

Return Series as ndarray or ndarray-like depending on the dtype

**Returns**

arr [numpy.ndarray or ndarary-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
[a, a, b, c]
Categories (3, object): [a, b, c]
```

Timezone aware datetime data is converted to UTC:

```python
>>> pd.Series(pd.date_range('20130101', periods=3,...
    tz='US/Eastern')).values
array(['2013-01-01T05:00:00.000000000',
    '2013-01-02T05:00:00.000000000',
    '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

**Methods**

- **abs()**
  Return a Series/DataFrame with absolute numeric value of each element.

- **add(other[, level, fill_value, axis])**
  Addition of series and other, element-wise (binary operator add).

- **add_prefix(prefix)**
  Prefix labels with string prefix.

- **add_suffix(suffix)**
  Suffix labels with string suffix.

- **agg(func[, axis])**
  Aggregate using one or more operations over the specified axis.

- **aggregate(func[, axis])**
  Aggregate using one or more operations over the specified axis.

- **align(other[, join, axis, level, copy, ...])**
  Align two objects on their axes with the specified join method for each axis Index

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### Table 25 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>all([axis, bool_only, skipna, level])</code></td>
<td>Return whether all elements are True over series or dataframe axis.</td>
</tr>
<tr>
<td><code>any([axis, bool_only, skipna, level])</code></td>
<td>Return whether any element is True over requested axis.</td>
</tr>
<tr>
<td><code>append(to_append[, ignore_index, ...])</code></td>
<td>Concatenate two or more Series.</td>
</tr>
<tr>
<td><code>apply(func[, convert_dtype, args])</code></td>
<td>Invoke function on values of Series.</td>
</tr>
<tr>
<td><code>argmax([axis, skipna])</code></td>
<td>(DEPRECATED) ..</td>
</tr>
<tr>
<td><code>argmin([axis, skipna])</code></td>
<td>(DEPRECATED) ..</td>
</tr>
<tr>
<td><code>argsort([axis, kind, order])</code></td>
<td>Overrides ndarray.argsort.</td>
</tr>
<tr>
<td><code>as_blocks([copy])</code></td>
<td>(DEPRECATED) Convert the frame to a dict of dtype -&gt; Constructor Types that each has a homogeneous dtype.</td>
</tr>
<tr>
<td><code>as_matrix([columns])</code></td>
<td>(DEPRECATED) Convert the frame to its Numpy-array representation.</td>
</tr>
<tr>
<td><code>asfreq(freq[, method, how, normalize, ...])</code></td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td><code>asof(where[, subset])</code></td>
<td>The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)</td>
</tr>
<tr>
<td><code>astype(dtype[, copy, errors])</code></td>
<td>Cast a pandas object to a specified dtype dtype.</td>
</tr>
<tr>
<td><code>at_time(time[, asof])</code></td>
<td>Select values at particular time of day (e.g. 9:00-9:30 AM).</td>
</tr>
<tr>
<td><code>autocorr([lag])</code></td>
<td>Lag-N autocorrelation</td>
</tr>
<tr>
<td><code>between(left, right[, inclusive])</code></td>
<td>Return boolean Series equivalent to left &lt;= series &lt;= right.</td>
</tr>
<tr>
<td><code>between_time(start_time, end_time[, ...])</code></td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td><code>bfill([axis, inplace, limit, downcast])</code></td>
<td>Synonym for DataFrame.fillna(method='bfill')</td>
</tr>
<tr>
<td><code>bool()</code></td>
<td>Return the bool of a single element PandasObject.</td>
</tr>
<tr>
<td><code>cat</code></td>
<td>alias of pandas.core.arrays.categorical.CategoricalAccessor</td>
</tr>
<tr>
<td><code>clip([lower, upper, axis, inplace])</code></td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td><code>clip_lower(threshold[, axis, inplace])</code></td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td><code>clip_upper(threshold[, axis, inplace])</code></td>
<td>Return copy of input with values above given value(s) truncated.</td>
</tr>
<tr>
<td><code>combine(other, func[, fill_value])</code></td>
<td>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</td>
</tr>
<tr>
<td><code>combine_first(other)</code></td>
<td>Combine Series values, choosing the calling Series’s values first.</td>
</tr>
<tr>
<td><code>compound([axis, skipna, level])</code></td>
<td>Return the compound percentage of the values for the requested axis</td>
</tr>
<tr>
<td><code>compress(condition, *args, **kwargs)</code></td>
<td>Return selected slices of an array along given axis as a Series</td>
</tr>
<tr>
<td><code>consolidate([inplace])</code></td>
<td>(DEPRECATED) Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray).</td>
</tr>
<tr>
<td><code>convert_objects([convert_dates, ...])</code></td>
<td>(DEPRECATED) Attempt to infer better dtype for object columns.</td>
</tr>
<tr>
<td><code>copy([deep])</code></td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
</tbody>
</table>

Continued on next page
Table 25 – continued from previous page

**corr**(other[, method, min_periods]) Compute correlation with other Series, excluding missing values

**count**(level) Return number of non-NA/null observations in the Series

**cov**(other[, min_periods]) Compute covariance with Series, excluding missing values

**cummax**(axis, skipna) Return cumulative maximum over a DataFrame or Series axis.

**cummin**(axis, skipna) Return cumulative minimum over a DataFrame or Series axis.

**cumprod**(axis, skipna) Return cumulative product over a DataFrame or Series axis.

**cumsum**(axis, skipna) Return cumulative sum over a DataFrame or Series axis.

**describe**(percentiles, include, exclude) Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

**diff**(periods) First discrete difference of element.

**div**(other[, level, fill_value, axis]) Floating division of series and other, element-wise (binary operator `truediv`).

**divide**(other[, level, fill_value, axis]) Floating division of series and other, element-wise (binary operator `truediv`).

**divmod**(other[, level, fill_value, axis]) Integer division and modulo of series and other, element-wise (binary operator `divmod`).

**dot**(other) Matrix multiplication with DataFrame or innerproduct with Series objects.

**drop**(labels, axis, index, columns, level, . . .) Return Series with specified index labels removed.

**drop_duplicates**(keep, inplace) Return Series with duplicate values removed.

**dropna**(axis, inplace) Return a new Series with missing values removed.

**dt** alias of pandas.core.indexes.accessors CombinedDatetimelikeProperties

**duplicated**(keep) Indicate duplicate Series values.

**eq**(other[, level, fill_value, axis]) Equal to of series and other, element-wise (binary operator `eq`).

**equals**(other) Determines if two NDFrame objects contain the same elements.

**ewm**(com, span, halflife, alpha, . . .) Provides exponential weighted functions

**expanding**(min_periods, center, axis) Provides expanding transformations.

**factorize**(sort, na_sentinel) Encode the object as an enumerated type or categorical variable.

**ffill**(axis, inplace, limit, downcast) Synonym for DataFrame.fillna(method='ffill')

**fillna**(value, method, axis, inplace, . . .) Fill NA/NaN values using the specified method

**filter**(items, like, regex, axis) Subset rows or columns of dataframe according to labels in the specified index.

**first**(offset) Convenience method for subsetting initial periods of time series data based on a date offset.

**first_valid_index** Return index for first non-NA/null value.

**floordiv**(other[, level, fill_value, axis]) Integer division of series and other, element-wise (binary operator `floordiv`).

Continued on next page
Table 25 – continued from previous page

- **from_array**(arr[, index, name, dtype, copy, ...]) Construct Series from array.
- **from_csv**(path[, sep, parse_dates, header, ...]) (DEPRECATED) Read CSV file.
- **ge**(other[, level, fill_value, axis]) Greater than or equal to of series and other, element-wise (binary operator `ge`).
- **get**(key[, default]) Get item from object for given key (DataFrame column, Panel slice, etc.).
- **get_dtype_counts()** Return counts of unique dtypes in this object.
- **get_ftype_counts()** (DEPRECATED) Return counts of unique ftypes in this object.
- **get_value**(label[, takeable]) (DEPRECATED) Quickly retrieve single value at passed index label.
- **get_values()** same as values (but handles sparseness conversions); is a view.
- **groupby**(by, axis[, level, as_index, sort, ...]) Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns.
- **gt**(other[, level, fill_value, axis]) Greater than of series and other, element-wise (binary operator `gt`).
- **head**(n) Return the first `n` rows.
- **hist**(by, ax[, grid, xlabelsize, xrot, ...]) Draw histogram of the input series using matplotlib.
- **idxmax**(axis[, skipna]) Return the row label of the maximum value.
- **idxmin**(axis[, skipna]) Return the row label of the minimum value.
- **infer_objects()** Attempt to infer better dtypes for object columns.
- **interpolate**(method[, axis, limit, inplace, ...]) Interpolate values according to different methods.
- **isin**(values) Check whether `values` are contained in Series.
- **isna()** Detect missing values.
- **isnull()** Detect missing values.
- **item()** return the first element of the underlying data as a python scalar.
- **items()** Lazily iterate over (index, value) tuples.
- **iteritems()** Lazily iterate over (index, value) tuples.
- **keys()** Alias for index.
- **kurt**(axis[, skipna, level, numeric_only]) Return unbiased kurtosis over requested axis using Fisher's definition of kurtosis (kurtosis of normal == 0.0).
- **kurtosis**(axis[, skipna, level, numeric_only]) Return unbiased kurtosis over requested axis using Fisher's definition of kurtosis (kurtosis of normal == 0.0).
- **last**(offset) Convenience method for subsetting final periods of time series data based on a date offset.
- **last_valid_index()** Return index for last non-NA/null value.
- **le**(other[, level, fill_value, axis]) Less than or equal to of series and other, element-wise (binary operator `le`).
- **lt**(other[, level, fill_value, axis]) Less than of series and other, element-wise (binary operator `lt`).
- **mad**(axis, skipna, level) Return the mean absolute deviation of the values for the requested axis.
- **map**(arg[, na_action]) Map values of Series using input correspondence (a dict, Series, or function).
Table 25 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>mask()</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from self where <code>cond</code> is False and otherwise from <code>other</code>.</td>
</tr>
<tr>
<td><code>max()</code></td>
<td>This method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>mean()</code></td>
<td>Return the mean of the values for the requested axis.</td>
</tr>
<tr>
<td><code>median()</code></td>
<td>Return the median of the values for the requested axis.</td>
</tr>
<tr>
<td><code>memory_usage()</code></td>
<td>Return the memory usage of the Series.</td>
</tr>
<tr>
<td><code>min()</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>mod()</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>mode()</code></td>
<td>Return the mode(s) of the dataset.</td>
</tr>
<tr>
<td><code>mul()</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>multiply()</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>ne()</code></td>
<td>Not equal to of series and other, element-wise (binary operator <code>ne</code>).</td>
</tr>
<tr>
<td><code>nlargest()</code></td>
<td>Return the largest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>nonzero()</code></td>
<td>Return the integer indices of the elements that are non-zero.</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nsmallest()</code></td>
<td>Return the smallest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>nunique()</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>pct_change()</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>pipe()</code></td>
<td>Apply func(self, *args, **kwargs)</td>
</tr>
<tr>
<td><code>plot()</code></td>
<td>alias of <code>pandas.plotting._core.SeriesPlotMethods</code></td>
</tr>
<tr>
<td><code>pop()</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>pow()</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>prod()</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>product()</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>ptp()</code></td>
<td>Returns the difference between the maximum value and the minimum value in the object.</td>
</tr>
<tr>
<td><code>put()</code></td>
<td>Applies the <code>put</code> method to its <code>values</code> attribute if it has one.</td>
</tr>
<tr>
<td><code>quantile()</code></td>
<td>Return value at the given quantile, a la <code>numpy.percentile</code>.</td>
</tr>
<tr>
<td><code>radd()</code></td>
<td>Addition of series and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>rank()</code></td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td><code>ravel()</code></td>
<td>Return the flattened underlying data as an ndarray.</td>
</tr>
</tbody>
</table>

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Table 25 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rdiv(other[, level, fill_value, axis])</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>reindex([index])</code></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><code>reindex_axis(labels[, axis])</code></td>
<td>(DEPRECATED) Conform Series to new index with optional filling logic.</td>
</tr>
<tr>
<td><code>reindex_like(other[, method, copy, limit, ...])</code></td>
<td>Return an object with matching indices to myself.</td>
</tr>
<tr>
<td><code>rename([index])</code></td>
<td>Alter Series index labels or name</td>
</tr>
<tr>
<td><code>rename_axis(mapper[, axis, copy, inplace])</code></td>
<td>Alter the name of the index or columns.</td>
</tr>
<tr>
<td><code>reorder_levels(order)</code></td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td><code>repeat(repeats, *args, **kwargs)</code></td>
<td>Repeat elements of an Series.</td>
</tr>
<tr>
<td><code>replace([to_replace, value, inplace, limit, ...])</code></td>
<td>Replace values given in <code>to_replace</code> with <code>value</code>.</td>
</tr>
<tr>
<td><code>resample(rule[, how, axis, fill_method, ...])</code></td>
<td>Convenience method for frequency conversion and resampling of time series.</td>
</tr>
<tr>
<td><code>reset_index([level, drop, name, inplace])</code></td>
<td>Generate a new DataFrame or Series with the index reset.</td>
</tr>
<tr>
<td><code>rfloordiv(other[, level, fill_value, axis])</code></td>
<td>Integer division of series and other, element-wise (binary operator <code>rfloordiv</code>).</td>
</tr>
<tr>
<td><code>rmod(other[, level, fill_value, axis])</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
<tr>
<td><code>rmul(other[, level, fill_value, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>rolling(window[, min_periods, center, ...])</code></td>
<td>Provides rolling window calculations.</td>
</tr>
<tr>
<td><code>round([decimals])</code></td>
<td>Round each value in a Series to the given number of decimals.</td>
</tr>
<tr>
<td><code>rpow(other[, level, fill_value, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>rsub(other[, level, fill_value, axis])</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>rtruediv(other[, level, fill_value, axis])</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>sample([n, frac, replace, weights, ...])</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>searchsorted(value[, side, sorter])</code></td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>select(crit[, axis])</code></td>
<td>(DEPRECATED) 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(labels[, axis, inplace])</code></td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td><code>set_value(label, value[, takeable])</code></td>
<td>(DEPRECATED) Quickly set single value at passed label.</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 Normalized by N-1.</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_index([axis, level, ascending, ...])</code></td>
<td>Sort Series by index labels.</td>
</tr>
<tr>
<td><code>sort_values([axis, ascending, inplace, ...])</code></td>
<td>Sort by the values.</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>sortlevel</code></td>
<td>(DEPRECATED) 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 sample standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>str</code></td>
<td>alias of pandas.core.strings.StringMethods</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 1 and 2 in a MultiIndex.</td>
</tr>
<tr>
<td><code>tail</code></td>
<td>Return the last n rows.</td>
</tr>
<tr>
<td><code>take</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>to_clipboard</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>to_csv</code></td>
<td>Write Series to a comma-separated values (csv) file.</td>
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<tr>
<td><code>to_dense</code></td>
<td>Return dense representation of NDFrame (as opposed to sparse)</td>
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<td><code>to_dict</code></td>
<td>Convert Series to {label -&gt; value} dict or dict-like object.</td>
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<td>Write Series to an excel sheet.</td>
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<td><code>to_frame</code></td>
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<td><code>to_hdf</code></td>
<td>Write the contained data to an HDF5 file using HDFStore.</td>
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<td>Convert the object to a JSON string.</td>
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<td><code>to_latex</code></td>
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<td>Convert Series from DatetimeIndex to PeriodIndex with desired frequency</td>
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<td></td>
<td>(inferred from index if not passed)</td>
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<td><code>to_pickle</code></td>
<td>Pickle (serialize) object to file.</td>
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<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
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<tr>
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<td>Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.</td>
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<td>Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.</td>
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pandas.Series.abs

Series.abs()

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

Returns abs

Series/DataFrame containing the absolute value of each element.

See also:

numpy.absolute calculate the absolute value element-wise.

Notes

For complex inputs, $1.2 + 1j$, the absolute value is $\sqrt{a^2 + b^2}$.

Examples

Absolute numeric values in a Series.

```python
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.
Absolute numeric values in a Series with a Timedelta element.

```python
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```python
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
   a  b  c
0  4 10 100
1  5 20  50
2  6 30 -30
3  7 40 -50
>>> df.loc[(df.c - 43).abs().argsort()]
   a  b  c
1  5 20  50
0  4 10 100
2  6 30 -30
3  7 40 -50
```

### pandas.Series.add

**`Series.add(other, level=None, fill_value=None, axis=0)`**

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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*

**Examples**

```python
def a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
def b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> a.add(b, fill_value=0)
```

**pandas.Series.add_prefix**

*Series.add_prefix*(prefix)

Prefix labels with string *prefix*.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

**Parameters**

prefix : str

The string to add before each label.

**Returns**

Series or DataFrame

New Series or DataFrame with updated labels.

See also:

*Series.add_suffix* Suffix row labels with string *suffix*.

*Dataframe.add_suffix* Suffix column labels with string *suffix*.

**Examples**

```python
def s = pd.Series([1, 2, 3, 4])
```
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```python
2 3
3 4
dtype: int64
```

```python
>>> s.add_prefix('item_')
item_0 1
item_1 2
item_2 3
item_3 4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```python
>>> df.add_prefix('col_')
   col_A  col_B
0      1      3
1      2      4
2      3      5
3      4      6
```

### pandas.Series.add_suffix

**Series.add_suffix**(*suffix*)

Suffix labels with string *suffix*.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

**Parameters**  

*suffix* : str

The string to add after each label.

**Returns**  

Series or DataFrame

New Series or DataFrame with updated labels.

**See also:**

*Series.add_prefix* Prefix row labels with string *prefix*.

*DataFrame.add_prefix* Prefix column labels with string *prefix*.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0  1
1  2
2  3
3  4
```
3  4
dtype: int64

```python
>>> s.add_suffix('_item')
0_item 1
1_item 2
2_item 3
3_item 4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```python
>>> df.add_suffix('_col')
   A_col  B_col
0     1     3
1     2     4
2     3     5
3     4     6
```

**pandas.Series.agg**

Series.agg(func, axis=0, *args, **kwargs)
Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

**Parameters**

- **func**: function, string, dictionary, or list of string/functions
  - Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
  - Accepted combinations are:
    - string function name.
    - function.
    - list of functions.
    - dict of column names -> functions (or list of functions).

- **axis**: {0 or 'index'}
  - Parameter needed for compatibility with DataFrame.

- **args**
  - Positional arguments to pass to func.

- **kwargs**
  - Keyword arguments to pass to func.
Returns

aggregated [Series]

See also:

pandas.Series.apply, pandas.Series.transform

Notes

agg is an alias for aggregate. Use the alias.
A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = Series(np.random.randn(10))

>>> s.agg('min')
-1.301805

>>> s.agg(['min', 'max'])
min  -1.301805
max   1.127688
dtype: float64
```

pandas.Series.aggregate

Series.aggregate(func, axis=0, *args, **kwargs)
Aggregate using one or more operations over the specified axis.
New in version 0.20.0.

Parameters

func : function, string, dictionary, or list of string/functions
Function to use for aggregating the data. If a function, must either work when passed a
Series or when passed to Series.apply. For a DataFrame, can pass a dict, if the keys are
DataFrame column names.

Accepted combinations are:
• string function name.
• function.
• list of functions.
• dict of column names -> functions (or list of functions).

axis : {0 or ‘index’}
Parameter needed for compatibility with DataFrame.

*args
Positional arguments to pass to func.

**kwargs
Keyword arguments to pass to `func`.

**Returns**

`aggregated` [Series]

**See also:**

`pandas.Series.apply`, `pandas.Series.transform`

**Notes**

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

**Examples**

```python
>>> s = Series(np.random.randn(10))

>>> s.agg('min')
-1.301805

>>> s.agg(['min', 'max'])
min -1.301805
max 1.127688
dtype: float64
```

**pandas.Series.align**

`Series.align` (`other`, `join='outer'`, `axis=None`, `level=None`, `copy=True`, `fill_value=None`, `method=None`, `limit=None`, `fill_axis=0`, `broadcast_axis=None`)

Align two objects on their axes with the specified join method 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 or ‘index’}, default 0
   Filling axis, method and limit
broadcast_axis : {0 or ‘index’}, default None
   Broadcast values along this axis, if aligning two objects of different dimensions

Returns (left, right) : (Series, type of other)
   Aligned objects

*pandas.Series.all*

Series.all (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether all elements are True over series or dataframe axis.

Returns True if all elements within a series or along a dataframe axis are non-zero, not-empty or not-False.

Parameters axis : int, default 0
   Select the axis which can be 0 for indices and 1 for columns.

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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**kwargs : any, default None
   Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns
   all [scalar or Series (if level specified)]

See also:

*pandas.Series.all* Return True if all elements are True
*pandas.DataFrame.any* Return True if one (or more) elements are True

Examples

Series

>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
Dataframes

Create a dataframe from a dictionary.

```python
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
  col1 col2
0   True  True
1   True False
```

Default behaviour checks if column-wise values all return True.

```python
>>> df.all()
   col1   col2
0   True   True
1   True False
   dtype: bool
```

Adding axis=1 argument will check if row-wise values all return True.

```python
>>> df.all(axis=1)
0   True
1   False
   dtype: bool
```

**pandas.Series.any**

`Series.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis.

Unlike `DataFrame.all()`, this performs an or operation. If any of the values along the specified axis is True, this will return True.

**Parameters**

- `axis` : int, default 0
  
  Select the axis which can be 0 for indices and 1 for columns.

- `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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

- `**kwargs` : any, default None
  
  Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- `any` [scalar or Series (if level specified)]

**See also**

- `pandas.DataFrame.all` Return whether all elements are True.
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Examples
Series
For Series input, the output is a scalar indicating whether any element is True.
>>> pd.Series([True, False]).any()
True

DataFrame
Whether each column contains at least one True element (the default).
>>> df =
>>> df
A B
0 1 0
1 2 2

pd.DataFrame({"A": [1, 2], "B": [0, 2], "C": [0, 0]})
C
0
0

>>> df.any()
A
True
B
True
C
False
dtype: bool

Aggregating over the columns.
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 2]})
>>> df
A B
0
True 1
1 False 2
>>> df.any(axis='columns')
0
True
1
True
dtype: bool
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 0]})
>>> df
A B
0
True 1
1 False 0
>>> df.any(axis='columns')
0
True
1
False
dtype: bool

any for an empty DataFrame is an empty Series.
>>> pd.DataFrame([]).any()
Series([], dtype: bool)

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pandas.Series.append

Series.append(to_append, ignore_index=False, verify_integrity=False)
Concatenate two or more Series.

Parameters

to_append [Series or list/tuple of Series]

ignore_index : boolean, default False
    If True, do not use the index labels.
    New in version 0.19.0.

verify_integrity : boolean, default False
    If True, raise Exception on creating index with duplicates

Returns

appended [Series]

See also:

pandas.concat General function to concatenate DataFrame, Series or Panel objects

Notes

Iteratively appending to a Series can be more computationally intensive than a single concatenate. A better solution is to append values to a list and then concatenate the list with the original Series all at once.

Examples

```python
>>> s1 = pd.Series([1, 2, 3])
>>> s2 = pd.Series([4, 5, 6])
>>> s3 = pd.Series([4, 5, 6], index=[3, 4, 5])
>>> s1.append(s2)
0  1
  1 2
  2 3
  0 4
  1 5
  2 6
dtype: int64

>>> s1.append(s3)
0  1
  1 2
  2 3
  3 4
  4 5
  5 6
dtype: int64
```

With ignore_index set to True:
```python
>>> s1.append(s2, ignore_index=True)
0  1
1  2
2  3
3  4
4  5
5  6
dtype: int64
```

With `verify_integrity` set to True:

```python
>>> s1.append(s2, verify_integrity=True)
Traceback (most recent call last):
...  
ValueError: Indexes have overlapping values: [0, 1, 2]
```

**pandas.Series.apply**

`Series.apply(func, convert_dtype=True, args=(), **kwargs)`

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
- `Series.agg` only perform aggregating type operations
- `Series.transform` only perform transforming type operations

**Examples**

Create a series with typical summer temperatures for each city.

```python
>>> import pandas as pd
>>> import numpy as np
>>> series = pd.Series([20, 21, 12], index=['London', ...
'New York','Helsinki'])
```

(continues on next page)
Square the values by defining a function and passing it as an argument to `apply()`.

```python
>>> def square(x):
...     return x**2

```

```python
>>> series.apply(square)
London   400
New York 441
Helsinki 144
```

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
```

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

```

```python
>>> series.apply(subtract_custom_value, args=(5,))
London    15
New York  16
Helsinki  7
```

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

```

```python
>>> series.apply(add_custom_values, june=30, july=20, august=25)
London   95
New York 96
Helsinki 87
```

Use a function from the Numpy library.

```python
>>> series.apply(np.log)
London   2.995732
New York 3.044522
Helsinki 2.484907
```

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

```

```python
>>> 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()`.

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>>> series.apply(lambda x: x**2)
London   400
New York 441
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Define a custom function that needs additional positional arguments and pass these additional arguments using the `args` keyword.

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>>> def subtract_custom_value(x, custom_value):
...     return x - custom_value

```

```python
>>> series.apply(subtract_custom_value, args=(5,))
London    15
New York  16
Helsinki  7
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>>> def add_custom_values(x, **kwargs):
...     for month in kwargs:
...         x += kwargs[month]
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```

```python
>>> series.apply(add_custom_values, june=30, july=20, august=25)
London   95
New York 96
Helsinki 87
```

Use a function from the Numpy library.

```python
>>> series.apply(np.log)
London   2.995732
New York 3.044522
Helsinki 2.484907
```

dtype: float64
pandas.Series.argmax

Series.argmax(axis=0, skipna=True, *args, **kwargs)

Deprecated since version 0.21.0:

‘argmax’ is deprecated, use ‘idxmax’ instead. The behavior of ‘argmax’ will be corrected to return
the positional maximum in the future. Use ‘series.values.argmax’ to get the position of the maxi-
mum now.

Return the row label of the maximum value.

If multiple values equal the maximum, the first row label with that value is returned.

Parameters

skipna : boolean, default True

Exclude NA/null values. If the entire Series is NA, the result will be NA.

axis : int, default 0

For compatibility with DataFrame.idxmax. Redundant for application on Series.

*args, **kwargs

Additional keywors have no effect but might be accepted for compatibility with NumPy.

Returns

idxmax [Index of maximum of values.]

Raises ValueError

If the Series is empty.

See also:

numpy.argmax Return indices of the maximum values along the given axis.

DataFrame.idxmax Return index of first occurrence of maximum over requested axis.

Series.idxmin Return index label of the first occurrence of minimum of values.

Notes

This method is the Series version of ndarray.argmax. This method returns the label of the maximum,
while ndarray.argmax returns the position. To get the position, use series.values.argmax().

Examples

```python
>>> s = pd.Series(data=[1, None, 4, 3, 4],
... index=['A', 'B', 'C', 'D', 'E'])
>>> s
A     1.0
B  NaN
C     4.0
D     3.0
E     4.0
dtype: float64
```
>>> s.idxmax()
'C'

If skipna is False and there is an NA value in the data, the function returns nan.

>>> s.idxmax(skipna=False)
nan

pandas.Series.argmin

Series.argmin(axis=None, skipna=True, *args, **kwargs)

Deprecated since version 0.21.0:
‘argmin’ is deprecated, use ‘idxmin’ instead. The behavior of ‘argmin’ will be corrected to return the positional minimum in the future. Use ‘series.values.argmin’ to get the position of the minimum now.

Return the row label of the minimum value.

If multiple values equal the minimum, the first row label with that value is returned.

Parameters

skipna : boolean, default True
  Exclude NA/null values. If the entire Series is NA, the result will be NA.

axis : int, default 0
  For compatibility with DataFrame.idxmin. Redundant for application on Series.

*args, **kwargs
  Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

idxmin  [Index of minimum of values.]

Raises ValueError
  If the Series is empty.

See also:

numpy.argmin  Return indices of the minimum values along the given axis.

DataFrame.idxmin  Return index of first occurrence of minimum over requested axis.

Series.idxmax  Return index label of the first occurrence of maximum of values.

Notes

This method is the Series version of ndarray.argmin. This method returns the label of the minimum, while ndarray.argmin returns the position. To get the position, use series.values.argmin().

Examples
```python
>>> s = pd.Series(data=[1, None, 4, 1],
...               index=['A', 'B', 'C', 'D'])
```  
```python
>>> s
A    1.0
B   NaN
C    4.0
D    1.0
dtype: float64
```  
```python
>>> s.idxmin()
'A'
```  
If `skipna` is False and there is an NA value in the data, the function returns `nan`.

```python
>>> s.idxmin(skipna=False)
nan
```  

**pandas.Series.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
- `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.

Deprecated since version 0.21.0.

**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.Series.as_matrix

Series.as_matrix(columns=None)
Convert the frame to its Numpy-array representation.

Deprecated since version 0.23.0: Use DataFrame.values() instead.

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. By numpy.find_common_type convention, mixing int64 and uint64 will
result in a float64 dtype.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

pandas.Series.asfreq

Series.asfreq(freq=None, method=None, how=None, normalize=False, fill_value=None)
Convert TimeSeries to specified frequency.
Optionally provide filling method to pad/backfill missing values.
Returns the original data conformed to a new index with the specified frequency. resample is more
appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

Parameters

freq [DateOffset object, or string]
method : {'backfill'/‘bfill’, ‘pad’/‘ffill’}, default None
Method to use for filling holes in reindexed Series (note this does not fill NaNs that
already were present):
• ‘pad’ / ‘ffill’: propagate last valid observation forward to next valid
• ‘backfill’ / ‘bfill’: use NEXT valid observation to fill
how : {'start', 'end'}, default end
For PeriodIndex only, see PeriodIndex.asfreq
normalize : bool, default False
Whether to reset output index to midnight

fill_value: scalar, optional

Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

New in version 0.20.0.

Returns

converted [type of caller]

See also:

reindex

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
          s
2000-01-01 00:00:00  0.0
2000-01-01 00:01:00  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:03:00  3.0
```

Upsample the series into 30 second bins.

```python
>>> df.asfreq(freq='30S')
          s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  NaN
2000-01-01 00:03:00  3.0
```

Upsample again, providing a fill value.

```python
>>> df.asfreq(freq='30S', fill_value=9.0)
          s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  9.0
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  9.0
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  9.0
2000-01-01 00:03:00  3.0
```
Upsample again, providing a method.

```python
>>> df.asfreq(freq='30S', method='bfill')
          s
2000-01-01 00:00:00   0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30   2.0
2000-01-01 00:02:00   2.0
2000-01-01 00:02:30   3.0
2000-01-01 00:03:00   3.0
```

**pandas.Series.asof**

```python
Series.asof( where, subset=None)
```

The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)

New in version 0.19.0: For DataFrame

If there is no good value, NaN is returned for a Series a Series of NaN values for a DataFrame

**Parameters**

- `where` [date or array of dates]
- `subset` : string or list of strings, default None
  - if not None use these columns for NaN propagation

**Returns**

- where is scalar
  - value or NaN if input is Series
  - Series if input is DataFrame

**where is Index: same shape object as input**

**See also:**

`merge_asof`

**Notes**

Dates are assumed to be sorted Raises if this is not the case

**pandas.Series.astype**

```python
Series.astype( dtype, copy=True, errors='raise', **kwargs)
```

Cast a pandas object to a specified dtype `dtype`

**Parameters**

- `dtype` : data type, or dict of column name -> data type
  - Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use `{col: dtype, ...}`, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame’s columns to column-specific types.
- `copy` : bool, default True.
Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

**errors** : {‘raise’, ‘ignore’}, default ‘raise’.

Control raising of exceptions on invalid data for provided dtype.
- **raise**: allow exceptions to be raised
- **ignore**: suppress exceptions. On error return original object

New in version 0.20.0.

**raise_on_error** : raise on invalid input

Deprecated since version 0.20.0: Use `errors` instead

**kwargs** [keyword arguments to pass on to the constructor]

**Returns**

**casted** [type of caller]

See also:

- **pandas.to_datetime** Convert argument to datetime.
- **pandas.to_timedelta** Convert argument to timedelta.
- **pandas.to_numeric** Convert argument to a numeric type.
- **numpy.ndarray.astype** Cast a numpy array to a specified type.

**Examples**

```python
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0  1
1  2
dtype: int32
>>> ser.astype('int64')
0  1
1  2
dtype: int64
```

Convert to categorical type:

```python
>>> ser.astype('category')
0  1
1  2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```python
>>> ser.astype('category', ordered=True, categories=[2, 1])
0  1
1  2
dtype: category
Categories (2, int64): [2 < 1]
```
Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```python
>>> s1 = pd.Series([1,2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1
# note that s1[0] has changed too
  0   10
  1    2
dtype: int64
```

**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]

**Raises** `TypeError`

If the index is not a `DatetimeIndex`

**See also:**

- `between_time` Select values between particular times of the day
- `first` Select initial periods of time series based on a date offset
- `last` Select final periods of time series based on a date offset

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4

>>> ts.at_time('12:00')
   A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```
pandas.Series.autocorr

Series.autocorr(lag=1)
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.

This function returns a boolean vector containing True wherever the corresponding Series element is between the boundary values left and right. NA values are treated as False.

Parameters  

left : scalar
Left boundary.

right : scalar
Right boundary.

inclusive : bool, default True
Include boundaries.

Returns  

Series
Each element will be a boolean.

See also:

pandas.Series.gt Greater than of series and other
pandas.Series.lt Less than of series and other

Notes

This function is equivalent to (left <= ser) & (ser <= right)

Examples

```python
>>> s = pd.Series([2, 0, 4, 8, np.nan])
```

Boundary values are included by default:

```python
>>> s.between(1, 4)
0   True
1  False
2   True
3  False
```

(continues on next page)
With *inclusive* set to `False` boundary values are excluded:

```python
>>> s.between(1, 4, inclusive=False)
0     True
1    False
2    False
3    False
4    False
dtype: bool
```

*left* and *right* can be any scalar value:

```python
>>> s = pd.Series(['Alice', 'Bob', 'Carol', 'Eve'])
>>> s.between('Anna', 'Daniel')
0    False
1     True
2     True
3    False
dtype: bool
```

### pandas.Series.between_time

**Series.between_time**(start_time, end_time, include_start=True, include_end=True)

Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting *start_time* to be later than *end_time*, you can get the times that are *not* between the two times.

**Parameters**

- **start_time** [datetime.time or string]
- **end_time** [datetime.time or string]
- **include_start** [boolean, default True]
- **include_end** [boolean, default True]

**Returns**

- **values_between_time** [type of caller]

**Raises** `TypeError`

If the index is not a `DatetimeIndex`

**See also:**

- `at_time` Select values at a particular time of the day
- `first` Select initial periods of time series based on a date offset
- `last` Select final periods of time series based on a date offset

*DatetimeIndex.indexer_between_time* Get just the index locations for values between particular times of the day
Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09  00:00:00    1
2018-04-10  00:20:00    2
2018-04-11  00:40:00    3
2018-04-12  01:00:00    4

>>> ts.between_time('0:15', '0:45')
   A
2018-04-10  00:20:00    2
2018-04-11  00:40:00    3

You get the times that are not between two times by setting `start_time` later than `end_time`:

```python
>>> ts.between_time('0:45', '0:15')
   A
2018-04-09  00:00:00    1
2018-04-12  01:00:00    4
```

pandas.Series.bfill

Series.bfill (axis=None, inplace=False, limit=None, downcast=None)

Synonym for DataFrame.fillna(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).

**Parameters**

- `data` [Series or CategoricalIndex]

**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, axis=None, inplace=False, *args, **kwargs)
Trim values at input threshold(s).
Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

**Parameters**

- **lower**: float or array_like, default None
  Minimum threshold value. All values below this threshold will be set to it.
- **upper**: float or array_like, default None
  Maximum threshold value. All values above this threshold will be set to it.
- **axis**: int or string axis name, optional
  Align object with lower and upper along the given axis.
- **inplace**: boolean, default False
  Whether to perform the operation in place on the data.
  New in version 0.21.0.
- ***args, **kwargs**
  Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

Series or DataFrame
Same type as calling object with the values outside the clip boundaries replaced

See also:

- **clip_lower** Clip values below specified threshold(s).
- **clip_upper** Clip values above specified threshold(s).

**Examples**

```python
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9     -2
1     -3     -7
```
Clips per column using lower and upper thresholds:

```python
>>> df.clip(-4, 6)
     col_0  col_1
0      6     -2
1      6     -4
2      6      6
3      6      6
4      6     -4
```

Clips using specific lower and upper thresholds per column element:

```python
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0   2
1  -4
2  -1
3   6
4   3
dtype: int64

>>> df.clip(t, t + 4, axis=0)
     col_0  col_1
0      6      2
1      6     -4
2      6      3
3      6      8
4      6      3
```

**pandas.Series.clip_lower**

Parameter `threshold` : numeric or array-like

Minimum value allowed. All values below threshold will be set to this value.

- **float** : every value is compared to `threshold`.
- array-like : The shape of `threshold` should match the object it’s compared to. When `self` is a Series, `threshold` should be the length. When `self` is a DataFrame, `threshold` should 2-D and the same shape as `self` for `axis=None`, or 1-D and the same length as the axis being compared.

- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  Align `self` with `threshold` along the given axis.

- **inplace** : boolean, default False
  Whether to perform the operation in place on the data.

New in version 0.21.0.
Returns

clipped [same type as input]

See also:

Series.clip Return copy of input with values below and above thresholds truncated.
Series.clip_upper Return copy of input with values above threshold truncated.

Examples

Series single threshold clipping:

```python
>>> s = pd.Series([5, 6, 7, 8, 9])
>>> s.clip_lower(8)
0    8
1    8
2    8
3    8
4    9
 dtype: int64
```

Series clipping element-wise using an array of thresholds. threshold should be the same length as the Series.

```python
>>> elemwise_thresholds = [4, 8, 7, 2, 5]
>>> s.clip_lower(elemwise_thresholds)
0    5
1    8
2    7
3    8
4    9
 dtype: int64
```

DataFrames can be compared to a scalar.

```python
>>> df = pd.DataFrame({'A': [1, 3, 5], 'B': [2, 4, 6]})
>>> df
   A  B
0  1  2
1  3  4
2  5  6

>>> df.clip_lower(3)
   A  B
0  3  3
1  3  4
2  5  6
```

Or to an array of values. By default, threshold should be the same shape as the DataFrame.

```python
>>> df.clip_lower(np.array([[3, 4], [2, 2], [6, 2]]))
   A  B
0  3  4
1  3  4
2  6  6
```
Control how \textit{threshold} is broadcast with \textit{axis}. In this case \textit{threshold} should be the same length as the axis specified by \textit{axis}.

```python
>>> df.clip_lower(np.array([3, 3, 5]), axis='index')
   A  B
0 3 3
1 3 4
2 5 6

>>> df.clip_lower(np.array([4, 5]), axis='columns')
   A  B
0 4 5
1 4 5
2 5 6
```

\textbf{pandas.Series.clip\_upper}

\texttt{Series.clip\_upper} (\textit{threshold}, \textit{axis}=\textit{None}, \textit{inplace}=\textit{False})

Return copy of input with values above given value(s) truncated.

**Parameters**

- \texttt{threshold} [float or array_like]
- \texttt{axis} : int or string axis name, optional
  
  Align object with threshold along the given axis.
- \texttt{inplace} : boolean, default False
  
  Whether to perform the operation in place on the data

**Returns**

- \texttt{clipped} [same type as input]

**See also:**

\texttt{clip}

\textbf{pandas.Series.combine}

\texttt{Series.combine} (\textit{other, func, fill\_value}=\textit{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**

- \texttt{other} [Series or scalar value]
- \texttt{func} : function
  
  Function that takes two scalars as inputs and return a scalar
- \texttt{fill\_value} [scalar value]

**Returns**
result  [Series]

See also:

**Series.combine_first** Combine Series values, choosing the calling Series’s values first

**Examples**

```python
>>> s1 = Series([1, 2])
>>> s2 = Series([0, 3])
>>> s1.combine(s2, lambda x1, x2: x1 if x1 < x2 else x2)
0    0
1    2
dtype: int64
```

**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**

combined  [Series]

**See also:**

**Series.combine** Perform elementwise operation on two Series using a given function

**Examples**

```python
>>> s1 = pd.Series([1, np.nan])
>>> s2 = pd.Series([3, 4])
>>> s1.combine_first(s2)
0  1.0
1  4.0
dtype: float64
```

**pandas.Series.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 when computing the result.
level : int or level name, default None
    If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into
    a scalar

numeric_only : boolean, default None
    Include only float, int, boolean columns. If None, will attempt to use everything, then
    use only numeric data. Not implemented for Series.

Returns

compounded [scalar or Series (if level specified)]

pandas.Series.compress

Series.compress(condition, *args, **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 ndarry).

    Deprecated since version 0.20.0: Consolidate will be an internal implementation only.

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.

    Deprecated since version 0.21.0.

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]
See also:

- pandas.to_datetime: Convert argument to datetime.
- pandas.to_timedelta: Convert argument to timedelta.
- pandas.to_numeric: Return a fixed frequency timedelta index, with day as the default.

**pandas.Series.copy**

Series.copy(\texttt{deep=True})

Make a copy of this object’s indices and data.

When \texttt{deep=True} (default), a new object will be created with a copy of the calling object’s data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When \texttt{deep=False}, a new object will be created without copying the calling object’s data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

**Parameters**

\texttt{deep} : bool, default True

Make a deep copy, including a copy of the data and the indices. With \texttt{deep=False}, neither the indices nor the data are copied.

**Returns**

\texttt{copy} : Series, DataFrame or Panel

Object type matches caller.

**Notes**

When \texttt{deep=True}, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to \texttt{copy.deepcopy} in the Standard Library, which recursively copies object data (see examples below).

While Index objects are copied when \texttt{deep=True}, the underlying numpy array is not copied for performance reasons. Since Index is immutable, the underlying data can be safely shared and a copy is not needed.

**Examples**

```python
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a    1
b    2
dtype: int64

>>> s_copy = s.copy()
>>> s_copy
a    1
b    2
dtype: int64
```

Shallow copy versus default (deep) copy:
Shallow copy shares data and index with original.

```python
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.

```python
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```python
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a  3  
b  4     
dtype: int64
>>> shallow
a  3  
b  4     
dtype: int64
>>> deep
a  1  
b  2     
dtype: int64
```

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```python
>>> s = pd.Series(([1, 2], [3, 4]))
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0  [10, 2]  
1  [3, 4]     
dtype: object
>>> shallow
0  [10, 2]  
1  [3, 4]     
dtype: object
```

**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, skipna=True, *args, **kwargs)
Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

Parameters axis : {0 or ‘index’, 1 or ‘columns’}, default 0
The index or the name of the axis. 0 is equivalent to None or ‘index’.
skipna : boolean, default True

Excluded NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs :

Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

cummax [scalar or Series]

See also:

pandas.core.window.Expanding.max Similar functionality but ignores NaN values.

Series.max Return the maximum over Series axis.

Series.cummax Return cumulative maximum over Series axis.

Series.cummin Return cumulative minimum over Series axis.

Series.cumsum Return cumulative sum over Series axis.

Series.cumprod Return cumulative product over Series axis.

Examples

Series

>>> s = pd.Series([2, np.nan, 5, -1, 0])

>>> s
0  2.0
1  NaN
2  5.0
3  -1.0
4   0.0
dtype: float64

By default, NA values are ignored.

>>> s.cummax()
0  2.0
1  NaN
2  5.0
3  5.0
4  5.0
dtype: float64

To include NA values in the operation, use skipna=False

>>> s.cummax(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64

DataFrame
```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                   columns=list('AB'))
>>> df
   A   B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cummax()
   A   B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```python
>>> df.cummax(axis=1)
   A   B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

**pandas.Series.cummin**

Series.cummin(axis=None, skipna=True, *args, **kwargs)

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

**Parameters**

- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  - The index or the name of the axis. 0 is equivalent to None or ‘index’.
- **skipna** : boolean, default True
  - Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **args, **kwargs**
  - Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- cummin [scalar or Series]

**See also:**

- pandas.core.window.Expanding.min Similar functionality but ignores NaN values.
- Series.min Return the minimum over Series axis.
- Series.cummax Return cumulative maximum over Series axis.
- Series.cummin Return cumulative minimum over Series axis.
**Series.cumsum**  Return cumulative sum over Series axis.

**Series.cumprod**  Return cumulative product over Series axis.

### Examples

#### Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])

>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
```

to include NA values in the operation, use `skipna=False`

```python
>>> s.cummin(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
```

#### DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],
                     ... [3.0, np.nan],
                     ... [1.0, 0.0]],
                     ... columns=list('AB'))

>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cummin()
   A  B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```
To iterate over columns and find the minimum in each row, use `axis=1`.

```python
>>> df.cummin(axis=1)
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

**pandas.Series.cumprod**

`Series.cumprod(axis=None, skipna=True, *args, **kwargs)`

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

- **Parameters**
  - `axis` : {0 or ‘index’, 1 or ‘columns’}, default 0
    - The index or the name of the axis. 0 is equivalent to None or ‘index’.
  - `skipna` : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA.
  - `*args, **kwargs` :
    - Additional keywords have no effect but might be accepted for compatibility with NumPy.

- **Returns**
  - `cumprod` [scalar or Series]

**See also:**

- `pandas.core.window.Expanding.prod` Similar functionality but ignores NaN values.
- `Series.prod` Return the product over Series axis.
- `Series.cummax` Return cumulative maximum over Series axis.
- `Series.cummin` Return cumulative minimum over Series axis.
- `Series.cumsum` Return cumulative sum over Series axis.
- `Series.cumprod` Return cumulative product over Series axis.

**Examples**

**Series**

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1  NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> s.cumprod()
0   2.0
1   NaN
2  10.0
3  -10.0
4   -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumprod(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

**DataFrame**

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                   columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumprod()
   A  B
0  2.0  2.0
1  6.0  NaN
2  6.0  0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```python
>>> df.cumprod(axis=1)
   A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```

---

**pandas.Series.cumsum**

Series.cumsum(\(axis=\text{None}, \ skipna=\text{True}, *\text{args}, **\text{kwargs}\))

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

**Parameters** **axis** : \{0 or ‘index’, 1 or ‘columns’\}, default 0

The index or the name of the axis. 0 is equivalent to None or ‘index’.
skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs :

Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

cumsum [scalar or Series]

See also:

pandas.core.window.Expanding.sum Similar functionality but ignores NaN values.
Series.sum Return the sum over Series axis.
Series.cummax Return cumulative maximum over Series axis.
Series.cummin Return cumulative minimum over Series axis.
Series.cumsum Return cumulative sum over Series axis.
Series.cumprod Return cumulative product over Series axis.

Examples

Series

>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0  2.0
1  NaN
2  5.0
3 -1.0
4  0.0
dtype: float64

By default, NA values are ignored.

>>> s.cumsum()
0  2.0
1  NaN
2  7.0
3  6.0
4  6.0
dtype: float64

To include NA values in the operation, use `skipna=False`

>>> s.cumsum(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64

DataFrame
>> df = pd.DataFrame([[2.0, 1.0],
...                   [3.0, np.nan],
...                   [1.0, 0.0]],
...                   columns=list('AB'))
>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0

By default, iterates over rows and finds the sum in each column. This is equivalent to axis=None or axis='index'.

>> df.cumsum()
    A    B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0

To iterate over columns and find the sum in each row, use axis=1

>> df.cumsum(axis=1)
   A  B
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0

pandas.Series.describe

Series.describe (percentiles=None, include=None, exclude=None)

Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters percentiles : list-like of numbers, optional

The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

include : ‘all’, list-like of dtypes or None (default), optional

A white list of data types to include in the result. Ignored for Series. Here are the options:

• ‘all’ : All columns of the input will be included in the output.

• A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit numpy.number. To limit it instead to object columns submit the numpy.object data type. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To select pandas categorical columns, use 'category'

• None (default) : The result will include all numeric columns.

exclude : list-like of dtypes or None (default), optional,
A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes: Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use 'category'

- None (default): The result will exclude nothing.

Returns

`summary`: Series/DataFrame of summary statistics

See also:

`DataFrame.count, DataFrame.max, DataFrame.min, DataFrame.mean, DataFrame.std, DataFrame.select_dtypes`

Notes

For numeric data, the result's index will include `count, mean, std, min, max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include `count, unique, top, and freq`. The top is the most common value. The freq is the most common value’s frequency. Timestamps also include the first and last items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

Examples

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
```

Describing a categorical Series.
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count 4
unique 3
top a
freq 2
dtype: object

Describing a timestamp Series.

```python
>>> s = pd.Series([
                    ... np.datetime64("2000-01-01"),
                    ... np.datetime64("2010-01-01"),
                    ... np.datetime64("2010-01-01")
                    ... ])
```

```python
>>> s.describe()
count 3
unique 2
top 2010-01-01 00:00:00
freq 2
first 2000-01-01 00:00:00
last 2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({
                        'object': ['a', 'b', 'c'],
                        'numeric': [1, 2, 3],
                        'categorical': pd.Categorical(['d','e','f'])
                        })
```

```python
>>> df.describe()
column
numeric
count 3.0
mean 2.0
std 1.0
min 1.0
25% 1.5
50% 2.0
75% 2.5
max 3.0
```

Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
categorical numeric object
count 3 3.0 3
unique 3 NaN 3
top f NaN c
freq 1 NaN 1
mean NaN 2.0 NaN
std NaN 1.0 NaN
min NaN 1.0 NaN
25% NaN 1.5 NaN
50% NaN 2.0 NaN
75% NaN 2.5 NaN
max NaN 3.0 NaN
```

Describing a column from a DataFrame by accessing it as an attribute.
Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
    numeric
       count   3.0
          mean   2.0
          std   1.0
          min   1.0
         25%   1.5
         50%   2.0
         75%   2.5
          max   3.0
Name: numeric, dtype: float64
```

Including only string columns in a DataFrame description.

```python
>>> df.describe(include=[np.object])
    object
       count    3
         unique    3
           top    c
          freq    1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
    categorical
       count    3
         unique    3
           top    f
          freq    1
```

Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
    categorical object
       count    3    3
         unique    3    3
           top    f    c
          freq    1    1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.object])
    categorical numeric
       count    3    3.0
         unique    3    NaN
```
pandas.Series.diff

Series.diff(periods=1)

First discrete difference of element.

Calculates the difference of a Series element compared with another element in the Series (default is element in previous row).

Parameters

periods : int, default 1

Periods to shift for calculating difference, accepts negative values.

Returns
diffed [Series]

See also:

Series.pct_change Percent change over given number of periods.

Series.shift Shift index by desired number of periods with an optional time freq.

DataFrame.diff First discrete difference of object

Examples

Difference with previous row

```python
>>> s = pd.Series([1, 1, 2, 3, 5, 8])
>>> s.diff()
0    NaN
1    0.0
2    1.0
3    1.0
4    2.0
5    3.0
dtype: float64
```

Difference with 3rd previous row

```python
>>> s.diff(periods=3)
0     NaN
1     NaN
2     NaN
3    2.0
4    4.0
```
Difference with following row

```python
>>> s.diff(periods=-1)
0  0.0
1 -1.0
2 -1.0
3 -2.0
4 -3.0
5  NaN
dtype: float64
```

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a  1.0
b  1.0
c  1.0
d  NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
0  1.0
1  NaN
2  1.0
3  NaN
```
>> a.add(b, fill_value=0)
>> b
NaN
d 1.0
e NaN
dtype: float64

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
```
pandas.Series.divmod

Series.divmod(other, level=None, fill_value=None, axis=0)

Integer division and modulo of series and other, element-wise (binary operator divmod).

Equivalent to series divmod other, but with support to substitute a fill_value for missing data in one of the inputs.

**Parameters**

- other [Series or scalar value]
- fill_value : None or float value, default None (NaN)
  Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```
pandas.Series.dot

Series.dot(other)
Matrix multiplication with DataFrame or inner-product with Series objects. Can also be called using self @ other in Python >= 3.5.

Parameters

other [Series or DataFrame]

Returns
dot_product [scalar or Series]

pandas.Series.drop

Series.drop(labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')
Return Series with specified index labels removed.
Remove elements of a Series based on specifying the index labels. When using a multi-index, labels on different levels can be removed by specifying the level.

Parameters
labels : single label or list-like
Index labels to drop.

axis : 0, default 0
Redundant for application on Series.

index, columns : None
Redundant for application on Series, but index can be used instead of labels.
New in version 0.21.0.

level : int or level name, optional
For MultiIndex, level for which the labels will be removed.

inplace : bool, default False
If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'
If 'ignore', suppress error and only existing labels are dropped.

Returns
dropped [pandas.Series]

Raises

KeyError
If none of the labels are found in the index.
See also:

**Series.reindex**  Return only specified index labels of Series.

**Series.dropna**  Return series without null values.

**Series.drop_duplicates**  Return Series with duplicate values removed.

**DataFrame.drop**  Drop specified labels from rows or columns.

**Examples**

```python
>>> s = pd.Series(data=np.arange(3), index=['A','B','C'])
>>> s
A 0
B 1
C 2
dtype: int64

Drop labels B en C

>>> s.drop(labels=['B','C'])
A 0
dtype: int64

Drop 2nd level label in MultiIndex Series

>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
... ['speed', 'weight', 'length']],
... labels=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
... [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> s = pd.Series([45, 200, 1.2, 30, 250, 1.5, 320, 1, 0.3],
... index=midx)
>>> s
lama speed 45.0
   weight 200.0
   length 1.2
cow speed 30.0
   weight 250.0
   length 1.5
falcon speed 320.0
   weight 1.0
   length 0.3
dtype: float64

>>> s.drop(labels='weight', level=1)
lama speed 45.0
   length 1.2
cow speed 30.0
   length 1.5
falcon speed 320.0
   length 0.3
dtype: float64
```
pandas.Series.drop_duplicates

Series.drop_duplicates(keep='first', inplace=False)
Return Series with duplicate values removed.

Parameters keep : {'first', 'last', False}, default 'first'
- 'first' : Drop duplicates except for the first occurrence.
- 'last' : Drop duplicates except for the last occurrence.
- False: Drop all duplicates.

inplace : boolean, default False
If True, performs operation inplace and returns None.

Returns

deduplicated [Series]

See also:

Index.drop_duplicates equivalent method on Index

DataFrame.drop_duplicates equivalent method on DataFrame

Series.duplicated related method on Series, indicating duplicate Series values.

Examples

Generate an Series with duplicated entries.

```python
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'],
                 name='animal')
>>> s
0   lama
1    cow
2   lama
3  beetle
4   lama
5   hippo
Name: animal, dtype: object
```

With the 'keep' parameter, the selection behaviour of duplicated values can be changed. The value 'first' keeps the first occurrence for each set of duplicated entries. The default value of keep is 'first'.

```python
>>> s.drop_duplicates()  
0   lama
1    cow
3  beetle
5   hippo
Name: animal, dtype: object
```

The value 'last' for parameter 'keep' keeps the last occurrence for each set of duplicated entries.

```python
>>> s.drop_duplicates(keep='last')
1    cow
3  beetle
```

(continues on next page)
The value `False` for parameter ‘keep’ discards all sets of duplicated entries. Setting the value of ‘inplace’ to `True` performs the operation inplace and returns `None`.

```python
>>> s.drop_duplicates(keep=False, inplace=True)
>>> s
1   cow
3  beetle
5  hippo
Name: animal, dtype: object
```

### pandas.Series.dropna

`Series.dropna(axis=0, inplace=False, **kwargs)`

Return a new Series with missing values removed.

See the *User Guide* for more on which values are considered missing, and how to work with missing data.

**Parameters**

- **axis** `{0 or 'index'}`, default 0
  
  There is only one axis to drop values from.

- **inplace** : bool, default False
  
  If True, do operation inplace and return None.

- **kwargs**
  
  Not in use.

**Returns**

- **Series**
  
  Series with NA entries dropped from it.

See also:

- **Series.isna** Indicate missing values.
- **Series.notna** Indicate existing (non-missing) values.
- **Series.fillna** Replace missing values.
- **DataFrame.dropna** Drop rows or columns which contain NA values.
- **Index.dropna** Drop missing indices.

### Examples

```python
>>> ser = pd.Series([1., 2., np.nan])
>>> ser
0   1.0
1   2.0
2   NaN
dtype: float64
```
Drop NA values from a Series.

```python
>>> ser.dropna()
0 1.0
1 2.0
dtype: float64
```

Keep the Series with valid entries in the same variable.

```python
>>> ser.dropna(inplace=True)
>>> ser
0 1.0
1 2.0
dtype: float64
```

Empty strings are not considered NA values. None is considered an NA value.

```python
>>> ser = pd.Series([np.NaN, 2, pd.NaT, '', None, 'I stay'])
>>> ser
0 NaN
1 2
2 NaT
3 None
4 I stay
dtype: object

>>> ser.dropna()
1 2
3
5 I stay
dtype: object
```

`pandas.Series.dt`

Series.dt()

Accessor object for datetimelike properties of the Series values.

**Examples**

```python
>>> 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(keep='first')

Indicate duplicate Series values.

Duplicated values are indicated as True values in the resulting Series. Either all duplicates, all except the first or all except the last occurrence of duplicates can be indicated.
Parameters keep : {‘first’, ‘last’, False}, default ‘first’

- ‘first’ : Mark duplicates as True except for the first occurrence.
- ‘last’ : Mark duplicates as True except for the last occurrence.
- False : Mark all duplicates as True.

Returns

pandas.core.series.Series

See also:

pandas.Index.duplicated Equivalent method on pandas.Index
pandas.Dataframe.duplicated Equivalent method on pandas.DataFrame
pandas.Series.drop_duplicates Remove duplicate values from Series

Examples

By default, for each set of duplicated values, the first occurrence is set on False and all others on True:

```python
>>> animals = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> animals.duplicated()
0   False
1   False
2    True
3   False
4    True
dtype: bool
```

which is equivalent to

```python
>>> animals.duplicated(keep='first')
0   False
1   False
2    True
3   False
4    True
dtype: bool
```

By using ‘last’, the last occurrence of each set of duplicated values is set on False and all others on True:

```python
>>> animals.duplicated(keep='last')
0    True
1   False
2    True
3   False
4   False
dtype: bool
```

By setting keep on False, all duplicates are True:

```python
>>> animals.duplicated(keep=False)
0    True
1   False
2    True
```

(continues on next page)
pandas.Series.eq

Series.eq(other, level=None, fill_value=None, axis=0)

Equal to of series and other, element-wise (binary operator eq).

Equivalent to series == other, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters

other [Series or scalar value]

fill_value : None or float value, default None (NaN)

Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a  1.0
b  1.0
c  1.0
d  NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a  1.0
b  NaN
d  1.0
e  NaN
dtype: float64
>>> a.add(b, fill_value=0)
a  2.0
b  1.0
c  1.0
d  1.0
e  NaN
dtype: float64
```
pandas.Series.equals

Series.equals(other)
Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Series.ewm

Series.ewm(com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0)
Provides exponential weighted functions
New in version 0.18.0.

Parameters
- com : float, optional
  Specify decay in terms of center of mass, \( \alpha = 1/(1 + \text{com}) \), for \( \text{com} \geq 0 \)
- span : float, optional
  Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \), for \( \text{span} \geq 1 \)
- halflife : float, optional
  Specify decay in terms of half-life, \( \alpha = 1 - \exp(\log(0.5)/\text{halflife}) \), for \( \text{halflife} > 0 \)
- alpha : float, optional
  Specify smoothing factor \( \alpha \) directly, \( 0 < \alpha \leq 1 \)
  New in version 0.18.0.
- min_periods : int, default 0
  Minimum number of observations in window required to have a value (otherwise result is NA).
- 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)
- ignore_na : boolean, default False
  Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

Returns
- a Window sub-classed for the particular operation

See also:
- rolling Provides rolling window calculations
- expanding Provides expanding transformations.

Notes

Exactly one of center of mass, span, half-life, and alpha must be provided. Allowed values and relationship between the parameters are specified in the parameter descriptions above; see the link at the end of this section for a detailed explanation.
When adjust is True (default), weighted averages are calculated using weights \((1-\alpha)^{*(n-1)}, (1-\alpha)^{*(n-2)}, \ldots, 1-\alpha, 1\).

**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 \([x, \text{None, y}]\) 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).


**Examples**

```python
>>> df = DataFrame({'B': [0, 1, 2, np.nan, 4]})
   B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0

>>> df.ewm(com=0.5).mean()
     B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213
```

**pandas.Series.expanding**

Series.\texttt{expanding}(\texttt{min\_periods=1, center=False, axis=0})

Provides expanding transformations.

New in version 0.18.0.

**Parameters** \texttt{min\_periods} : int, default 1

Minimum number of observations in window required to have a value (otherwise result is NA).

\texttt{center} : boolean, default False

Set the labels at the center of the window.

\texttt{axis} [int or string, default 0]

**Returns**

a Window sub-classed for the particular operation

See also:
**rolling** Provides rolling window calculations

**ewm** Provides exponential weighted functions

**Notes**

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting center=True.

**Examples**

```python
>>> df = DataFrame({'B': [0, 1, 2, np.nan, 4]})
          B
0      0.0
1      1.0
2      2.0
3    NaN
4      4.0

>>> df.expanding(2).sum()
          B
0       NaN
1      1.0
2      3.0
3      3.0
4      7.0
```

**pandas.Series.factorize**

Series.factorize(sort=False, na_sentinel=-1)

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. factorize is available as both a top-level function pandas.factorize(), and as a method Series.factorize() and Index.factorize().

**Parameters**

- **sort** : boolean, default False
  Sort uniques and shuffle labels to maintain the relationship.

- **na_sentinel** : int, default -1
  Value to mark “not found”.

**Returns**

- **labels** : ndarray
  An integer ndarray that’s an indexer into uniques. uniques.take(labels) will have the same values as values.

- **uniques** : ndarray, Index, or Categorical
  The unique valid values. When values is Categorical, uniques is a Categorical. When values is some other pandas object, an Index is returned. Otherwise, a 1-D ndarray is returned.
Note: Even if there’s a missing value in values, uniques will not contain an entry for it.

See also:

pandas.cut Discretize continuous-valued array.
pandas.unique Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like pd.factorize(values). The results are identical for methods like Series.factorize().

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> labels
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With sort=True, the uniques will be sorted, and labels will be shuffled so that the relationship is maintained.

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> labels
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in labels with na_sentinel (-1 by default). Note that missing values are never included in uniques.

```python
>>> labels, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> labels
array([ 0, -1, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we’ve only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of uniques will differ. For Categoricals, a Categorical is returned.

```python
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]
```

Notice that 'b' is in uniques.categories, despite not being present in cat.values.

For all other pandas objects, an Index of the appropriate type is returned.

```python
>>> cat = pd.Series(['a', 'a', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
(continues on next page)```
pandas: powerful Python data analysis toolkit, Release 0.23.1

array([0, 0, 1])
>>> uniques
Index([a', 'c'], dtype='object')

pandas.Series.ffill

Series.ffill(\texttt{axis=None, inplace=False, limit=None, downcast=None})

Synonym for DataFrame.fillna(method='ffill')

pandas.Series.fillna

Series.fillna(\texttt{value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs})

Fill NA/NaN values using the specified method

\textbf{Parameters} \texttt{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.

\texttt{method} : \texttt{\{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None\}}, default \texttt{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

\texttt{axis} : \texttt{[0 or ‘index’]}

\texttt{inplace} : boolean, default \texttt{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).

\texttt{limit} : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

\texttt{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)

\textbf{Returns}

\texttt{filled} [Series]

\textbf{See also:}

\texttt{interpolate} Fill NaN values using interpolation.

\texttt{reindex, asfreq}
Examples

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                     columns=list('ABCD'))
>>> df
   A  B  C  D
0  NaN 2.0 NaN 0
1  3.0 4.0 NaN 1
2  NaN NaN NaN 5
3  NaN 3.0 NaN 4

Replace all NaN elements with 0s.

```python
>>> df.fillna(0)
   A  B  C  D
0  0.0 2.0 0.0 0.0
1  3.0 4.0 0.0 1.0
2  0.0 0.0 0.0 5.0
3  0.0 3.0 0.0 4.0
```

We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
   A  B  C  D
0  NaN 2.0 NaN 0.0
1  3.0 4.0 NaN 1.0
2  3.0 4.0 NaN 5.0
3  3.0 3.0 NaN 4.0
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
   A  B  C  D
0  0.0 2.0 2.0 0.0
1  3.0 4.0 2.0 1.0
2  0.0 1.0 2.0 5.0
3  0.0 3.0 2.0 4.0
```

Only replace the first NaN element.

```python
>>> df.fillna(value=values, limit=1)
   A  B  C  D
0  0.0 2.0 2.0 0.0
1  3.0 4.0 NaN 1.0
2  NaN 1.0 NaN 5.0
3  NaN 3.0 NaN 4.0
```

**pandas.Series.filter**

`Series.filter(items=None, like=None, regex=None, axis=None)`

Subset rows or columns of dataframe according to labels in the specified index.
Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

**Parameters**

- **items**: list-like
  - 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 string axis name
  - The axis to filter on. By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame

**Returns**

same type as input object

**See also:**

pandas.DataFrame.loc

**Notes**

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.

`axis` defaults to the info axis that is used when indexing with `[]`.

**Examples**

```python
>>> df
one  two  three
mouse 1  2  3
rabbit 4  5  6

>>> # select columns by name
>>> df.filter(items=['one', 'three'])
one  three
mouse 1  3
rabbit 4  6

>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
one  three
mouse 1  3
rabbit 4  6

>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
one  two  three
rabbit 4  5  6
```
**pandas.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]

Raises TypeError

If the index is not a `DatetimeIndex`

See also:

- last: Select final periods of time series based on a date offset
- at_time: Select values at a particular time of the day
- between_time: Select values between particular times of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the first 3 days:

```python
>>> ts.first('3D')
   A
2018-04-09  1
2018-04-11  2
```  

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

**pandas.Series.first_valid_index**

Series.first_valid_index()

Return index for first non-NA/null value.

**Returns**

scalar [type of index]
Notes

If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```
pandas.Series.from_array

**classmethod** Series.from_array(arr, index=None, name=None, dtype=None, copy=False, fastpath=False)

Construct Series from array.

Deprecated since version 0.23.0: Use pd.Series(..) constructor instead.

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.

Deprecated since version 0.21.0: 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 will often be a large parsing speed-up.

**Returns**
y [Series]

See also:

*pandas.read_csv*

**pandas.Series.ge**

*Series.ge*(other, level=None, fill_value=None, axis=0)

Greater than or equal to of series and other, element-wise (binary operator ge).

Equivalent to *series >= other*, but with support to substitute a *fill_value* for missing data in one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value**: None or float value, default None (NaN)
  - Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None*

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a  1.0
b  1.0
c  1.0
d  NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a  1.0
b  NaN
d  1.0
e  NaN
dtype: float64
>>> a.add(b, fill_value=0)
```

```
a  2.0
b  1.0
c  1.0
d  1.0
e  NaN
dtype: float64
```
pandas.Series.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 counts of unique dtypes in this object.

Returns dtype : Series
Series with the count of columns with each dtype.

See also:
dtypes Return the dtypes in this object.

Examples

```python
>>> a = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
>>> df = pd.DataFrame(a, columns=['str', 'int', 'float'])
>>> df
   str  int  float
0   a    1    1.0
1   b    2    2.0
2   c    3    3.0

>>> df.get_dtype_counts()
float64    1
int64      1
object     1
dtype: int64
```

pandas.Series.get_ftype_counts

Series.get_ftype_counts()
Return counts of unique ftypes in this object.

Deprecated since version 0.23.0.
This is useful for SparseDataFrame or for DataFrames containing sparse arrays.

Returns dtype : Series
Series with the count of columns with each type and sparsity (dense/sparse)

See also:
ftypes  Return ftypes (indication of sparse/dense and dtype) in this object.

Examples

```python
>>> a = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
>>> df = pd.DataFrame(a, columns=['str', 'int', 'float'])
>>> df
   str int float
0   a  1  1.0
1   b  2  2.0
2   c  3  3.0
```

```python
>>> df.get_ftype_counts()
float64:dense 1
int64:dense 1
object:dense 1
dtype: int64
```

**pandas.Series.get_value**

`Series.get_value(label, takeable=False)`

Quickly retrieve single value at passed index label

Deprecated since version 0.21.0: Please use `.at` or `.iat` accessors.

**Parameters**

- **label** [object]
- **takeable** [interpret the index as indexers, default False]

**Returns**

- **value** [scalar value]

**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, observed=False, **kwargs)`

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, label, or list of labels
  Used to determine the groups for the groupby. If `by` is a function, it’s called on each value of the object’s index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series’ values are first aligned; see `.align()` method). If an ndarray is passed, the values are used as-is determine the groups. A label
or list of labels may be passed to group by the columns in `self`. Notice that a tuple is interpreted a (single) key.

**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

**observed**: boolean, default False

This only applies if any of the groupers are Categoricals If True: only show observed values for categorical groupers. If False: show all values for categorical groupers. New in version 0.23.0.

**Returns**

GroupBy object

**See also**

`resample` Convenience method for frequency conversion and resampling of time series.

**Notes**

See the user guide for more.

**Examples**

DataFrame results

```python
>>> data.groupby(func, axis=0).mean()
```

```python
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```python
>>> data.groupby(['col1', 'col2']).mean()
```
**pandas.Series.gt**

Series.gt(other, level=None, fill_value=None, axis=0)

Greater than of series and other, element-wise (binary operator gt).

Equivalent to series > other, but with support to substitute a fill_value for missing data in one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** : None or float value, default None (NaN)
  Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```
This function returns the first \( n \) rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

**Parameters** 

\( n \) : int, default 5

Number of rows to select.

**Returns** 

\( \text{obj.head} \) : type of caller

The first \( n \) rows of the caller object.

**See also:**

\texttt{pandas.DataFrame.tail} Returns the last \( n \) rows.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion', ...
                      'monkey', 'parrot', 'shark', 'whale', 'zebra']})
```

Viewing the first 5 lines

```python
>>> df.head()
    animal
0   alligator
1      bee
2   falcon
3      lion
4   monkey
```

Viewing the first \( n \) lines (three in this case)

```python
>>> df.head(3)
    animal
0   alligator
1      bee
2   falcon
```

**pandas.Series.hist**

\texttt{Series.hist(by=None, ax=None, grid=True, xlabels=None, xrot=None, ylabels=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 or sequence, default 10
    Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

**kwds** : keywords
    To be passed to the actual plotting function

See also:

matplotlib.axes.Axes.hist  Plot a histogram using matplotlib.

pandas.Series.idxmax

Series.idxmax (axis=0, skipna=True, *args, **kwargs)
    Return the row label of the maximum value.
    If multiple values equal the maximum, the first row label with that value is returned.

Parameters

- skipna : boolean, default True
    Exclude NA/null values. If the entire Series is NA, the result will be NA.

- axis : int, default 0
    For compatibility with DataFrame.idxmax. Redundant for application on Series.

- *args, **kwargs
    Additional keywords have no effect but might be accepted for compatibility with NumPy.
Returns

**idxmax** [Index of maximum of values.]

**Raises ValueError**
If the Series is empty.

**See also:**

- **numpy.argmax** Return indices of the maximum values along the given axis.
- **DataFrame.idxmax** Return index of first occurrence of maximum over requested axis.
- **Series.idxmin** Return index label of the first occurrence of minimum of values.

**Notes**

This method is the Series version of `ndarray.argmax`. This method returns the label of the maximum, while `ndarray.argmax` returns the position. To get the position, use `series.values.argmax()`.

**Examples**

```python
>>> s = pd.Series(data=[1, None, 4, 3, 4],
                   index=['A', 'B', 'C', 'D', 'E'])
>>> s
A    1.0
B    NaN
C    4.0
D    3.0
E    4.0
dtype: float64

>>> s.idxmax()
'C'

If `skipna` is False and there is an NA value in the data, the function returns `nan`.
```

```python
>>> s.idxmax(skipna=False)
'nan'
```

---

**pandas.Series.idxmin**

**Series.idxmin**(axis=None, skipna=True, *args, **kwargs)
Return the row label of the minimum value.

If multiple values equal the minimum, the first row label with that value is returned.

**Parameters**

- **skipna** : boolean, default True
  Exclude NA/null values. If the entire Series is NA, the result will be NA.

- **args**

- ****kwargs

For compatibility with DataFrame.idxmin. Redundant for application on Series.
Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

idxmin  [Index of minimum of values.]

**Raises** ValueError

If the Series is empty.

**See also:**

- numpy.argmin  Return indices of the minimum values along the given axis.
- DataFrame.idxmin  Return index of first occurrence of minimum over requested axis.
- Series.idxmax  Return index label of the first occurrence of maximum of values.

**Notes**

This method is the Series version of ndarray.argmin. This method returns the label of the minimum, while ndarray.argmin returns the position. To get the position, use series.values.argmin().

**Examples**

```python
>>> s = pd.Series(data=[1, None, 4, 1],
    index=['A', 'B', 'C', 'D'])
```

```plaintext
   A   B   C   D
0   1  NaN  4.0  1.0
```

```python
>>> s.idxmin()
'A'
```

If `skipna` is False and there is an NA value in the data, the function returns `nan`.

```python
>>> s.idxmin(skipna=False)
nan
```

---

**pandas.Series.infer_objects**

**Series.infer_objects()**

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

New in version 0.21.0.

**Returns**

converted  [same type as input object]

**See also:**
pandas.to_datetime Convert argument to datetime.
pandas.to_timedelta Convert argument to timedelta.
pandas.to_numeric Convert argument to numeric type

**Examples**

```python
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
A
1 1
2 2
3 3
```

```python
>>> df.dtypes
A  object
dtype: object
```

```python
>>> df.infer_objects().dtypes
A  int64
dtype: object
```

**pandas.Series.interpolate**

Series.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

**Parameters method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline', 'piecewise_polynomial', 'from_derivatives', 'pchip', 'akima'}

- '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', 'pchip' and 'akima' are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. For more information on their behavior, see the scipy documentation and tutorial documentation
- 'from_derivatives' refers to BPoly.from_derivatives which replaces 'piecewise_polynomial' interpolation method in scipy 0.18
New in version 0.18.1: Added support for the ‘akima’ method Added interpolate method ‘from_derivatives’ which replaces ‘piecewise_polynomial’ in scipy 0.18; backwards-compatible with scipy < 0.18

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. Must be greater than 0.

limit_direction : [{‘forward’, ‘backward’, ‘both’}, default ‘forward’]

limit_area : {‘inside’, ‘outside’}, default None
- None: (default) no fill restriction
- ‘inside’ Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’ Only fill NaNs outside valid values (extrapolate).
If limit is specified, consecutive NaNs will be filled in this direction.
New in version 0.21.0.

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.Series.isin

Series.isin(values)
Check whether values are contained in Series.

Return a boolean Series showing whether each element in the Series matches an element in the passed sequence of values exactly.

Parameters values: set or list-like
The sequence of values to test. Passing in a single string will raise a TypeError. Instead, turn a single string into a list of one element.

New in version 0.18.1: Support for values as a set.

Returns
isin [Series (bool dtype)]

Raises TypeError
- If values is a string

See also:
pandas.DataFrame.isin equivalent method on DataFrame

Examples

```python
code
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'], name='animal')
>>> s.isin(['cow', 'lama'])
0   True
1   True
2   True
3  False
4   True
5  False
Name: animal, dtype: bool
```

Passing a single string as s.isin('lama') will raise an error. Use a list of one element instead:

```python
code
>>> s.isin(['lama'])
0   True
1  False
2   True
3  False
4   True
5  False
Name: animal, dtype: bool
```

pandas.Series.isna

Series.isna()
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.Nan, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty
strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

**Returns Series**

Mask of bool values for each element in Series that indicates whether an element is not an NA value.

**See also:**

- `Series.isnull` alias of isna
- `Series.notna` boolean inverse of isna
- `Series.dropna` omit axes labels with missing values
- `isna` top-level isna

**Examples**

Show which entries in a DataFrame are NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>age</th>
<th>born</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5.0</td>
<td>NaT</td>
<td>Alfred</td>
<td>None</td>
</tr>
<tr>
<td>1</td>
<td>6.0</td>
<td>1939-05-27</td>
<td>Batman</td>
<td>Batmobile</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>1940-04-25</td>
<td>Joker</td>
<td></td>
</tr>
</tbody>
</table>
```

```python
>>> df.isna()
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>age</th>
<th>born</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>False</td>
<td>True</td>
<td>False</td>
<td>True</td>
</tr>
<tr>
<td>1</td>
<td>False</td>
<td>False</td>
<td>False</td>
<td>False</td>
</tr>
<tr>
<td>2</td>
<td>True</td>
<td>False</td>
<td>False</td>
<td>False</td>
</tr>
</tbody>
</table>
```

Show which entries in a Series are NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>age</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>6.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

```python
>>> ser.isna()
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>age</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>False</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>False</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>True</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

`````
pandas.Series.isnull

Series.isnull()
 Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy
NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty
strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.
use_inf_as_na = True).

Returns Series
 Mask of bool values for each element in Series that indicates whether an element is not
an NA value.

See also:

Series.isnull alias of isna
Series.notna boolean inverse of isna
Series.dropna omit axes labels with missing values
isna top-level isna

Examples

Show which entries in a DataFrame are NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
... 'born': [pd.NaT, pd.Timestamp('1939-05-27'),
... pd.Timestamp('1940-04-25')],
... 'name': ['Alfred', 'Batman', ''],
... 'toy': [None, 'Batmobile', 'Joker']})

>>> df
   age  born    name  toy
0   5.0   NaT  Alfred  None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN  1940-04-25    Joker

>>> df.isna()
   age  born    name  toy
0  False  True  False  True
1  False  False  False  False
2  True  False  False  False
```

Show which entries in a Series are NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])

>>> ser
0  5.0
1  6.0
2  NaN
dtype: float64

>>> ser.isna()
0  False
```

(continues on next page)
**pandas.Series.item**

Series.item()

return the first element of the underlying data as a python scalar

**pandas.Series.items**

Series.items()

Lazily iterate over (index, value) tuples

**pandas.Series.iteritems**

Series.iteritems()

Lazily iterate over (index, value) tuples

**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 Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**

- **axis**: [index (0)]
- **skipna**: boolean, default True
  
  Exclude NA/null values when computing the result.
- **level**: int or level name, default None
  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar
- **numeric_only**: boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **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 Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis [[index (0)]]

skipna : boolean, default True
Exclude NA/null values when computing the result.

level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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]

Raises TypeError
If the index is not a DatetimeIndex.

See also:
first Select initial periods of time series based on a date offset
at_time Select values at a particular time of the day
between_time Select values between particular times of the day

Examples

>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09  1
Get the rows for the last 3 days:

```python
>>> ts.last('3D')
A
2018-04-13 3
2018-04-15 4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

### pandas.Series.last_valid_index

Series.last_valid_index()  
Return index for last non-NA/null value.

- **Returns**
  - scalar [type of index]

- **Notes**
  - If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

### pandas.Series.le

Series.le(other, level=None, fill_value=None, axis=0)  
Less than or equal to of series and other, element-wise (binary operator le).

- **Equivalent to series <= other**, but with support to substitute a fill_value for missing data in one of the inputs.

- **Parameters**
  - other [Series or scalar value]
  - fill_value: None or float value, default None (NaN)
    - Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None
Examples

```python
c = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
c
a  1.0  
b  1.0  
c  1.0  
d  NaN  
dtype: float64
```

```python
c.add(b, fill_value=0)
c
a  2.0  
b  1.0  
c  1.0  
d  1.0  
e  NaN  
dtype: float64
```

```
pandas.Series.lt
```

Series.lt (other, level=None, fill_value=None, axis=0)

Less than of series and other, element-wise (binary operator lt).

Equivalent to series < other, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters

other [Series or scalar value]

fill_value : None or float value, default None (NaN)

Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None

Examples
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64

pandas.Series.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 when computing the result.
level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into
a scalar
numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then
use only numeric data. Not implemented for Series.

Returns
mad [scalar or Series (if level specified)]

pandas.Series.map

Series.map(arg, na_action=None)
Map values of Series using input correspondence (a dict, Series, or function).

Parameters arg : function, dict, or Series
Mapping correspondence.
na_action : {None, ‘ignore’}
If ‘ignore’, propagate NA values, without passing them to the mapping correspondence.

**Returns** y : Series

Same index as caller.

**See also:**

*Series.apply* For applying more complex functions on a Series.

*DataFrame.apply* Apply a function row-/column-wise.

*DataFrame.applymap* Apply a function elementwise on a whole DataFrame.

**Notes**

When *arg* is a dictionary, values in Series that are not in the dictionary (as keys) are converted to NaN. However, if the dictionary is a dict subclass that defines __missing__ (i.e. provides a method for default values), then this default is used rather than NaN:

```python
>>> from collections import Counter
>>> counter = Counter()
>>> counter['bar'] += 1
>>> y.map(counter)
1 0
2 1
3 0
dtype: int64
```

**Examples**

Map inputs to outputs (both of type *Series*):

```python
>>> x = pd.Series([1, 2, 3], index=['one', 'two', 'three'])
>>> x
one 1
two 2
three 3
dtype: int64

>>> y = pd.Series(['foo', 'bar', 'baz'], index=[1, 2, 3])
>>> y
1  foo
2  bar
3  baz

>>> x.map(y)
one  foo
two  bar
three baz
```

If *arg* is a dictionary, return a new Series with values converted according to the dictionary’s mapping:

```python
>>> z = {1: 'A', 2: 'B', 3: 'C'}
```
Use `na_action` to control whether NA values are affected by the mapping function.

```python
>>> s = pd.Series([1, 2, 3, np.nan])
```

```python
>>> s2 = s.map('this is a string/{}'.format, na_action=None)
0  this is a string 1.0
1  this is a string 2.0
2  this is a string 3.0
3  this is a string nan
dtype: object
```

```python
>>> s3 = s.map('this is a string/{}'.format, na_action='ignore')
0  this is a string 1.0
1  this is a string 2.0
2  this is a string 3.0
3  NaN
dtype: object
```

### pandas.Series.mask

`s.Series.mask`  

`Series.mask`(condition, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)  

Return an object of same shape as self and whose corresponding entries are from self where `condition` is False and otherwise are from `other`.

**Parameters**

- **cond** : boolean NDFrame, array-like, or callable  
  Where `cond` is False, keep the original value. Where True, replace with corresponding value from `other`. If `cond` is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

  New in version 0.18.1: A callable can be used as cond.

- **other** : scalar, NDFrame, or callable  
  Entries where `cond` is True are replaced with corresponding value from `other`. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

  New in version 0.18.1: A callable can be used as other.

- **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]  

- **errors** : str, {‘raise’, ‘ignore’}, default ‘raise’  
  - `raise`: allow exceptions to be raised
• **ignore**: suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

**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)

Deprecated since version 0.21.0.

Returns

**wh** [same type as caller]

See also:

*DataFrame.where()*

### Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if **cond** is False the element is used; otherwise the corresponding element from the DataFrame **other** is used.

The signature for **DataFrame.where()** differs from **numpy.where()**. Roughly df1.where(m, df2) is equivalent to np.where(m, df1, df2).

For further details and examples see the **mask** documentation in **indexing**.

### Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0

>>> s.mask(s > 0)
0      0.0
1      NaN
2      NaN
3      NaN
4      NaN

>>> s.where(s > 1, 10)
0    10.0
1    10.0
2    2.0
3    3.0
4    4.0
```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
    A   B
0   0  -1
1  -2   3
2  -4  -5
3   6  -7
4  -8   9

>>> df.where(m, -df) == np.where(m, df, -df)
    A   B
0   True  True
1   True  True
2   True  True
3   True  True
4   True  True

>>> df.where(m, -df) == df.mask(~m, -df)
    A   B
0   True  True
1   True  True
2   True  True
3   True  True
4   True  True

pandas.Series.max

Series.max (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

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

Excluding NA/null values when computing the result.

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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
Excluding NA/null values when computing the result.
level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into
a scalar
numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then
use only numeric data. Not implemented for Series.

Returns
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
Excluding NA/null values when computing the result.
level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into
a scalar
numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then
use only numeric data. Not implemented for Series.

Returns
median [scalar or Series (if level specified)]

**pandas.Series.memory_usage**

Series.memory_usage (index=True, deep=False)
Return the memory usage of the Series.
The memory usage can optionally include the contribution of the index and of elements of object dtype.

Parameters index : bool, default True
Specifies whether to include the memory usage of the Series index.
depth : bool, default False
If True, introspect the data deeply by interrogating object dtypes for system-level memory consumption, and include it in the returned value.
Returns int
Bytes of memory consumed.

See also:

numpy.ndarray.nbytes Total bytes consumed by the elements of the array.
DataFrame.memory_usage Bytes consumed by a DataFrame.

Examples

```python
>>> s = pd.Series(range(3))
>>> s.memory_usage()
104

Not including the index gives the size of the rest of the data, which is necessarily smaller:

```python
>>> s.memory_usage(index=False)
24

The memory footprint of object values is ignored by default:

```python
>>> s = pd.Series(["a", "b"])
>>> s.values
array(["a", "b"], dtype=object)
>>> s.memory_usage()
96
>>> s.memory_usage(deep=True)
212
```

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
  Excluding NA/null values when computing the result.
- **level** : int or level name, default None
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **numeric_only** : boolean, default None
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

- **min** [scalar or Series (if level specified)]
pandas.Series.mod

Series.\texttt{mod}(\texttt{other}, \texttt{level}=None, \texttt{fill\_value}=None, \texttt{axis}=0)
Modulo of series and other, element-wise (binary operator mod).

Equivalent to \texttt{series \% other}, but with support to substitute a \texttt{fill\_value} for missing data in one of the inputs.

**Parameters**

- \texttt{other} [Series or scalar value]
- \texttt{fill\_value}: None or float value, default None (NaN)
  - Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing
- \texttt{level} : int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- \texttt{result} [Series]

**See also:**

- Series.\texttt{rmod}

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

pandas.Series.mode

Series.\texttt{mode}()
Return the mode(s) of the dataset.
Always returns Series even if only one value is returned.

**Returns**

**modes** [Series (sorted)]

### pandas.Series.mul

**pandas.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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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*

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```
pandas.Series.multiply

Series.multiply(\texttt{other}, \texttt{level}=None, \texttt{fill\_value}=None, \texttt{axis}=0)  
Multiplication of series and other, element-wise (binary operator musl).

Equivalent to \texttt{series * other}, but with support to substitute a fill\_value for missing data in one of the inputs.

\textbf{Parameters}

- \texttt{other} [Series or scalar value]
- \texttt{fill\_value} : None or float value, default None (NaN)
  
  Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing
- \texttt{level} : int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

\textbf{Returns}

- \texttt{result} [Series]

\textbf{See also:}

Series.rmul

\textbf{Examples}

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

pandas.Series.ne

Series.ne(\texttt{other}, \texttt{level}=None, \texttt{fill\_value}=None, \texttt{axis}=0)  
Not equal to of series and other, element-wise (binary operator ne).
Equivalent to `series != other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

**Parameters**

- `other` [Series or scalar value]
- `fill_value` : None or float value, default None (NaN)

  Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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.None`

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a   1.0
b   NaN
d   1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```

**pandas.Series.nlargest**

Series. `nlargest(n=5, keep='first')`  
Return the largest `n` elements.

**Parameters**

- `n` : int

  Return this many descending sorted values

- `keep` : ['first', 'last'], default 'first'
Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

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(10**6))
>>> s.nlargest(10)  # only sorts up to the N requested
219921   4.644710
32124    4.608745
421689    4.556464
425277    4.447014
718691    4.414137
43154     4.403520
283187    4.313922
595519    4.273635
503969    4.250236
121637    4.240952
dtype: float64
```

pandas.Series.nonzero

Series.nonzero()
Return the integer 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.iloc[s.nonzero()[0]]
```

(continues on next page)
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```python
1  3
3  4
dtype: int64
```

```python
>>> s = pd.Series([0, 3, 0, 4], index=['a', 'b', 'c', 'd'])
# same return although index of s is different
>>> s.nonzero()
(array([1, 3]),)
>>> s.iloc[s.nonzero()[0]]
b 3
d 4
dtype: int64
```

**pandas.Series.notna**

Series.notna()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns Series

Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

- **Series.notnull** alias of notna
- **Series.isna** boolean inverse of notna
- **Series.dropna** omit axes labels with missing values
- **notna** top-level notna

**Examples**

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
```

```python
>>> df
   age  born    name  toy
0  5.0  NaT  Alfred   None
1  6.0 1939-05-27  Batman  Batmobile
2 NaN 1940-04-25  Batman    Joker
```
>>> df.notna()

<table>
<thead>
<tr>
<th></th>
<th>age</th>
<th>born</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>True</td>
<td>False</td>
<td>True</td>
<td>False</td>
</tr>
<tr>
<td>1</td>
<td>True</td>
<td>True</td>
<td>True</td>
<td>True</td>
</tr>
<tr>
<td>2</td>
<td>False</td>
<td>True</td>
<td>True</td>
<td>True</td>
</tr>
</tbody>
</table>

Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0 5.0
1 6.0
2 NaN
dtype: float64
```

```python
>>> ser.notna()
0 True
1 True
2 False
dtype: bool
```

### pandas.Series.notnull

**Series.notnull()**

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

**Returns** Series

Mask of bool values for each element in Series that indicates whether an element is not an NA value.

**See also:**

- **Series.notnull** alias of notna
- **Series.isna** boolean inverse of notna
- **Series.dropna** omit axes labels with missing values
- **notna** top-level notna

**Examples**

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                    'name': ['Alfred', 'Batman', ''],
...                    'toy': [None, 'Batmobile', 'Joker']})
```
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```
>>> df
   age  born    name   toy
0   5.0  NaT    Alfred  None
1  6.0  1939-05-27 Batman  Batmobile
2  NaN  1940-04-25    Joker

>>> df.notna()
   age  born    name   toy
0  True False  True  False
1  True  True  True  True
2 False  True  True  True

Show which entries in a Series are not NA.

>>> ser = pd.Series([5, 6, np.NaN])

>>> ser
0    5.0
1    6.0
2   NaN
dtype: float64

>>> ser.notna()
0  True
1  True
2 False
dtype: bool
```

**pandas.Series.nsmallest**

Series.nsmallest\(n=5,\,\text{keep='first'}\)

Return the smallest \(n\) elements.

- **Parameters**
  - \(n\) : int
    
    Return this many ascending sorted values
  
    - **keep** : {'first', 'last'}, default 'first'
      
      Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

- **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(10**6))

>>> s.nsmallest(10) # only sorts up to the N requested
288532  -4.954580
732345  -4.835960
64803   -4.812550
446457  -4.609998
501225  -4.483945
669476  -4.472935
973615  -4.401699
621279  -4.355126
773916  -4.347355
359919  -4.331927
dtype: float64
```

**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.pct_change**

```
Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)
```

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

Parameters periods : int, default 1

Periods to shift for forming percent change.

fill_method : str, default ‘pad’

How to handle NAs before computing percent changes.

limit : int, default None

The number of consecutive NAs to fill before stopping.

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. ‘M’ or BDay()).

**kwargs

Additional keyword arguments are passed into DataFrame.shift or Series.shift.
Returns chg : Series or DataFrame
    The same type as the calling object.

See also:

Series.diff  Compute the difference of two elements in a Series.
DataFrame.diff  Compute the difference of two elements in a DataFrame.
Series.shift  Shift the index by some number of periods.
DataFrame.shift  Shift the index by some number of periods.

Examples

Series

```python
>>> s = pd.Series([90, 91, 85])
>>> s
0  90
1  91
2  85
dtype: int64

>>> s.pct_change()
0   NaN
1  0.011111
2 -0.065934
dtype: float64

>>> s.pct_change(periods=2)
0   NaN
1   NaN
2 -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```python
>>> s = pd.Series([90, 91, None, 85])
>>> s
0   90.0
1   91.0
2   NaN
3   85.0
dtype: float64

>>> s.pct_change(fill_method='ffill')
0   NaN
1  0.011111
2  0.000000
3 -0.065934
dtype: float64
```

DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.
>>> df = pd.DataFrame(
...     {'FR': [4.0405, 4.0963, 4.3149],
...      'GR': [1.7246, 1.7482, 1.8519],
...      'IT': [804.74, 810.01, 860.13]},
...     index=['1980-01-01', '1980-02-01', '1980-03-01'])

>>> df
       FR    GR    IT
1980-01-01  4.0405  1.7246 804.74
1980-02-01  4.0963  1.7482 810.01
1980-03-01  4.3149  1.8519 860.13

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

>>> df = pd.DataFrame(
...     {'2016': [1769950, 30586265],
...      '2015': [1500923, 40912316],
...      '2014': [1371819, 41403351]},
...     index=['GOOG', 'APPL'])

>>> df
       2016   2015   2014
GOOG    1769950 1500923 1371819
APPL    30586265 40912316 41403351

>>> df.pct_change(axis='columns')
       2016          2015          2014
GOOG  NaN  -0.151997       -0.086016
APPL  NaN  0.337604        0.012002

pandas.Series.pipe

Series.pipe(func, *args, **kwargs)
Apply func(self, *args, **kwargs)

Parameters
func : function
    function to apply to the 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 : iterable, optional
    positional arguments passed into func.

kwargs : mapping, optional
    a dictionary of keyword arguments passed into func.

Returns
object  [the return type of func.]
See also:

pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map

Notes

Use .pipe when chaining together functions that expect Series, DataFrames or GroupBy objects. 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 or list
    Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and subplots is True, print each item in the list above the corresponding subplot.

grid : 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)

**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

**kwargs** : keywords

Options to pass to matplotlib plotting method

**Returns**

**axes** [matplotlib.axes.Axes or numpy.ndarray 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.

**Parameters**

**item** : str

Column label to be popped

**Returns**

**popped** [Series]

**Examples**
```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                   columns=('name', 'class', 'max_speed'))
```

```plaintext
name   class  max_speed
----    -----   ------
  0  falcon  bird    389.0
  1  parrot  bird     24.0
  2    lion  mammal   80.5
  3  monkey  mammal    NaN
```

```python
>>> df.pop('class')
```

```plaintext
0  bird
1  bird
2  mammal
3  mammal
Name: class, dtype: object
```

```plaintext
name  max_speed
----    ------
  0  falcon   389.0
  1  parrot   24.0
  2    lion   80.5
  3  monkey    NaN
```

**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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64

>>> a.add(b, fill_value=0)
a    2.0  
b    1.0  
c    1.0  
d    1.0  
e    NaN  
dtype: float64
```

**pandas.Series.prod**

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the product of the values for the requested axis

**Parameters**

- `axis` ([index (0)])
- `skipna` : boolean, default True
  Exclude NA/null values when computing the result.
- `level` : int or level name, default None
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar
- `numeric_only` : boolean, default None
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- `min_count` : int, default 0
  The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**Returns**

- `prod` [scalar or Series (if level specified)]
Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

**pandas.Series.product**

```python
Series.product(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)
```

Returns the product of the values for the requested axis

**Parameters**

- `axis` : int or axis name, default 0
- `skipna` : boolean, default True
- `level` : int or level name, default None
- `numeric_only` : boolean, default None
- `min_count` : int, default 0

The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**Returns**

- `prod` : scalar or Series (if level specified)
Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

**pandas.Series.ptp**

`Series.ptp(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Returns the difference between the maximum value and the minimum value in the object. This is the equivalent of the `numpy.ndarray` method `ptp`.

**Parameters**

- `axis` ([index (0)])
- `skipna` : boolean, default True
  
  Exclude NA/null values when computing the result.
- `level` : int or level name, default None
  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar
- `numeric_only` : boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- `ptp` [scalar or Series (if level specified)]

**pandas.Series.put**

`Series.put(*args, **kwargs)`

Applies the `put` method to its `values` attribute if it has one.

See also:

- `numpy.ndarray.put`
**pandas.Series.quantile**

Series.quantile(q=0.5, interpolation='linear')  
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

- **interpolation**: {'linear', 'lower', 'higher', 'midpoint', 'nearest'}  
  New in version 0.18.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points $i$ and $j$:

- **linear**: $i + (j - i) * \text{fraction}$, where fraction is the fractional part of the index surrounded by $i$ and $j$.
- **lower**: $i$.
- **higher**: $j$.
- **nearest**: $i$ or $j$ whichever is nearest.
- **midpoint**: $(i + j) / 2$.

**Returns**

- **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.

See also:

pandas.core.window.Rolling.quantile

**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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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`

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

**pandas.Series.rank**

`Series.rank` (`axis=0`, `method='average'`, `numeric_only=None`, `na_option='keep'`, `ascending=True`, `pct=False`)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values.

**Parameters**

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  - index to direct ranking

- **method**: {'average', 'min', 'max', 'first', 'dense'}
  - 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

numeric_only : boolean, default None
   Include only float, int, boolean data. Valid only for DataFrame or Panel objects

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 [same type as caller]

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64

>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

pandas.Series.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**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>index</td>
<td>array-like, optional (should be specified using keywords)</td>
</tr>
<tr>
<td>method</td>
<td>{None, ‘backfill’/‘bfill’, ‘pad’/‘ffill’, ‘nearest’}, optional</td>
</tr>
<tr>
<td>copy</td>
<td>boolean, default True</td>
</tr>
<tr>
<td>level</td>
<td>int or name</td>
</tr>
<tr>
<td>fill_value</td>
<td>scalar, default np.NaN</td>
</tr>
<tr>
<td>limit</td>
<td>int, default None</td>
</tr>
</tbody>
</table>

New labels / index to conform to. Preferably an Index object to avoid duplicating data

method: method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- 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: return a new object, even if the passed indexes are the same

level: Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value: Value to use for missing values. Defaults to NaN, but can be any “compatible” value

limit: int, default None

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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 \( \text{abs(index}[\text{indexer}] - \text{target}) <= \text{tolerance} \).

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

Returns

reindexed [Series]

Examples

DataFrame.reindex supports two calling conventions

• (index=index_labels, columns=column_labels, ...)
• (labels, axis={‘index’, ‘columns’}, ...)

We highly recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({
... 'http_status': [200, 200, 404, 404, 301],
... 'response_time': [0.04, 0.02, 0.07, 0.08, 1.0],
... 'index'=index)
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```
>>> new_index= ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10', 'Chrome']
>>> df.reindex(new_index)
```

We can fill in the missing values by passing a value to the keyword fill_value. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword method to fill the NaN values.
We can also reindex the columns.

```
>>> df.reindex(columns=['http_status', 'user_agent'])
   http_status user_agent
Firefox   200    NaN
Chrome    200    NaN
Safari    404    NaN
IE10      404    NaN
Konqueror 301    NaN
```

Or we can use “axis-style” keyword arguments

```
>>> df.reindex(["http_status", "user_agent"], axis="columns")
   http_status user_agent
Firefox   200    NaN
Chrome    200    NaN
Safari    404    NaN
IE10      404    NaN
Konqueror 301    NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]},
                      index=date_index)
>>> df2
   prices
2010-01-01  100
2010-01-02  101
2010-01-03  NaN
2010-01-04  100
2010-01-05  89
2010-01-06  88
```

Suppose we decide to expand the dataframe to cover a wider date range.

```
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
   prices
2009-12-29  NaN
```

(continues on next page)
The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with NaN. If desired, we can fill in the missing values using one of several options.

For example, to backpropagate the last valid value to fill the NaN values, pass bfill as an argument to the method keyword.

```python
>>> df2.reindex(date_index2, method='bfill')
```

```
prices
2009-12-29  100
2009-12-30  100
2009-12-31  100
2010-01-01  100
2010-01-02  101
2010-01-03  NaN
2010-01-04  100
2010-01-05  89
2010-01-06  88
2010-01-07  NaN
```

Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the fillna() method.

See the user guide for more.

**pandas.Series.reindex_axis**

```
Series.reindex_axis(labels, axis=0, **kwargs)
Conform Series to new index with optional filling logic.
```

Deprecated since version 0.21.0: Use Series.reindex instead.

**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. Can be list-like.

New in version 0.21.0: (list-like tolerance)

Returns

reindexed [same as input]

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)
pandas.Series.rename_axis

Series.rename_axis(mapper, axis=0, copy=True, inplace=False)
Alter the name of the index or columns.

Parameters mapper : scalar, list-like, optional
Value to set as the axis name attribute.

axis : {0 or ‘index’, 1 or ‘columns’}, default 0
The index or the name of the axis.

copy : boolean, default True
Also copy underlying data.

inplace : boolean, default False
Modifies the object directly, instead of creating a new Series or DataFrame.

Returns renamed : Series, DataFrame, or None
The same type as the caller or None if inplace is True.

See also:

pandas.Series.rename Alter Series index labels or name
pandas.DataFrame.rename Alter DataFrame index labels or name
pandas.Index.rename Set new names on index

Notes

Prior to version 0.21.0, rename_axis could also be used to change the axis labels by passing a mapping or scalar. This behavior is deprecated and will be removed in a future version. Use rename instead.
Examples

Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s.rename_axis("foo")
foo
0  1
1  2
2  3
dtype: int64
```

DataFrame

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename_axis("foo")
A   B
foo
0  1  4
1  2  5
2  3  6
```

```python
>>> df.rename_axis("bar", axis="columns")
bar A   B
  0  1  4
  1  2  5
  2  3  6
```

`pandas.Series.reorder_levels`

Series.reorder_levels(order)
Rearrange index levels using input order. May not drop or duplicate levels

Parameters

- **order**: list of int representing new level order.
  
  (reference level by number or key)

- **axis**: [where to reorder levels]

Returns

type of caller (new object)

`pandas.Series.repeat`

Series.repeat(repeats, *args, **kwargs)
Repeat elements of an Series. Refer to numpy.ndarray.repeat for more information about the repeats argument.

See also:

numpy.ndarray.repeat
pandas.Series.replace

Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')
Replace values given in to_replace with value.

Values of the Series are replaced with other values dynamically. This differs from updating with .loc or .iloc, which require you to specify a location to update with some value.

**Parameters**

- **to_replace**: str, regex, list, dict, Series, int, float, or None  
  How to find the values that will be replaced.
  - numeric, str or regex:
    - numeric: numeric values equal to to_replace will be replaced with value
    - str: string exactly matching to_replace will be replaced with value
    - regex: REGEXs matching to_replace will be replaced with value
  - list of str, regex, or numeric:
    - First, if to_replace and value are both lists, they must be the same length.
    - Second, if regex=True then all of the strings in both lists will be interpreted as REGEXs otherwise they will match directly. This doesn’t matter much for value since there are only a few possible substitution REGEXs you can use.
    - str, regex and numeric rules apply as above.
  - dict:
    - DICTs can be used to specify different replacement values for different existing values. For example, {’a’: ’b’, ’y’: ’z’} replaces the value ’a’ with ’b’ and ’y’ with ’z’. To use a dict in this way the value parameter should be None.
    - For a DataFrame a dict can specify that different values should be replaced in different columns. For example, {’a’: 1, ’b’: ’z’} looks for the value 1 in column ’a’ and the value ’z’ in column ’b’ and replaces these values with whatever is specified in value. The value parameter should not be None in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
    - For a DataFrame nested dictionaries, e.g., {’a’: {’b’: np.nan}}, are read as follows: look in column ’a’ for the value ’b’ and replace it with NaN. The value parameter should be None to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  - None:
    - This means that the regex argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If value is also None then this must be a nested dictionary or Series.

See the examples section for examples of each of these.

**value**: scalar, dict, list, str, regex, default None

Value to replace any values matching to_replace with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular 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 from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill.

regex : bool or same types as to_replace, default False

Whether to interpret to_replace and/or value as regular expressions. If this is True then to_replace must be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case to_replace must be None.

method : {'pad', 'ffill', 'bfill', None}

The method to use when for replacement, when to_replace is a scalar, list or tuple and value is None.

Changed in version 0.23.0: Added to DataFrame.

Returns Series

Object after replacement.

Raises AssertionError

- If regex is not a bool and to_replace is not None.

TypeError

- If to_replace is a dict and value is not a list, dict, ndarray, or Series
- If to_replace is None and regex is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple bool or datetime64 objects and the arguments to to_replace does not match the type of the value being replaced

ValueError

- If a list or an ndarray is passed to to_replace and value but they are not the same length.

See also:

Series.fillna Fill NA values

Series.where Replace values based on boolean condition

Series.str.replace Simple string replacement.

Notes

- Regex substitution is performed under the hood with re.sub. The rules for substitution for re.sub are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers are strings, then you can do this.
• This method has a lot of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
• When dict is used as the to_replace value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar ‘to_replace’ and ‘value’

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0 5
1 1
2 2
3 3
4 4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
                      'B': [5, 6, 7, 8, 9],
                      'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

List-like ‘to_replace’

```python
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```

```python
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```python
>>> s.replace([1, 2], method='bfill')
0 0
1 3
2 3
3 3
4 4
dtype: int64
```
dict-like `to_replace`

```
>>> df.replace({0: 10, 1: 100})
   A  B  C
0  10  5  a
1 100  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

```
>>> df.replace({'A': 0, 'B': 5}, 100)
   A  B  C
0 100 100  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

```
>>> df.replace({'A': {0: 100, 4: 400}})
   A  B  C
0 100  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4 400  9  e
```

**Regular expression `to_replace`**

```
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                    'B': ['abc', 'bar', 'xyz']})
```

```
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
   A  B
0 new abc
1(foo new
2 bait xyz
```

```
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
   A  B
0 new abc
1  bar
2 bait xyz
```

```
>>> df.replace(regex=r'^ba.$', value='new')
   A  B
0 new abc
1 new
2 bait xyz
```

```
>>> df.replace(regex={r'^ba.$':'new', 'foo':'xyz'})
   A  B
0 new abc
1  xyz
2 bait xyz
```

```
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
   A  B
(continues on next page)
```
Note that when replacing multiple `bool` or `datetime64` objects, the data types in the `to_replace` parameter must match the data type of the value being replaced:

```python
>>> df = pd.DataFrame({'A': [True, False, True],
                     'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False})  # raises
Traceback (most recent call last):
  ...  
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a `TypeError` because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the `to_replace` parameter:

```python
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
When one uses a dict as the `to_replace` value, it is like the value(s) in the dict are equal to the `value` parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None},
value=None, method=None):

```python
>>> s.replace({'a': None})
 0  10
 1  None
 2  None
 3   b
 4  None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the method parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`

```python
>>> s.replace('a', None)
 0  10
 1  10
 2  10
 3   b
 4   b
dtype: object
```

**pandas.Series.resample**

Series`resample` *(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0, on=None, level=None)*

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (DatetimeIndex, PeriodIndex, or TimedeltaIndex), or pass datetime-like values to the on or level keyword.
**Parameters**

- **rule**: string
  
  the offset string or object representing target conversion

- **axis**: [int, optional, default 0]

- **closed**: {'right', 'left'}
  
  Which side of bin interval is closed. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

- **label**: {'right', 'left'}
  
  Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

- **convention**: {'start', 'end', 's', 'e'}
  
  For PeriodIndex only, controls whether to use the start or end of rule

- **kind**: {'timestamp', 'period'}, optional
  
  Pass ‘timestamp’ to convert the resulting index to a DateTimeIndex or ‘period’ to convert it to a PeriodIndex. By default the input representation is retained.

- **loffset**: timedelta
  
  Adjust the resampled time labels

- **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

- **on**: string, optional
  
  For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.
  
  New in version 0.19.0.

- **level**: string or int, optional
  
  For a MultiIndex, level (name or number) to use for resampling. Level must be datetime-like.
  
  New in version 0.19.0.

**Returns**

Resampler object

**See also:**

*groupby*  Group by mapping, function, label, or list of labels.
Notes

See the user guide for more.

To learn more about the offset strings, please see this link.

Examples

Start by creating a series with 9 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T').sum()
2000-01-01 00:00:00    3
2000-01-01 00:03:00   12
2000-01-01 00:06:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket 2000-01-01 00:03:00 contains the value 3, but the summed value in the resampled bucket with the label 2000-01-01 00:03:00 does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```python
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00    3
2000-01-01 00:06:00   12
2000-01-01 00:09:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00    0
2000-01-01 00:03:00    6
2000-01-01 00:06:00   15
2000-01-01 00:09:00   15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.
Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```python
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 0
2000-01-01 00:01:00 1
2000-01-01 00:01:30 1
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```python
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 1
2000-01-01 00:01:00 1
2000-01-01 00:01:30 2
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00 8
2000-01-01 00:03:00 17
2000-01-01 00:06:00 26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword `convention` can be used to control whether to use the start or end of `rule`.

```python
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
               freq='A',
               periods=2))

>>> s
2012 1
2013 2
Freq: A-DEC, dtype: int64
```

Resample by month using `start` `convention`. Values are assigned to the first month of the period.

```python
>>> s.resample('M', convention='start').asfreq().head()
2012-01 1.0
2012-02 NaN
2012-03 NaN
2012-04 NaN
```
Resample by month using ‘end’ convention. Values are assigned to the last month of the period.

```python
>>> s.resample('M', convention='end').asfreq()
2012-12 1.0
2013-01 NaN
2013-02 NaN
2013-03 NaN
2013-04 NaN
2013-05 NaN
2013-06 NaN
2013-07 NaN
2013-08 NaN
2013-09 NaN
2013-10 NaN
2013-11 NaN
2013-12 2.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword `on` can be used to specify the column instead of the index for resampling.

```python
>>> df = pd.DataFrame(data=9*range(4), columns=['a', 'b', 'c', 'd'])
>>> df['time'] = pd.date_range('1/1/2000', periods=9, freq='T')
>>> df.resample('3T', on='time').sum()
a  b  c  d
+----+----+----+----+
time
2000-01-01 00:00:00 0 3 6 9
2000-01-01 00:03:00 0 3 6 9
2000-01-01 00:06:00 0 3 6 9
```

For a DataFrame with MultiIndex, the keyword `level` can be used to specify on level the resampling needs to take place.

```python
>>> time = pd.date_range('1/1/2000', periods=5, freq='T')
>>> df2 = pd.DataFrame(data=10*range(4), columns=['a', 'b', 'c', 'd'],
                    index=pd.MultiIndex.from_product([time, [1, 2]])
                )
>>> df2.resample('3T', level=0).sum()
a  b  c  d
+----+----+----+----+
time
2000-01-01 00:00:00 0 6 12 18
2000-01-01 00:03:00 0 4 8 12
```

**pandas.Series.reset_index**

`Series.reset_index(level=None, drop=False, name=None, inplace=False)`

Generate a new DataFrame or Series with the index reset.

This is useful when the index needs to be treated as a column, or when the index is meaningless and needs to be reset to the default before another operation.

**Parameters**

- `level` : int, str, tuple, or list, default optional
For a Series with a MultiIndex, only remove the specified levels from the index. Removes all levels by default.

**drop**: bool, default False
Just reset the index, without inserting it as a column in the new DataFrame.

**name**: object, optional
The name to use for the column containing the original Series values. Uses `self.name` by default. This argument is ignored when `drop` is True.

**inplace**: bool, default False
Modify the Series in place (do not create a new object).

**Returns** Series or DataFrame
When `drop` is False (the default), a DataFrame is returned. The newly created columns will come first in the DataFrame, followed by the original Series values. When `drop` is True, a Series is returned. In either case, if `inplace=True`, no value is returned.

See also:

`DataFrame.reset_index` Analogous function for DataFrame.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4], name='foo',
...                index=pd.Index(['a', 'b', 'c', 'd'], name='idx'))

Generate a DataFrame with default index.

```reset_index()`

```
 idx  foo
0  a   1
1  b   2
2  c   3
3  d   4
```

To specify the name of the new column use `name`.

```reset_index(name='values')

```

```
 idx  values
0  a   1
1  b   2
2  c   3
3  d   4
```

To generate a new Series with the default set `drop` to True.

```reset_index(drop=True)

```

```
  0  1
  1  2
  2  3
  3  4
Name: foo, dtype: int64
```
To update the Series in place, without generating a new one set `inplace` to True. Note that it also requires `drop=True`.

```python
>>> s.reset_index(inplace=True, drop=True)
>>> s
0  1
1  2
2  3
3  4
Name: foo, dtype: int64
```

The `level` parameter is interesting for Series with a multi-level index.

```python
>>> arrays = [np.array(['bar', 'bar', 'baz', 'baz']),
             np.array(['one', 'two', 'one', 'two'])]
>>> s2 = pd.Series(
    ...     range(4), name='foo',
    ...     index=pd.MultiIndex.from_arrays(arrays,
    ...     names=['a', 'b']))
```

To remove a specific level from the Index, use `level`.

```python
>>> s2.reset_index(level='a')
   a  foo
   b
   one  bar  0
   two  bar  1
   one  baz  2
   two  baz  3
```

If `level` is not set, all levels are removed from the Index.

```python
>>> s2.reset_index()
    a  b  foo
   0  bar one  0
   1  bar two  1
   2  baz one  2
   3  baz two  3
```

**pandas.Series.rfloordiv**

Series `rfloordiv` (`other`, `level=None`, `fill_value=None`, `axis=0`)

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

pandas.Series.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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

pandas.Series.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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

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Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64

>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e    NaN
dtype: float64
```
**closed**: string, default None

Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’. Remaining cases not implemented for fixed windows.

New in version 0.20.0.

**axis**  [int or string, default 0]

**Returns**

a Window or Rolling sub-classed for the particular operation

**See also:**

- **expanding**  Provides expanding transformations.
- **ewm**  Provides exponential weighted functions

**Notes**

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see this link.

The recognized `win_types` are:

- boxcar
- triang
- blackman
- hamming
- bartlett
- parzen
- bohman
- blackmanharris
- nuttall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general_gaussian (needs power, width)
- slepian (needs width).

If `win_type=None` all points are evenly weighted. To learn more about different window types see `scipy.signal window functions`. 

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Examples

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
```

```
>>> df
B
0 0.0
1 1.0
2 2.0
3 NaN
4 4.0
```

Rolling sum with a window length of 2, using the 'triang' window type.

```python
>>> df.rolling(2, win_type='triang').sum()
```

```
   B
0  NaN
1  1.0
2  2.5
3  NaN
4  NaN
```

Rolling sum with a window length of 2, min_periods defaults to the window length.

```python
>>> df.rolling(2).sum()
```

```
   B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN
```

Same as above, but explicitly set the min_periods

```python
>>> df.rolling(2, min_periods=1).sum()
```

```
   B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                   index=[pd.Timestamp('20130101 09:00:00'),
                          pd.Timestamp('20130101 09:00:02'),
                          pd.Timestamp('20130101 09:00:03'),
                          pd.Timestamp('20130101 09:00:05'),
                          pd.Timestamp('20130101 09:00:06'))
```

```
   B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```
Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```python
>>> df.rolling('2s').sum()
B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

**pandas.Series.round**

`Series.round(decimals=0, *args, **kwargs)`

Round each value in a Series to the given number of decimals.

**Parameters**

- **decimals** : int
  Number of decimal places to round to (default: 0). If decimals is negative, it specifies the number of positions to the left of the decimal point.

**Returns**

Series object

**See also:**

`numpy.around`, `DataFrame.round`

**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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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`
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```

**pandas.Series.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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples
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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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`

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
```

```python
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
```

```python
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```

```python
>>> a.rtruediv(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
```
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64

pandas.Series.sample

Series.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)
Return a random sample of items from an axis of object.
You can use random_state for reproducibility.

Parameters:

- n : int, optional
  Number of items from axis to return. Cannot be used with frac. Default = 1 if frac = None.

- frac : float, optional
  Fraction of axis items to return. Cannot be used with n.

- replace : 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.

Examples

Generate an example Series and DataFrame:

```python
def s = pd.Series(np.random.randn(50))
s.head()
0   -0.038497
1    1.820773
2    -0.972766
3    -1.598270
4   -1.095526
dtype: float64
def df = pd.DataFrame(np.random.randn(50, 4), columns=list('ABCD'))
df.head()
A     B     C     D
0  0.016443 -2.318952 -0.566372 -1.028078
1 -1.051921  0.438836  0.658280 -0.175797
2 -1.243569 -0.364626 -0.215065  0.057736
3  1.768216  0.404512 -0.385604 -1.457834
4  1.072446 -1.337172  0.314194 -0.046661
```

Next extract a random sample from both of these objects...

3 random elements from the Series:

```python
def s.sample(n=3)
27   -0.994689
55    1.049016
67   -0.224565
dtype: float64
def df.sample(frac=0.1, replace=True)
A     B     C     D
35  1.981780  0.142106  1.817165 -0.290805
49 -1.336199 -0.448634 -0.789640  0.217116
40  0.823173 -0.078816  1.009536  1.015108
15  1.421154 -0.055301 -1.922594 -0.019696
  6 -0.148339  0.832938  1.787600 -1.383767
```

And a random 10% of the DataFrame with replacement:

```python
def df.sample(frac=0.1, replace=True)
A     B     C     D
35  1.981780  0.142106  1.817165 -0.290805
49 -1.336199 -0.448634 -0.789640  0.217116
40  0.823173 -0.078816  1.009536  1.015108
15  1.421154 -0.055301 -1.922594 -0.019696
  6 -0.148339  0.832938  1.787600 -1.383767
```

You can use random state for reproducibility:

```python
def df.sample(random_state=1)
A     B     C     D
37  -2.027662  0.103611  0.237496 -0.165867
43 -0.259323 -0.583426  1.516140 -0.479118
12 -1.686325 -0.579510  0.985195 -0.460286
  8  1.167946  0.429082  1.215742 -1.636041
  9  1.197475 -0.864188  1.554031 -1.505264
```

34.3. Series
pandas.Series.searchsorted

Series.searchsorted(value, side='left', sorter=None)
Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series self such that, if the corresponding elements in value were inserted before the indices, the order of self would be preserved.

Parameters value : array_like
Values to insert into self.
side : {'left', 'right'}, optional
If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of self).

sorter : 1-D array_like, optional
Optional array of integer indices that sort self into ascending order. They are typically the result of np.argsort.

Returns indices : array of ints
Array of insertion points with the same shape as value.

See also:
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])
```
```python
>>> x = pd.Categorical(['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True)
[apple, bread, bread, cheese, milk]
Categories (4, object): [apple < bread < cheese < milk]

>>> x.searchsorted('bread')
array([1])  # Note: an array, not a scalar

>>> x.searchsorted(['bread'], side='right')
array([3])
```

**pandas.Series.select**

Series.select (crit, axis=0)
Return data corresponding to axis labels matching criteria

Deprecated since version 0.21.0: Use df.loc[df.index.map(crit)] to select via labels

- **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
  - ddof : int, default 1
    Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
  - numeric_only : boolean, default None
    Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

- **Returns**
sem  [scalar or Series (if level specified)]

pandas.Series.set_axis

Series.set_axis(labels, axis=0, inplace=None)
Assign desired index to given axis.
Indexes for column or row labels can be changed by assigning a list-like or Index.
Changed in version 0.21.0: The signature is now labels and axis, consistent with the rest of pandas API.
Previously, the axis and labels arguments were respectively the first and second positional arguments.

Parameters labels : list-like, Index
The values for the new index.
axis : {0 or ‘index’, 1 or ‘columns’}, default 0
The axis to update. The value 0 identifies the rows, and 1 identifies the columns.
inplace : boolean, default None
Whether to return a new %(klass)s instance.

Returns renamed : %(klass)s or None
An object of same type as caller if inplace=False, None otherwise.

See also:
pandas.DataFrame.rename_axis Alter the name of the index or columns.

Examples

Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0  1
1  2
2  3
dtype: int64
```

```python
>>> s.set_axis(['a', 'b', 'c'], axis=0, inplace=False)
a  1
b  2
c  3
dtype: int64
```
The original object is not modified.
DataFrame

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
```

Change the row labels.

```python
>>> df.set_axis(['a', 'b', 'c'], axis='index', inplace=False)
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>b</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>c</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

Change the column labels.

```python
>>> df.set_axis(['I', 'II'], axis='columns', inplace=False)
```

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

Now, update the labels inplace.

```python
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
```

<table>
<thead>
<tr>
<th></th>
<th>i</th>
<th>ii</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

**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.

Deprecated since version 0.21.0: Please use .at[] or .iat[] accessors.

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 the tseries module or time rule (e.g. ‘EOM’). See Notes.
- **axis**: [0 or ‘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 when computing the result.
- **level**: int or level name, default None  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar
- **numeric_only**: boolean, default None  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- 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_index**

```python
Series.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True)
```

Sort Series by index labels.

Returns a new Series sorted by label if `inplace` argument is `False`, otherwise updates the original series and returns `None`.

**Parameters**

- **axis**: int, default 0
  
  Axis to direct sorting. This can only be 0 for Series.

- **level**: int, optional
  
  If not None, sort on values in specified index level(s).

- **ascending**: bool, default true
  
  Sort ascending vs. descending.

- **inplace**: bool, default False
  
  If True, perform operation in-place.

- **kind**: {'quicksort', 'mergesort', 'heapsort'}, default ‘quicksort’
  
  Choice of sorting algorithm. See also `numpy.sort()` for more information. ‘mergesort’ is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

- **na_position**: {'first', 'last'}, default ‘last’
  
  If ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end. Not implemented for MultiIndex.

- **sort_remaining**: bool, default True
  
  If true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.

**Returns** pandas.Series

The original Series sorted by the labels

See also:

- `DataFrame.sort_index`  Sort DataFrame by the index
- `DataFrame.sort_values`  Sort DataFrame by the value
- `Series.sort_values`  Sort Series by the value
Examples

```python
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, 4])
>>> s.sort_index()
1  c
2  b
3  a
4  d
dtype: object

Sort Descending

```python
>>> s.sort_index(ascending=False)
4  d
3  a
2  b
1  c
dtype: object
``` 

Sort Inplace

```python
>>> s.sort_index(inplace=True)
>>> s
1  c
2  b
3  a
4  d
dtype: object
``` 

By default NaNs are put at the end, but use `na_position` to place them at the beginning

```python
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, np.nan])
>>> s.sort_index(na_position='first')
NaN  d
1.0  c
2.0  b
3.0  a
dtype: object
``` 

Specify index level to sort

```python
>>> arrays = [np.array(['qux', 'qux', 'foo', 'foo',
... 'baz', 'baz', 'bar', 'bar']),
... np.array(['two', 'one', 'two', 'one',
... 'two', 'one', 'two', 'one'])]
>>> s = pd.Series([1, 2, 3, 4, 5, 6, 7, 8], index=arrays)
>>> s.sort_index(level=1)
bar  one  8
baz  one  6
foo  one  4
qux  one  2
bar  two  7
baz  two  5
foo  two  3
qux  two  1
dtype: int64
```

Does not sort by remaining levels when sorting by levels
pandas.Series.sort_values

Series.sort_values (axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
Sort by the values.
Sort a Series in ascending or descending order by some criterion.

Parameters

axis : {0 or ‘index’}, default 0
   Axis to direct sorting. The value ‘index’ is accepted for compatibility with DataFrame.sort_values.

ascending : bool, default True
   If True, sort values in ascending order, otherwise descending.

inplace : bool, default False
   If True, perform operation in-place.

kind : {'quicksort', 'mergesort' or 'heapsort'}, default ‘quicksort’
   Choice of sorting algorithm. See also numpy.sort() for more information.
   ‘mergesort’ is the only stable algorithm.

na_position : {‘first’ or ‘last’}, default ‘last’
   Argument ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end.

Returns

Series
Series ordered by values.

See also:
Series.sort_index Sort by the Series indices.
DataFrame.sort_values Sort DataFrame by the values along either axis.
DataFrame.sort_index Sort DataFrame by indices.

Examples

>>> s = pd.Series([np.nan, 1, 3, 10, 5])
>>> s
0   NaN
1   1.0
(continues on next page)
Sort values ascending order (default behaviour)

```python
>>> s.sort_values(ascending=True)
1   1.0
2   3.0
4   5.0
3  10.0
0   NaN
dtype: float64
```

Sort values descending order

```python
>>> s.sort_values(ascending=False)
3  10.0
4   5.0
2   3.0
1   1.0
0   NaN
dtype: float64
```

Sort values inplace

```python
>>> s.sort_values(ascending=False, inplace=True)
>>> s
3  10.0
4   5.0
2   3.0
1   1.0
0   NaN
dtype: float64
```

Sort values putting NAs first

```python
>>> s.sort_values(na_position='first')
0   NaN
1   1.0
2   3.0
4   5.0
3  10.0
dtype: float64
```

Sort a series of strings

```python
>>> s = pd.Series(['z', 'b', 'd', 'a', 'c'])
>>> s
0   z
1   b
2   d
3   a
4   c
dtype: object
```
```python
>>> s.sort_values()
3  a
1  b
4  c
2  d
0  z
dtype: object
```

**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).

Deprecated since version 0.20.0: Use `Series.sort_index()`

**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(axis=None)`

Squeeze length 1 dimensions.

**Parameters**

- `axis` [None, integer or string axis name, optional]
  - The axis to squeeze if 1-sized.
  - New in version 0.20.0.

**Returns**

- `scalar` if 1-sized, else original object

**pandas.Series.std**

`Series.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

**Parameters**

- `axis` [(index (0))]
- `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

ddof : int, default 1
    Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only : boolean, default None
    Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
```  
```python
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64
```  

**pandas.Series.subtract**

`Series.subtract(\text{other}, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator \text{sub}).

Equivalent to \text{series} - \text{other}, but with support to substitute a \text{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 existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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`

**Examples**
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.add(b, fill_value=0)
a 2.0
b 1.0
c 1.0
d 1.0
e NaN
dtype: float64

**pandas.Series.sum**

`Series.sum(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the sum of the values for the requested axis

**Parameters**

- `axis` [[index (0)]]
- `skipna` : boolean, default True
  
  Exclude NA/null values when computing the result.
- `level` : int or level name, default None
  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar
- `numeric_only` : boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- `min_count` : int, default 0

  The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

  New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**Returns**

- `sum` [scalar or Series (if level specified)]
Examples

By default, the sum of an empty or all-NA Series is 0.

```python
>>> pd.Series([]).sum()  # min_count=0 is the default
0
```

This can be controlled with the `min_count` parameter. For example, if you’d like the sum of an empty series to be NaN, pass `min_count=1`.

```python
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).sum()
0.0

>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

**pandas.Series.swapaxes**

`Series.swapaxes(axis1, axis2, copy=True)`

Interchange axes and swap values axes appropriately

**Returns**

- `y` [same as input]

**pandas.Series.swaplevel**

`Series.swaplevel(i=-2, j=-1, copy=True)`

Swap levels `i` and `j` in a MultiIndex

**Parameters**

- `i, j`: int, string (can be mixed)

  Level of index to be swapped. Can pass level name as string.

**Returns**

- `swapped` [Series]

.. versionchanged:: 0.18.1

  The indexes `i` and `j` are now optional, and default to the two innermost levels of the index.

**pandas.Series.tail**

`Series.tail(n=5)`

Return the last `n` rows.

This function returns last `n` rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.
Parameters  

- **n**: int, default 5
  
  Number of rows to select.

Returns  

- type of caller

  The last $n$ rows of the caller object.

See also:

- **pandas.DataFrame.head**  
  
  The first $n$ rows of the caller object.

Examples

```python
>>> df = pd.DataFrame({
    'animal': ['alligator', 'bee', 'falcon', 'lion', ...
        'monkey', 'parrot', 'shark', 'whale', 'zebra']
})

>>> df
animal
0 alligator
1 bee
2 falcon
3 lion
4 monkey
5 parrot
6 shark
7 whale
8 zebra

Viewing the last 5 lines

```python
>>> df.tail()
animal
4 monkey
5 parrot
6 shark
7 whale
8 zebra
```

Viewing the last $n$ lines (three in this case)

```python
>>> df.tail(3)
animal
6 shark
7 whale
8 zebra
```

**pandas.Series.take**

- **Series.take**(indices, axis=0, convert=None, is_copy=True, **kwargs)

  Return the elements in the given positional indices along an axis.

  This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

  Parameters  

  - **indices**: array-like

    An array of ints indicating which positions to take.
**axis**: {0 or 'index', 1 or 'columns', None}, default 0

The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.

**convert**: bool, default True

Whether to convert negative indices into positive ones. For example, -1 would map to the `len(axis) - 1`. The conversions are similar to the behavior of indexing a regular Python list.

Deprecated since version 0.21.0: In the future, negative indices will always be converted.

**is_copy**: bool, default True

Whether to return a copy of the original object or not.

**kwargs

For compatibility with `numpy.take()`. Has no effect on the output.

**Returns** taken: type of caller

An array-like containing the elements taken from the object.

**See also:**

- `DataFrame.loc` Select a subset of a DataFrame by labels.
- `DataFrame.iloc` Select a subset of a DataFrame by positions.
- `numpy.take` Take elements from an array along an axis.

**Examples**

```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                     ('parrot', 'bird', 24.0),
...                     ('lion', 'mammal', 80.5),
...                     ('monkey', 'mammal', np.nan)],
...                     columns=['name', 'class', 'max_speed'],
...                     index=[0, 2, 3, 1])
>>> df
     name  class  max_speed
0  falcon  bird     389.0
1   parrot  bird      24.0
2    lion  mammal     80.5
3  monkey  mammal       NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That’s because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```python
>>> df.take([0, 3])
     name  class  max_speed
0  falcon  bird     389.0
1  monkey  mammal       NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).
>>> df.take([1, 2], axis=1)
  class  max_speed
 0  bird     389.0
 2  bird     24.0
 3 mammal    80.5
 1 mammal    NaN

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

>>> df.take([-1, -2])
  name  class  max_speed
 1 monkey  mammal    NaN
 3   lion  mammal     80.5

pandas.Series.to_clipboard

Series.to_clipboard(excel=True, sep=None, **kwargs)
Copy object to the system clipboard.
Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

Parameters excel : bool, default True
- True, use the provided separator, writing in a csv format for allowing easy pasting into excel.
- False, write a string representation of the object to the clipboard.

sep : str, default ' \t '  
Field delimiter.

**kwargs
These parameters will be passed to DataFrame.to_csv.

See also:

DataFrame.to_csv Write a DataFrame to a comma-separated values (csv) file.
read_clipboard Read text from clipboard and pass to read_table.

Notes
Requirements for your platform.
- Linux : xclip, or xsel (with gtk or PyQt4 modules)
- Windows : none
- OS X : none

Examples
Copy the contents of a DataFrame to the clipboard.
```python
>>> df = pd.DataFrame(
    
```
```
...
```
```
```
```
```
```
```
```
```
```
```
```
```
```
```
```
```
```
```
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```
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```
```
```
```
```
```
A string representing the compression to use in the output file. Allowed values are ‘gzip’, ‘bz2’, ‘zip’, ‘xz’. This input is only used when the first argument is a filename.

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(into=<class 'dict'>)
Convert Series to {label -> value} dict or dict-like object.
Parameters into: class, default dict
The collections.Mapping subclass to use as the return object. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

Returns
value_dict [collections.Mapping]

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_dict()
{0: 1, 1: 2, 2: 3, 3: 4}
>>> from collections import OrderedDict, defaultdict
>>> s.to_dict(OrderedDict)
OrderedDict([(0, 1), (1, 2), (2, 3), (3, 4)])
>>> dd = defaultdict(list)
>>> s.to_dict(dd)
defaultdict(<type 'list'>, {0: 1, 1: 2, 2: 3, 3: 4})
```

pandas.Series.to_excel

Series.to_excel(excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True)
Write Series to an excel sheet
New in version 0.20.0.
**Parameters**

`excel_writer` : string or ExcelWriter object
  File path or existing ExcelWriter

`sheets` : 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 the column names. If a list of strings 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)

`freeze_panes` : tuple of integer (length 2), default None
  Specifies the one-based bottommost row and rightmost column that is to be frozen
  New in version 0.20.0.
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 = pd.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.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)` Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the [user guide](#).

**Parameters**

- **path_or_buf** : str or pandas.HDFStore
  
  File path or HDFStore object.

- **key** : str
  
  Identifier for the group in the store.

- **mode** : {'a', 'w', 'r+'}, default 'a'
  
  Mode to open file:
  
  - 'w': write, a new file is created (an existing file with the same name would be deleted).
  
  - 'a': append, an existing file is opened for reading and writing, and if the file does not exist it is created.
  
  - 'r+': similar to 'a', but the file must already exist.

- **format** : {'fixed', 'table'}, default 'fixed'
Possible values:

- ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

```python
append : bool, default False
```

For Table formats, append the input data to the existing.

```python
data_columns : list of columns or True, optional
```

List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See Query via Data Columns. Applicable only to format='table'.

```python
complevel : {0-9}, optional
```

Specifies a compression level for data. A value of 0 disables compression.

```python
complib : {'zlib', 'lzo', 'bzip2', 'blosc'}, default 'zlib'
```

Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {'blosc:hloclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd'}. Specifying a compression library which is not available issues a ValueError.

```python
fletcher32 : bool, default False
```

If applying compression use the fletcher32 checksum.

```python
dropna : bool, default False
```

If true, ALL nan rows will not be written to store.

```python
errors : str, default 'strict'
```

Specifies how encoding and decoding errors are to be handled. See the errors argument for open() for a full list of options.

See also:

- **DataFrame**.read_hdf Read from HDF file.
- **DataFrame**.to_parquet Write a DataFrame to the binary parquet format.
- **DataFrame**.to_sql Write to a sql table.
- **DataFrame**.to_feather Write out feather-format for DataFrames.
- **DataFrame**.to_csv Write out to a csv file.

Examples

```python
>>> df = pd.DataFrame({
...     'A': [1, 2, 3],
...     'B': [4, 5, 6],
...     'C': ['a', 'b', 'c']
... })
... >>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```python
34.3. Series 1603
```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')

Reading from HDF file:

```python
>>> pd.read_hdf('data.h5', 'df')
A   B
a  1   4
b  2   5
c  3   6
```  

```python
>>> pd.read_hdf('data.h5', 's')
0  1
1  2
2  3
3  4
dtype: int64
```

Deleting file with data:

```python
>>> import os
>>> os.remove('data.h5')
```

### pandas.Series.to_json

`Series.to_json(path_or_buf=None, orient=None, date_format=None, double_precision=10, force_ascii=True, date_unit='ms', default_handler=None, lines=False, compression=None, index=True)`

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**: string or file handle, optional
  - File path or object. If not specified, the result is returned as a string.
- **orient**: string
  - Indication of expected JSON string format.
    - **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
- ‘table’: dict like `{schema}: {schema}, 'data': {data}` describing the data, and the data component is like orient='records'.

   Changed in version 0.20.0.

date_format: {None, ‘epoch’, ‘iso’}

   Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the orient. For orient='table', the default is ‘iso’. For all other orients, the default is ‘epoch’.

double_precision: int, default 10

   The number of decimal places to use when encoding floating point values.

force_ascii: boolean, default True

   Force encoded string to be ASCII.

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.

lines: boolean, default False

   If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

   New in version 0.19.0.


   A string representing the compression to use in the output file, only used when the first argument is a filename.

   New in version 0.21.0.

index: boolean, default True

   Whether to include the index values in the JSON string. Not including the index (index=False) is only supported when orient is ‘split’ or ‘table’.

   New in version 0.23.0.

See also:
pandas.read_json

Examples

```python
>>> df = pd.DataFrame([[‘a’, ‘b’], [‘c’, ‘d’]],
...                   index=[‘row 1’, ‘row 2’],
...                   columns=[‘col 1’, ‘col 2’])
>>> df.to_json(orient=’split’)
```

(continues on next page)
Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved with this encoding.

```python
>>> df.to_json(orient='records')
'(["col 1":"a","col 2":"b"],
 ["col 1":"c","col 2":"d"])
```

Encoding/decoding a Dataframe using 'index' formatted JSON:

```python
>>> df.to_json(orient='index')
'(["row 1":{"col 1":"a","col 2":"b"},
"row 2":{"col 1":"c","col 2":"d"}])
```

Encoding/decoding a Dataframe using 'columns' formatted JSON:

```python
>>> df.to_json(orient='columns')
'(["col 1":{"row 1":"a","row 2":"c"},
"col 2":{"row 1":"b","row 2":"d"}])
```

Encoding/decoding a Dataframe using 'values' formatted JSON:

```python
>>> df.to_json(orient='values')
'(["a","b"],
 ["c","d"])
```

Encoding with Table Schema

```python
>>> df.to_json(orient='table')
'("schema": [
  "fields": [
    {"name": "index", "type": "string"},
    {"name": "col 1", "type": "string"},
    {"name": "col 2", "type": "string"}
  ],
  "primaryKey": "index",
  "pandas_version": "0.20.0"],
"data": [
  {"index": "row 1", "col 1": "a", "col 2": "b"},
  {"index": "row 2", "col 1": "c", "col 2": "d"}])
```

**pandas.Series.to_latex**

Series.to_latex(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal='. ', multicolumn=None, multicolumn_format=None, multirow=None)

Render an object to a tabular environment table. You can splice this into a LaTeX document. Requires \usepackage{booktabs}.

Changed in version 0.20.2: Added to Series

to_latex-specific options:

bold_rows [boolean, default False] 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 will be read from the pandas config module] Default: False. Use a longtable environment instead of tabular. Requires adding a \usepackage{longtable} to your LaTeX preamble.
**pandas.Series.to_msgpack**

Series.to_msgpack(path_or_buf=None, encoding='utf-8', **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]

**Returns**

- **ts** [Series with PeriodIndex]
pandas.Series.to_pickle

Series.to_pickle(path, compression='infer', protocol=4)
Pickle (serialize) object to file.

Parameters
- path : str
  File path where the pickled object will be stored.
- compression : {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'
  A string representing the compression to use in the output file. By default, infers
  from the file extension in specified path.
  New in version 0.20.0.
- protocol : int
  Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [R27] paragraph 12.1.2). The possible values for this parameter depend on the version of Python. For Python 2.x, possible values are 0, 1, 2. For Python>=3.0, 3 is a valid value. For Python >= 3.4, 4 is a valid value. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.
  New in version 0.21.0.

See also:
- read_pickle Load pickled pandas object (or any object) from file.
- DataFrame.to_hdf Write DataFrame to an HDF5 file.
- DataFrame.to_sql Write DataFrame to a SQL database.
- DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Examples

```python
>>> original_df = pd.DataFrame({'foo': range(5), 'bar': range(5, 10)})
>>> original_df
   foo  bar
0    0   5
1    1   6
2    2   7
3    3   8
4    4   9
>>> original_df.to_pickle('./dummy.pkl')

>>> unpickled_df = pd.read_pickle('./dummy.pkl')
>>> unpickled_df
   foo  bar
0    0   5
1    1   6
2    2   7
3    3   8
4    4   9
```
```python
>>> import os
>>> os.remove("./dummy.pkl")
```

**pandas.Series.to_sparse**

Series.to_sparse(kind='block', fill_value=None)

Convert Series to SparseSeries

**Parameters**

- **kind**
  - Value: {'block', 'integer'}
  - Default: 'block'

- **fill_value**
  - Value: float
  - Default: NaN

**Returns**

- **sp**
  - Type: SparseSeries

**pandas.Series.to_sql**

Series.to_sql(name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [R28] are supported. Tables can be newly created, appended to, or overwritten.

**Parameters**

- **name**
  - Type: string
  - Description: Name of SQL table.

- **con**
  - Type: sqlalchemy.engine.Engine or sqlite3.Connection
  - Description: Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects.

- **schema**
  - Type: string, optional
  - Description: Specify the schema (if database flavor supports this). If None, use default schema.

- **if_exists**
  - Value: {'fail', 'replace', 'append'}
  - Default: 'fail'
  - Description: How to behave if the table already exists.
    - fail: Raise a ValueError.
    - replace: Drop the table before inserting new values.
    - append: Insert new values to the existing table.

- **index**
  - Type: boolean, default True
  - Description: Write DataFrame index as a column. Uses index_label as the column name in the table.

- **index_label**
  - Type: string or sequence, default None
  - Description: 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**
  - Type: int, optional
Rows will be written in batches of this size at a time. By default, all rows will be written at once.

**dtype**: dict, optional

Specifying the datatype for columns. The keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode.

**Raises** ValueError

When the table already exists and if_exists is `fail` (the default).

**See also:**

*pandas.read_sql* read a DataFrame from a table

**References**

[R28], [R29]

**Examples**

Create an in-memory SQLite database.

```python
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```python
>>> df = pd.DataFrame({'name': ['User 1', 'User 2', 'User 3']})
>>> df
   name
0  User 1
1  User 2
2  User 3

>>> df.to_sql('users', con=engine)
```

```sql
SELECT * FROM users
```

```python
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

```python
>>> df1 = pd.DataFrame({'name': ['User 4', 'User 5']})
>>> df1.to_sql('users', con=engine, if_exists='append')
```

```sql
SELECT * FROM users
```

```python
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'), (0, 'User 4'), (1, 'User 5')]
```

Overwrite the table with just `df1`.

```python
>>> df1.to_sql('users', con=engine, if_exists='replace',
           ... index_label='id')
```

```sql
SELECT * FROM users
```

```python
[(0, 'User 4'), (1, 'User 5')]
```
Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```python
>>> df = pd.DataFrame({"A": [1, None, 2]})
>>> df
   A
0  1.0
1  NaN
2  2.0
```

```python
from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
...   dtype={"A": Integer()})
```

```python
engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

### pandas.Series.to_string

`Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, index=True, length=False, dtype=False, name=False, max_rows=None)`

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)
- **index**: bool, optional
  - Add index (row) labels, default True
- **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.to_xarray**

Series.to_xarray()

Return an xarray object from the pandas object.

**Returns**
- a DataArray for a Series
- a Dataset for a DataFrame
- a DataArray for higher dims

**Notes**

See the xarray docs

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 1, 2],
                   'B': ['foo', 'bar', 'foo'],
                   'C': np.arange(4.,7)})
>>> df
   A  B  C
0  1  foo  4.0
1  1   bar  5.0
2  2  foo  6.0

>>> df.to_xarray()
<xarray.Dataset>
Dimensions: (index: 3)
Coordinates:
* index (index) int64 0 1 2
Data variables:
  A (index) int64 1 1 2
  B (index) object 'foo' 'bar' 'foo'
  C (index) float64 4.0 5.0 6.0
```
```python
>>> df = pd.DataFrame({'A' : [1, 1, 2],
                   'B' : ['foo', 'bar', 'foo'],
                   'C' : np.arange(4.,7) ),
                   .set_index(['B','A'])

>>> df
B A  
foo 1 4.0
bar 1 5.0
foo 2 6.0

>>> df.to_xarray()
<xarray.Dataset>
Dimensions: (A: 2, B: 2)
Coordinates:
    * B  (B) object 'bar' 'foo'
    * A  (A) int64 1 2
Data variables:
    C  (B, A) float64 5.0 nan 4.0 6.0

>>> p = pd.Panel(np.arange(24).reshape(4,3,2),
               items=list('ABCD'),
               major_axis=pd.date_range('20130101', periods=3),
               minor_axis=['first', 'second'])

>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: A to D
Major_axis axis: 2013-01-01 00:00:00 to 2013-01-03 00:00:00
Minor_axis axis: first to second

>>> p.to_xarray()
<xarray.DataArray (items: 4, major_axis: 3, minor_axis: 2)>
array([[ 0,  1],
       [ 2,  3],
       [ 4,  5],
       [ 6,  7],
       [ 8,  9],
       [10, 11],
       [12, 13],
       [14, 15],
       [16, 17],
       [18, 19],
       [20, 21],
       [22, 23]])
Coordinates:
    * items  (items) object 'A' 'B' 'C' 'D'
    * major_axis  (major_axis) datetime64[ns] 2013-01-01 2013-01-02 2013-01-03
      # noqa
    * minor_axis (minor_axis) object 'first' 'second'

pandas.Series.tolist

Series.tolist()
    Return a list of the values.
```
These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

See also:

numpy.ndarray.tolist

df

df.transform

Series.transform(func, *args, **kwargs)

Call function producing a like-indexed NDFrame and return a NDFrame with the transformed values

New in version 0.20.0.

Parameters

func : callable, string, dictionary, or list of string/callables

To apply to column

Accepted Combinations are:

• string function name
• function
• list of functions
• dict of column names -> functions (or list of functions)

Returns

transformed [NDFrame]

See also:

pandas.NDFrame.aggregate, pandas.NDFrame.apply

Examples

>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
...                   index=pd.date_range('1/1/2000', periods=10))
...       df.iloc[3:7] = np.nan

>>> df.transform(lambda x: (x - x.mean()) / x.std())

A          B          C
2000-01-01  0.579457   1.236184  0.123424
2000-01-02  0.370357  -0.605875 -1.231325
2000-01-03  1.455756  -0.277446  0.288967
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  -0.498658  1.274522  1.642524
2000-01-09  -0.540524  -1.012676  -0.828968
2000-01-10  -1.366388  -0.614710  0.005378
pandas.Series.transpose

Series.transpose(*args, **kwargs)
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 value, default None (NaN)
    Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result 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

Examples

```python
g>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
g>>> a
a    1.0
b    1.0
c    1.0
d     NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
g>>> b
a    1.0
b  NaN
d    1.0
e  NaN
dtype: float64
>>> a.add(b, fill_value=0)
    a  b  c  d  e
--|--|--|--|--
a  2.0 1.0 1.0 1.0 NaN
```

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pandas.Series.truncate

Series.truncate(before=None, after=None, axis=None, copy=True)

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

- **before**: date, string, int
  Truncate all rows before this index value.

- **after**: date, string, int
  Truncate all rows after this index value.

- **axis**: {0 or 'index', 1 or 'columns'}, optional
  Axis to truncate. Truncates the index (rows) by default.

- **copy**: boolean, default is True,
  Return a copy of the truncated section.

Returns
type of caller

The truncated Series or DataFrame.

See also:

- **DataFrame.loc**: Select a subset of a DataFrame by label.
- **DataFrame.iloc**: Select a subset of a DataFrame by position.

Notes

If the index being truncated contains only datetime values, **before** and **after** may be specified as strings instead of Timestamps.

Examples

```python
given
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                    'B': ['f', 'g', 'h', 'i', 'j'],
...                    'C': ['k', 'l', 'm', 'n', 'o']},
...                   index=[1, 2, 3, 4, 5])
```
```python
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```
```python
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
4  d  i  n
```

The columns of a DataFrame can be truncated.
For Series, only rows can be truncated.

```python
>>> df['A'].truncate(before=2, after=4)
2  b
3  c
4  d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```python
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
    A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01 00:00:00  1
```

```python
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
               ... after=pd.Timestamp('2016-01-10')).tail()
    A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Because the index is a `DatetimeIndex` containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```python
>>> df.truncate('2016-01-05', '2016-01-10').tail()
    A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```python
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
    A
2016-01-10 23:59:55  1
2016-01-10 23:59:56  1
2016-01-10 23:59:57  1
```

(continues on next page)
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 the tseries 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 (tz, axis=0, level=None, copy=True, ambiguous='raise')
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

Raises TypeError
    If the TimeSeries is tz-aware and tz is not None.

pandas.Series.unique

Series.unique()
    Return unique values of Series object.
    Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

Returns ndarray or Categorical
    The unique values returned as a NumPy array. In case of categorical data type, returned as a Categorical.

See also:

pandas.unique top-level unique method for any 1-d array-like object.
Index.unique return Index with unique values from an Index object.

Examples

```python
>>> pd.Series([2, 1, 3, 3], name='A').unique()
arrray([2, 1, 3])
```

```python
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
arrray(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```python
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern') for _ in range(3)]).unique()
array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')], dtype=object)
```

An unordered Categorical will return categories in the order of appearance.
An ordered Categorical preserves the category ordering.

```python
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'), ordered=True)).unique()
[b, a, c]
Categories (3, object): [a < b < c]
```

**pandas.Series.unstack**

`Series.unstack(level=-1, fill_value=None)`

Unstack, 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
  - `fill_value`: replace NaN with this value if the unstack produces missing values

- **Returns**
  - *unstacked* [DataFrame]

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4],
...                   index=pd.MultiIndex.from_product([['one', 'two'], ['a', 'b']]))
>>> s
one a 1
   b 2
two a 3
   b 4
dtype: int64

>>> s.unstack(level=-1)
   a b
one 1 2
two 3 4

>>> s.unstack(level=0)
    one two
   a 1 3
   b 2 4
```
pandas.Series.update

Series.update(other)
Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters
other [Series]

Examples

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6]))
>>> s
0 4
1 5
2 6
dtype: int64

>>> s = pd.Series(['a', 'b', 'c'])
>>> s.update(pd.Series(['d', 'e'], index=[0, 2]))
>>> s
0 d
1 b
2 e
dtype: object

>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, np.nan, 6]))
>>> s
0 4
1 2
2 6
dtype: int64
```

If other contains NaNs the corresponding values are not updated in the original Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, np.nan, 6]))
>>> s
0 4
1 2
2 6
dtype: int64
```

pandas.Series.valid

Series.valid(inplace=False, **kwargs)
Return Series without null values.

Deprecated since version 0.23.0: Use Series.dropna() instead.
**pandas.Series.value_counts**

```python
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**

```python
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

- **ddof** : int, default 1
  
  Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

- **numeric_only** : boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
Returns

var [scalar or Series (if level specified)]

pandas.Series.view

Series.view(dt=\texttt{None})

Create a new view of the Series.

This function will return a new Series with a view of the same underlying values in memory, optionally
reinterpreted with a new data type. The new data type must preserve the same size in bytes as to not cause
index misalignment.

Parameters \texttt{dtype} : data type

Data type object or one of their string representations.

Returns Series

A new Series object as a view of the same data in memory.

See also:

\texttt{numpy.ndarray.view} Equivalent numpy function to create a new view of the same data in memory.

Notes

Series are instantiated with \texttt{dtype=float64} by default. While \texttt{numpy.ndarray.view()} will re-
turn a view with the same data type as the original array, \texttt{Series.view()} (without specified \texttt{dtype})
will try using \texttt{float64} and may fail if the original data type size in bytes is not the same.

Examples

\begin{verbatim}
>>> s = pd.Series([-2, -1, 0, 1, 2], dtype='int8')
>>> s
0    -2
1    -1
2     0
3     1
4     2
dtype: int8

The 8 bit signed integer representation of \texttt{-1} is \texttt{0b11111111}, but the same bytes represent 255 if read as
an 8 bit unsigned integer:

>>> us = s.view('uint8')
>>> us
0    254
1    255
2     0
3     1
4     2
dtype: uint8

The views share the same underlying values:
\end{verbatim}
pandas.Series.where

Series.where(cond=True, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)

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, array-like, or callable

Where cond is True, keep the original value. Where False, replace with corresponding value from other. If cond is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as cond.

other : scalar, NDFrame, or callable

Entries where cond is False are replaced with corresponding value from other. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as other.

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]

errors : str, {'raise', 'ignore'}, default 'raise'

- raise: allow exceptions to be raised
- ignore: suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

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)

Deprecated since version 0.21.0.

Returns
wh  [same type as caller]

See also:

DataFrame.mask()

Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if cond is True the element is used; otherwise the corresponding element from the DataFrame other is used.

The signature for DataFrame.where() differs from numpy.where(). Roughly df1.where(m, df2) is equivalent to np.where(m, df1, df2).

For further details and examples see the where documentation in indexing.

Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0  NaN
1  1.0
2  2.0
3  3.0
4  4.0

>>> s.mask(s > 0)
0  0.0
1  NaN
2  NaN
3  NaN
4  NaN

>>> s.where(s > 1, 10)
0  10.0
1  10.0
2  2.0
3  3.0
4  4.0

>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A   B
0  0  -1
1 -2   3
2 -4  -5
3  6  -7
4 -8   9

>>> df.where(m, -df) == np.where(m, df, -df)
   A   B
0 True True
1 True True
2 True True

(continues on next page)
3  True  True
4  True  True

```python
>>> df.where(m, -df) == df.mask(~m, -df)
A   B
0  True True
1  True True
2  True True
3  True True
4  True True
```

**pandas.Series.xs**

`Series.xs(key, axis=0, level=None, drop_level=True)`

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.
- `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
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

Name: a
>>> df.xs('C', axis=1)
a  2
b  9
c  3
Name: C

>>> df
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>first</td>
<td>second</td>
<td>third</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>one</td>
<td>1</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>two</td>
<td>1</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>baz</td>
<td>one</td>
<td>1</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>three</td>
<td>2</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

>>> df.xs(('baz', 'three'))
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>third</td>
<td></td>
<td>2</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

>>> df.xs('one', level=1)
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>first</td>
<td>third</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>baz</td>
<td>1</td>
<td>6</td>
<td>6</td>
<td>8</td>
</tr>
</tbody>
</table>

>>> df.xs(('baz', 2), level=[0, 'third'])
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>second</td>
<td></td>
<td>three</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

### 34.3.2 Attributes

#### Axes

**Series.index**

The index (axis labels) of the Series.

**Series.values**

Return Series as ndarray or ndarray-like depending on the dtype

**Series.dtype**

return the dtype object of the underlying data

**Series.itype**

return if the data is sparses dense

**Series.shape**

return a tuple of the shape of the underlying data

**Series nbytes**

return the number of bytes in the underlying data

**Series ndim**

return the number of dimensions of the underlying data, by definition 1

**Series.size**

return the number of elements in the underlying data

**Series.strides**

return the strides of the underlying data

**Series.itemsize**

return the size of the dtype of the item of the underlying data

**Series.base**

return the base object if the memory of the underlying data is shared

**Series.T**

return the transpose, which is by definition self

**Series.memory_usage([index, deep])**

Return the memory usage of the Series.

**Series.hasnans**

return if I have any nans; enables various perf speedups

Continued on next page
Table 27 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.flags</td>
<td>return the dtype object of the underlying data</td>
</tr>
<tr>
<td>Series.empty</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.dtypes</td>
<td>return the data pointer of the underlying data</td>
</tr>
<tr>
<td>Series.ftypes</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.data</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.is_copy</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.name</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.put(*)</td>
<td>Applies the put method to its values attribute if it has one.</td>
</tr>
</tbody>
</table>

### 34.3.2.1 pandas.Series.empty

Series.empty

### 34.3.2.2 pandas.Series.is_copy

Series.is_copy

### 34.3.2.3 pandas.Series.name

Series.name

### 34.3.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.astype()</td>
<td>Cast a pandas object to a specified dtype dtype.</td>
</tr>
<tr>
<td>Series.infer_objects()</td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td>Series.convert_objects()</td>
<td>(DEPRECATED) Attempt to infer better dtype for object columns.</td>
</tr>
<tr>
<td>Series.copy([deep])</td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td>Series.bool()</td>
<td>Return the bool of a single element PandasObject.</td>
</tr>
<tr>
<td>Series.to_period([freq, copy])</td>
<td>Convert Series from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)</td>
</tr>
<tr>
<td>Series.to_timestamp([freq, how, copy])</td>
<td>Cast to datetimeindex of timestamps, at beginning of period</td>
</tr>
<tr>
<td>Series.tolist()</td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td>Series.get_values()</td>
<td>same as values (but handles sparseness conversions); is a view</td>
</tr>
</tbody>
</table>

### 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.).</td>
</tr>
<tr>
<td>Series.at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>Series.iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
</tbody>
</table>

Continued on next page
Table 29 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.loc</code></td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td><code>Series.iloc</code></td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td><code>Series.__iter__()</code></td>
<td>Return an iterator of the values.</td>
</tr>
<tr>
<td><code>Series.iteritems()</code></td>
<td>Lazily iterate over (index, value) tuples</td>
</tr>
<tr>
<td><code>Series.items()</code></td>
<td>Lazily iterate over (index, value) tuples</td>
</tr>
<tr>
<td><code>Series.keys()</code></td>
<td>Alias for index</td>
</tr>
<tr>
<td><code>Series.pop(item)</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>Series.item()</code></td>
<td>Return the first element of the underlying data as a python scalar.</td>
</tr>
<tr>
<td><code>Series.xs(key[, axis, level, drop_level])</code></td>
<td>Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.</td>
</tr>
</tbody>
</table>

### 34.3.4.1 pandas.Series.__iter__

Series.__iter__()

Return an iterator of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

For more information on .at, .iat, .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><code>Series.add()</code></td>
<td>Addition of series and other, element-wise (binary operator <code>add</code>).</td>
</tr>
<tr>
<td><code>Series.sub()</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>Series.mul()</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>Series.div()</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>Series.truediv()</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>Series.floordiv()</code></td>
<td>Integer division of series and other, element-wise (binary operator <code>floordiv</code>).</td>
</tr>
<tr>
<td><code>Series.mod()</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>Series.pow()</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>Series.radd()</code></td>
<td>Addition of series and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>Series.rsub()</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>Series.rmul()</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>Series.rdiv()</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
</tbody>
</table>

Continued on next page
Table 30 – continued from previous page

- **Series.rtruediv**\(\text{other[, level, fill_value, axis]}\) Floating division of series and other, element-wise (binary operator \text{rtruediv}).
- **Series.rfloordiv**\(\text{other[, level, fill_value, ...]}\) Integer division of series and other, element-wise (binary operator \text{rfloordiv}).
- **Series.rmod**\(\text{other[, level, fill_value, axis]}\) Modulo of series and other, element-wise (binary operator \text{rmod}).
- **Series.rpow**\(\text{other[, level, fill_value, axis]}\) Exponential power of series and other, element-wise (binary operator \text{rpow}).
- **Series.combine**\(\text{other, func[, fill_value]}\) 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.
- **Series.combine_first**\(\text{other}\) Combine Series values, choosing the calling Series’s values first.
- **Series.round**\([\text{decimals}]\) Round each value in a Series to the given number of decimals.
- **Series.lt**\(\text{other[, level, fill_value, axis]}\) Less than of series and other, element-wise (binary operator \text{lt}).
- **Series.gt**\(\text{other[, level, fill_value, axis]}\) Greater than of series and other, element-wise (binary operator \text{gt}).
- **Series.le**\(\text{other[, level, fill_value, axis]}\) Less than or equal to of series and other, element-wise (binary operator \text{le}).
- **Series.ge**\(\text{other[, level, fill_value, axis]}\) Greater than or equal to of series and other, element-wise (binary operator \text{ge}).
- **Series.ne**\(\text{other[, level, fill_value, axis]}\) Not equal to of series and other, element-wise (binary operator \text{ne}).
- **Series.eq**\(\text{other[, level, fill_value, axis]}\) Equal to of series and other, element-wise (binary operator \text{eq}).
- **Series.product**\([\text{axis, skipna, level, ...}]\) Return the product of the values for the requested axis.
- **Series.dot**\(\text{other}\) Matrix multiplication with DataFrame or inner-product with Series objects.

### 34.3.6 Function application, GroupBy & Window

- **Series.apply**\(\text{func[, convert_dtype, args]}\) Invoke function on values of Series.
- **Series.agg**\(\text{func[, axis]}\) Aggregate using one or more operations over the specified axis.
- **Series.aggregate**\(\text{func[, axis]}\) Aggregate using one or more operations over the specified axis.
- **Series.transform**\(\text{func, *args, **kwargs}\) Call function producing a like-indexed NDFrame and return a NDFrame with the transformed values.
- **Series.map**\(\text{arg[, na_action]}\) Map values of Series using input correspondence (a dict, Series, or function).
- **Series.groupby**\(\text{[by, axis, level, as_index, ...]}\) Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns.
- **Series.rolling**\(\text{window[, min_periods, ...]}\) Provides rolling window calculations.
- **Series.expanding**\(\text{[min_periods, center, axis]}\) Provides expanding transformations.
- **Series.ewm**\(\text{[com, span, halflife, alpha, ...]}\) Provides exponential weighted functions.
- **Series.pipe**\(\text{func, *args, **kwargs}\) Apply func(self, *args, **kwargs).
### 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 a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td><code>Series.all()</code></td>
<td>Return whether all elements are True over series or dataframe axis.</td>
</tr>
<tr>
<td><code>Series.any()</code></td>
<td>Return whether any element is True over requested axis.</td>
</tr>
<tr>
<td><code>Series.autocorr()</code></td>
<td>Lag-N autocorrelation</td>
</tr>
<tr>
<td><code>Series.between()</code></td>
<td>Return boolean Series equivalent to left &lt;= series &lt;= right.</td>
</tr>
<tr>
<td><code>Series.clip()</code></td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td><code>Series.clip_lower()</code></td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td><code>Series.clip_upper()</code></td>
<td>Return copy of input with values above given value(s) truncated.</td>
</tr>
<tr>
<td><code>Series.corr()</code></td>
<td>Compute correlation with other Series, excluding missing values</td>
</tr>
<tr>
<td><code>Series.count()</code></td>
<td>Return number of non-NA/null observations in the Series</td>
</tr>
<tr>
<td><code>Series.cov()</code></td>
<td>Compute covariance with Series, excluding missing values</td>
</tr>
<tr>
<td><code>Series.cummax()</code></td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Series.cummin()</code></td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Series.cumprod()</code></td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Series.cumsum()</code></td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Series.describe()</code></td>
<td>Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.</td>
</tr>
<tr>
<td><code>Series.diff()</code></td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td><code>Series.factorize()</code></td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td><code>Series.kurt()</code></td>
<td>Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).</td>
</tr>
<tr>
<td><code>Series.mad()</code></td>
<td>Return the mean absolute deviation of the values for the requested axis.</td>
</tr>
<tr>
<td><code>Series.max()</code></td>
<td>This method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>Series.median()</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>Series.min()</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>Series.mode()</code></td>
<td>Return the mode(s) of the dataset.</td>
</tr>
<tr>
<td><code>Series.nlargest()</code></td>
<td>Return the largest $n$ elements.</td>
</tr>
<tr>
<td><code>Series.nsmallest()</code></td>
<td>Return the smallest $n$ elements.</td>
</tr>
<tr>
<td><code>Series.pct_change()</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>Series.prod()</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
</tbody>
</table>

Continued on next page.
### 34.3.8 Reindexing / Selection / Label manipulation

<table>
<thead>
<tr>
<th>DataFrame method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Series.align</strong></td>
<td>Align two objects on their axes with the specified join method for each axis</td>
</tr>
<tr>
<td><strong>Series.drop</strong></td>
<td>Return Series with specified index labels removed.</td>
</tr>
<tr>
<td><strong>Series.drop_duplicates</strong></td>
<td>Return Series with duplicate values removed.</td>
</tr>
<tr>
<td><strong>Series.equals</strong></td>
<td>Indicates duplicate Series values.</td>
</tr>
<tr>
<td><strong>Series.first</strong></td>
<td>Convenience method for subsetting initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><strong>Series.head</strong></td>
<td>Return the first n rows.</td>
</tr>
<tr>
<td><strong>Series.idxmax</strong></td>
<td>Return the row label of the maximum value.</td>
</tr>
<tr>
<td><strong>Series.idxmin</strong></td>
<td>Return the row label of the minimum value.</td>
</tr>
<tr>
<td><strong>Series.isin</strong></td>
<td>Check whether values are contained in Series.</td>
</tr>
<tr>
<td><strong>Series.last</strong></td>
<td>Convenience method for subsetting final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><strong>Series.reindex</strong></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>
</tbody>
</table>

Continued on next page
Table 33 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.reindex_like(other[, method, copy, ...])</td>
<td>Return an object with matching indices to myself.</td>
</tr>
<tr>
<td>Series.rename(index)</td>
<td>Alter Series index labels or name</td>
</tr>
<tr>
<td>Series.rename_axis(mapper[, axis, copy, inplace])</td>
<td>Alter the name of the index or columns.</td>
</tr>
<tr>
<td>Series.reset_index([level, drop, name, inplace])</td>
<td>Generate a new DataFrame or Series with the index reset.</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>(DEPRECATED) Return data corresponding to axis labels matching criteria</td>
</tr>
<tr>
<td>Series.set_axis(labels[, axis, inplace])</td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td>Series.take(indices[, axis, convert, is_copy])</td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td>Series.tail(n)</td>
<td>Return the last n rows.</td>
</tr>
<tr>
<td>Series.truncate([before, after, axis, copy])</td>
<td>Truncate a Series or DataFrame before and after some index value.</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 self where cond is True and otherwise 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 self where cond is False and otherwise are from other.</td>
</tr>
<tr>
<td>Series.add_prefix(prefix)</td>
<td>Prefix labels with string prefix.</td>
</tr>
<tr>
<td>Series.add_suffix(suffix)</td>
<td>Suffix labels with string suffix.</td>
</tr>
<tr>
<td>Series.filter([items, like, regex, axis])</td>
<td>Subset rows or columns of dataframe according to labels in the specified index.</td>
</tr>
</tbody>
</table>

### 34.3.9 Missing data handling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.isna()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td>Series.notna()</td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td>Series.dropna([axis, inplace])</td>
<td>Return a new Series with missing values removed.</td>
</tr>
<tr>
<td>Series.fillna([value, method, axis, ...])</td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td>Series.interpolate([method, axis, limit, ...])</td>
<td>Interpolate values according to different methods.</td>
</tr>
</tbody>
</table>

### 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.argmin([axis, skipna])</td>
<td>(DEPRECATED) ..</td>
</tr>
<tr>
<td>Series.argmax([axis, skipna])</td>
<td>(DEPRECATED) ..</td>
</tr>
<tr>
<td>Series.reorder_levels(order)</td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td>Series.sort_values([axis, ascending, ...])</td>
<td>Sort by the values.</td>
</tr>
<tr>
<td>Series.sort_index([axis, level, ascending, ...])</td>
<td>Sort Series by index labels.</td>
</tr>
<tr>
<td>Series.swaplevel([i, j, copy])</td>
<td>Swap levels i and j in a MultiIndex</td>
</tr>
<tr>
<td>Series.unstack([level, fill_value])</td>
<td>Unstack, a.k.a.</td>
</tr>
<tr>
<td>Series.searchsorted(value[, side, sorter])</td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td>Series.ravel([order])</td>
<td>Return the flattened underlying data as an ndarray</td>
</tr>
<tr>
<td>Series.repeat(repeats, *args, **kwargs)</td>
<td>Repeat elements of an Series.</td>
</tr>
<tr>
<td>Series.squeeze([axis])</td>
<td>Squeeze length 1 dimensions.</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 35 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.view([dtype])</code></td>
<td>Create a new view of the Series.</td>
</tr>
<tr>
<td><code>Series.sortlevel([level, ascending, ...])</code></td>
<td>(DEPRECATED) Sort Series with MultiIndex by chosen level.</td>
</tr>
</tbody>
</table>

#### 34.3.11 Combining / joining / merging

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.append(to_append[, ignore_index, ...])</code></td>
<td>Concatenate two or more Series.</td>
</tr>
<tr>
<td><code>Series.replace([to_replace, value, inplace, ...])</code></td>
<td>Replace values given in <code>to_replace</code> with <code>value</code>.</td>
</tr>
<tr>
<td><code>Series.update(other)</code></td>
<td>Modify Series in place using non-NA values from passed Series.</td>
</tr>
</tbody>
</table>

#### 34.3.12 Time series-related

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.asfreq(freq[, method, how, ...])</code></td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td><code>Series.asof(where[, subset])</code></td>
<td>The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)</td>
</tr>
<tr>
<td><code>Series.shift([periods, freq, axis])</code></td>
<td>Shift index by desired number of periods with an optional time freq</td>
</tr>
<tr>
<td><code>Series.first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>Series.last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
<tr>
<td><code>Series.resample(rule[, how, axis, ...])</code></td>
<td>Convenience method for frequency conversion and resampling of time series.</td>
</tr>
<tr>
<td><code>Series.tz_convert(tz[, axis, level, copy])</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>Series.tz_localize(tz[, axis, level, copy, ...])</code></td>
<td>Localize tz-naive TimeSeries to target time zone.</td>
</tr>
<tr>
<td><code>Series.at_time(time[, asof])</code></td>
<td>Select values at particular time of day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td><code>Series.between_time(start_time, end_time[, ...])</code></td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td><code>Series.tshift([periods, freq, axis])</code></td>
<td>Shift the time index, using the index’s frequency if available.</td>
</tr>
<tr>
<td><code>Series.slice_shift([periods, axis])</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
</tbody>
</table>

#### 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>`.

**Datetime Properties**

<table>
<thead>
<tr>
<th>Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.dt.date</code></td>
<td>Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).</td>
</tr>
<tr>
<td><code>Series.dt.time</code></td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td><code>Series.dt.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>
</tbody>
</table>

Continued on next page
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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dt.microsecond</td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td>Series.dt.nanosecond</td>
<td>The nanoseconds of the datetime</td>
</tr>
<tr>
<td>Series.dt.week</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>Series.dt.weekofyear</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>Series.dt.dayofweek</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>Series.dt.weekday</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>Series.dt.dayofyear</td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td>Series.dt.quarter</td>
<td>The quarter of the date</td>
</tr>
<tr>
<td>Series.dt.is_month_start</td>
<td>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td>Series.dt.is_month_end</td>
<td>Indicator for whether the date is the last day of the month.</td>
</tr>
<tr>
<td>Series.dt.is_quarter_start</td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td>Series.dt.is_quarter_end</td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td>Series.dt.is_year_start</td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td>Series.dt.is_year_end</td>
<td>Indicate whether the date is the last day of the year.</td>
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<tr>
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</table>

34.3.13.1 pandas.Series.dt.date

Series.dt.date

Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

34.3.13.2 pandas.Series.dt.time

Series.dt.time

Returns numpy array of datetime.time. The time part of the Timestamps.

34.3.13.3 pandas.Series.dt.year

Series.dt.year

The year of the datetime

34.3.13.4 pandas.Series.dt.month

Series.dt.month

The month as January=1, December=12

34.3.13.5 pandas.Series.dt.day

Series.dt.day

The days of the datetime
### 34.3.13.6 pandas.Series.dt.hour

Series.dt.hour
   The hours of the datetime

### 34.3.13.7 pandas.Series.dt.minute

Series.dt.minute
   The minutes of the datetime

### 34.3.13.8 pandas.Series.dt.second

Series.dt.second
   The seconds of the datetime

### 34.3.13.9 pandas.Series.dt.microsecond

Series.dt.microsecond
   The microseconds of the datetime

### 34.3.13.10 pandas.Series.dt.nanosecond

Series.dt.nanosecond
   The nanoseconds of the datetime

### 34.3.13.11 pandas.Series.dt.week

Series.dt.week
   The week ordinal of the year

### 34.3.13.12 pandas.Series.dt.weekofyear

Series.dt.weekofyear
   The week ordinal of the year

### 34.3.13.13 pandas.Series.dt.dayofweek

Series.dt.dayofweek
   The day of the week with Monday=0, Sunday=6

### 34.3.13.14 pandas.Series.dt.weekday

Series.dt.weekday
   The day of the week with Monday=0, Sunday=6
34.3.13.15 pandas.Series.dt.dayofyear

Series.dt.dayofyear
The ordinal day of the year

34.3.13.16 pandas.Series.dt.quarter

Series.dt.quarter
The quarter of the date

34.3.13.17 pandas.Series.dt.is_month_start

Series.dt.is_month_start
Logical indicating if first day of month (defined by frequency)

34.3.13.18 pandas.Series.dt.is_month_end

Series.dt.is_month_end
Indicator for whether the date is the last day of the month.

Returns Series or array
For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Indicator for whether the date is the first day of the month.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> dates
0  2018-02-27
1  2018-02-28
2  2018-03-01
dtype: datetime64[ns]
>>> dates.dt.is_month_end
0   False
1    True
2   False
dtype: bool
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_end
array([False,  True, False], dtype=bool)
```
34.3.13.19 pandas.Series.dt.is_quarter_start

Series.dt.is_quarter_start
Indicator for whether the date is the first day of a quarter.

Returns is_quarter_start : Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.
is_quarter_end Similar property for indicating the quarter start.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", periods=4))
>>> df.assign(quarter=df.dates.dt.quarter, is_quarter_start=df.dates.dt.is_quarter_start)
   dates    quarter  is_quarter_start
0 2017-03-30       1          False
1 2017-03-31       1          False
2 2017-04-01       2           True
3 2017-04-02       2          False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
dtype='datetime64[ns]', freq='D')
```

```python
>>> idx.is_quarter_start
array([False, False, True, False])
```

34.3.13.20 pandas.Series.dt.is_quarter_end

Series.dt.is_quarter_end
Indicator for whether the date is the last day of a quarter.

Returns is_quarter_end : Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.
is_quarter_start Similar property indicating the quarter start.
Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", periods=4))
```  
```python
>>> df.assign(quarter=df.dates.dt.quarter, is_quarter_end=df.dates.dt.is_quarter_end)
```  
```
dates quarter is_quarter_end
0 2017-03-30 1 False
1 2017-03-31 1 True
2 2017-04-01 2 False
3 2017-04-02 2 False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
```  
```python
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'], dtype='datetime64[ns]', freq='D')
```  
```python
>>> idx.is_quarter_end
array([False, True, False, False])
```  

### 34.3.13.21 pandas.Series.dt.is_year_start

**Series.dt.is_year_start**

Indicate whether the date is the first day of a year.

**Returns** Series or DatetimeIndex

The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

* is_year_end Similar property indicating the last day of the year.

**Examples**

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
```  
```python
>>> dates
0 2017-12-30
1 2017-12-31
2 2018-01-01
dtype: datetime64[ns]
```  
```python
>>> dates.dt.is_year_start
0 False
1 False
2 True
dtype: bool
```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')

>>> idx.is_year_start
array([False, False,  True])

34.3.13.22 pandas.Series.dt.is_year_end

Series.dt.is_year_end
Indicate whether the date is the last day of the year.

Returns Series or DatetimeIndex

The same type as the original data with boolean values. Series will have the same
name and index. DatetimeIndex will have the same name.

See also:

is_year_start Similar property indicating the start of the year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0    2017-12-30
1    2017-12-31
2    2018-01-01
dtype: datetime64[ns]

>>> dates.dt.is_year_end
0   False
1   True
2   False
dtype: bool

>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')

>>> idx.is_year_end
array([False,  True, False])

34.3.13.23 pandas.Series.dt.is_leap_year

Series.dt.is_leap_year

Boolean indicator if the date belongs to a leap year.
A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

**Returns** Series or ndarray

Booleans indicating if dates belong to a leap year.

**Examples**

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
 DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
                  dtype='datetime64[ns]', freq='A-DEC')
>>> idx.is_leap_year
array([ True, False, False], dtype=bool)
```

```python
>>> dates = pd.Series(idx)
>>> dates_series
0   2012-12-31
1   2013-12-31
2   2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
0   True
1   False
2   False
dtype: bool
```

### 34.3.13.24 pandas.Series.dt.daysinmonth

Series.dt. **daysinmonth**

The number of days in the month

### 34.3.13.25 pandas.Series.dt.days_in_month

Series.dt. **days_in_month**

The number of days in the month

### 34.3.13.26 pandas.Series.dt.tz

Series.dt. **tz**

### 34.3.13.27 pandas.Series.dt.freq

Series.dt. **freq**

**Datetime Methods**

*Series.dt.to_period(*args, **kwargs)*

Cast to PeriodIndex at a particular frequency.
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<tr>
<th>Method</th>
<th>Description</th>
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<td><code>Series.dt.to_pydatetime()</code></td>
<td>Return the data as an array of native Python datetime objects</td>
</tr>
<tr>
<td><code>Series.dt.tz_localize(*args, **kwargs)</code></td>
<td>Localize tz-naive DatetimeIndex to tz-aware DatetimeIndex.</td>
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<td><code>Series.dt.tz_convert(*args, **kwargs)</code></td>
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<td><code>Series.dt.normalize(*args, **kwargs)</code></td>
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<td><code>Series.dt.strftime(*args, **kwargs)</code></td>
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<td><code>Series.dt.round(*args, **kwargs)</code></td>
<td>round the data to the specified freq.</td>
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<td>floor the data to the specified freq.</td>
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<td><code>Series.dt.ceil(*args, **kwargs)</code></td>
<td>ceil the data to the specified freq.</td>
</tr>
<tr>
<td><code>Series.dt.month_name(*args, **kwargs)</code></td>
<td>Return the month names of the DateTimeIndex with specified locale.</td>
</tr>
<tr>
<td><code>Series.dt.day_name(*args, **kwargs)</code></td>
<td>Return the day names of the DateTimeIndex with specified locale.</td>
</tr>
</tbody>
</table>

34.3.13.28 pandas.Series.dt.to_period

`Series.dt.to_period(*args, **kwargs)`  
Cast to PeriodIndex at a particular frequency.

Converts DatetimeIndex to PeriodIndex.

**Parameters**

- `freq`: string or Offset, optional  
  One of pandas’ offset strings or an Offset object. Will be inferred by default.

**Returns**

PeriodIndex

**Raises**  
ValueError  
When converting a DatetimeIndex with non-regular values, so that a frequency cannot be inferred.

**See also:**

- `pandas.PeriodIndex`  
  Immutable ndarray holding ordinal values
- `pandas.DatetimeIndex.to_pydatetime`  
  Return DatetimeIndex as object

**Examples**

```python
>>> df = pd.DataFrame({'y': [1, 2, 3]},
                    index=pd.to_datetime(['2000-03-31 00:00:00',
                                          '2000-05-31 00:00:00',
                                          '2000-08-31 00:00:00']))
>>> df.index.to_period('M')  
PeriodIndex(['2000-03', '2000-05', '2000-08'],  
dtype='period[M]', freq='M')
```

Infer the daily frequency
34.3.13.29 pandas.Series.dt.to_pydatetime

Series.dt.to_pydatetime()

Return the data as an array of native Python datetime objects

Timezone information is retained if present.

**Warning:** Python’s datetime uses microsecond resolution, which is lower than pandas (nanosecond). The values are truncated.

**Returns** numpy.ndarray

object dtype array containing native Python datetime objects.

See also:

datetime.datetime Standard library value for a datetime.

Examples

```python
>>> s = pd.Series(pd.date_range('20180310', periods=2))
>>> s
0  2018-03-10
1  2018-03-11
dtype: datetime64[ns]
```

```python
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 11, 0, 0)], dtype=object)
```

Pandas’ nanosecond precision is truncated to microseconds.

```python
>>> s = pd.Series(pd.date_range('20180310', periods=2, freq='ns'))
```

```python
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0, 0, 0),
       datetime.datetime(2018, 3, 11, 0, 0, 0, 0)], dtype=object)
```

34.3.13.30 pandas.Series.dt.tz_localize

Series.dt.tz_localize(*args, **kwargs)

Localize tz-naive DatetimeIndex to tz-aware DatetimeIndex.
This method takes a time zone (tz) naive DatetimeIndex object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

**Parameters**  
```
Parameters tz : string, pytz.timezone, dateutil.tz.tzfile or None
```
Time zone to convert timestamps to. Passing None will remove the time zone information preserving local time.

```
ambiguous : str {'infer', 'NaT', 'raise'} or bool array, 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

```
errors : {'raise', 'coerce'}, default 'raise'
```
- ‘raise’ will raise a NonExistentTimeError if a timestamp is not valid in the specified time zone (e.g. due to a transition from or to DST time)
- ‘coerce’ will return NaT if the timestamp can not be converted to the specified time zone

New in version 0.19.0.

**Returns**  
```
Returns DatetimeIndex
```
Index converted to the specified time zone.

**Raises**  
```
TypeError
```
If the DatetimeIndex is tz-aware and tz is not None.

See also:
```
DatetimeIndex.tz_convert  Convert tz-aware DatetimeIndex from one time zone to another.
```

**Examples**

```python
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
              '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```python
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')
```

With the `tz=None`, we can remove the time zone information while keeping the local time (not converted to UTC):
34.3.13.31 pandas.Series.dt.tz_convert

Series.dt.tz_convert(*args,**kwargs)
Convert tz-aware DatetimeIndex from one time zone to another.

**Parameters**

- **tz**: string, pytz.timezone, dateutil.tz.tzfile or None
  
  Time zone for time. Corresponding timestamps would be converted to this time zone of the DatetimeIndex. A tz of None will convert to UTC and remove the timezone information.

**Returns**

- **normalized** [DatetimeIndex]

**Raises**

- TypeError
  
  If DatetimeIndex is tz-naive.

**See also**:

- DatetimeIndex.tz
  
  A timezone that has a variable offset from UTC

- DatetimeIndex.tz_localize
  
  Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

**Examples**

With the tz parameter, we can change the DatetimeIndex to other time zones:

```python
>>> dti = pd.DatetimeIndex(start='2014-08-01 09:00',
                        freq='H', periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```python
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
              dtype='datetime64[ns, US/Central]', freq='H')
```

With the tz=None, we can remove the timezone (after converting to UTC if necessary):

```python
>>> dti = pd.DatetimeIndex(start='2014-08-01 09:00',
                        freq='H',
                        periods=3, tz='Europe/Berlin')
```
```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
'2014-08-01 10:00:00+02:00',
'2014-08-01 11:00:00+02:00'],
dtype='datetime64[ns, Europe/Berlin]', freq='H')

>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
'2014-08-01 08:00:00',
'2014-08-01 09:00:00'],
dtype='datetime64[ns]', freq='H')
```

### 34.3.13.32 pandas.Series.dt.normalize

Series.dt.normalize(*args, **kwargs)

Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

**Returns** DatetimeIndex or Series

The same type as the original data. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

floor  Floor the datetimes to the specified freq.

ceil  Ceil the datetimes to the specified freq.

round  Round the datetimes to the specified freq.

**Examples**

```python
>>> idx = pd.DatetimeIndex(start='2014-08-01 10:00', freq='H',
...                         periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
'2014-08-01 11:00:00+05:30',
'2014-08-01 12:00:00+05:30'],
dtype='datetime64[ns, Asia/Calcutta]', freq='H')

>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
'2014-08-01 00:00:00+05:30',
'2014-08-01 00:00:00+05:30'],
dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

### 34.3.13.33 pandas.Series.dt.strftime

Series.dt.strftime(*args, **kwargs)

Convert to Index using specified date_format.
Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc

Parameters  **date_format** : str

Date format string (e.g. "%Y-%m-%d").

Returns **Index**

Index of formatted strings

See also:

- **pandas.to_datetime** Convert the given argument to datetime
- **DatetimeIndex.normalize** Return DatetimeIndex with times to midnight.
- **DatetimeIndex.round** Round the DatetimeIndex to the specified freq.
- **DatetimeIndex.floor** Floor the DatetimeIndex to the specified freq.

Examples

```python
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                     periods=3, freq='s')

Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

34.3.13.34 **pandas.Series.dt.round**

Series.dt.round(*args, **kwargs)

round the data to the specified `freq`.

Parameters  **freq** : str or Offset

The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible `freq` values.

Returns **DatetimeIndex, TimedeltaIndex, or Series**

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the ‘freq’ cannot be converted.

Examples

**DatetimeIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')

DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
```
>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>> rng
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
               dtype='datetime64[ns]', freq='T')
>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
               dtype='datetime64[ns]', freq=None)

Series
dt.round('H')
Series
>> pd.Series(rng).dt.round("H")
0 2018-01-01 12:00:00
1 2018-01-01 12:00:00
2 2018-01-01 12:00:00
dtype: datetime64[ns]
34.3.13.36 pandas.Series.dt.ceil

Series.dt.ceil(*args, **kwargs)

ceil the data to the specified freq.

**Parameters**

freq : str or Offset
    The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

**Returns**

DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**

ValueError if the ‘freq‘ cannot be converted.

**Examples**

**DatetimeIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
              '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')

>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
              '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

**Series**

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 13:00:00
dtype: datetime64[ns]
```

34.3.13.37 pandas.Series.dt.month_name

Series.dt.month_name(*args, **kwargs)

Return the month names of the DateTimeIndex with specified locale.

**Parameters**

locale : string, default None (English locale)
    locale determining the language in which to return the month name

**Returns**

month_names : Index
    Index of month names

.. versionadded:: 0.23.0
34.3.13.38 pandas.Series.dt.day_name

Series.dt.day_name(*args, **kwargs)
Return the day names of the DateTimeIndex with specified locale.

Parameters locale : string, default None (English locale)
locale determining the language in which to return the day name

Returns month_names : Index
Index of day names

.. versionadded:: 0.23.0

Timedelta Properties

<table>
<thead>
<tr>
<th>Series.dt.days</th>
<th>Number of days for each element.</th>
</tr>
</thead>
<tbody>
<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, nanoseconds) of the Timedeltas.</td>
</tr>
</tbody>
</table>

34.3.13.39 pandas.Series.dt.days

Series.dt.days
Number of days for each element.

34.3.13.40 pandas.Series.dt.seconds

Series.dt.seconds
Number of seconds (>= 0 and less than 1 day) for each element.

34.3.13.41 pandas.Series.dt.microseconds

Series.dt.microseconds
Number of microseconds (>= 0 and less than 1 second) for each element.

34.3.13.42 pandas.Series.dt.nanoseconds

Series.dt.nanoseconds
Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

34.3.13.43 pandas.Series.dt.components

Series.dt.components
Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
onds) of the Timedeltas.

Returns

a DataFrame

Timedelta Methods

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<td><code>Series.dt.to_pytimedelta()</code></td>
<td>Return an array of native <code>datetime.timedelta</code> objects.</td>
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<tr>
<td><code>Series.dt.total_seconds(*args, **kwargs)</code></td>
<td>Return total duration of each element expressed in seconds.</td>
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34.3.13.44 pandas.Series.dt.to_pytimedelta

Series.dt.to_pytimedelta()

Return an array of native `datetime.timedelta` objects.

Python’s standard `datetime` library uses a different representation timedelta’s. This method converts a Series of pandas Timedeltas to `datetime.timedelta` format with the same length as the original Series.

Returns a : numpy.ndarray

1D array containing data with `datetime.timedelta` type.

See also:

datetime.timedelta

Examples

```python
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
datetime64[ns]

0    0 days
1    1 days
2    2 days
3    3 days
4    4 days
dtype: timedelta64[ns]

>>> s.dt.to_pytimedelta()
datetime64[ns]

array([datetime.timedelta(0),
       datetime.timedelta(1),
       datetime.timedelta(2),
       datetime.timedelta(3),
       datetime.timedelta(4)],
      dtype=object)
```

34.3.13.45 pandas.Series.dt.total_seconds

Series.dt.total_seconds(*args, **kwargs)

Return total duration of each element expressed in seconds.

This method is available directly on TimedeltaIndex and on Series containing timedelta values under the .dt namespace.

Returns seconds : Float64Index or Series
When the calling object is a TimedeltaIndex, the return type is a Float64Index. When the calling object is a Series, the return type is Series of type float64 whose index is the same as the original.

See also:

datetime.timedelta.total_seconds Standard library version of this method.

TimedeltaIndex.components Return a DataFrame with components of each Timedelta.

Examples

Series

```python
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
0   0 days
1   1 days
2   2 days
3   3 days
4   4 days
dtype: timedelta64[ns]

>>> s.dt.total_seconds()
0   0.0
1  86400.0
2 172800.0
3 259200.0
4 345600.0
dtype: float64
```

TimedeltaIndex

```python
>>> idx = pd.to_timedelta(np.arange(5), unit='d')
>>> idx
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
                dtype='timedelta64[ns]', freq=None)

>>> idx.total_seconds()
Float64Index([0.0, 86400.0, 172800.0, 259200.0, 345600.0],
               dtype='float64')
```

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>.

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<td>Convert strings in the Series/Index to be capitalized.</td>
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<td><code>Series.str.cat([others, sep, na_rep, join])</code></td>
<td>Concatenate strings in the Series/Index with given separator.</td>
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<td><code>Series.str.center(width[, fillchar])</code></td>
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<td><code>Series.str.count()</code></td>
<td>Count occurrences of pattern in each string of the Series/Index.</td>
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<td><code>Series.str.decode()</code></td>
<td>Decode character string in the Series/Index using indicated encoding.</td>
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<tr>
<td><code>Series.str.encode()</code></td>
<td>Encode character string in the Series/Index using indicated encoding.</td>
</tr>
<tr>
<td><code>Series.str.endswith()</code></td>
<td>Test if the end of each string element matches a pattern.</td>
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<tr>
<td><code>Series.str.extract()</code></td>
<td>For each subject string in the Series, extract groups from the first match of regular expression pat.</td>
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<td><code>Series.str.extractall()</code></td>
<td>For each subject string in the Series, extract groups from all matches of regular expression pat.</td>
</tr>
<tr>
<td><code>Series.str.find()</code></td>
<td>Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end].</td>
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<td><code>Series.str.findall()</code></td>
<td>Find all occurrences of pattern or regular expression in the Series/Index.</td>
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<tr>
<td><code>Series.str.get()</code></td>
<td>Extract element from each component at specified position.</td>
</tr>
<tr>
<td><code>Series.str.index()</code></td>
<td>Return lowest indexes in each strings where the substring is fully contained between [start:end].</td>
</tr>
<tr>
<td><code>Series.str.join()</code></td>
<td>Join lists contained as elements in the Series/Index with passed delimiter.</td>
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<td>Compute length of each string in the Series/Index.</td>
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<tr>
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<td>Filling right side of strings in the Series/Index with an additional character.</td>
</tr>
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<td>Convert strings in the Series/Index to lowercase.</td>
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<td><code>Series.str.pad()</code></td>
<td>Pad strings in the Series/Index with an additional character to specified side.</td>
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<tr>
<td><code>Series.str.partition()</code></td>
<td>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.</td>
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<tr>
<td><code>Series.str.repeat()</code></td>
<td>Duplicate each string in the Series/Index by indicated number of times.</td>
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<tr>
<td><code>Series.str.replace()</code></td>
<td>Replace occurrences of pattern/regex in the Series/Index with some other string.</td>
</tr>
<tr>
<td><code>Series.str.rfind()</code></td>
<td>Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start:end].</td>
</tr>
<tr>
<td><code>Series.str.rindex()</code></td>
<td>Return highest indexes in each strings where the substring is fully contained between [start:end].</td>
</tr>
<tr>
<td><code>Series.str.rjust()</code></td>
<td>Filling left side of strings in the Series/Index with an additional character.</td>
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<tr>
<td><code>Series.str.rpartition([pat, expand])</code></td>
<td>Split the string at the last occurrence of <code>sep</code>, and return 3 elements containing the part before the separator, the separator itself, and the part after the separator.</td>
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<tr>
<td><code>Series.str.rstrip([to_strip])</code></td>
<td>Strip whitespace (including newlines) from each string in the Series/Index from right side.</td>
</tr>
<tr>
<td><code>Series.str.slice([start, stop, step])</code></td>
<td>Slice substrings from each element in the Series/Index.</td>
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<tr>
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<tr>
<td><code>Series.str.split([pat, n, expand])</code></td>
<td>Split strings around given separator/delimiter.</td>
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<tr>
<td><code>Series.str.rsplit([pat, n, expand])</code></td>
<td>Split each string in the Series/Index by the given delimiter string, starting at the end of the string and working to the front.</td>
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<tr>
<td><code>Series.str.startswith(pat[, na])</code></td>
<td>Test if the start of each string element matches a pattern.</td>
</tr>
<tr>
<td><code>Series.str.strip([to_strip])</code></td>
<td>Strip whitespace (including newlines) from each string in the Series/Index from left and right sides.</td>
</tr>
<tr>
<td><code>Series.str.swapcase()</code></td>
<td>Convert strings in the Series/Index to be swapcased.</td>
</tr>
<tr>
<td><code>Series.str.title()</code></td>
<td>Convert strings in the Series/Index to titlecase.</td>
</tr>
<tr>
<td><code>Series.str.translate(table[, deletechars])</code></td>
<td>Map all characters in the string through the given mapping table.</td>
</tr>
<tr>
<td><code>Series.str.upper()</code></td>
<td>Convert strings in the Series/Index to uppercase.</td>
</tr>
<tr>
<td><code>Series.str.wrap(width, **kwargs)</code></td>
<td>Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given width.</td>
</tr>
<tr>
<td><code>Series.str.zfill(width)</code></td>
<td>Filling left side of strings in the Series/Index with 0.</td>
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<tr>
<td><code>Series.str.isalnum()</code></td>
<td>Check whether all characters in each string in the Series/Index are alphanumeric.</td>
</tr>
<tr>
<td><code>Series.str.isalpha()</code></td>
<td>Check whether all characters in each string in the Series/Index are alphabetic.</td>
</tr>
<tr>
<td><code>Series.str.isdigit()</code></td>
<td>Check whether all characters in each string in the Series/Index are digits.</td>
</tr>
<tr>
<td><code>Series.str.isspace()</code></td>
<td>Check whether all characters in each string in the Series/Index are whitespace.</td>
</tr>
<tr>
<td><code>Series.str.islower()</code></td>
<td>Check whether all characters in each string in the Series/Index are lowercase.</td>
</tr>
<tr>
<td><code>Series.str.isupper()</code></td>
<td>Check whether all characters in each string in the Series/Index are uppercase.</td>
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<tr>
<td><code>Series.str.istitle()</code></td>
<td>Check whether all characters in each string in the Series/Index are titlecase.</td>
</tr>
<tr>
<td><code>Series.str.isnumeric()</code></td>
<td>Check whether all characters in each string in the Series/Index are numeric.</td>
</tr>
<tr>
<td><code>Series.str.isdecimal()</code></td>
<td>Check whether all characters in each string in the Series/Index are decimal.</td>
</tr>
<tr>
<td><code>Series.str.get_dummies([sep])</code></td>
<td>Split each string in the Series by sep and return a frame of dummy/indicator variables.</td>
</tr>
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</table>

### 34.3.14.1 pandas.Series.str.capitalize

```python
def capitalize():
    # Convert strings in the Series/Index to be capitalized.
    # Equivalent to `str.capitalize()`.
    Returns:
    Series/Index of objects
```

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See also:

**Series.str.lower** Converts all characters to lowercase.

**Series.str.upper** Converts all characters to uppercase.

**Series.str.title** Converts first character of each word to uppercase and remaining to lowercase.

**Series.str.capitalize** Converts first character to uppercase and remaining to lowercase.

**Series.str.swapcase** Converts uppercase to lowercase and lowercase to uppercase.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
    0    lower
    1   CAPITALS
    2  this is a sentence
    3    SwApCaSe
      dtype: object

>>> s.str.lower()
    0    lower
    1  capitals
    2  this is a sentence
    3    swapcase
      dtype: object

>>> s.str.upper()
    0    LOWER
    1   CAPITALS
    2  THIS IS A SENTENCE
    3   SWAPCASE
      dtype: object

>>> s.str.title()
    0    Lower
    1  Capitals
    2  This Is A Sentence
    3   Swapcase
      dtype: object

>>> s.str.capitalize()
    0    Lower
    1  Capitals
    2  This is a sentence
    3   Swapcase
      dtype: object

>>> s.str.swapcase()
    0    LOWER
    1  capitals
    2  THIS IS A SENTENCE
    3   sWaPcAsE
      dtype: object
```
34.3.14.2 pandas.Series.str.cat

**Series.str.cat** *(`others=None, sep=None, na_rep=None, join=None`)*

Concatenate strings in the Series/Index with given separator.

If `others` is specified, this function concatenates the Series/Index and elements of `others` element-wise. If `others` is not passed, then all values in the Series/Index are concatenated into a single string with a given `sep`.

**Parameters**

- **others**: Series, Index, DataFrame, np.ndarray or list-like
  - Series, Index, DataFrame, np.ndarray (one- or two-dimensional) and other list-likes of strings must have the same length as the calling Series/Index, with the exception of indexed objects (i.e. Series/Index/DataFrame) if `join` is not None.
  - If `others` is a list-like that contains a combination of Series, np.ndarray (1-dim) or list-like, then all elements will be unpacked and must satisfy the above criteria individually.
  - If `others` is None, the method returns the concatenation of all strings in the calling Series/Index.

- **sep**: string or None, default None
  - If None, concatenates without any separator.

- **na_rep**: string or None, default None
  - Representation that is inserted for all missing values:
    - If `na_rep` is None, and `others` is None, missing values in the Series/Index are omitted from the result.
    - If `na_rep` is None, and `others` is not None, a row containing a missing value in any of the columns (before concatenation) will have a missing value in the result.

- **join**: {'left', 'right', 'outer', 'inner'}, default None
  - Determines the join-style between the calling Series/Index and any Series/Index/DataFrame in `others` (objects without an index need to match the length of the calling Series/Index). If None, alignment is disabled, but this option will be removed in a future version of pandas and replaced with a default of 'left'. To disable alignment, use `.values` on any Series/Index/DataFrame in `others`.
  - New in version 0.23.0.

**Returns**

`concat` : str or Series/Index of objects

If `others` is None, `str` is returned, otherwise a `Series/Index` (same type as caller) of objects is returned.

See also:

- **split** Split each string in the Series/Index

**Examples**

When not passing `others`, all values are concatenated into a single string:
By default, NA values in the Series are ignored. Using `na_rep`, they can be given a representation:

```python
>>> s.str.cat(sep=' ', na_rep='?')
a b ? d
```

If `others` is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=',')
0 a,A
1 b,B
2 NaN
3 d,D
dtype: object
```

Missing values will remain missing in the result, but can again be represented using `na_rep`

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=':', na_rep='-')
0 a:A
1 b:B
2 -:C
3 d:D
dtype: object
```

If `sep` is not specified, the values are concatenated without separation.

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], na_rep='-
')
0 aA
1 bB
2 -C
3 dD
dtype: object
```

Series with different indexes can be aligned before concatenation. The `join`-keyword works as in other methods.

```python
>>> t = pd.Series(['d', 'a', 'e', 'c'], index=[3, 0, 4, 2])
>>> s.str.cat(t, join=None, na_rep='-')
0 ad
1 ba
2 -c
3 dc
dtype: object
```
```
>>> s.str.cat(t, join='left', na_rep='-')
0 aa
1 b-
2 -c
3 dd
dtype: object
```
```
>>> s.str.cat(t, join='outer', na_rep='-')
0 aa
1 b-
2 -c
(continues on next page)
For more examples, see here.

34.3.14.3 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]

34.3.14.4 pandas.Series.str.contains

Series.str.contains(pat, case=True, flags=0, na=nan, regex=True)
Test if pattern or regex is contained within a string of a Series or Index.

Return boolean Series or Index based on whether a given pattern or regex is contained within a string of a Series or Index.

Parameters

pat : str
Character sequence or regular expression.

case : bool, default True
If True, case sensitive.

flags : int, default 0 (no flags)
Flags to pass through to the re module, e.g. re.IGNORECASE.

na : default NaN
Fill value for missing values.

regex : bool, default True

If True, assumes the pat is a regular expression.
If False, treats the pat as a literal string.

Returns Series or Index of boolean values

A Series or Index of boolean values indicating whether the given pattern is contained within the string of each element of the Series or Index.

See also:

match analogous, but stricter, relying on re.match instead of re.search

Examples

 Returning a Series of booleans using only a literal pattern.

```python
>>> s1 = pd.Series(['Mouse', 'dog', 'house and parrot', '23', np.NaN])
>>> s1.str.contains('og', regex=False)
0    False
1     True
2    False
3    False
4     NaN
dtype: object
```

 Returning an Index of booleans using only a literal pattern.

```python
>>> ind = pd.Index(['Mouse', 'dog', 'house and parrot', '23.0', np.NaN])
>>> ind.str.contains('23', regex=False)
Index([False, False, False, True, nan], dtype='object')
```

 Specifying case sensitivity using case.

```python
>>> s1.str.contains('oG', case=True, regex=True)
0    False
1    False
2    False
3    False
4     NaN
dtype: object
```

 Specifying na to be False instead of NaN replaces NaN values with False. If Series or Index does not contain NaN values the resultant dtype will be bool, otherwise, an object dtype.

```python
>>> s1.str.contains('og', na=False, regex=True)
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

 Returning 'house' and 'parrot' within same string.
>>> s1.str.contains('house|parrot', regex=True)
0    False
1     False
2     True
3     False
4      NaN
dtype: object

Ignoring case sensitivity using flags with regex.

>>> import re

>>> s1.str.contains('PARROT', flags=re.IGNORECASE, regex=True)
0    False
1     False
2     True
3     False
4      NaN
dtype: object

Returning any digit using regular expression.

>>> s1.str.contains('\d', regex=True)
0    False
1     False
2     False
3     True
4      NaN
dtype: object

Ensure pat is a not a literal pattern when regex is set to True. Note in the following example one might expect only s2[1] and s2[3] to return True. However, '.0' as a regex matches any character followed by a 0.

>>> s2 = pd.Series(['40','40.0','41','41.0','35'])

>>> s2.str.contains('.0', regex=True)
0    True
1    True
2   False
3    True
4   False
dtype: bool

34.3.14.5 pandas.Series.str.count

Series.str.count(pat, flags=0, **kwargs)

Count occurrences of pattern in each string of the Series/Index.

This function is used to count the number of times a particular regex pattern is repeated in each of the string elements of the Series.

Parameters

- **pat**: str
  - Valid regular expression.
  - **flags**: int, default 0, meaning no flags
    - Flags for the re module. For a complete list, see here.
  - **kwargs**
For compatibility with other string methods. Not used.

**Returns counts**: Series or Index

Same type as the calling object containing the integer counts.

### See also:

- **re** Standard library module for regular expressions.
- **str.count** Standard library version, without regular expression support.

### Notes

Some characters need to be escaped when passing in *pat*. eg. '\$' has a special meaning in regex and must be escaped when finding this literal character.

### Examples

```python
>>> s = pd.Series(['A', 'B', 'Aaba', 'Baca', np.nan, 'CABA', 'cat'])
>>> s.str.count('a')
0    0.0
1    0.0
2    2.0
3    2.0
4    NaN
5    0.0
6    1.0
dtype: float64
```

Escape '\$' to find the literal dollar sign.

```python
>>> s = pd.Series(['$', 'B', 'Aab$', '$$ca', 'C$B$', 'cat'])
>>> s.str.count('\$')
0    1
1    0
2    1
3    2
4    2
5    0
dtype: int64
```

This is also available on Index

```python
>>> pd.Index(['A', 'A', 'Aaba', 'cat']).str.count('a')
Int64Index([0, 0, 2, 1], dtype='int64')
```

### 34.3.14.6 pandas.Series.str.decode

Series.str.decode(*encoding, errors='strict'*)

Decode character string in the Series/Index using indicated encoding. Equivalent to *str.decode()* in python2 and *bytes.decode()* in python3.

### Parameters

- **encoding** [str]
errors  [str, optional]

Returns

decoded  [Series/Index of objects]

34.3.14.7 pandas.Series.str.encode

Series.str.encode  (encoding, errors='strict')

Encode character string in the Series/Index using indicated encoding. Equivalent to str.encode().

Parameters

encoding  [str]

errors  [str, optional]

Returns

coded  [Series/Index of objects]

34.3.14.8 pandas.Series.str.endswith

Series.str.endswith  (pat, na=nan)

Test if the end of each string element matches a pattern.

Equivalent to str.endswith().

Parameters

pat : str

Character sequence. Regular expressions are not accepted.

na : object, default NaN

Object shown if element tested is not a string.

Returns

Series or Index of bool

A Series of booleans indicating whether the given pattern matches the end of each string element.

See also:

str.endswith  Python standard library string method.

Series.str.startswith  Same as endswith, but tests the start of string.

Series.str.contains  Tests if string element contains a pattern.

Examples

```python
>>> s = pd.Series(['bat', 'bear', 'caT', np.nan])
>>> s
0    bat
1   bear
2    caT
3      NaN
dtype: object
```
```python
>>> s.str.endswith('t')
0   True
1  False
2  False
3    NaN
dtype: object

Specifying `na` to be `False` instead of `NaN`.
```}

```python
>>> s.str.endswith('t', na=False)
0   True
1  False
2  False
3  False
dtype: bool
```

### 34.3.14.9 pandas.Series.str.extract

`Series.str.extract` *(`pat`, `flags=0`, `expand=True`)*

For each subject string in the Series, extract groups from the first match of regular expression `pat`.

**Parameters**

- **`pat`**: string
  
  Regular expression pattern with capturing groups

- **`flags`**: int, default 0 (no flags)
  
  `re` module flags, e.g. `re.IGNORECASE`

- **`expand`**: bool, default True
  
  - If True, return DataFrame.
  - If False, return Series/Index/DataFrame.

  New in version 0.18.0.

**Returns**

DataFrame with one row for each subject string, and one column for each group. Any capture group names in regular expression `pat` will be used for column names; otherwise capture group numbers will be used. The `dtype` of each result column is always object, even when no match is found. If `expand=False` and `pat` has only one capture group, then return a Series (if subject is a Series) or Index (if subject is an Index).

**See also:**

- `extractall` returns all matches (not just the first match)

**Examples**

A pattern with two groups will return a DataFrame with two columns. Non-matches will be NaN.
>>> s = Series(['a1', 'b2', 'c3'])
>>> s.str.extract(r'([ab])(\d)')
    0  1
   -- ---
  0  a  1
  1  b  2
  2  NaN NaN

A pattern may contain optional groups.

>>> s.str.extract(r'([ab])?(\d)')
    0  1
   -- ---
  0  a  1
  1  b  2
  2  NaN 3

Named groups will become column names in the result.

>>> s.str.extract(r'(\P<letter>[ab])\P<digit>(\d)')
     letter  digit
   0       a   1
   1       b   2
   2  NaN  NaN

A pattern with one group will return a DataFrame with one column if expand=True.

>>> s.str.extract(r'([ab])(\d)', expand=True)
   0  1
   -- ---
  0  1
  1  2
  2 NaN

A pattern with one group will return a Series if expand=False.

>>> s.str.extract(r'([ab])(\d)', expand=False)
   0  1
   -- ---
  0  1
  1  2
  2 NaN
   dtype: object

34.3.14.10 pandas.Series.str.extractall

Series.str.extractall (pat, flags=0)

For each subject string in the Series, extract groups from all matches of regular expression pat. When each subject string in the Series has exactly one match, extractall(pat).xs(0, level='match') is the same as extract(pat).

New in version 0.18.0.

Parameters

- **pat**: string
  - Regular expression pattern with capturing groups

- **flags**: int, default 0 (no flags)
  - re module flags, e.g. re.IGNORECASE

Returns

- A DataFrame with one row for each match, and one column for each
group. Its rows have a MultiIndex with first levels that come from the subject Series. The last level is named ‘match’ and indicates the order in the subject. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used.

See also:

`extract` returns first match only (not all matches)

**Examples**

A pattern with one group will return a DataFrame with one column. Indices with no matches will not appear in the result.

```python
>>> s = Series(["ala2", "bl", "cl"], index=["A", "B", "C"]) >>> s.str.extractall(r"[ab](\d)")
0
match
A 0 1
1 2
B 0 1
```

Capture group names are used for column names of the result.

```python
>>> s.str.extractall(r"[ab](?P<digit>\d)")
digit
match
A 0 1
1 2
B 0 1
```

A pattern with two groups will return a DataFrame with two columns.

```python
>>> s.str.extractall(r"(?P<letter>[ab])(?P<digit>\d)")
letter digit
match
A 0 a 1
1 a 2
B 0 b 1
```

Optional groups that do not match are NaN in the result.

```python
>>> s.str.extractall(r"(?P<letter>[ab])?(?P<digit>\d)")
letter digit
match
A 0 a 1
1 a 2
B 0 b 1
C 0 NaN 1
```
34.3.14.11 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

34.3.14.12 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 applying re.findall() to all the elements in the Series/Index.

Parameters pat : string
Pattern or regular expression.
flags : int, default 0
re module flags, e.g. re.IGNORECASE (default is 0, which means no flags).

Returns Series/Index of lists of strings
All non-overlapping matches of pattern or regular expression in each string of this Series/Index.

See also:
count Count occurrences of pattern or regular expression in each string of the Series/Index.
extractall For each string in the Series, extract groups from all matches of regular expression and return a DataFrame with one row for each match and one column for each group.
re.findall The equivalent re function to all non-overlapping matches of pattern or regular expression in string, as a list of strings.

Examples

```python
>>> s = pd.Series(['Lion', 'Monkey', 'Rabbit'])
```

The search for the pattern ‘Monkey’ returns one match:
On the other hand, the search for the pattern ‘MONKEY’ doesn’t return any match:

```
>>> s.str.findall('MONKEY')
0    []
1    []
2    []
dtype: object
```

Flags can be added to the pattern or regular expression. For instance, to find the pattern ‘MONKEY’ ignoring the case:

```
>>> import re
>>> s.str.findall('MONKEY', flags=re.IGNORECASE)
0    []
1    [Monkey]
2    []
dtype: object
```

When the pattern matches more than one string in the Series, all matches are returned:

```
>>> s.str.findall('on')
0    [on]
1    [on]
2    []
dtype: object
```

Regular expressions are supported too. For instance, the search for all the strings ending with the word ‘on’ is shown next:

```
>>> s.str.findall('on$')
0    [on]
1    []
2    []
dtype: object
```

If the pattern is found more than once in the same string, then a list of multiple strings is returned:

```
>>> s.str.findall('b')
0    []
1    []
2    [b, b]
dtype: object
```

### 34.3.14.13 pandas.Series.str.get

Series.str.get(i)

Extract element from each component at specified position.

Extract element from lists, tuples, or strings in each element in the Series/Index.

**Parameters**

i : int
Position of element to extract.

Returns

**items** [Series/Index of objects]

**Examples**

```python
>>> s = pd.Series(['String',
                 (1, 2, 3),
                 ['a', 'b', 'c'],
                 123, -456,
                 {1: 'Hello', '2': 'World'}])

>>> s
0    String
1    (1, 2, 3)
2    [a, b, c]
3    123
4    -456
5      {1: 'Hello', '2': 'World'}
dtype: object

>>> s.str.get(1)
0    t
1    2
2   NaN
3   NaN
4   NaN
5    Hello
dtype: object

>>> s.str.get(-1)
0   g
1   3
2   c
3   NaN
4   NaN
5   NaN
dtype: object
```

34.3.14.14 *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

34.3.14.15 pandas.Series.str.join

Series.str.join(sep)

Join lists contained as elements in the Series/Index with passed delimiter.

If the elements of a Series are lists themselves, join the content of these lists using the delimiter passed to the function. This function is an equivalent to str.join().

Parameters sep : str

Delimiter to use between list entries.

Returns

Series/Index: object

See also:

str.join Standard library version of this method.

Series.str.split Split strings around given separator/delimiter.

Notes

If any of the lists does not contain string objects the result of the join will be NaN.

Examples

Example with a list that contains non-string elements.

```python
>>> s = pd.Series([['lion', 'elephant', 'zebra'],
... [1.1, 2.2, 3.3],
... ['cat', np.nan, 'dog'],
... ['cow', 4.5, 'goat'],
... ['duck', ['swan', 'fish'], 'guppy']])

>>> s
0   [lion, elephant, zebra]
1   [1.1, 2.2, 3.3]
2    [cat, nan, dog]
3     [cow, 4.5, goat]
4  [duck, [swan, fish], guppy]
dtype: object
```

Join all lists using an ‘-‘; the lists containing object(s) of types other than str will become a NaN.
>>> s.str.join('-')
0  lion-elephant-zebra
1           NaN
2           NaN
3           NaN
4           NaN
dtype: object

34.3.14.16 pandas.Series.str.len

Series.str.len()

Compute length of each string in the Series/Index.

Returns

lengths  [Series/Index of integer values]

34.3.14.17 pandas.Series.str.ljust

Series.str.ljust(width, fillchar=' ')

Filling 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]

34.3.14.18 pandas.Series.str.lower

Series.str.lower()

Convert strings in the Series/Index to lowercase.

Equivalent to str.lower().

Returns

Series/Index of objects

See also:

Series.str.lower  Converts all characters to lowercase.
Series.str.upper  Converts all characters to uppercase.
Series.str.title  Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize  Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase  Converts uppercase to lowercase and lowercase to uppercase.
Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0    lower
1   CAPITALS
2  this is a sentence
3    SwApCaSe
dtype: object

>>> s.str.lower()
0    lower
1  capitals
2  this is a sentence
3    swapcase
dtype: object

>>> s.str.upper()
0     LOWER
1    CAPITALS
2  THIS IS A SENTENCE
3   SWAPCASE
dtype: object

>>> s.str.title()
0   Lower
1  Capitals
2 This Is A Sentence
3  Swapcase
dtype: object

>>> s.str.capitalize()
0    Lower
1   Capitals
2  This is a sentence
3    Swapcase
dtype: object

>>> s.str.swapcase()
0     LOWER
1   capitals
2  THIS IS A SENTENCE
3   sWaPcAsE
dtype: object
```

34.3.14.19 pandas.Series.str.lstrip

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]
See also:

contains analogous, but less strict, relying on re.search instead of re.match
extract extract matched groups

34.3.14.21 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 uniconodedata.normalize() function.


Unicode form

Returns

normalized [Series/Index of objects]

34.3.14.22 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
34.3.14.23 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
>>> 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
```

34.3.14.24 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]

34.3.14.25 pandas.Series.str.replace

Series.str.replace(pat, repl, n=-1, case=None, flags=0, regex=True)
Replace occurrences of pattern/regex in the Series/Index with some other string. Equivalent to str.replace() or re.sub().

Parameters pat : string or compiled regex

String can be a character sequence or regular expression.
New in version 0.20.0: pat also accepts a compiled regex.

repl : string or callable

Replacement string or a callable. The callable is passed the regex match object and must return a replacement string to be used. See re.sub().
New in version 0.20.0: repl also accepts a callable.

n : int, default -1 (all)
Number of replacements to make from start

case : boolean, default None

• If True, case sensitive (the default if pat is a string)
• Set to False for case insensitive
• Cannot be set if pat is a compiled regex

flags : int, default 0 (no flags)

• re module flags, e.g. re.IGNORECASE
• Cannot be set if pat is a compiled regex

regex : boolean, default True

• If True, assumes the passed-in pattern is a regular expression.
• If False, treats the pattern as a literal string
• Cannot be set to False if pat is a compiled regex or repl is a callable.

New in version 0.23.0.

Returns

replaced [Series/Index of objects]

Raises ValueError

• if regex is False and repl is a callable or pat is a compiled regex
• if pat is a compiled regex and case or flags is set

Notes

When pat is a compiled regex, all flags should be included in the compiled regex. Use of case, flags, or regex=False with a compiled regex will raise an error.
Examples

When `pat` is a string and `regex` is True (the default), the given `pat` is compiled as a regex. When `repl` is a string, it replaces matching regex patterns as with `re.sub()`. NaN value(s) in the Series are left as is:

```python
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f.', 'ba', regex=True)
0   bao
1   baz
2  NaN
dtype: object
```

When `pat` is a string and `regex` is False, every `pat` is replaced with `repl` as with `str.replace()`:

```python
>>> pd.Series(['f.o', 'fuz', np.nan]).str.replace('f.', 'ba', regex=False)
0   bao
1   fuz
2  NaN
dtype: object
```

When `repl` is a callable, it is called on every `pat` using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

To get the idea:

```python
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f', repr)
0  <_sre.SRE_Match object; span=(0, 1), match='f'>oo
1  <_sre.SRE_Match object; span=(0, 1), match='f'>uz
2    NaN
dtype: object
```

Reverse every lowercase alphabetic word:

```python
>>> repl = lambda m: m.group(0)[::-1]
>>> pd.Series(['foo 123', 'bar baz', np.nan]).str.replace(r'[a-z]+', repl)
0  oof 123
1  rab zab
2    NaN
dtype: object
```

Using regex groups (extract second group and swap case):

```python
>>> pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"
>>> repl = lambda m: m.group('two').swapcase()
>>> pd.Series(['One Two Three', 'Foo Bar Baz']).str.replace(pat, repl)
0    tWO
1     bAR
dtype: object
```

Using a compiled regex with flags

```python
>>> regex_pat = re.compile(r'FUZ', flags=re.IGNORECASE)
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace(regex_pat, 'bar')
0      foo
1      bar
2     NaN
dtype: object
```
34.3.14.26 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

34.3.14.27 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

34.3.14.28 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]

34.3.14.29 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
g%df
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
 0    A_B_C
 1    D_E_F
 2     X
Name: 0, dtype: object

>>> s.str.partition('_')
   0   1   2
 0  A   _   C
 1  D   _   F
 2     X

>>> s.str.rpartition('_')
   0   1   2
 0  A_B   _   C
 1  D_E   _   F
 2     X
```

34.3. Series
34.3.14.30 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]

34.3.14.31 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]

34.3.14.32 pandas.Series.str.slice_replace

Series.str.slice_replace(start=None, stop=None, repl=None)
Replace a positional slice of a string with another value.

Parameters
start : int, optional
Left index position to use for the slice. If not specified (None), the slice is unbounded on the left, i.e. slice from the start of the string.

stop : int, optional
Right index position to use for the slice. If not specified (None), the slice is unbounded on the right, i.e. slice until the end of the string.

repl : str, optional
String for replacement. If not specified (None), the sliced region is replaced with an empty string.

Returns
replaced : Series or Index
Same type as the original object.

See also:

Series.str.slice Just slicing without replacement.

Examples
>>> s = pd.Series(['a', 'ab', 'abc', 'abdc', 'abcde'])

>>> s
0    a
1   ab
2   abc
3  abdc
4  abcde
dtype: object

Specify just start, meaning replace start until the end of the string with repl.

>>> s.str.slice_replace(1, repl='X')
0    aX
1    aX
2    aX
3    aX
4    aX
dtype: object

Specify just stop, meaning the start of the string to stop is replaced with repl, and the rest of the string is included.

>>> s.str.slice_replace(stop=2, repl='X')
0     X
1     Xc
2     Xdc
3     Xcde
4     Xcde
dtype: object

Specify start and stop, meaning the slice from start to stop is replaced with repl. Everything before or after start and stop is included as is.

>>> s.str.slice_replace(start=1, stop=3, repl='X')
0    aX
1    aX
2    aX
3    aXc
4    aXde
dtype: object

34.3.14.33 pandas.Series.str.split

Series.str.split(pat=None, n=-1, expand=False)

Split strings around given separator/delimiter.

Split each string in the caller’s values by given pattern, propagating NaN values. Equivalent to str.split().

Parameters pat : str, optional

String or regular expression to split on. If not specified, split on whitespace.

n : int, default -1 (all)

Limit number of splits in output. None, 0 and -1 will be interpreted as return all splits.

expand : bool, default False

Expand the splitted strings into separate columns.
If `True`, return DataFrame/MultiIndex expanding dimensionality.

If `False`, return Series/Index, containing lists of strings.

Returns Series, Index, DataFrame or MultiIndex

Type matches caller unless `expand=True` (see Notes).

See also:

- `str.split` Standard library version of this method.
- `Series.str.get_dummies` Split each string into dummy variables.
- `Series.str.partition` Split string on a separator, returning the before, separator, and after components.

Notes

The handling of the `n` keyword depends on the number of found splits:

- If found splits > `n`, make first `n` splits only
- If found splits <= `n`, make all splits
- If for a certain row the number of found splits < `n`, append `None` for padding up to `n` if `expand=True`

If using `expand=True`, Series and Index callers return DataFrame and MultiIndex objects, respectively.

Examples

```python
>>> s = pd.Series(["this is good text", "but this is even better"])

By default, split will return an object of the same size having lists containing the split elements

```python
>>> s.str.split()
0    [this, is, good, text]
1    [but, this, is, even, better]
dtype: object
>>> s.str.split("random")
0    [this is good text]
1    [but this is even better]
dtype: object
```

When using `expand=True`, the split elements will expand out into separate columns.

For Series object, output return type is DataFrame.

```python
>>> s.str.split(expand=True)
        0   1   2   3
0 this is good text  None
1 but this is even better

>>> s.str.split(" is ", expand=True)
        0   1
0 this  good text
1 but this even better
```

For Index object, output return type is MultiIndex.
>>> i = pd.Index(["ba 100 001", "ba 101 002", "ba 102 003"])  
>>> i.str.split(expand=True)  
MultiIndex(levels=[['ba'], ['100', '101', '102'], ['001', '002', '003']], 
        labels=[[0, 0, 0], [0, 1, 2], [0, 1, 2]])
Parameter `n` can be used to limit the number of splits in the output.

```python  
>>> s.str.split("is", n=1)  
0    [th, is good text]  
1    [but th, is even better]  
dtype: object  
>>> s.str.split("is", n=1, expand=True)  
  0  1  
0    th is good text  
1    but th is even better
```

If NaN is present, it is propagated throughout the columns during the split.

```python  
>>> s = pd.Series(["this is good text", "but this is even better", np.nan])  
>>> s.str.split(n=3, expand=True)  
  0  1  2  3  
0  this is good text  
1  but this is even better  
2  NaN  NaN  NaN  NaN
```

### 34.3.14.34 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()`.

- **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]

### 34.3.14.35 pandas.Series.str.startswith

Series.str.

#### startswith (pat, na=nan)

Test if the start of each string element matches a pattern.

- **Equivalent to** `str.startswith()`.

- **Parameters**
  - `pat` : str
    - Character sequence. Regular expressions are not accepted.
na : object, default NaN

Object shown if element tested is not a string.

Returns Series or Index of bool

A Series of booleans indicating whether the given pattern matches the start of each string element.

See also:

str.startswith Python standard library string method.
Series.str.endswith Same as startswith, but tests the end of string.
Series.str.contains Tests if string element contains a pattern.

Examples

```python
>>> s = pd.Series(['bat', 'Bear', 'cat', np.nan])
```
```python
0    bat
1    Bear
2     cat
3      NaN
dtype: object
```

```python
>>> s.str.startswith('b')
```
```python
0   True
1  False
2  False
3   NaN
dtype: object
```

Specifying na to be False instead of NaN.

```python
>>> s.str.startswith('b', na=False)
```
```python
0   True
1  False
2  False
3  False
dtype: bool
```

34.3.14.36 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]
34.3.14.37 pandas.Series.str.swapcase

Series.str.swapcase()
   Convert strings in the Series/Index to be swapcased.

   Equivalent to str.swapcase().

   Returns
   
   Series/Index of objects

See also:

Series.str.lower  Converts all characters to lowercase.
Series.str.upper  Converts all characters to uppercase.
Series.str.title  Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize  Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase  Converts uppercase to lowercase and lowercase to uppercase.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0   lower
1   CAPITALS
2   this is a sentence
3   SwApCaSe
dtype: object

>>> s.str.lower()
0   lower
1   capitals
2   this is a sentence
3   swapcase
dtype: object

>>> s.str.upper()
0   LOWER
1   CAPITALS
2   THIS IS A SENTENCE
3   SWAPCASE
dtype: object

>>> s.str.title()
0   Lower
1   Capitals
2   This Is A Sentence
3   Swapcase
dtype: object

>>> s.str.capitalize()
0   Lower
1   Capitals
```
(continues on next page)
This is a sentence

Swapcase
dtype: object

```python
>>> s.str.swapcase()
0    LOWER
1    capitals
2    THIS IS A SENTENCE
3    sWaPcAsE
dtype: object
```

### 34.3.14.38 pandas.Series.str.title

`Series.str.title()`

Convert strings in the Series/Index to titlecase.

Equivalent to `str.title()`.

**Returns**

Series/Index of objects

**See also:**

- `Series.str.lower` Converts all characters to lowercase.
- `Series.str.upper` Converts all characters to uppercase.
- `Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.
- `Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.
- `Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

### Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0    lower
1  CAPITALS
2    this is a sentence
3    SwApCaSe
dtype: object

>>> s.str.lower()
0    lower
1    capitals
2    this is a sentence
3    swapcase
dtype: object

>>> s.str.upper()
0    LOWER
1  CAPITALS
2    THIS IS A SENTENCE
34.3.14.39 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]

34.3.14.40 pandas.Series.str.upper

Series.str.upper()

Convert strings in the Series/Index to uppercase.

Equivalent to str.upper().
Returns

Series/Index of objects

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.

Examples

```python
generate_series()

>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])

>>> s
0    lower
1   CAPITALS
2  this is a sentence
3     SwApCaSe
dtype: object

>>> s.str.lower()
0    lower
1  capitals
2  this is a sentence
3    swapcase
dtype: object

>>> s.str.upper()
0      LOWER
1   CAPITALS
2    THIS IS A SENTENCE
3     SWAPCASE
dtype: object

>>> s.str.title()
0    Lower
1  Capitals
2  This Is A Sentence
3     Swapcase
dtype: object

>>> s.str.capitalize()
0    Lower
1  Capitals
2  This is a sentence
3     Swapcase
dtype: object

>>> s.str.swapcase()
0      LOWER
(continues on next page)
34.3.14.41 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 white spaces 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
   wrapped
1  another line
   to be
   wrapped
```

### 34.3.14.42 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]

### 34.3.14.43 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]

### 34.3.14.44 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]

### 34.3.14.45 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]

### 34.3.14.46 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]

34.3.14.47 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]

34.3.14.48 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]

34.3.14.49 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]

34.3.14.50 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]

34.3.14.51 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]

34.3.14.52 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

Pandas defines a custom data type for representing data that can take only a limited, fixed set of values. The dtype of a `Categorical` can be described by a `pandas.api.types.CategoricalDtype`.

```python
api.types.CategoricalDtype([categories, ordered])
```

Type for categorical data with the categories and orderedness

Changed in version 0.21.0.

Parameters:
categories : sequence, optional
    Must be unique, and must not contain any nulls.

ordered [bool, default False]

See also:
pandas.Categorical

Notes

This class is useful for specifying the type of a `Categorical` independent of the values. See `CategoricalDtype` for more.
Examples

```python
>>> t = CategoricalDtype(categories=['b', 'a'], ordered=True)
>>> pd.Series(['a', 'b', 'a', 'c'], dtype=t)
0    a
1    b
2    a
3  NaN
dtype: category
Categories (2, object): [b < a]
```

Attributes

- **categories**: An Index containing the unique categories allowed.
- **ordered**: Whether the categories have an ordered relationship

```python
pandas.api.types.CategoricalDtype.categories
```

CategoricalDtype.categories

An Index containing the unique categories allowed.

```python
pandas.api.types.CategoricalDtype.ordered
```

CategoricalDtype.ordered

Whether the categories have an ordered relationship

Methods

None

```python
api.types.CategoricalDtype.categories
```

An Index containing the unique categories allowed.

```python
api.types.CategoricalDtype.ordered
```

Whether the categories have an ordered relationship

Categorical data can be stored in a `pandas.Categorical`

```python
Categorical(values[, categories, ordered, ...])
```

Represents a categorical variable in classic R / S-plus fashion

### 34.3.15.2 pandas.Categorical

```python
class pandas.Categorical(values, categories=None, ordered=None, dtype=None, fastpath=False)
```

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.
- **dtype**: CategoricalDtype
  - An instance of `CategoricalDtype` to use for this categorical

**Raises**

- **ValueError**
  - If the categories do not validate.
- **TypeError**
  - If an explicit `ordered=True` is given but no `categories` and the `values` are not sortable.

**See also:**

- `pandas.api.types.CategoricalDtype` Type for categorical data
- `CategoricalIndex` An Index with an underlying `Categorical`

**Notes**

See the user guide for more.

**Examples**

```
>>> pd.Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1, 2, 3]
```

```
>>> pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
[a, b, c, a, b, c]
Categories (3, object): [a, b, c]
```

Ordered `Categoricals` can be sorted according to the custom order of the categories and can have a min and max value.
>>> c = pd.Categorical(['a','b','c','a','b','c'], ordered=True,
...     categories=['c', 'b', 'a'])
>>> c
[a, b, c, a, b, c]
Categories (3, object): [c < b < a]
>>> c.min()
'c'

Attributes

**pandas.Categorical.categories**

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the
new categories must be the same as the number of items in the old categories.

Assigning to `categories` is an inplace operation!

**Raises ValueError**

If the new categories do not validate as categories or if the number of new cate-
gories is unequal the number of old categories

**See also:**

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

**pandas.Categorical.codes**

The category codes of this categorical.

Level codes are an array if integer which are the positions of the real values in the categories array.

There is not setter, use the other categorical methods and the normal item setter to change values in the
categorical.

**pandas.Categorical.ordered**

Whether the categories have an ordered relationship
pandas.Categorical.dtype

Categorical.dtype

The CategoricalDtype for this instance

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_codes</td>
<td>Make a Categorical type from codes and categories arrays.</td>
</tr>
<tr>
<td><strong>array</strong> (dtype)</td>
<td>The numpy array interface.</td>
</tr>
</tbody>
</table>

pandas.Categorical.from_codes

classmethod Categorical.from_codes(codes, categories, ordered=False)

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.

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

The alternative Categorical.from_codes() constructor can be used when you have the categories and integer codes already:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_codes</td>
<td>Make a Categorical type from codes and categories arrays.</td>
</tr>
</tbody>
</table>

The dtype information is available on the Categorical
np.asarray(categorical) works by implementing the array interface. Be aware, that this converts the Categorical back to a NumPy array, so categories and order information is not preserved!

A Categorical can be stored in a Series or DataFrame. To create a Series of dtype category, use cat = s.astype(dtype) or Series(..., dtype=dtype) where dtype is either

* the string 'category'

* an instance of CategoricalDtype.

If the Series is of dtype CategoricalDtype, Series.cat can be used to change the categorical data. This accessor is similar to the Series.dt or Series.str and has the following usable methods and properties:

34.3.15.3 pandas.Series.cat.categories

Series.cat.categories
The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to categories is an inplace operation!

Raises ValueError
If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

34.3.15.4 pandas.Series.cat.ordered

Series.cat.ordered
Whether the categories have an ordered relationship

34.3.15.5 pandas.Series.cat.codes

Series.cat.codes
### pandas.Series.cat.rename_categories

**Series.cat.rename_categories(*args, **kwargs)**  
Renames categories.

**Parameters**

- **new_categories**: list-like, dict-like or callable
  - list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
  - dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
    
    New in version 0.21.0.
    
  - callable: a callable that is called on all items in the old categories and whose return values comprise the new categories.
    
    New in version 0.23.0.

**inplace**: boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

**Returns**

- **cat**: Categorical or None

  With **inplace=False**, the new categorical is returned. With **inplace=True**, there is no return value.

**Raises**

- **ValueError**: If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

**See also**

- reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

### Code Snippet

```python
Series.cat.rename_categories(*args, **kwargs)
```
Examples

```python
>>> c = Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like `new_categories`, extra keys are ignored and categories not in the dictionary are passed through

```python
>>> c.rename_categories({'a': 'A', 'c': 'C'})
[A, A, b]
Categories (2, object): [A, b]
```

You may also provide a callable to create the new categories

```python
>>> c.rename_categories(lambda x: x.upper())
[A, A, B]
Categories (2, object): [A, B]
```

### 34.3.15.7 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

### 34.3.15.8 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

34.3.15.9 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.

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

34.3.15.10 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

34.3.15.11 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 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

34.3.15.12 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

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories

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34.3.15.13 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

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

Series.plot.area(**kwds) Area plot
Series.plot.bar(**kwds) Vertical bar plot
Series.plot.barh(**kwds) Horizontal bar plot
Series.plot.box(**kwds) Boxplot
Series.plot.density([bw_method, ind]) Generate Kernel Density Estimate plot using Gaussian
kernels.
Series.plot.hist([bins]) Histogram
Series.plot.kde([bw_method, ind]) Generate Kernel Density Estimate plot using Gaussian
kernels.
Series.plot.line(**kwds) Line plot
Series.plot.pie(**kwds) Pie chart

34.3.16.1 pandas.Series.plot.area

Series.plot.area(**kwds)
Area plot

Parameters **kwds : optional
Additional keyword arguments are documented in pandas.Series.plot().

Returns
axes [matplotlib.axes.Axes or numpy.ndarray of them]

34.3.16.2 pandas.Series.plot.bar

Series.plot.bar(**kwds)
Vertical bar plot

Parameters **kwds : optional
Additional keyword arguments are documented in pandas.Series.plot().

Returns
axes [matplotlib.axes.Axes or numpy.ndarray of them]
34.3.16.3 pandas.Series.plot.barh

Series.plot.barh(**kwds)
Horizontal bar plot

Parameters **kwds : optional
Additional keyword arguments are documented in pandas.Series.plot().

Returns
axes [matplotlib.axes.Axes or numpy.ndarray of them]

34.3.16.4 pandas.Series.plot.box

Series.plot.box(**kwds)
Boxplot

Parameters **kwds : optional
Additional keyword arguments are documented in pandas.Series.plot().

Returns
axes [matplotlib.axes.Axes or numpy.ndarray of them]

34.3.16.5 pandas.Series.plot.density

Series.plot.density(bw_method=None, ind=None, **kwds)
Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwith determination.

Parameters bw_method : str, scalar or callable, optional
The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.

ind : NumPy array or integer, optional
Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If ind is a NumPy array, the KDE is evaluated at the points passed. If ind is an integer, ind number of equally spaced points are used.

**kwds : optional
Additional keyword arguments are documented in pandas.Series.plot().

Returns
axes [matplotlib.axes.Axes or numpy.ndarray of them]

See also:
scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

DataFrame.plot.kde Generate a KDE plot for a DataFrame.
Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```python
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to overfitting, while using a large bandwidth value may result in underfitting:

```python
>>> ax = s.plot.kde(bw_method=0.3)
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

34.3.16.6 pandas.Series.plot.hist

Series.plot.hist(bins=10, **kwds)

Histogram

Parameters

- bins: integer, default 10
  Number of histogram bins to be used

- **kwds**: optional
  Additional keyword arguments are documented in pandas.Series.plot().

Returns

- axes: [matplotlib.axes.Axes or numpy.ndarray of them]

34.3.16.7 pandas.Series.plot.kde

Series.plot.kde(bw_method=None, ind=None, **kwds)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

- bw_method: str, scalar or callable, optional
  The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.

- ind: NumPy array or integer, optional
  Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If `ind` is a NumPy array, the KDE is evaluated at the points passed. If `ind` is an integer, `ind` number of equally spaced points are used.

- **kwds**: optional
Additional keyword arguments are documented in `pandas.Series.plot()`.

**Returns**

- **axes** [matplotlib.axes.Axes or numpy.ndarray of them]

**See also:**

- `scipy.stats.gaussian_kde` Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.
- `DataFrame.plot.kde` Generate a KDE plot for a DataFrame.

**Examples**

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```bash
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to overfitting, while using a large bandwidth value may result in underfitting:

```bash
>>> ax = s.plot.kde(bw_method=0.3)
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```bash
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

### 34.3.16.8 pandas.Series.plot.line

`Series.plot.line(**kwds)`

Line plot

**Parameters** `{**kwds}`: optional

Additional keyword arguments are documented in `pandas.Series.plot()`.

**Returns**

- **axes** [matplotlib.axes.Axes or numpy.ndarray of them]

**Examples**

```bash
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```

### 34.3.16.9 pandas.Series.plot.pie

`Series.plot.pie(**kwds)`

Pie chart
Parameters *kwds : optional

Additional keyword arguments are documented in pandas.Series.plot().

Returns

axes [matplotlib.axes.Axes or numpy.ndarray of them]

Series.hist([by, ax, grid, xlabels, ...]) Draw histogram of the input series using matplotlib

34.3.17 Serialization / IO / Conversion

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34.3.18 Sparse

<table>
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34.3.18.1 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).

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>
>>> A.todense()
matrix([[ 0., 0., 1., 3.],
[ 3., 0., 0., 0.],
[ 0., 0., 0., 0.]])
>>> rows
[(1, 1), (1, 2), (2, 1)]
>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

34.3.18.2 pandas.SparseSeries.from_coo

classmethod SparseSeries.from_coo(A, dense_index=False)

Create a SparseSeries from a scipy.sparse.coo_matrix.

Parameters

- `A` [scipy.sparse.coo_matrix]
- `dense_index` : bool, default False

If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original coo_matrix. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the coo_matrix.

Returns

- `s` [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))
>>> A
t<3x4 sparse matrix of type '<class 'numpy.float64'>'
    with 3 stored elements in COOrdinate format>
>>> A.todense()
matrix([[ 0., 0., 1., 2.],
        [ 3., 0., 0., 0.],
        [ 0., 0., 0., 0.]])
>>> ss = SparseSeries.from_coo(A)
```

34.4 DataFrame

34.4.1 Constructor

```
DataFrame([data, index, columns, dtype, copy]) Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns).
```

34.4.1.1 pandas.DataFrame

class pandas.DataFrame(data=None, index=None, columns=None, dtype=None, copy=False)

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

Changed in version 0.23.0: If data is a dict, argument order is maintained for Python 3.6 and later.

index: Index or array-like

Index to use for resulting frame. Will default to RangeIndex 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 RangeIndex (0, 1, 2, ..., n) if no column labels are provided

dtype: dtype, default None
Data type to force. Only a single dtype is allowed. If None, infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

See also:

DataFrame.from_records constructor from tuples, also record arrays
DataFrame.from_dict from dicts of Series, arrays, or dicts
DataFrame.from_items from sequence of (key, value) pairs

pandas.read_csv, pandas.read_table, pandas.read_clipboard

Examples

Constructing DataFrame from a dictionary.

```python
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df
col1  col2
0    1    3
1    2    4
```

Notice that the inferred dtype is int64.

```python
>>> df.dtypes
col1  int64
col2  int64
dtype: object
```

To enforce a single dtype:

```python
>>> df = pd.DataFrame(data=d, dtype=np.int8)
>>> df.dtypes
col1  int8
col2  int8
dtype: object
```

Constructing DataFrame from numpy ndarray:

```python
>>> df2 = pd.DataFrame(np.random.randint(low=0, high=10, size=(5, 5)),
                     columns=['a', 'b', 'c', 'd', 'e'])
>>> df2
   a  b  c  d  e
0  2  8  8  3  4
1  4  2  9  0  9
2  1  0  7  8  0
3  5  1  7  1  3
4  6  0  2  4  2
```

Attributes
Transposing a DataFrame can be accomplished with the `.T` accessor. This property is equivalent to the `transpose()` method, which returns a transposed DataFrame.

**Pandas.DataFrame.T**

The `DataFrame.T` property transposes the DataFrame, effectively swapping the rows and columns. This is useful for reorienting data for analysis or visualization. The transposed DataFrame is returned directly:

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

In [2]: df = pd.DataFrame({'A': ['a', 'b', 'c'], 'B': ['d', 'e', 'f'], 'C': ['g', 'h', 'i']})

In [3]: df
Out[3]:
   A  B  C
0  a  d  g
1  b  e  h
2  c  f  i

In [4]: df.T
Out[4]:
   A  B  C
0  a  d  g
1  b  e  h
2  c  f  i
```

**Parameters**

- `copy` : bool, default False
  - If True, the underlying data is copied. Otherwise (default), no copy is made if possible.

**Returns**

- DataFrame
  - The transposed DataFrame.

**See also:**

- `numpy.transpose` Permute the dimensions of a given array.
Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the object dtype. In such a case, a copy of the data is always made.

Examples

Square DataFrame with homogeneous dtype

```python
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
   col1  col2
0    1    3
1    2    4

>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
   0  1
   col1 1  2
      col2 3  4

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```python
>>> df1.dtypes
col1 int64
col2 int64
dtype: object

>>> df1_transposed.dtypes
   0  1
   int64 int64
dtype: object
```

Non-square DataFrame with mixed dtypes

```python
>>> d2 = {'name': ['Alice', 'Bob'], ...
    ...    'score': [9.5, 8], ...
    ...    'employed': [False, True], ...
    ...    'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
    name  score  employed  kids
0  Alice   9.5       False    0
1   Bob    8.0       True     0

>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
   0  1
   name Alice Bob
      score 9.5  8
      employed False True
      kids 0  0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the object dtype:
>>> df2.dtypes
name    object
score   float64
employed  bool
kids    int64
dtype: object
>>> df2_transposed.dtypes
0    object
1    object
dtype: object

pandas.DataFrame.at

DataFrame.at

Access a single value for a row/column label pair.

Similar to loc, in that both provide label-based lookups. Use at if you only need to get or set a single value in a DataFrame or Series.

Raises KeyError

When label does not exist in DataFrame

See also:

dataframe.iat Access a single value for a row/column pair by integer position
dataframe.loc Access a group of rows and columns by label(s)
series.at Access a single value using a label

Examples

>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
... index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
   A  B  C
4  0  2  3
5  0  4  1
6 10 20 30

Get value at specified row/column pair

>>> df.at[4, 'B']
2

Set value at specified row/column pair

>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10

Get value within a Series

>>> df.loc[5].at['B']
4
pandas.DataFrame.axes

DataFrame.axes
Return a list representing the axes of the DataFrame.
It has the row axis labels and column axis labels as the only members. They are returned in that order.

Examples

```python
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.axes
[RangeIndex(start=0, stop=2, step=1), Index(['col1', 'col2'], dtype='object')]
```

pandas.DataFrame.blocks

DataFrame.blocks
Internal property, property synonym for as_blocks()
Deprecated since version 0.21.0.

pandas.DataFrame.columns

DataFrame.columns
The column labels of the DataFrame.

pandas.DataFrame.dtypes

DataFrame.dtypes
Return the dtypes in the DataFrame.
This returns a Series with the data type of each column. The result’s index is the original DataFrame’s columns. Columns with mixed types are stored with the object dtype. See the User Guide for more.

Returns pandas.Series
The data type of each column.

See also:

pandas.DataFrame.ftypes dtype and sparsity information.

Examples

```python
>>> df = pd.DataFrame({'float': [1.0],
...    'int': [1],
...    'datetime': [pd.Timestamp('20180310')],
...    'string': ['foo']})
>>> df.dtypes
float float64
int int64
```

(continues on next page)
pandas.DataFrame.empty

DataFrame.empty
Indicator whether DataFrame is empty.
True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

Returns bool
If DataFrame is empty, return True, if not return False.

See also:
pandas.Series.dropna, pandas.DataFrame.dropna

Notes
If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples
An example of an actual empty DataFrame. Notice the index is empty:

```python
>>> df_empty = pd.DataFrame({'A' : []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: [A]
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```python
>>> df = pd.DataFrame({'A' : [np.nan]})
>>> df
A
0 NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

pandas.DataFrame.ftypes

DataFrame.ftypes
Return the ftypes (indication of sparse/dense and dtype) in DataFrame.
This returns a Series with the data type of each column. The result’s index is the original DataFrame’s columns. Columns with mixed types are stored with the object dtype. See the User Guide for more.

Returns pandas.Series

The data type and indication of sparse/dense of each column.

See also:

pandas.DataFrame.dtypes Series with just dtype information.
pandas.SparseDataFrame Container for sparse tabular data.

Notes

Sparse data should have the same dtypes as its dense representation.

Examples

```python
>>> import numpy as np
>>> arr = np.random.RandomState(0)..randn(100, 4)
>>> arr[arr < .8] = np.nan
>>> pd.DataFrame(arr).ftypes
0 float64:dense
1 float64:dense
2 float64:dense
3 float64:dense
dtype: object
```

```python
>>> pd.SparseDataFrame(arr).ftypes
0 float64:sparse
1 float64:sparse
2 float64:sparse
3 float64:sparse
dtype: object
```

pandas.DataFrame.iat

DataFrame.iat
Access a single value for a row/column pair by integer position.

Similar to iloc, in that both provide integer-based lookups. Use iat if you only need to get or set a single value in a DataFrame or Series.

Raises IndexError

When integer position is out of bounds

See also:

DataFrame.at Access a single value for a row/column label pair
DataFrame.loc Access a group of rows and columns by label(s)
DataFrame.iloc Access a group of rows and columns by integer position(s)
Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
                    columns=['A', 'B', 'C'])
>>> df
   A  B  C
0  0  2  3
1  0  4  1
2 10 20 30

Get value at specified row/column pair

```python
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```python
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```python
>>> df.loc[0].iat[1]
2
```

**pandas.DataFrame.iloc**

**DataFrame.iloc**

Purely integer-location based indexing for selection by position.

.iloc[] is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

.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.index**

**DataFrame.index**

The index (row labels) of the DataFrame.
**pandas.DataFrame.ix**

*pandas.DataFrame.ix*

A primarily label-location based indexer, with integer position fallback.

Warning: Starting in 0.20.0, the .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers.

_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**

*pandas.DataFrame.loc*

Access a group of rows and columns by label(s) or a boolean array.

_.loc[_]_ is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a label of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, **both** the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. [True, False, True].
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

See more at Selection by Label

**Raises** *KeyError:*

when any items are not found

See also:

- **Dataframe.at** Access a single value for a row/column label pair
- **Dataframe.iloc** Access group of rows and columns by integer position(s)
- **Dataframe.xs** Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
- **Series.loc** Access group of values using labels
Examples

Getting values

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=['cobra', 'viper', 'sidewinder'],
                   columns=['max_speed', 'shield'])
>>> df
   max_speed  shield
  cobra     1       2
  viper     4       5
  sidewinder 7       8

Single label. Note this returns the row as a Series.

>>> df.loc['viper']
max_speed  4
shield     5
Name: viper, dtype: int64

List of labels. Note using [[]] returns a DataFrame.

>>> df.loc[['viper', 'sidewinder']]
   max_speed  shield
  cobra     1       2
  viper     4       5
  sidewinder 7       8

Single label for row and column

>>> df.loc['cobra', 'shield']
2

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

>>> df.loc['cobra':'viper', 'max_speed']
   max_speed
  cobra     1
  viper     4
Name: max_speed, dtype: int64

Boolean list with the same length as the row axis

>>> df.loc[[False, True]]
   max_speed  shield
  sidewinder     7

Conditional that returns a boolean Series

>>> df.loc[df['shield'] > 6]
   max_speed  shield
  sidewinder     7

Conditional that returns a boolean Series with column labels specified

>>> df.loc[df['shield'] > 6, ['max_speed']]
   max_speed
  sidewinder     7
```
Callable that returns a boolean Series

```python
>>> df.loc[lambda df: df['shield'] == 8]
max_speed  shield
sidewinder    7   8
```

**Setting values**

Set value for all items matching the list of labels

```python
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
max_speed  shield
cobra       1   2
viper       4   50
sidewinder   7   50
```

Set value for an entire row

```python
>>> df.loc['cobra'] = 10
>>> df
max_speed  shield
cobra      10  10
viper        4  50
sidewinder   7   50
```

Set value for an entire column

```python
>>> df.loc[:, 'max_speed'] = 30
>>> df
max_speed  shield
cobra      30  10
viper        30  50
sidewinder  30   50
```

Set value for rows matching callable condition

```python
>>> df.loc[df['shield'] > 35] = 0
>>> df
max_speed  shield
cobra       30  10
viper         0  0
sidewinder    0  0
```

**Getting values on a DataFrame with an index that has integer labels**

Another example using integers for the index

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...                    index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
max_speed  shield
7           1   2
8           4   5
9           7   8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.
Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```python
>>> tuples = [
... ('cobra', 'mark i'), ('cobra', 'mark ii'),
... ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
... ('viper', 'mark ii'), ('viper', 'mark iii')
... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
... [1, 4], [7, 1], [16, 36]]
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
    max_speed  shield
cobra mark i   12   2
   mark ii    0   4
sidewinder mark i 10  20
   mark ii    1   4
viper mark ii    7   1
   mark iii   16  36
```

Single label. Note this returns a DataFrame with a single index.

```python
>>> df.loc['cobra']
    max_speed  shield
mark i   12   2
mark ii    0   4
```

Single index tuple. Note this returns a Series.

```python
>>> df.loc[('cobra', 'mark ii')]
max_speed 0
Name: (cobra, mark ii), dtype: int64
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```python
>>> df.loc['cobra', 'mark i']
max_speed 12
shield    2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using [[]] returns a DataFrame.

```python
>>> df.loc[['cobra', 'mark ii']]
    max_speed  shield
cobra mark ii    0   4
```

Single tuple for the index with a single label for the column
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> df.loc[('cobra', 'mark i'), 'shield']
2

Slice from index tuple to single label

```python
>>> df.loc[('cobra', 'mark i'):'viper']
max_speed    shield
cobra mark i     12     2
mark ii        0      4
sidewinder mark i 10    20
mark ii        1      4
viper mark ii    7      1
mark iii       16     36
```

Slice from index tuple to index tuple

```python
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]
max_speed    shield
cobra mark i     12     2
mark ii        0      4
sidewinder mark i 10    20
mark ii        1      4
viper mark ii    7      1
```

```
pandas.DataFrame.ndim

DataFrame.ndim
Return an int representing the number of axes / array dimensions.
Return 1 if Series. Otherwise return 2 if DataFrame.
See also:
ndarray.ndim
```

```
Examples

```python
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.ndim
1

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.ndim
2
```

```
pandas.DataFrame.shape

DataFrame.shape
Return a tuple representing the dimensionality of the DataFrame.
See also:
ndarray.shape
```
Examples

```python
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.shape
(2, 2)

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4],
...                     'col3': [5, 6]})
>>> df.shape
(2, 3)
```

df.style

```
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.size
3

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.size
4
```

DataFrame.size

Return an int representing the number of elements in this object.

Return the number of rows if Series. Otherwise return the number of rows times number of columns if DataFrame.

See also:

ndarray.size

Examples

DataFrame.style

Property returning a Styler object containing methods for building a styled HTML representation for the DataFrame.

See also:

pandas.io.formats.style.Styler

DataFrame.values

Return a Numpy representation of the DataFrame.

Only the values in the DataFrame will be returned, the axes labels will be removed.

Returns numpy.ndarray

The values of the DataFrame.
**See also:**

*`pandas.DataFrame.index`*  Retrieve the index labels

*`pandas.DataFrame.columns`*  Retrieving the column names

**Notes**

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcast to int32. By *`numpy.find_common_type()`* convention, mixing int64 and uint64 will result in a float64 dtype.

**Examples**

A DataFrame where all columns are the same type (e.g., int64) results in an array of the same type.

```python
>>> df = pd.DataFrame({'age': [3, 29],
...                    'height': [94, 170],
...                    'weight': [31, 115]})
>>> df
age  height  weight
0    3      94     31
1    29     170    115
>>> df.dtypes
age    int64
height    int64
weight    int64
dtype: object
>>> df.values
array([[ 3, 94, 31],
       [29, 170, 115]], dtype=int64)
```

A DataFrame with mixed type columns (e.g., str/object, int64, float32) results in an ndarray of the broadest type that accommodates these mixed types (e.g., object).

```python
>>> df2 = pd.DataFrame([('parrot', 24.0, 'second'), ('lion', 80.5, 1),
...                     ('monkey', np.nan, None)], columns=('name', 'max_speed', 'rank'))
>>> df2.dtypes
name     object
max_speed  float64
rank       object
dtype: object
>>> df2.values
array([['parrot', 24.0, 'second'],
       ['lion', 80.5, 1],
       ['monkey', nan, None]], dtype=object)
```
Methods

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<tr>
<th>Method</th>
<th>Description</th>
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</thead>
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<tr>
<td><code>abs()</code></td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td><code>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>add_prefix(prefix)</code></td>
<td>Prefix labels with string <code>prefix</code>.</td>
</tr>
<tr>
<td><code>add_suffix(suffix)</code></td>
<td>Suffix labels with string <code>suffix</code>.</td>
</tr>
<tr>
<td><code>agg(func[, axis])</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>aggregate(func[, axis])</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>align(other[, join, axis, level, copy, . . .])</code></td>
<td>Align two objects on their axes with the specified join method for each axis Index.</td>
</tr>
<tr>
<td><code>all([axis, bool_only, skipna, level])</code></td>
<td>Return whether all elements are True over series or dataframe axis.</td>
</tr>
<tr>
<td><code>any([axis, bool_only, skipna, level])</code></td>
<td>Return whether any element is True over requested axis.</td>
</tr>
<tr>
<td><code>append(other[, ignore_index, . . .])</code></td>
<td>Append rows of <code>other</code> to the end of this frame, returning a new object.</td>
</tr>
<tr>
<td><code>apply(func[, axis, broadcast, raw, reduce, . . .])</code></td>
<td>Apply a function along an axis of the DataFrame.</td>
</tr>
<tr>
<td><code>applymap(func)</code></td>
<td>Apply a function to a Dataframe elementwise.</td>
</tr>
<tr>
<td><code>as_blocks([copy])</code></td>
<td>(DEPRECATED) Convert the frame to a dict of dtype -&gt; Constructor Types that each has a homogeneous dtype.</td>
</tr>
<tr>
<td><code>as_matrix([columns])</code></td>
<td>(DEPRECATED) Convert the frame to its Numpy-array representation.</td>
</tr>
<tr>
<td><code>asfreq(freq[, method, how, normalize, . . .])</code></td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td><code>asof(where[, subset])</code></td>
<td>The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame).</td>
</tr>
<tr>
<td><code>assign(**kwargs)</code></td>
<td>Assign new columns to a DataFrame, returning a new object (a copy) with the new columns added to the original ones.</td>
</tr>
<tr>
<td><code>astype(dtype[, copy, errors])</code></td>
<td>Cast a pandas object to a specified dtype <code>dtype</code>.</td>
</tr>
<tr>
<td><code>at_time(time[, asof])</code></td>
<td>Select values at particular time of day (e.g. <code>9:00-9:30 AM</code>).</td>
</tr>
<tr>
<td><code>between_time(start_time, end_time[, . . .])</code></td>
<td>Select values between particular times of the day (e.g., <code>9:00-9:30 AM</code>).</td>
</tr>
<tr>
<td><code>bfill([axis, inplace, limit, downcast])</code></td>
<td>Synonym for <code>DataFrame.fillna(method='bfill')</code>.</td>
</tr>
<tr>
<td><code>bool()</code></td>
<td>Return the bool of a single element PandasObject.</td>
</tr>
<tr>
<td><code>boxplot([column, by, ax, fontsize, rot, . . .])</code></td>
<td>Make a box plot from DataFrame columns.</td>
</tr>
<tr>
<td><code>clip([lower, upper, axis, inplace])</code></td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td><code>clip_lower(threshold[, axis, inplace])</code></td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td><code>clip_upper(threshold[, axis, inplace])</code></td>
<td>Return copy of input with values above given value(s) truncated.</td>
</tr>
<tr>
<td><code>combine(other, func[, fill_value, overwrite])</code></td>
<td>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).</td>
</tr>
</tbody>
</table>
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<table>
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<tr>
<th>Method</th>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>combine_first</strong>(other)</td>
<td>Combine two DataFrame objects and default to non-null values in frame calling the method.</td>
</tr>
<tr>
<td><strong>compound</strong>(axis, skipna, level)</td>
<td>Return the compound percentage of the values for the requested axis</td>
</tr>
<tr>
<td><strong>consolidate</strong>(inplace)</td>
<td>(DEPRECATED) Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray).</td>
</tr>
<tr>
<td><strong>convert_objects</strong>(convert_dates,...)</td>
<td>(DEPRECATED) Attempt to infer better dtype for object columns.</td>
</tr>
<tr>
<td><strong>copy</strong>(deep)</td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td><strong>corr</strong>(method, min_periods)</td>
<td>Compute pairwise correlation of columns, excluding NA/null values</td>
</tr>
<tr>
<td><strong>corrwith</strong>(other[, axis, drop])</td>
<td>Compute pairwise correlation between rows or columns of two DataFrame objects.</td>
</tr>
<tr>
<td><strong>count</strong>(axis, level, numeric_only)</td>
<td>Count non-NA cells for each column or row.</td>
</tr>
<tr>
<td><strong>cov</strong>(min_periods)</td>
<td>Compute pairwise covariance of columns, excluding NA/null values.</td>
</tr>
<tr>
<td><strong>cummax</strong>(axis, skipna)</td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><strong>cummin</strong>(axis, skipna)</td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><strong>cumprod</strong>(axis, skipna)</td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><strong>cumsum</strong>(axis, skipna)</td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><strong>describe</strong>(percentiles, include, exclude)</td>
<td>Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.</td>
</tr>
<tr>
<td><strong>diff</strong>(periods, axis)</td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td><strong>div</strong>(other[, axis, level, fill_value])</td>
<td>Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><strong>divide</strong>(other[, axis, level, fill_value])</td>
<td>Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><strong>dot</strong>(other)</td>
<td>Matrix multiplication with DataFrame or Series objects.</td>
</tr>
<tr>
<td><strong>drop</strong>(labels, axis, index, columns, level, ...)</td>
<td>Drop specified labels from rows or columns.</td>
</tr>
<tr>
<td><strong>drop_duplicates</strong>(subset, keep, inplace)</td>
<td>Return DataFrame with duplicate rows removed, optionally only considering certain columns</td>
</tr>
<tr>
<td><strong>dropna</strong>(axis, how, thresh, subset, inplace)</td>
<td>Remove missing values.</td>
</tr>
<tr>
<td><strong>duplicated</strong>(subset, keep)</td>
<td>Return boolean Series denoting duplicate rows, optionally only considering certain columns</td>
</tr>
<tr>
<td><strong>eq</strong>(other[, axis, level])</td>
<td>Wrapper for flexible comparison methods eq</td>
</tr>
<tr>
<td><strong>equals</strong>(other)</td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td><strong>eval</strong>(expr[, inplace])</td>
<td>Evaluate a string describing operations on DataFrame columns.</td>
</tr>
<tr>
<td><strong>ewm</strong>(com, span, halflife, alpha,...)</td>
<td>Provides exponential weighted functions</td>
</tr>
<tr>
<td><strong>expanding</strong>(min_periods, center, axis)</td>
<td>Provides expanding transformations.</td>
</tr>
<tr>
<td><strong>ffill</strong>(axis, inplace, limit, downcast)</td>
<td>Synonym for DataFrame. <strong>ffill</strong></td>
</tr>
<tr>
<td><strong>fillna</strong>(value, method, axis, inplace,...)</td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>filter(...)</code></td>
<td>Subset rows or columns of dataframe according to labels in the specified index.</td>
</tr>
<tr>
<td><code>first(offset)</code></td>
<td>Convenience method for subsetting initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>floordiv(other[, axis, level, fill_value])</code></td>
<td>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>(DEPRECATED) Read CSV file.</td>
</tr>
<tr>
<td><code>from_dict(data[, orient, dtype, columns])</code></td>
<td>Construct DataFrame from dict of array-like or dicts.</td>
</tr>
<tr>
<td><code>from_items(items[, columns, orient])</code></td>
<td>(DEPRECATED) Construct a dataframe from a list of tuples</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_dtypes()</code></td>
<td>Return counts of unique dtypes in this object.</td>
</tr>
<tr>
<td><code>get_ftypes()</code></td>
<td>(DEPRECATED) Return counts of unique ftypes in this object.</td>
</tr>
<tr>
<td><code>get_value(index, col[, takeable])</code></td>
<td>(DEPRECATED) Quickly retrieve single value at passed column and index.</td>
</tr>
<tr>
<td><code>get_values()</code></td>
<td>Return an ndarray after converting sparse values to dense.</td>
</tr>
<tr>
<td><code>groupby(...)</code></td>
<td>Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns.</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>Return the first n rows.</td>
</tr>
<tr>
<td><code>hist([column, by, grid, xlabelsize, xrot, ...])</code></td>
<td>Make a histogram of the DataFrame's.</td>
</tr>
<tr>
<td><code>idxmax([axis, skipna])</code></td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td><code>idxmin([axis, skipna])</code></td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
<tr>
<td><code>infer_objects()</code></td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td><code>info([verbose, buf, max_cols, memory_usage, ...])</code></td>
<td>Print a concise summary of a DataFrame.</td>
</tr>
<tr>
<td><code>insert(loc, column, value[, allow_duplicates])</code></td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td><code>interpolate([method, axis, limit, inplace, ...])</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>isin(values)</code></td>
<td>Return boolean DataFrame showing whether each element in the DataFrame is contained in values.</td>
</tr>
<tr>
<td><code>isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>isnull()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>items()</code></td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td><code>iteritems()</code></td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td><code>iterrows()</code></td>
<td>Iterate over DataFrame rows as (index, Series) pairs.</td>
</tr>
<tr>
<td><code>itertuples([index, name])</code></td>
<td>Iterate over DataFrame rows as namedtuples, with index value as first element of the 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>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>kurt([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).</td>
</tr>
<tr>
<td><code>kurtosis([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Convenience method for subsetting final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
<tr>
<td><code>le(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods le</td>
</tr>
<tr>
<td><code>lookup(row_labels, col_labels)</code></td>
<td>Label-based “fancy indexing” function for DataFrame.</td>
</tr>
<tr>
<td><code>lt(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods lt</td>
</tr>
<tr>
<td><code>mad([axis, skipna, level])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>mask(cond[, other, inplace, axis, level, ...])</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.</td>
</tr>
<tr>
<td><code>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>mean([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>median([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>melt([id_vars, value_vars, var_name, ...])</code></td>
<td>“Un pivots” a DataFrame from wide format to long format, optionally leaving identifier variables set.</td>
</tr>
<tr>
<td><code>memory_usage([index, deep])</code></td>
<td>Return the memory usage of each column in bytes.</td>
</tr>
<tr>
<td><code>merge(right[, how, on, left_on, right_on, ...])</code></td>
<td>Merge DataFrame objects by performing a database-style join operation by columns or indexes.</td>
</tr>
<tr>
<td><code>min([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>mod(other[, axis, level, fill_value])</code></td>
<td>Modulo of dataframe and other, element-wise (binary operator mod).</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 mul).</td>
</tr>
<tr>
<td><code>multiply(other[, axis, level, fill_value])</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td><code>ne(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods ne</td>
</tr>
<tr>
<td><code>nlargest(n, columns[, keep])</code></td>
<td>Return the first n rows ordered by columns in descending order.</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nsmallest(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>nunique([axis, dropna])</code></td>
<td>Return Series with number of distinct observations over requested axis.</td>
</tr>
<tr>
<td><code>pct_change([periods, fill_method, limit, freq])</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>pipe(func, *args, **kwargs)</code></td>
<td>Apply func(self, *args, **kwargs)</td>
</tr>
</tbody>
</table>

Continued on next page
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- `pivot(index, columns, values)`
  Return reshaped DataFrame organized by given index / column values.

- `pivot_table(values, index, columns, ....)`
  Create a spreadsheet-style pivot table as a DataFrame.

- `plot`
  alias of pandas.plotting._core.DataFramePlotMethods
  Return item and drop from frame.

- `pow(other[, axis, level, fill_value])`
  Exponential power of dataframe and other, element-wise (binary operator `pow`).

- `prod(axis, skipna, level, numeric_only, ....)`
  Return the product of the values for the requested axis

- `product(axis, skipna, level, numeric_only, ....)`
  Return the product of the values for the requested axis

- `quantile(q, axis, numeric_only, interpolation)`
  Return values at the given quantile over requested axis, a la numpy.percentile.

- `query(expr[, inplace])`
  Query the columns of a frame with a boolean expression.

- `radd(other[, axis, level, fill_value])`
  Addition of dataframe and other, element-wise (binary operator `radd`).

- `rank(axis, method, numeric_only, ....)`
  Compute numerical data ranks (1 through n) along axis.

- `rdiv(other[, axis, level, fill_value])`
  Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

- `reindex(labels, index, columns, axis, ....)`
  Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.

- `reindex_axis(labels[, axis, method, level, ....])`
  Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.

- `rename_axis(mapping[, axis, copy, inplace])`
  Alter the name of the index or columns.

- `reorder_levels(order[, axis])`
  Rearrange index levels using input order.

- `replace(to_replace, value, inplace, limit, ....)`
  Replace values given in `to_replace` with `value`.

- `resample(rule[, how, axis, fill_method, ....])`
  Convenience method for frequency conversion and resampling of time series.

- `reset_index([level, drop, inplace, ....])`
  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.

- `rfloordiv(other[, axis, level, fill_value])`
  Integer division of dataframe and other, element-wise (binary operator `rfloordiv`).

- `rmod(other[, axis, level, fill_value])`
  Modulo of dataframe and other, element-wise (binary operator `rmod`).

- `rmul(other[, axis, level, fill_value])`
  Multiplication of dataframe and other, element-wise (binary operator `rmul`).

- `rolling(window[, min_periods, center, ....])`
  Provides rolling window calculations.

- `round([decimals])`
  Round a DataFrame to a variable number of decimal places.

- `rpow(other[, axis, level, fill_value])`
  Exponential power of dataframe and other, element-wise (binary operator `rpow`).

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rsub()</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>rtruediv()</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>sample()</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>select()</code></td>
<td>(DEPRECATED) Return data corresponding to axis labels matching criteria.</td>
</tr>
<tr>
<td><code>select_dtypes()</code></td>
<td>Return a subset of the DataFrame’s columns based on the column dtypes.</td>
</tr>
<tr>
<td><code>sem()</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>set_axis()</code></td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td><code>set_index()</code></td>
<td>Set the DataFrame index (row labels) using one or more existing columns.</td>
</tr>
<tr>
<td><code>set_value()</code></td>
<td>(DEPRECATED) Put single value at passed column and index.</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 Normalized by N-1.</td>
</tr>
<tr>
<td><code>slice_shift()</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>sort_index()</code></td>
<td>Sort 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>(DEPRECATED) Sort multilevel index by chosen axis and primary level.</td>
</tr>
<tr>
<td><code>squeeze()</code></td>
<td>Squeeze length 1 dimensions.</td>
</tr>
<tr>
<td><code>stack()</code></td>
<td>Stack the prescribed level(s) from columns to index.</td>
</tr>
<tr>
<td><code>std()</code></td>
<td>Return sample standard deviation over requested index.</td>
</tr>
<tr>
<td><code>sub()</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>subtract()</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator <code>subtract</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 on a particular axis</td>
</tr>
<tr>
<td><code>tail()</code></td>
<td>Return the last n rows.</td>
</tr>
<tr>
<td><code>take()</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>to_clipboard()</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>to_csv()</code></td>
<td>Write DataFrame 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 the DataFrame to a dictionary.</td>
</tr>
<tr>
<td><code>to_excel()</code></td>
<td>Write DataFrame to an excel sheet</td>
</tr>
<tr>
<td><code>to_gbg()</code></td>
<td>Write a DataFrame to a Google BigQuery table.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_hdf</code></td>
<td>Write the contained data to an HDF5 file using HDFStore.</td>
</tr>
<tr>
<td><code>to_html</code></td>
<td>Render a DataFrame as an HTML table.</td>
</tr>
<tr>
<td><code>to_json</code></td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td><code>to_latex</code></td>
<td>Render an object to a tabular environment table.</td>
</tr>
<tr>
<td><code>to_msgpack</code></td>
<td>msgpack (serialize) object to input file path.</td>
</tr>
<tr>
<td><code>to_panel</code></td>
<td>(DEPRECATED) Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.</td>
</tr>
<tr>
<td><code>to_parquet</code></td>
<td>Write a DataFrame to the binary parquet format.</td>
</tr>
<tr>
<td><code>to_period</code></td>
<td>Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)</td>
</tr>
<tr>
<td><code>to_pickle</code></td>
<td>Pickle (serialize) object to file.</td>
</tr>
<tr>
<td><code>to_records</code></td>
<td>Convert DataFrame to a NumPy record array.</td>
</tr>
<tr>
<td><code>to_sparse</code></td>
<td>Convert to SparseDataFrame</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_stata</code></td>
<td>Export Stata binary dta files.</td>
</tr>
<tr>
<td><code>to_string</code></td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td><code>to_timestamp</code></td>
<td>Cast to DatetimeIndex of timestamps, at beginning of period</td>
</tr>
<tr>
<td><code>to_xarray</code></td>
<td>Return an xarray object from the pandas object.</td>
</tr>
<tr>
<td><code>transform</code></td>
<td>Call function producing a like-indexed NDFrame and return a NDFrame with the transformed values</td>
</tr>
<tr>
<td><code>transpose</code></td>
<td>Transpose index and columns.</td>
</tr>
<tr>
<td><code>truediv</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>truncate</code></td>
<td>Truncate a Series or DataFrame before and after some index value.</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-naive TimeSeries to target time zone.</td>
</tr>
<tr>
<td><code>unstack</code></td>
<td>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.</td>
</tr>
<tr>
<td><code>update</code></td>
<td>Modify in place using non-NA values from another DataFrame.</td>
</tr>
<tr>
<td><code>var</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td><code>where</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.</td>
</tr>
<tr>
<td><code>xs</code></td>
<td>Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.abs**

DataFrame.abs()

Return a Series/DataFrame with absolute numeric value of each element.
This function only applies to elements that are all numeric.

**Returns** abs

Series/DataFrame containing the absolute value of each element.

**See also:**

`numpy.absolute` calculate the absolute value element-wise.

**Notes**

For complex inputs, \(1.2 + 1j\), the absolute value is \(\sqrt{a^2 + b^2}\).

**Examples**

Absolute numeric values in a Series.

```python
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```python
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```python
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0    1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```python
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
    a  b  c
0  4  10 100
1  5   2  50
2  6  30 -30
3  7  40 -50
>>> df.loc[(df.c - 43).abs().argsort()]
    a  b  c
0  5  20  50
```

(continues on next page)
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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
    Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.radd

Notes

Mismatched indices will be unioned together

Examples

```python
>>> a = pd.DataFrame([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'],
                   columns=['one'])
>>> a
   one
a  1.0
b  1.0
c  1.0
d  NaN
>>> b = pd.DataFrame(dict(one=[1, np.nan, 1, np.nan],
                        two=[np.nan, 2, np.nan, 2]),
                   index=['a', 'b', 'd', 'e'])
>>> b
   one  two
a  1.0  NaN
b     2.0  NaN
c  1.0  NaN
d  NaN   2.0
```

(continues on next page)
```python
one  two
a  1.0  NaN
b  NaN  2.0
d  1.0  NaN
e  NaN  2.0

>>> a.add(b, fill_value=0)
  one  two
a  2.0  NaN
b  1.0  2.0
c  1.0  NaN
d  1.0  NaN
e  NaN  2.0
```

### pandas.DataFrame.add_prefix

DataFrame.add_prefix(prefix)

Prefix labels with string prefix.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

**Parameters**

- **prefix**: str

  The string to add before each label.

**Returns**

Series or DataFrame

New Series or DataFrame with updated labels.

**See also:**

Series.add_suffix Suffix row labels with string suffix.

DataFrame.add_suffix Suffix column labels with string suffix.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0  1
1  2
2  3
3  4
dtype: int64

>>> s.add_prefix('item_')
  item_0  1
  item_1  2
  item_2  3
  item_3  4
dtype: int64

>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
  A  B
0  1  3
1  2  4
2  3  5
3  4  6
```
pandas.DataFrame.add_suffix

DataFrame.add_suffix(suffix)
Suffix labels with string suffix.
For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

Parameters suffix : str
The string to add after each label.

Returns Series or DataFrame
New Series or DataFrame with updated labels.

See also:
Series.add_prefix Prefix row labels with string prefix.
DataFrame.add_prefix Prefix column labels with string prefix.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
```

```python
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```python
>>> s.add_suffix('_item')
```

```python
0_item  1
1_item  2
2_item  3
3_item  4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
```

```python
>>> df
```

```python
  A  B
0  1  3
```
pandas.DataFrame.add_suffix

```python
>>> df.add_suffix('_col')
   A_col  B_col
0     1     3
1     2     4
2     3     5
3     4     6
```

### pandas.DataFrame.agg

DataFrame.agg(func, axis=0, *args, **kwargs)

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

**Parameters**

- **func**: function, string, dictionary, or list of string/functions
  
  Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
  
  Accepted combinations are:
  
  - string function name.
  - function.
  - list of functions.
  - dict of column names -> functions (or list of functions).

- **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.

- **args**

  Positional arguments to pass to func.

- **kwargs**

  Keyword arguments to pass to func.

**Returns**

- aggregated [DataFrame]

**See also:**

- DataFrame.apply Perform any type of operations.
- DataFrame.transform Perform transformation type operations.
- pandas.core.groupby.GroupBy Perform operations over groups.
- pandas.core.resample.Resampler Perform operations over resampled bins.
- pandas.core.window.Rolling Perform operations over rolling window.
pandas.core.window.Expanding Perform operations over expanding window.

pandas.core.window.EWM Perform operation over exponential weighted window.

Notes

agg is an alias for aggregate. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from numpy aggregation functions (mean, median, prod, sum, std, var), where the default is to compute the aggregation of the flattened array, e.g., numpy.mean(arr_2d) as opposed to numpy.mean(arr_2d, axis=0).

agg is an alias for aggregate. Use the alias.

Examples

```python
>>> df = pd.DataFrame([[1, 2, 3],
...                     [4, 5, 6],
...                     [7, 8, 9],
...                     [np.nan, np.nan, np.nan]],
...                    columns=['A', 'B', 'C'])

Aggregate these functions over the rows.

```python
>>> df.agg(['sum', 'min'])

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum</td>
<td>12.0</td>
<td>15.0</td>
<td>18.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
<td>2.0</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Different aggregations per column.

```python
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>NaN</td>
<td>8.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>sum</td>
<td>12.0</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Aggregate over the columns.

```python
>>> df.agg("mean", axis="columns")

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.0</td>
<td>5.0</td>
<td>8.0</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

dtype: float64
```

pandas.DataFrame.aggregate

DataFrame.aggregate(func, axis=0, *args, **kwargs)

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.
Parameters `func`: function, string, dictionary, or list of string/functions

Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.

Accepted combinations are:
- string function name.
- function.
- list of functions.
- dict of column names -> functions (or list of functions).

`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.

`*args`

Positional arguments to pass to `func`.

`**kwargs`

Keyword arguments to pass to `func`.

Returns

`aggregated` [DataFrame]

See also:

* `DataFrame.apply` Perform any type of operations.
* `DataFrame.transform` Perform transformation type operations.
* `pandas.core.groupby.GroupBy` Perform operations over groups.
* `pandas.core.resample.Resampler` Perform operations over resampled bins.
* `pandas.core.window.Rolling` Perform operations over rolling window.
* `pandas.core.window.Expanding` Perform operations over expanding window.
* `pandas.core.window.EWM` Perform operation over exponential weighted window.

Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from `numpy` aggregation functions (`mean`, `median`, `prod`, `sum`, `std`, `var`), where the default is to compute the aggregation of the flattened array, e.g., `numpy.mean(arr_2d)` as opposed to `numpy.mean(arr_2d, axis=0)`.

`agg` is an alias for `aggregate`. Use the alias.
Examples

```python
>>> df = pd.DataFrame([[1, 2, 3],
...                    [4, 5, 6],
...                    [7, 8, 9],
...                    [np.nan, np.nan, np.nan]],
...                    columns=['A', 'B', 'C'])

Aggregate these functions over the rows.

```python
>>> df.agg(['sum', 'min'])

A   B   C
sum 12.0 15.0 18.0
min  1.0  2.0  3.0

Different aggregations per column.

```python
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})

A   B
max  NaN  8.0
min  1.0  2.0
sum 12.0 NaN

Aggregate over the columns.

```python
>>> df.agg("mean", axis="columns")

0  2.0
1  5.0
2  8.0
3  NaN
```

dtype: float64

**pandas.DataFrame.align**

DataFrame.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0, broadcast_axis=None)

Align two objects on their axes with the specified join method 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 or ‘index’, 1 or ‘columns’}, default 0
Filling axis, method and limit

broadcast_axis : {0 or ‘index’, 1 or ‘columns’}, default None
Broadcast values along this axis, if aligning two objects of different dimensions

Returns (left, right) : (DataFrame, type of other)
Aligned objects

pandas.DataFrame.all

DataFrame.all (axis=None, bool_only=None, skipna=None, level=None, **kwags)
Return whether all elements are True over series or dataframe axis.
Returns True if all elements within a series or along a dataframe axis are non-zero, not-empty or not-False.

Parameters axis : int, default 0
Select the axis which can be 0 for indices and 1 for columns.

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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**kwags : any, default None
Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

all [Series or DataFrame (if level specified)]

See also:

pandas.Series.all Return True if all elements are True
pandas.DataFrame.any Return True if one (or more) elements are True
Examples

Series

```python
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
```

Dataframes

Create a dataframe from a dictionary.

```python
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
  col1  col2
0  True  True
1  True  False
```

Default behaviour checks if column-wise values all return True.

```python
>>> df.all()
  col1  True
  col2  False
dtype: bool
```

Adding axis=1 argument will check if row-wise values all return True.

```python
>>> df.all(axis=1)
0  True
1  False
dtype: bool
```

**pandas.DataFrame.any**

DataFrame.

:func:`any`

```
DataFrame.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)
```

Return whether any element is True over requested axis.

Unlike `DataFrame.all()`, this performs an or operation. If any of the values along the specified axis is True, this will return True.

**Parameters**

- axis : int, default 0
  Select the axis which can be 0 for indices and 1 for columns.

- 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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

- **kwargs : any, default None
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Additional keywords have no effect but might be accepted for compatibility with
NumPy.
Returns
any [Series or DataFrame (if level specified)]
See also:
pandas.DataFrame.all Return whether all elements are True.
Examples
Series
For Series input, the output is a scalar indicating whether any element is True.
>>> pd.Series([True, False]).any()
True

DataFrame
Whether each column contains at least one True element (the default).
>>> df =
>>> df
A B
0 1 0
1 2 2

pd.DataFrame({"A": [1, 2], "B": [0, 2], "C": [0, 0]})
C
0
0

>>> df.any()
A
True
B
True
C
False
dtype: bool

Aggregating over the columns.
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 2]})
>>> df
A B
0
True 1
1 False 2
>>> df.any(axis='columns')
0
True
1
True
dtype: bool
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 0]})
>>> df
A B
0
True 1
1 False 0

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```python
>>> df.any(axis='columns')
0    True
1   False
dtype: bool
```

any for an empty DataFrame is an empty Series.

```python
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

**Pandas.DataFrame.append**

DataFrame. **append** *(other, ignore_index=False, verify_integrity=False, sort=None)*

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.
- **sort**: boolean, default None
  - Sort columns if the columns of *self* and *other* are not aligned. The default sorting is deprecated and will change to not-sorting in a future version of pandas. Explicitly pass *sort=True* to silence the warning and sort. Explicitly pass *sort=False* to silence the warning and not sort.

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.

Iteratively appending rows to a DataFrame can be more computationally intensive than a single concatenate. A better solution is to append those rows to a list and then concatenate the list with the original DataFrame all at once.
Examples

```python
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> 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
```

The following, while not recommended methods for generating DataFrames, show two ways to generate a DataFrame from multiple data sources.

Less efficient:

```python
>>> df = pd.DataFrame(columns=['A'])
>>> for i in range(5):
...    df = df.append({'A': i}, ignore_index=True)

```

More efficient:

```python
>>> pd.concat([pd.DataFrame([i], columns=['A']) for i in range(5)], ignore_index=True)
   A
0  0
1  1
2  2
3  3
4  4
```

**pandas.DataFrame.apply**

DataFrame.apply(func, axis=0, broadcast=None, raw=False, reduce=None, result_type=None, args=(), **kwds)**

Apply a function along an axis of the DataFrame.
Objects passed to the function are Series objects whose index is either the DataFrame’s index (`axis=0`) or the DataFrame’s columns (`axis=1`). By default (`result_type=None`), the final return type is inferred from the return type of the applied function. Otherwise, it depends on the `result_type` argument.

### Parameters

- **func**: function
  - Function to apply to each column or row.

- **axis**: `{0 or 'index', 1 or 'columns'}`, default 0
  - Axis along which the function is applied:
    - 0 or 'index': apply function to each column.
    - 1 or 'columns': apply function to each row.

- **broadcast**: bool, optional
  - Only relevant for aggregation functions:
    - `False` or `None`: returns a Series whose length is the length of the index or the number of columns (based on the `axis` parameter)
    - `True`: results will be broadcast to the original shape of the frame, the original index and columns will be retained.

  Deprecated since version 0.23.0: This argument will be removed in a future version, replaced by `result_type='broadcast'`.

- **raw**: bool, default `False`
  - `False`: passes each row or column as a Series to the function.
  - `True`: the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

- **reduce**: bool 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=None` (the default), `apply`'s return value will be guessed by calling `func` on an empty Series (note: while guessing, exceptions raised by `func` will be ignored). If `reduce=True` a Series will always be returned, and if `reduce=False` a DataFrame will always be returned.

  Deprecated since version 0.23.0: This argument will be removed in a future version, replaced by `result_type='reduce'`.

- **result_type**: `{‘expand’, ‘reduce’, ‘broadcast’, None}`, default `None`
  - These only act when `axis=1` (columns):
    - ‘expand’: list-like results will be turned into columns.
    - ‘reduce’: returns a Series if possible rather than expanding list-like results. This is the opposite of ‘expand’.
    - ‘broadcast’: results will be broadcast to the original shape of the DataFrame, the original index and columns will be retained.

  The default behaviour (None) depends on the return value of the applied function: list-like results will be returned as a Series of those. However if the apply function returns a Series these are expanded to columns.

  New in version 0.23.0.
args: tuple

Positional arguments to pass to func in addition to the array/series.

**kwds

Additional keyword arguments to pass as keywords arguments to func.

Returns

applied [Series or DataFrame]

See also:

DataFrame.applymap For elementwise operations

DataFrame.aggregate only perform aggregating type operations

DataFrame.transform only perform transforming type 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 = pd.DataFrame([[4, 9], ] * 3, columns=['A', 'B'])
>>> df
   A  B
0  4  9
1  4  9
2  4  9

Using a numpy universal function (in this case the same as np.sqrt(df)):

```python
>>> df.apply(np.sqrt)
   A  B
0  2.0  3.0
1  2.0  3.0
2  2.0  3.0
```

Using a reducing function on either axis

```python
>>> df.apply(np.sum, axis=0)
   A
0  12
1  27
dtype: int64
```

```python
>>> df.apply(np.sum, axis=1)
   0
0  13
1  13
2  13
dtype: int64
```

Retuning a list-like will result in a Series
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```python
def apply(lambda x: [1, 2], axis=1)
```
```
0  [1, 2]
1  [1, 2]
2  [1, 2]
dtype: object
```

Passing result_type='expand' will expand list-like results to columns of a Dataframe.

```python
def apply(lambda x: [1, 2], axis=1, result_type='expand')
```
```
0 1
0 1 2
1 1 2
2 1 2
```

Returning a Series inside the function is similar to passing result_type='expand'. The resulting column names will be the Series index.

```python
def apply(lambda x: pd.Series([1, 2], index=['foo', 'bar']), axis=1)
```
```
  foo  bar  
0 1 2
1 1 2
2 1 2
```

Passing result_type='broadcast' will ensure the same shape result, whether list-like or scalar is returned by the function, and broadcast it along the axis. The resulting column names will be the originals.

```python
def apply(lambda x: [1, 2], axis=1, result_type='broadcast')
```
```
   A  B  
0 1 2
1 1 2
2 1 2
```

**pandas.DataFrame.applymap**

Dataframe.applymap(func)

Apply a function to a DataFrame elementwise.

This method applies a function that accepts and returns a scalar to every element of a DataFrame.

**Parameters**

- **func**: callable

  Python function, returns a single value from a single value.

**Returns**

DataFrame

Transformed DataFrame.

**See also:**

- **DataFrame.apply** Apply a function along input axis of DataFrame

**Examples**
>>> df = pd.DataFrame([[1, 2.12], [3.356, 4.567]])

>>> df
   0   1
0  1.000 2.120
1 3.356  4.567

>>> df.applymap(lambda x: len(str(x)))
   0   1
0   3   4
1   5   5

Note that a vectorized version of `func` often exists, which will be much faster. You could square each number elementwise.

>>> df.applymap(lambda x: x**2)
   0   1
0 1.000000 4.494400
1 11.262736 20.857489

But it’s better to avoid applymap in that case.

>>> df ** 2
   0   1
0 1.000000 4.494400
1 11.262736 20.857489

**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.

Deprecated since version 0.21.0.

**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.

Deprecated since version 0.23.0: Use `DataFrame.values()` instead.

**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. By numpy.find_common_type convention, mixing int64 and uint64 will result in a float64 dtype.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

pandas.DataFrame.asfreq

DataFrame.asfreq(freq=None, method=None, how=None, normalize=False, fill_value=None)

Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. resample is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

Parameters

- freq [DateOffset object, or string]
- method : {'backfill'/'bfill', ‘pad’/'ffill’}, default None
  Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):
  • ‘pad’ / ‘ffill’: propagate last valid observation forward to next valid
  • ‘backfill’ / ‘bfill’: use NEXT valid observation to fill
- how : {'start', ‘end’}, default end
  For PeriodIndex only, see PeriodIndex.asfreq
- normalize : bool, default False
  Whether to reset output index to midnight
- fill_value: scalar, optional
  Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

New in version 0.20.0.

Returns

- converted [type of caller]

See also:

reindex
Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
          s
2000-01-01 00:00:00 0.0
2000-01-01 00:01:00 NaN
2000-01-01 00:02:00 2.0
2000-01-01 00:03:00 3.0
```

Upsample the series into 30 second bins.

```python
>>> df.asfreq(freq='30S')
          s
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 NaN
2000-01-01 00:01:30 NaN
2000-01-01 00:02:00 2.0
2000-01-01 00:02:30 NaN
2000-01-01 00:03:00 3.0
```

Upsample again, providing a fill value.

```python
>>> df.asfreq(freq='30S', fill_value=9.0)
          s
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 9.0
2000-01-01 00:01:00 NaN
2000-01-01 00:01:30 9.0
2000-01-01 00:02:00 2.0
2000-01-01 00:02:30 9.0
2000-01-01 00:03:00 3.0
```

Upsample again, providing a method.

```python
>>> df.asfreq(freq='30S', method='bfill')
          s
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 NaN
2000-01-01 00:01:30 2.0
2000-01-01 00:02:00 2.0
2000-01-01 00:02:30 3.0
2000-01-01 00:03:00 3.0
```
pandas.DataFrame.asof

DataFrame.asof(where, subset=None)

The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)

New in version 0.19.0: For DataFrame

If there is no good value, NaN is returned for a Series a Series of NaN values for a DataFrame

Parameters

where [date or array of dates]

subset : string or list of strings, default None
if not None use these columns for NaN propagation

Returns where is scalar

• value or NaN if input is Series
• Series if input is DataFrame

where is Index: same shape object as input

See also:
merge_asof

Notes

Dates are assumed to be sorted Raises if this is not the case

pandas.DataFrame.assign

DataFrame.assign(**kwargs)

Assign new columns to a DataFrame, returning a new object (a copy) with the new columns added to the original ones. Existing columns that are re-assigned will be overwritten.

Parameters kwars : 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. The callable must not change input DataFrame (though pandas doesn’t check it). If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns df : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Assigning multiple columns within the same assign is possible. For Python 3.6 and above, later items in ‘**kwargs’ may refer to newly created or modified columns in ‘df’; items are computed and assigned into ‘df’ in order. For Python 3.5 and below, the order of keyword arguments is not specified, you cannot refer to newly created or modified columns. All items are computed first, and then assigned in alphabetical order.
Changed in version 0.23.0: Keyword argument order is maintained for Python 3.6 and later.

**Examples**

```python
>>> df = pd.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))
```

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<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>ln_A</td>
</tr>
<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>
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<tr>
<td>3</td>
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<td>6</td>
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<td>7</td>
<td>1.649697</td>
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<td>7</td>
<td>8</td>
<td>-1.495604</td>
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<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'])
>>> df.assign(ln_A=newcol)
```

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<table>
<thead>
<tr>
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<tbody>
<tr>
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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>
```

Where the keyword arguments depend on each other

```python
>>> df = pd.DataFrame({'A': [1, 2, 3]})

>>> df.assign(B=df.A, C= lambda x:x['A'] + x['B'])
```

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<tbody>
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<tr>
<td>2</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.astype**

DataFrame.astype (dtype, copy=True, errors='raise', **kwargs)

Cast a pandas object to a specified dtype dtype.

Parameters:
- **dtype**: data type, or dict of column name -> data type
Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use `{col: dtype, ...}`, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame’s columns to column-specific types.

**copy**: bool, default True.

Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

**errors**: {'raise', 'ignore'}, default 'raise'.

Control raising of exceptions on invalid data for provided dtype.

- **raise**: allow exceptions to be raised
- **ignore**: suppress exceptions. On error return original object

New in version 0.20.0.

**raise_on_error**: raise on invalid input

Deprecated since version 0.20.0: Use `errors` instead

**kwargs** [keyword arguments to pass on to the constructor]

Returns

**casted** [type of caller]

See also:

- `pandas.to_datetime` Convert argument to datetime.
- `pandas.to_timedelta` Convert argument to timedelta.
- `pandas.to_numeric` Convert argument to a numeric type.
- `numpy.ndarray.astype` Cast a numpy array to a specified type.

Examples

```python
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0 1
1 2
dtype: int32
>>> ser.astype('int64')
0 1
1 2
dtype: int64
```

Convert to categorical type:

```python
>>> ser.astype('category')
0 1
1 2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:
Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1  # note that s1[0] has changed too
0    10
1     2
```

### 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]

- **Raises**
  - `TypeError`
    - If the index is not a `DatetimeIndex`

**See also:**

- `between_time` Select values between particular times of the day
- `first` Select initial periods of time series based on a date offset
- `last` Select final periods of time series based on a date offset
- `DatetimeIndex.indexer_at_time` Get just the index locations for values at particular time of the day

**Examples**

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09 00:00:00  1
2018-04-09 12:00:00  2
2018-04-10 00:00:00  3
2018-04-10 12:00:00  4
```
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).

By setting start_time to be later than end_time, you can get the times that are *not* between the two times.

**Parameters**
- start_time [datetime.time or string]
- end_time [datetime.time or string]
- include_start [boolean, default True]
- include_end [boolean, default True]

**Returns**
- values_between_time [type of caller]

**Raises**
- TypeError
  If the index is not a DatetimeIndex

**See also:**
- at_time Select values at a particular time of the day
- first Select initial periods of time series based on a date offset
- last Select final periods of time series based on a date offset
- DatetimeIndex.indexer_between_time Get just the index locations for values between particular times of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09 00:00:00 1
2018-04-10 00:20:00 2
2018-04-11 00:40:00 3
2018-04-12 01:00:00 4
```

```python
>>> ts.between_time('00:15', '00:45')
   A
2018-04-10 00:20:00 2
2018-04-11 00:40:00 3
```

You get the times that are *not* between two times by setting start_time later than end_time:
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> ts.between_time('0:45', '0:15')
A
2018-04-09 00:00:00 1
2018-04-12 01:00:00 4
```

**pandas.DataFrame.bfill**

DataFrame. **bfill** *(axis=None, inplace=False, limit=None, downcast=None)*

Synonym for DataFrame. **fillna(method='bfill')**

**pandas.DataFrame.bool**

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 columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of the box to show the range of the data. The position of the whiskers is set by default to 1.5 * IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia’s entry for boxplot.

**Parameters**

- **column** : str or list of str, optional
  
  Column name or list of names, or vector. Can be any valid input to pandas. **DataFrame.groupby()**.

- **by** : str or array-like, optional
  
  Column in the DataFrame to pandas.DataFrame.groupby(). One box-plot will be done per value of columns in by.

- **ax** : object of class matplotlib.axes.Axes, optional
  
  The matplotlib axes to be used by boxplot.

- **fontsize** : float or str
  
  Tick label font size in points or as a string (e.g., large).

- **rot** : int or float, default 0
  
  The rotation angle of labels (in degrees) with respect to the screen coordinate system.

- **grid** : boolean, default True
  
  Setting this to True will show the grid.
**figsize** : A tuple (width, height) in inches

The size of the figure to create in matplotlib.

**layout** : tuple (rows, columns), optional

For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.

**return_type** : {'axes', 'dict', 'both'} or None, default 'axes'

The kind of object to return. The default is axes.

- 'axes' returns the matplotlib axes the boxplot is drawn on.
- 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot.
- 'both' returns a namedtuple with the axes and dict.
- when grouping with by, a Series mapping columns to return_type is returned.

If return_type is None, a NumPy array of axes with the same shape as layout is returned.

**kwds**

All other plotting keyword arguments to be passed to matplotlib.pyplot.boxplot().

**Returns**

The return type depends on the return_type parameter:

- 'axes' : object of class matplotlib.axes.Axes
- 'dict' : dict of matplotlib.axes.Line2D objects
- 'both' : a namedtuple with structure (ax, lines)

For data grouped with by:

- Series
- array (for return_type = None)

**See also:**

* Series.plot.hist Make a histogram.

* matplotlib.pyplot.boxplot Matplotlib equivalent plot.

**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.

**Examples**

Boxplots can be created for every column in the dataframe by df.boxplot() or indicating the columns to be used:
Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```python
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                   columns=['Col1', 'Col2'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. ['X', 'Y']) can be passed to `boxplot` in order to group the data by combination of the variables in the x-axis:

```python
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                   columns=['Col1', 'Col2', 'Col3'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```

The layout of boxplot can be adjusted giving a tuple to `layout`:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       layout=(2, 1))
```

Additional formatting can be done to the boxplot, like suppressing the grid (`grid=False`), rotating the labels in the x-axis (i.e. `rot=45`) or changing the fontsize (i.e. `fontsize=15`):

```python
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```

The parameter `return_type` can be used to select the type of element returned by `boxplot`. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with by, a Series mapping columns to `return_type` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```
pandas.DataFrame.clip

DataFrame.clip(lower=None, upper=None, axis=None, inplace=False, *args, **kwargs)
Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and
in the latter case the clipping is performed element-wise in the specified axis.

**Parameters**

- **lower**: float or array_like, default None
  Minimum threshold value. All values below this threshold will be set to it.

- **upper**: float or array_like, default None
  Maximum threshold value. All values above this threshold will be set to it.

- **axis**: int or string axis name, optional
  Align object with lower and upper along the given axis.

- **inplace**: boolean, default False
  Whether to perform the operation in place on the data.
  New in version 0.21.0.

- ***args, **kwargs
  Additional keywords have no effect but might be accepted for compatibility with
  numpy.

**Returns**

Series or DataFrame

Same type as calling object with the values outside the clip boundaries replaced

**See also:**

- **clip_lower** Clip values below specified threshold(s).
- **clip_upper** Clip values above specified threshold(s).

**Examples**

```python
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9    -2
1     -3    -7
2      0     6
3     -1     8
4      5    -5
```

Clips per column using lower and upper thresholds:

```python
>>> df.clip(-4, 6)
   col_0  col_1
0      6     -2
1     -3     -4
2      0      6
```
(continues on next page)
Clips using specific lower and upper thresholds per column element:

```python
>>> df = pd.DataFrame([[3, 4, 5], [6, 7, 8]], columns=['col_0', 'col_1', 'col_2'])

>>> df
   col_0  col_1  col_2
0       3       4       5
1       6       7       8

>>> df.clip(t, t + 4, axis=0)
   col_0  col_1
0       6       2
1       2       3
2       3       8
3       5       3
```

**pandas.DataFrame.clip_lower**

_pandas.DataFrame.clip_lower (threshold, axis=None, inplace=False)_

Return copy of the input with values below a threshold truncated.

**Parameters**

- **threshold** : numeric or array-like
  - Minimum value allowed. All values below threshold will be set to this value.
  - _float_ : every value is compared to _threshold_.
  - _array-like_ : The shape of _threshold_ should match the object it’s compared to. When _self_ is a Series, _threshold_ should be the length. When _self_ is a DataFrame, _threshold_ should 2-D and the same shape as _self_ for _axis=None_, or 1-D and the same length as the axis being compared.

- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  - Align _self_ with _threshold_ along the given axis.

- **inplace** : boolean, default False
  - Whether to perform the operation in place on the data.
  - New in version 0.21.0.

**Returns**

- **clipped** [same type as input]

**See also:**

- _Series.clip_ Return copy of input with values below and above thresholds truncated.
- _Series.clip_upper_ Return copy of input with values above threshold truncated.
Examples

Series single threshold clipping:

```python
>>> s = pd.Series([5, 6, 7, 8, 9])
>>> s.clip_lower(8)
    0  8
   1  8
   2  8
   3  8
   4  9
   dtype: int64
```

Series clipping element-wise using an array of thresholds. `threshold` should be the same length as the Series.

```python
>>> elemwise_thresholds = [4, 8, 7, 2, 5]
>>> s.clip_lower(elemwise_thresholds)
    0  5
    1  8
    2  7
    3  8
    4  9
   dtype: int64
```

DataFrames can be compared to a scalar.

```python
>>> df = pd.DataFrame({"A": [1, 3, 5], "B": [2, 4, 6]})
>>> df
   A  B
0  1  2
1  3  4
2  5  6
```

```python
>>> df.clip_lower(3)
   A  B
0  3  3
1  3  4
2  5  6
```

Or to an array of values. By default, `threshold` should be the same shape as the DataFrame.

```python
>>> df.clip_lower(np.array([[3, 4], [2, 2], [6, 2]]))
   A  B
0  3  4
1  3  4
2  6  6
```

Control how `threshold` is broadcast with `axis`. In this case `threshold` should be the same length as the axis specified by `axis`.

```python
>>> df.clip_lower(np.array([[3, 3], [3, 5]], axis='index'))
   A  B
0  3  3
1  3  4
2  5  6
```
>> df.clip_lower(np.array([4, 5]), axis='columns')

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.clip_upper**

Dataframe.clip_upper(threshold, axis=None, inplace=False)
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.
- **inplace** : boolean, default False
  Whether to perform the operation in place on the data
  New in version 0.21.0.

**Returns**
- **clipped** [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
  Function that takes two series as inputs and return a Series or a scalar
- **fill_value** [scalar value]
- **overwrite** : boolean, default True
  If True then overwrite values for common keys in the calling frame

**Returns**
- **result** [DataFrame]

**See also:**

Dataframe.combine_first Combine two DataFrame objects and default to non-null values in frame calling the method
Examples

```python
>>> df1 = DataFrame({'A': [0, 0], 'B': [4, 4]})
>>> df2 = DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, lambda s1, s2: s1 if s1.sum() < s2.sum() else s2)
    A  B
0  0  3
1  0  3
```

**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]

**See also:**

*DataFrame.combine* Perform series-wise operation on two DataFrames using a given function

**Examples**

df1’s values prioritized, use values from df2 to fill holes:

```python
>>> df1 = pd.DataFrame([[1, np.nan]])
>>> df2 = pd.DataFrame([[3, 4]])
>>> df1.combine_first(df2)
   0 1
0  1 4.0
```

**pandas.DataFrame.compound**

DataFrame . **compound** (axis=None, skipna=None, level=None)

Return the compound percentage of the values for the requested axis

**Parameters**

axis [{index (0), columns (1)}]

skipna : boolean, default True

Exclude NA/null values when computing the result.

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

**compounded** [Series or DataFrame (if level specified)]

### pandas.DataFrame.consolidate

DataFrame.consolidate(\(inplace=False\))

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray).

Deprecated since version 0.20.0: Consolidate will be an internal implementation only.

### pandas.DataFrame.convert_objects

DataFrame.convert_objects(\(convert\_dates=True, \ convert\_numeric=False, \ convert\_timedeltas=True, \ copy=True\))

Attempt to infer better dtype for object columns.

Deprecated since version 0.21.0.

**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]

**See also:**

- **pandas.to_datetime** Convert argument to datetime.
- **pandas.to_timedelta** Convert argument to timedelta.
- **pandas.to_numeric** Return a fixed frequency timedelta index, with day as the default.

### pandas.DataFrame.copy

DataFrame.copy(\(deep=True\))

Make a copy of this object’s indices and data.
When `deep=True` (default), a new object will be created with a copy of the calling object’s data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When `deep=False`, a new object will be created without copying the calling object’s data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

**Parameters**

- **deep** : bool, default True
  
  Make a deep copy, including a copy of the data and the indices. With `deep=False` neither the indices nor the data are copied.

**Returns**

- **copy** : Series, DataFrame or Panel
  
  Object type matches caller.

**Notes**

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to `copy.deepcopy` in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

**Examples**

```python
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a  1
b  2
dtype: int64

>>> s_copy = s.copy()
>>> s_copy
a  1
b  2
dtype: int64
```

**Shallow copy versus default (deep) copy:**

```python
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)
```

Shallow copy shares data and index with original.

```python
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.
Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

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, Series]
- `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)
```

Count non-NA cells for each column or row.

The values `None`, `NaN`, `NaT`, and optionally `numpy.inf` (depending on `pandas.options.mode.use_inf_as_na`) are considered NA.

**Parameters**
- `axis` : {0 or ‘index’, 1 or ‘columns’}, default 0
  - If 0 or ‘index’ counts are generated for each column. If 1 or ‘columns’ counts are generated for each row.
- `level` : int or str, optional
  - If the axis is a `MultiIndex` (hierarchical), count along a particular level, collapsing into a `DataFrame`. A str specifies the level name.
- `numeric_only` : boolean, default False
  - Include only float, int or boolean data.

**Returns**
- Series or DataFrame
  - For each column/row the number of non-NA/null entries. If `level` is specified returns a `DataFrame`.

See also:

- `Series.count` number of non-NA elements in a Series
- `DataFrame.shape` number of DataFrame rows and columns (including NA elements)
- `DataFrame.isna` boolean same-sized DataFrame showing places of NA elements

Examples

Constructing DataFrame from a dictionary:
```python
>>> df = pd.DataFrame({"Person": ["John", "Myla", None, "John", "Myla"],
                    "Age": [24., np.nan, 21., 33, 26],
                    "Single": [False, True, True, True, False]})

>>> df
   Person  Age  Single
0    John  24.0   False
1     Myla   NaN    True
2     None  21.0    True
3    John  33.0    True
4     Myla  26.0   False

Notice the uncounted NA values:

>>> df.count()
Person    4
Age       4
Single    5
dtype: int64

Counts for each row:

>>> df.count(axis='columns')
0     3
1     2
2     2
3     3
4     3
dtype: int64

Counts for one level of a MultiIndex:

>>> df.set_index(["Person", "Single"]).count(level="Person")
   Age
Person
  John  2
  Myla  1

pandas.DataFrame.cov

DataFrame.cov(min_periods=None)

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

Parameters

- **min_periods**: int, optional
  
  Minimum number of observations required per pair of columns to have a valid result.
Returns DataFrame

The covariance matrix of the series of the DataFrame.

See also:

pandas.Series.cov: compute covariance with another Series
pandas.core.window.EWM.cov: exponential weighted sample covariance
pandas.core.window.Expanding.cov: expanding sample covariance
pandas.core.window.Rolling.cov: rolling sample covariance

Notes

Returns the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-1.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

Examples

```python
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
                    columns=['dogs', 'cats'])
>>> df.cov()
   dogs  cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667

>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(1000, 5),
                    columns=['a', 'b', 'c', 'd', 'e'])
>>> df.cov()
     a     b     c     d     e
  a 0.998438 -0.020161 0.059277 -0.008943 0.014144
  b -0.020161 1.059352 -0.008543 -0.024738 0.009826
  c  0.059277 -0.008543 1.010670 -0.001486 -0.000271
  d -0.008943 -0.024738 -0.001486 0.921297 -0.013692
  e  0.014144 0.009826 -0.000271 -0.013692 0.977795

Minimum number of periods

This method also supports an optional min_periods keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```
pandas.DataFrame.cummax

DataFrame.cummax (axis=None, skipna=True, *args, **kwargs)
Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

Parameters
axis : {0 or 'index', 1 or 'columns'}, default 0
The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs :
Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns
cummax [Series or DataFrame]

See also:
pandas.core.window.Expanding.max Similar functionality but ignores NaN values.
DataFrame.max Return the maximum over DataFrame axis.
DataFrame.cummax Return cumulative maximum over DataFrame axis.
DataFrame.cummin Return cumulative minimum over DataFrame axis.
DataFrame.cumsum Return cumulative sum over DataFrame axis.
DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1   NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.
```python
>>> s.cummax()
0   2.0
1   NaN
2   5.0
3   5.0
4   5.0
dtype: float64
To include NA values in the operation, use skipna=False

```}

```python
>>> s.cummax(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

```python
DataFrame

```}

```python
>>> df = pd.DataFrame(
    [[2.0, 1.0],
     [3.0, np.nan],
     [1.0, 0.0]],
    columns=list('AB'))
```

```python
>>> df.cummax()
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  1.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cummax(axis=1)
   A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```python
>>> df.cummax(axis=1)
   A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

`pandas.DataFrame.cummin`
skipna : boolean, default True
   Exclude NA/null values. If an entire row/column is NA, the result will be NA.
*args, **kwargs :
   Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns
   cummin [Series or DataFrame]

See also:

pandas.core.window.Expanding.min  Similar functionality but ignores NaN values.
DataFrame.min  Return the minimum over DataFrame axis.
DataFrame.cummax  Return cumulative maximum over DataFrame axis.
DataFrame.cummin  Return cumulative minimum over DataFrame axis.
DataFrame.cumsum  Return cumulative sum over DataFrame axis.
DataFrame.cumprod  Return cumulative product over DataFrame axis.

Examples

Series

>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0   2.0
1  NaN
2   5.0
3  -1.0
4   0.0
dtype: float64

By default, NA values are ignored.

>>> s.cummin()
0   2.0
1  NaN
2   2.0
3  -1.0
4  -1.0
dtype: float64

To include NA values in the operation, use skipna=False

>>> s.cummin(skipna=False)
0   2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64

DataFrame
```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummin()
   A  B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```
>>> df.cummin(axis=1)
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

### pandas.DataFrame.cumprod

DataFrame.cumprod(axis=None, skipna=True, *args, **kwargs)

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

**Parameters**

- axis : {0 or ‘index’, 1 or ‘columns’}, default 0
  
  The index or the name of the axis. 0 is equivalent to None or ‘index’.  

- skipna : boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA.

- *args, **kwargs :
  
  Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

cumprod [Series or DataFrame]

See also:

- pandas.core.window.Expanding.prod
  
  Similar functionality but ignores NaN values.

- DataFrame.prod
  
  Return the product over DataFrame axis.

- DataFrame.cummax
  
  Return cumulative maximum over DataFrame axis.

- DataFrame.cummin
  
  Return cumulative minimum over DataFrame axis.
DataFrame.cumsum  Return cumulative sum over DataFrame axis.

DataFrame.cumprod  Return cumulative product over DataFrame axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
0  2.0
1  NaN
2  5.0
3  -1.0
4   0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cumprod()
0  2.0
1  NaN
2  10.0
3  -10.0
4   -0.0
dtype: float64
```

To include NA values in the operation, use skipna=False

```python
>>> s.cumprod(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64
```

DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
0     A     B
A  2.0  1.0
B 3.0  NaN
C 1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to axis=None or axis='index'.

```python
>>> df.cumprod()
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```
To iterate over columns and find the product in each row, use `axis=1`:

```python
>>> df.cumprod(axis=1)
      A   B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```

### pandas.DataFrame.cumsum

`DataFrame.cumsum(axis=None, skipna=True, *args, **kwargs)`

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

**Parameters**

- `axis`: {0 or ‘index’, 1 or ‘columns’}, default 0
  
  The index or the name of the axis. 0 is equivalent to None or ‘index’.

- `skipna`: boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA.

- `*args`, `**kwargs`:
  
  Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- `cumsum` [Series or DataFrame]

**See also:**

- `pandas.core.window.Expanding.sum` Similar functionality but ignores NaN values.
- `DataFrame.sum` Return the sum over DataFrame axis.
- `DataFrame.cummax` Return cumulative maximum over DataFrame axis.
- `DataFrame.cummin` Return cumulative minimum over DataFrame axis.
- `DataFrame.cumsum` Return cumulative sum over DataFrame axis.
- `DataFrame.cumprod` Return cumulative product over DataFrame axis.

**Examples**

### Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0   2.0
1  NaN
2   5.0
3  -1.0
4   0.0
dtype: float64
```

By default, NA values are ignored.
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> s.cumsum()
0   2.0
1   NaN
2   7.0
3   6.0
4   6.0
dtype: float64

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumsum(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))

>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumsum()
   A  B
0  2.0  3.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```python
>>> df.cumsum(axis=1)
   A  B
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0
```

pandas.DataFrame.describe

DataFrame.describe(percentiles=None, include=None, exclude=None)

Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters percentiles : list-like of numbers, optional
The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

**include**: ‘all’, list-like of dtypes or None (default), optional

A white list of data types to include in the result. Ignored for Series. Here are the options:

- ‘all’: All columns of the input will be included in the output.
- A list-like of dtypes: Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
- None (default): The result will include all numeric columns.

**exclude**: list-like of dtypes or None (default), optional,

A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes: Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use 'category'
- None (default): The result will exclude nothing.

**Returns**

- summary: Series/DataFrame of summary statistics

**See also:**

`DataFrame.count`, `DataFrame.max`, `DataFrame.min`, `DataFrame.mean`, `DataFrame.std`, `DataFrame.select_dtypes`

**Notes**

For numeric data, the result’s index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value’s frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a DataFrame, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a DataFrame are analyzed for the output. The parameters are ignored when analyzing a Series.
Examples

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count 3
mean 2
std 1
min 1
25% 1.5
50% 2
75% 2.5
max 3
```

Describing a categorical Series.

```python
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count 4
unique 3
top a
freq 2
dtype: object
```

Describing a timestamp Series.

```python
>>> s = pd.Series([np.datetime64('2000-01-01'),
... np.datetime64('2010-01-01'),
... np.datetime64('2010-01-01')])
>>> s.describe()
count 3
unique 2
top 2010-01-01 00:00:00
freq 2
first 2000-01-01 00:00:00
last 2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({ 'object': ['a', 'b', 'c'],
... 'numeric': [1, 2, 3],
... 'categorical': pd.Categorical(['d', 'e', 'f'])
... })
>>> df.describe()
count 3
mean 2
std 1
min 1
25% 1.5
50% 2
75% 2.5
max 3
```
Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
categorical  numeric  object
count   3        3.0     3
unique  3        NaN     3
top     f        NaN     c
freq    1        NaN     1
mean    NaN      2.0     NaN
std     NaN      1.0     NaN
min     NaN      1.0     NaN
25%     NaN      1.5     NaN
50%     NaN      2.0     NaN
75%     NaN      2.5     NaN
max     NaN      3.0     NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()
count 3.0
mean 2.0
std 1.0
min 1.0
25% 1.5
50% 2.0
75% 2.5
max 3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
numeric
count 3.0
mean 2.0
std 1.0
min 1.0
25% 1.5
50% 2.0
75% 2.5
max 3.0
```

Including only string columns in a DataFrame description.

```python
>>> df.describe(include=[np.object])
object
count 3
unique 3
top c
freq 1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
categorical
count 3
unique 3
```
Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
categorical object
count 3 3
unique 3 3
top  f  c
freq  1  1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.object])
categorical  numeric
count  3  3.0
unique  3  NaN
top  f  NaN
def  1  NaN
mean  NaN  2.0
std  NaN  1.0
min  NaN  1.0
25%  NaN  1.5
50%  NaN  2.0
75%  NaN  2.5
max  NaN  3.0
```

**pandas.DataFrame.diff**

DataFrame.diff(periods=1, axis=0)

First discrete difference of element.

Calculates the difference of a DataFrame element compared with another element in the DataFrame (default is the element in the same column of the previous row).

**Parameters**

- **periods**: int, default 1
  
  Periods to shift for calculating difference, accepts negative values.

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  
  Take difference over rows (0) or columns (1).

  New in version 0.16.1..

**Returns**

- **diffed** [DataFrame]

**See also:**

- **Series.diff** First discrete difference for a Series.

- **DataFrame.pct_change** Percent change over given number of periods.

- **DataFrame.shift** Shift index by desired number of periods with an optional time freq.
Examples

Difference with previous row

```python
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                    'b': [1, 2, 3, 5, 8],
...                    'c': [1, 4, 9, 16, 25, 36]})
```

```plaintext
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>16</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>36</td>
</tr>
</tbody>
</table>
```

```python
>>> df.diff()
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>1.0</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>1.0</td>
<td>5.0</td>
</tr>
<tr>
<td>3</td>
<td>1.0</td>
<td>1.0</td>
<td>7.0</td>
</tr>
<tr>
<td>4</td>
<td>1.0</td>
<td>2.0</td>
<td>9.0</td>
</tr>
<tr>
<td>5</td>
<td>1.0</td>
<td>3.0</td>
<td>11.0</td>
</tr>
</tbody>
</table>
```

Difference with previous column

```python
>>> df.diff(axis=1)
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NaN</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>1</td>
<td>NaN</td>
<td>-1.0</td>
<td>3.0</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>-1.0</td>
<td>7.0</td>
</tr>
<tr>
<td>3</td>
<td>NaN</td>
<td>-1.0</td>
<td>13.0</td>
</tr>
<tr>
<td>4</td>
<td>NaN</td>
<td>0.0</td>
<td>20.0</td>
</tr>
<tr>
<td>5</td>
<td>NaN</td>
<td>2.0</td>
<td>28.0</td>
</tr>
</tbody>
</table>
```

Difference with 3rd previous row

```python
>>> df.diff(periods=3)
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>1</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>3</td>
<td>3.0</td>
<td>2.0</td>
<td>15.0</td>
</tr>
<tr>
<td>4</td>
<td>3.0</td>
<td>4.0</td>
<td>21.0</td>
</tr>
<tr>
<td>5</td>
<td>3.0</td>
<td>6.0</td>
<td>27.0</td>
</tr>
</tbody>
</table>
```

Difference with following row

```python
>>> df.diff(periods=-1)
```

```plaintext
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1.0</td>
<td>0.0</td>
<td>-3.0</td>
</tr>
<tr>
<td>1</td>
<td>-1.0</td>
<td>-1.0</td>
<td>-5.0</td>
</tr>
<tr>
<td>2</td>
<td>-1.0</td>
<td>-1.0</td>
<td>-7.0</td>
</tr>
<tr>
<td>3</td>
<td>-1.0</td>
<td>-2.0</td>
<td>-9.0</td>
</tr>
<tr>
<td>4</td>
<td>-1.0</td>
<td>-3.0</td>
<td>-11.0</td>
</tr>
<tr>
<td>5</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>
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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
    Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:
DataFrame.rtruediv

Notes

Mismatched indices will be unioned together

Examples

None

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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None

Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns
result [DataFrame]

See also:
DataFrame.rtruediv

Notes
Mismatched indices will be unioned together

Examples
None

pandas.DataFrame.dot

DataFrame.dot (other)
Matrix multiplication with DataFrame or Series objects. Can also be called using self @ other in Python >= 3.5.

Parameters
other [DataFrame or Series]

Returns
dot_product [DataFrame or Series]

pandas.DataFrame.drop

DataFrame.drop (labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')
Drop specified labels from rows or columns.

Remove rows or columns by specifying label names and corresponding axis, or by specifying directly index or column names. When using a multi-index, labels on different levels can be removed by specifying the level.

Parameters labels : single label or list-like
    Index or column labels to drop.

axis : {0 or ‘index’, 1 or ‘columns’}, default 0
    Whether to drop labels from the index (0 or ‘index’) or columns (1 or ‘columns’).

index, columns : single label or list-like
Alternative to specifying axis (labels, axis=1 is equivalent to columns=labels).

New in version 0.21.0.

level : int or level name, optional

For MultiIndex, level from which the labels will be removed.

inplace : bool, default False

If True, do operation inplace and return None.

eerrors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and only existing labels are dropped.

Returns

dropped [pandas.DataFrame]

Raises KeyError

If none of the labels are found in the selected axis

See also:

DataFrame.loc Label-location based indexer for selection by label.

DataFrame.dropna Return DataFrame with labels on given axis omitted where (all or any) data are missing

DataFrame.drop_duplicates Return DataFrame with duplicate rows removed, optionally only considering certain columns

Series.drop Return Series with specified index labels removed.

Examples

```python
>>> df = pd.DataFrame(np.arange(12).reshape(3,4),
...                     columns=['A', 'B', 'C', 'D'])
>>> df
   A  B  C  D
0  0  1  2  3
1  4  5  6  7
2  8  9 10 11

Drop columns

>>> df.drop(['B', 'C'], axis=1)
   A  D
0  0  3
1  4  7
2  8 11
```

```python
>>> df.drop(columns=['B', 'C'])
   A  D
0  0  3
1  4  7
2  8 11
```
Drop a row by index

```python
>>> df.drop([0, 1])
    A  B  C  D
2  8  9 10 11
```

Drop columns and/or rows of MultiIndex DataFrame

```python
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
                                 ['speed', 'weight', 'length']],
                           labels=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
                                   [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> df = pd.DataFrame(index=midx, columns=['big', 'small'],
                    data=[[45, 30], [200, 100], [1.5, 1], [30, 20],
                          [250, 150], [1.5, 0.8], [320, 250],
                          [1, 0.8], [0.3, 0.2]])
>>> df
   big  small
lama speed  45.0  30.0
    weight 200.0 100.0
    length  1.5  1.0
cow  speed  30.0  20.0
    weight 250.0 150.0
    length  1.5  0.8
falcon speed 320.0 250.0
    weight  1.0  0.8
    length  0.3  0.2
>>> df.drop(index='cow', columns='small')
   big
lama speed  45.0
    weight 200.0
    length  1.5
falcon speed 320.0
    weight  1.0
    length  0.3
>>> df.drop(index='length', level=1)
   big  small
lama speed  45.0  30.0
    weight 200.0 100.0
    length  1.5
cow  speed  30.0  20.0
    weight 250.0 150.0
falcon speed 320.0 250.0
    weight  1.0
    length  0.3
```

```python
>>> df.drop(index='cow', columns='small')
   big
lama speed  45.0
    weight 200.0
    length  1.5
falcon speed 320.0
    weight  1.0
    length  0.3
```

```python
>>> df.drop(index='length', level=1)
   big  small
lama speed  45.0  30.0
    weight 200.0 100.0
    length  1.5
cow  speed  30.0  20.0
    weight 250.0 150.0
falcon speed 320.0 250.0
    weight  1.0  0.8
    length  0.3  0.2
```

```
pandas.DataFrame.drop_duplicates
```

DataFrame.drop_duplicates(subset=None, keep='first', inplace=False)

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.
  
  **inplace** : boolean, default **False**
  
  Whether to drop duplicates in place or to return a copy

**Returns**

**deduplicated** [DataFrame]

**pandas.DataFrame.dropna**

**DataFrame.dropna** *(axis=0, how='any', thresh=None, subset=None, inplace=False)*

Remove missing values.

See the *User Guide* for more on which values are considered missing, and how to work with missing data.

**Parameters**

- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  
  Determine if rows or columns which contain missing values are removed.
  
  - 0, or ‘index’ : Drop rows which contain missing values.
  
  - 1, or ‘columns’ : Drop columns which contain missing value.

  Deprecated since version 0.23.0:: Pass tuple or list to drop on multiple axes.

- **how** : {‘any’, ‘all’}, default ‘any’
  
  Determine if row or column is removed from DataFrame, when we have at least one NA or all NA.
  
  - ‘any’ : If any NA values are present, drop that row or column.
  
  - ‘all’ : If all values are NA, drop that row or column.

- **thresh** : int, optional
  
  Require that many non-NA values.

- **subset** : array-like, optional
  
  Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include.

- **inplace** : bool, default **False**
  
  If True, do operation inplace and return None.

**Returns** **DataFrame**

DataFrame with NA entries dropped from it.

**See also**

**DataFrame.isna** Indicate missing values.

**DataFrame.notna** Indicate existing (non-missing) values.

**DataFrame.fillna** Replace missing values.
Series.dropna  Drop missing values.

Index.dropna  Drop missing indices.

Examples

```python
>>> df = pd.DataFrame({"name": ['Alfred', 'Batman', 'Catwoman'],
... "toy": [np.nan, 'Batmobile', 'Bullwhip'],
... "born": [pd.NaT, pd.Timestamp("1940-04-25"),
... pd.NaT])
>>> df
   name   toy    born
0   Alfred  NaN  NaT
1  Batman  Batmobile 1940-04-25
2  Catwoman  Bullwhip  NaT

Drop the rows where at least one element is missing.

```python
>>> df.dropna()
   name   toy    born
0   Alfred  NaN  NaT
1  Batman  Batmobile 1940-04-25
2  Catwoman  Bullwhip  NaT

Drop the columns where at least one element is missing.

```python
>>> df.dropna(axis='columns')
   name
0   Alfred
1   Batman
2   Catwoman

Drop the rows where all elements are missing.

```python
>>> df.dropna(how='all')
   name   toy    born
0   Alfred  NaN  NaT
1  Batman  Batmobile 1940-04-25
2  Catwoman  Bullwhip  NaT

Keep only the rows with at least 2 non-NA values.

```python
>>> df.dropna(thresh=2)
   name   toy    born
0   Alfred  NaN  NaT
1  Batman  Batmobile 1940-04-25
2  Catwoman  Bullwhip  NaT

Define in which columns to look for missing values.

```python
>>> df.dropna(subset=['name', 'born'])
   name   toy    born
1  Batman  Batmobile 1940-04-25

Keep the DataFrame with valid entries in the same variable.

```python
>>> df.dropna(inplace=True)
>>> df
   name   toy    born
1  Batman  Batmobile 1940-04-25
```
pandas.DataFrame.duplicated

DataFrame.duplicated(subset=None, keep='first')

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.

**Returns**

duplicated [Series]

pandas.DataFrame.eq

DataFrame.eq(other, axis='columns', level=None)

Wrapper for flexible comparison methods eq

pandas.DataFrame.equals

DataFrame.equals(other)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.DataFrame.eval

DataFrame.eval(expr, inplace=False, **kwargs)

Evaluate a string describing operations on DataFrame columns.

Operates on columns only, not specific rows or elements. This allows eval to run arbitrary code, which can make you vulnerable to code injection if you pass user input to this function.

**Parameters**

- **expr**: str
  - The expression string to evaluate.

- **inplace**: bool, default False
  - If the expression contains an assignment, whether to perform the operation inplace and mutate the existing DataFrame. Otherwise, a new DataFrame is returned.

New in version 0.18.0..

**kwargs**: dict
  - See the documentation for eval() for complete details on the keyword arguments accepted by query().

**Returns**

ndarray, scalar, or pandas object
The result of the evaluation.

See also:

**DataFrame.query** Evaluates a boolean expression to query the columns of a frame.

**DataFrame.assign** Can evaluate an expression or function to create new values for a column.

**pandas.eval** Evaluate a Python expression as a string using various backends.

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```python
>>> df = pd.DataFrame({'A': range(1, 6), 'B': range(10, 0, -2)})
>>> df
   A  B
0  1 10
1  2  8
2  3  6
3  4  4
4  5  2
```

```python
>>> df.eval('A + B')
   A  B   C
0  11
1 10
2  9
3  8
4  7
```

dtype: int64

Assignment is allowed though by default the original DataFrame is not modified.

```python
>>> df.eval('C = A + B')
   A  B  C
0  1 10 11
1  2  8 10
2  3  6  9
3  4  4  8
4  5  2  7
```

```python
>>> df
   A  B
0  1 10
1  2  8
2  3  6
3  4  4
4  5  2
```

Use `inplace=True` to modify the original DataFrame.

```python
>>> df.eval('C = A + B', inplace=True)
```

(continues on next page)
DataFrame.ewm

DataFrame.ewm (com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0)

Provides exponential weighted functions

New in version 0.18.0.

Parameters com : float, optional

Specify decay in terms of center of mass, \( \alpha = 1/(1 + \text{com}) \), for \( \text{com} \geq 0 \)

span : float, optional

Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \), for \( \text{span} \geq 1 \)

halflife : float, optional

Specify decay in terms of half-life, \( \alpha = 1 - \exp(\log(0.5)/\text{halflife}) \), for \( \text{halflife} > 0 \)

alpha : float, optional

Specify smoothing factor \( \alpha \) directly, \( 0 < \alpha \leq 1 \)

New in version 0.18.0.

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

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)

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

Returns

a Window sub-classed for the particular operation

See also:

rolling Provides rolling window calculations
expanding Provides expanding transformations.
Notes

Exactly one of center of mass, span, half-life, and alpha must be provided. Allowed values and relationship between the parameters are specified in the parameter descriptions above; see the link at the end of this section for a detailed explanation.

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:

\[
\text{weighted_average}[i] = (1 - \alpha) \times \text{weighted_average}[i-1] + \alpha \times \text{arg}[i].
\]

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).

More details can be found at http://pandas.pydata.org/pandas-docs/stable/computation.html#exponentially-weighted-windows

Examples

```python
>>> df = DataFrame({'B': [0, 1, 2, np.nan, 4]})
   B
0  0.0
1  1.0
2  2.0
3 NaN
4  4.0

>>> df.ewm(com=0.5).mean()
   B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213
```

pandas.DataFrame.expanding

DataFrame.expanding (min_periods=1, center=False, axis=0)

Provides expanding transformations.

New in version 0.18.0.

**Parameters**

- **min_periods**: int, default 1
  - Minimum number of observations in window required to have a value (otherwise result is NA).

- **center**: boolean, default False
  - Set the labels at the center of the window.
axis  [int or string, default 0]

Returns

a Window sub-classed for the particular operation

See also:

rolling  Provides rolling window calculations
ewm  Provides exponential weighted functions

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the
window by setting center=True.

Examples

```python
>>> df = DataFrame({'B': [0, 1, 2, np.nan, 4]})

B
0 0.0
1 1.0
2 2.0
3 NaN
4 4.0

>>> df.expanding(2).sum()

B
0 NaN
1 1.0
2 3.0
3 3.0
4 7.0
```

**pandas.DataFrame.ffill**

DataFrame.**ffill**(axis=None, inplace=False, limit=None, downcast=None)

Synonym for DataFrame.fillna(method='ffill')

**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 or 'index', 1 or '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. Must be greater than 0 if not None.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns

filled [DataFrame]

See also:

interpolate Fill NaN values using interpolation.

reindex, asfreq

Examples

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                  columns=list('ABCD'))

>>> df
     A      B      C      D
0  NaN    2.0  NaN    0.0
1  3.0    4.0  NaN    1.0
2  NaN  NaN  NaN    5.0
3  NaN    3.0  NaN    4.0

Replace all NaN elements with 0s.

>>> df.fillna(0)
     A      B      C      D
0  0.0    2.0  0.0    0.0
1  3.0    4.0  0.0    1.0
2  0.0    0.0  0.0    5.0
3  0.0    3.0  0.0    4.0
```
We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
A  B  C  D
0  NaN 2.0  NaN 0
1  3.0 4.0  NaN 1
2  3.0 4.0  NaN 5
3  3.0 3.0  NaN 4
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
A  B  C  D
0  0.0 2.0  2.0 0
1  3.0 4.0  2.0 1
2  0.0 1.0  2.0 5
3  0.0 3.0  2.0 4
```

Only replace the first NaN element.

```python
>>> df.fillna(value=values, limit=1)
A  B  C  D
0  0.0 2.0  2.0 0
1  3.0 4.0  NaN 1
2  NaN 1.0  NaN 5
3  NaN 3.0  NaN 4
```

**pandas.DataFrame.filter**

DataFrame.filter( items=None, like=None, regex=None, axis=None )

Subset rows or columns of dataframe according to labels in the specified index.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

**Parameters**

- `items` : list-like
  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 string axis name
  The axis to filter on. By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame

**Returns**

- `same type as input object`

**See also:**

- `pandas.DataFrame.loc`
Notes

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.
`axis` defaults to the `info axis` that is used when indexing with `[]`.

Examples

```python
>>> df
one  two  three
mouse 1 2 3
rabbit 4 5 6

>>> # select columns by name
>>> df.filter(items=['one', 'three'])
one  three
mouse 1 3
rabbit 4 6

>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
one  three
mouse 1 3
rabbit 4 6

>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
one  two  three
rabbit 4 5 6
```

`pandas.DataFrame.first`

`DataFrame.first(offset)`
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]

**Raises** `TypeError`
If the index is not a `DatetimeIndex`

**See also:**

- `last` Select final periods of time series based on a date offset
- `at_time` Select values at a particular time of the day
- `between_time` Select values between particular times of the day
Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the first 3 days:

```python
>>> ts.first('3D')
   A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

**pandas.DataFrame.first_valid_index**

DataFrame.first_valid_index()  
Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

**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  
level : int or name  
Broadcast across a level, matching Index values on the passed MultiIndex level  
fill_value : None or float value, default None
Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

result [DataFrame]

See also:

DataFrame.rfloordiv

Notes

Mismatched indices will be unioned together

Examples

None

pandas.DataFrame.from_csv

classmethod DataFrame.from_csv(path, header=0, sep=',', index_col=0, parse_dates=True, encoding=None, tupleize_cols=None, infer_datetime_format=False)

Read CSV file.

Deprecated since version 0.21.0: 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*

```python
pandas.DataFrame.from_dict
classmethod DataFrame.from_dict(data, orient='columns', dtype=None, columns=None) Constructs DataFrame from dict of array-like or dicts.

Parameters data : dict
Of the form {field : array-like} or {field : dict}.

orient : {'columns', 'index'}, default 'columns'
The “orientation” of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass ‘columns’ (default). Otherwise if the keys should be rows, pass ‘index’.

dtype : dtype, default None
Data type to force, otherwise infer.

columns : list, default None
Column labels to use when orient='index'. Raises a ValueError if used with orient='columns'.

New in version 0.23.0.

Returns

pandas.DataFrame

See also:

*DataFrame.from_records* DataFrame from ndarray (structured dtype), list of tuples, dict, or DataFrame
*DataFrame* DataFrame object creation using constructor
Examples

By default the keys of the dict become the DataFrame columns:

```python
>>> data = {'col_1': [3, 2, 1, 0], 'col_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data)
   col_1 col_2
0     3     a
1     2     b
2     1     c
3     0     d
```

Specify `orient='index'` to create the DataFrame using dictionary keys as rows:

```python
>>> data = {'row_1': [3, 2, 1, 0], 'row_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data, orient='index')
   0  1  2  3
row_1 3  2  1  0
row_2  a  b  c  d
```

When using the ‘index’ orientation, the column names can be specified manually:

```python
>>> pd.DataFrame.from_dict(data, orient='index',
... columns=['A', 'B', 'C', 'D'])
   A  B  C  D
row_1 3  2  1  0
row_2  a  b  c  d
```

**pandas.DataFrame.from_items**

**classmethod** `DataFrame.from_items(items, columns=None, orient='columns')`

Construct a dataframe from a list of tuples

Deprecated since version 0.23.0: `from_items` is deprecated and will be removed in a future version. Use `DataFrame.from_dict(dict(items))` instead. `DataFrame.from_dict(OrderedDict(items))` may be used to preserve the key order.

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 of 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_dtypes**

`DataFrame.get_dtypes()`

Return counts of unique dtypes in this object.

**Returns**

- `dtype` : Series
Series with the count of columns with each dtype.

See also:

**dtypes** Return the dtypes in this object.

**Examples**

```python
>>> a = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
>>> df = pd.DataFrame(a, columns=['str', 'int', 'float'])
>>> df
    str  int   float
0   a   1  1.0
1   b   2  2.0
2   c   3  3.0
```

```python
>>> df.get_dtype_counts()
float64 1
int64   1
object  1
dtype: int64
```

### pandas.DataFrame.get_fstype_counts

DataFrame.get_fstype_counts() Return counts of unique ftypes in this object.

**Since version 0.23.0.**

This is useful for SparseDataFrame or for DataFrames containing sparse arrays.

**Returns dtype** : Series

Series with the count of columns with each type and sparsity (dense/sparse)

See also:

**ftypes** Return ftypes (indication of sparse/dense and dtype) in this object.

**Examples**

```python
>>> a = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
>>> df = pd.DataFrame(a, columns=['str', 'int', 'float'])
>>> df
    str  int   float
0   a   1  1.0
1   b   2  2.0
2   c   3  3.0
```

```python
>>> df.get_fstype_counts()
float64:dense 1
int64:dense   1
object:dense  1
dtype: int64
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

pandas.DataFrame.get_value
DataFrame.get_value(index, col, takeable=False)
Quickly retrieve single value at passed column and index
Deprecated since version 0.21.0: Use .at[] or .iat[] accessors instead.
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()
Return an ndarray after converting sparse values to dense.
This is the same as .values for non-sparse data. For sparse data contained in a pandas.SparseArray,
the data are first converted to a dense representation.
Returns numpy.ndarray
Numpy representation of DataFrame
See also:
values Numpy representation of DataFrame.
pandas.SparseArray Container for sparse data.
Examples
>>> df = pd.DataFrame({'a': [1, 2], 'b': [True, False],
...
'c': [1.0, 2.0]})
>>> df
a
b
c
0 1
True 1.0
1 2 False 2.0
>>> df.get_values()
array([[1, True, 1.0], [2, False, 2.0]], dtype=object)
>>> df = pd.DataFrame({"a": pd.SparseArray([1, None, None]),
...
"c": [1.0, 2.0, 3.0]})
>>> df
a
c
0 1.0 1.0
1 NaN 2.0
2 NaN 3.0

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```python
>>> df.get_values()
array([[ 1.,  1.],
       [nan,  2.],
       [nan,  3.]])
```

**pandas.DataFrame.groupby**

`DataFrame.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False, observed=False, **kwargs)`

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, label, or list of labels
  
  Used to determine the groups for the groupby. If by is a function, it's called on each value of the object’s index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series’ values are first aligned; see `.align()` method). If an ndarray is passed, the values are used as-is determine the groups. A label or list of labels may be passed to group by the columns in self. Notice that a tuple is interpreted a (single) key.

- **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

- **observed**: boolean, default False
  
  This only applies if any of the groupers are Categoricals If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

  New in version 0.23.0.

**Returns**

- GroupBy object

**See also:**
**resample** Convenience method for frequency conversion and resampling of time series.

**Notes**

See the user guide for more.

**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.

```
(pandas.DataFrame.gt (other, axis='columns', level=None)
Wrapper for flexible comparison methods gt
```

**pandas.DataFrame.head**

DataFrame.

```
(pandas.DataFrame.head (n=5)
Return the first n rows.

This function returns the first n rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

Parameters n : int, default 5
Number of rows to select.

Returns obj_head : type of caller
The first n rows of the caller object.

See also:

pandas.DataFrame.tail Returns the last n rows.

**Examples**

```python
>>> df = pd.DataFrame({'animal':['alligator', 'bee', 'falcon', 'lion',
... 'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
animal
0  alligator
1    bee
2  falcon
3   lion
```
Viewing the first 5 lines

```python
>>> df.head()
animal
0  alligator
1       bee
2   falcon
3      lion
4     monkey
```

Viewing the first $n$ lines (three in this case)

```python
>>> df.head(3)
animal
0  alligator
1       bee
2   falcon
```

**pandas.DataFrame.hist**

```python
pandas.DataFrame.hist(  
    column=None,  
    by=None,  
    grid=True,  
    xlabelsize=None,  
    xrot=None,  
    ylabelsize=None,  
    yrot=None,  
    ax=None,  
    sharex=False,  
    sharey=False,  
    figsize=None,  
    layout=None,  
    bins=10,  
    **kwds)  
```

Make a histogram of the DataFrame's.

A histogram is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

**Parameters**

- **data** : DataFrame

  The pandas object holding the data.

- **column** : 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. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.

- **ylabelsize** : int, default None

  Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.
If specified changes the y-axis label size.

**yrot** : float, default None

Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.

**ax** : Matplotlib axes object, default None

The axes to plot the histogram on.

**sharex** : 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. Note 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 in inches of the figure to create. Uses the value in `matplotlib.rcParams` by default.

**layout** : tuple, optional

Tuple of (rows, columns) for the layout of the histograms.

**bins** : integer or sequence, default 10

Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

**Returns**

- **axes** : [matplotlib.AxesSubplot or numpy.ndarray of them]

**See also:**

- `matplotlib.pyplot.hist` Plot a histogram using matplotlib.

**Examples**

This example draws a histogram based on the length and width of some animals, displayed in three bins.

```python
>>> df = pd.DataFrame(
...     {'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1],
...     }, index= ['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```
pandas.DataFrame.idxmax

DataFrame.idxmax(\textit{axis}=0, \textit{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

\textit{skipna}: boolean, default True  
Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns  
\textit{idxmax} [Series]

Raises ValueError  
• If the row/column is empty

See also:  
\textit{Series.idxmax}

Notes  
This method is the DataFrame version of \texttt{ndarray.argmax}.

pandas.DataFrame.idxmin

DataFrame.idxmin(\textit{axis}=0, \textit{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

\textit{skipna}: boolean, default True  
Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns  
\textit{idxmin} [Series]

Raises ValueError  
• If the row/column is empty

See also:  
\textit{Series.idxmin}

Notes  
This method is the DataFrame version of \texttt{ndarray.argmin}.
**pandas.DataFrame.infer_objects**

DataFrame.infer_objects()  
Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

New in version 0.21.0.

**Returns**

- **converted** [same type as input object]

**See also:**

- **pandas.to_datetime** Convert argument to datetime.
- **pandas.to_timedelta** Convert argument to timedelta.
- **pandas.to_numeric** Convert argument to numeric type

**Examples**

```python
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
  A
0  1
1  2
2  3

>>> df.dtypes
A  object
dtype: object

>>> df.infer_objects().dtypes
A  int64
dtype: object
```

**pandas.DataFrame.info**

DataFrame.info(verbose=None, buf=None, max_cols=None, memory_usage=None, null_counts=None)  
Print a concise summary of a DataFrame.

This method prints information about a DataFrame including the index dtype and column dtypes, non-null values and memory usage.

**Parameters**

- **verbose** : bool, optional  
  Whether to print the full summary. By default, the setting in pandas.options.display.max_info_columns is followed.

- **buf** : writable buffer, defaults to sys.stdout  
  Where to send the output. By default, the output is printed to sys.stdout. Pass a writable buffer if you need to further process the output.
max_cols : int, optional

When to switch from the verbose to the truncated output. If the DataFrame has more than max_cols columns, the truncated output is used. By default, the setting in pandas.options.display.max_info_columns is used.

memory_usage : bool, str, optional

Specifies whether total memory usage of the DataFrame elements (including the index) should be displayed. By default, this follows the pandas.options.display.memory_usage setting.

True always show memory usage. False never shows memory usage. A value of ‘deep’ is equivalent to ‘True with deep introspection’. Memory usage is shown in human-readable units (base-2 representation). Without deep introspection a memory estimation is made based in column dtype and number of rows assuming values consume the same memory amount for corresponding dtypes. With deep memory introspection, a real memory usage calculation is performed at the cost of computational resources.

null_counts : bool, optional

Whether to show the non-null counts. By default, this is shown only if the frame is smaller than pandas.options.display.max_info_rows and pandas.options.display.max_info_columns. A value of True always shows the counts, and False never shows the counts.

Returns None

This method prints a summary of a DataFrame and returns None.

See also:

*DataFrame.describe* Generate descriptive statistics of DataFrame columns.

*DataFrame.memory_usage* Memory usage of DataFrame columns.

Examples

```python
>>> int_values = [1, 2, 3, 4, 5]
>>> text_values = ['alpha', 'beta', 'gamma', 'delta', 'epsilon']
>>> float_values = [0.0, 0.25, 0.5, 0.75, 1.0]
>>> df = pd.DataFrame({"int_col": int_values, "text_col": text_values, ...
"float_col": float_values})
>>> df
   int_col  text_col  float_col
0      1      alpha   0.00
1      2       beta   0.25
2      3     gamma   0.50
3      4     delta   0.75
4      5    epsilon   1.00
```

Prints information of all columns:

```python
>>> df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 3 columns):
```

(continues on next page)
int_col  5 non-null int64
text_col  5 non-null object
float_col  5 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 200.0+ bytes

Prints a summary of columns count and its dtypes but not per column information:

```python
>>> df.info( verbose=False)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Columns: 3 entries, int_col to float_col
dtypes: float64(1), int64(1), object(1)
memory usage: 200.0+ bytes
```

Pipe output of DataFrame.info to buffer instead of sys.stdout, get buffer content and writes to a text file:

```python
>>> import io

>>> buffer = io.StringIO()

>>> df.info(buf=buffer)

>>> s = buffer.getvalue()

>>> with open("df_info.txt", "w", encoding="utf-8") as f:
...     f.write(s)

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The `memory_usage` parameter allows deep introspection mode, specially useful for big DataFrames and fine-tune memory optimization:

```python
>>> random_strings_array = np.random.choice(['a', 'b', 'c'], 10 ** 6)

>>> df = pd.DataFrame(
...     'column_1': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_2': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_3': np.random.choice(['a', 'b', 'c'], 10 ** 6)
... )

>>> df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
column_1  1000000 non-null object
column_2  1000000 non-null object
column_3  1000000 non-null object
dtypes: object(3)
memory usage: 22.9+ MB

>>> df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
column_1  1000000 non-null object
column_2  1000000 non-null object
column_3  1000000 non-null object
dtypes: object(3)
memory usage: 188.8 MB
```
**pandas.DataFrame.insert**

```python
DataFrame.insert(loc, column, value, allow_duplicates=False)
```

Insert column into DataFrame at specified location. Raises a ValueError if `column` is already contained in the DataFrame, unless `allow_duplicates` is set to True.

**Parameters**

- **loc**: int
  Insertion index. Must verify `0 <= loc <= len(columns)`
- **column**: string, number, or hashable object
  label of the inserted column
- **value**: [int, Series, or array-like]
- **allow_duplicates**: [bool, optional]

**pandas.DataFrame.interpolate**

```python
DataFrame.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)
```

Interpolate values according to different methods. Please note that only `method='linear'` is supported for DataFrames/Series with a MultiIndex.

**Parameters**

- **method**: {'linear', 'time', 'index', 'values', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial', 'spline', 'piecewise_polynomial', 'from_derivatives', 'pchip', 'akima'}
  - `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`, `pchip` and `akima` are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. For more information on their behavior, see the scipy documentation and tutorial documentation
  - `from_derivatives` refers to BPoly.from_derivatives which replaces `piecewise_polynomial` interpolation method in scipy 0.18

New in version 0.18.1: Added support for the ‘akima’ method Added interpolate method ‘from_derivatives’ which replaces ‘piecewise_polynomial’ in scipy 0.18; backwards-compatible with scipy < 0.18
**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. Must be greater than 0.

**limit_direction**: [‘forward’, ‘backward’, ‘both’], default ‘forward’

**limit_area**: {‘inside’, ‘outside’}, default None
- None: (default) no fill restriction
- ‘inside’ Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’ Only fill NaNs outside valid values (extrapolate).
If limit is specified, consecutive NaNs will be filled in this direction.
New in version 0.21.0.

**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
g old = pd.Series([0, 1, np.nan, 3])
g old.interpolate()
g 0 0
 1 1
 2 2
 3 3
dtype: float64
```

**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 = pd.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:**

```python
>>> df = pd.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 = pd.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
```

**pandas.DataFrame.isna**

`DataFrame.isna()`

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

**Returns** `DataFrame`

Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

**See also:**

`DataFrame.isnull` alias of `isna`
**DataFrame.notna** boolean inverse of isna

**DataFrame.dropna** omit axes labels with missing values

**isna** top-level isna

**Examples**

Show which entries in a DataFrame are NA.

```python
df = pd.DataFrame({'age': [5, 6, np.NaN],
                            pd.Timestamp('1940-04-25')],
                   'name': ['Alfred', 'Batman', ''],
                   'toy': [None, 'Batmobile', 'Joker']})

>>> df
   age    born      name     toy
0  5.0  NaT    Alfred   None
1  6.0 1939-05-27  Batman  Batmobile
2 NaN  1940-04-25  Joker

>>> df.isna()
   age    born      name     toy
0  False   True    False   True
1  False    False    False  False
2   True    False    False  False
```

Show which entries in a Series are NA.

```python
ser = pd.Series([5, 6, np.NaN])

>>> ser
0  5.0
1  6.0
2  NaN
dtype: float64

>>> ser.isna()
0  False
1  False
2   True
dtype: bool
```

**pandas.DataFrame.isnull**

DataFrame.isnull()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.nan, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

**Returns** DataFrame

Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.
See also:

- **DataFrame.isnull** alias of isna
- **DataFrame.notna** boolean inverse of isna
- **DataFrame.dropna** omit axes labels with missing values
- **isna** top-level isna

### Examples

Show which entries in a DataFrame are NA.

```python
def = pd.DataFrame({'age': [5, 6, np.NaN],
                            pd.Timestamp('1940-04-25')],
                   'name': ['Alfred', 'Batman', ''],
                   'toy': [None, 'Batmobile', 'Joker']})
```

```python
>>> df
  age  born        name  toy
0  5.0  NaT     Alfred  None
1  6.0 1939-05-27  Batman  Batmobile
2 NaN 1940-04-25   Joker  
```

```python
>>> df.isna()
  age  born        name  toy
 0  False  True     False  True
 1  False  False     False  False
 2  True  False     False  False
```

Show which entries in a Series are NA.

```python
ser = pd.Series([5, 6, np.NaN])
```

```python
>>> ser
0  5.0
1  6.0
2  NaN
dtype: float64
```

```python
>>> ser.isna()
0  False
1  False
2  True
dtype: bool
```

**pandas.DataFrame.items**

*DataFrame.items()*

Iterator over (column name, Series) pairs.

See also:

- **iterrows** Iterate over DataFrame rows as (index, Series) pairs.
- **itertuples** Iterate over DataFrame rows as namedtuples of the values.
pandas.DataFrame.iteritems

Data Frame .iteritems() 
Iterator over (column name, Series) pairs.

See also:

iterrows Iterate over DataFrame rows as (index, Series) pairs.
itertuples Iterate over DataFrame rows as namedtuples of the values.

pandas.DataFrame.iterrows

Data Frame .iterrows() 
Iterate over DataFrame rows as (index, Series) pairs.

Returns it : generator 
A generator that iterates over the rows of the frame.

See also:

itertuples Iterate over DataFrame rows as namedtuples 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,

```python
>>> df = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
>>> row = next(df.iterrows())[1]
>>> row
int 1.0
float 1.5
Name: 0, dtype: float64
>>> print(row['int'].dtype)
float64
>>> print(df['int'].dtype)
int64
```

To preserve dtypes while iterating over the rows, it is better to use itertuples() which returns namedtuples of the values and which is generally faster than iterrows.

2. You should never modify something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect.

pandas.DataFrame.itertuples

Data Frame .itertuples (index=True, name='Pandas') 
Iterate over DataFrame rows as namedtuples, 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.

**name**: string, default “Pandas”

The name of the returned namedtuples or None to return regular tuples.

**See also:**

* `iterrows` Iterate over DataFrame rows as (index, Series) pairs.
* `iteritems` Iterate over (column name, Series) pairs.

**Notes**

The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. With a large number of columns (>255), regular tuples are returned.

**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)
...Pandas(Index='a', col1=1, col2=0.10000000000000001)
Pandas(Index='b', col1=2, col2=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**: name, tuple/list of names, or array-like
    - Column or index level name(s) in the caller to join on the index in *other*, otherwise joins index-on-index. If multiple values given, the *other* DataFrame must have a MultiIndex. Can pass an array as the join key if it is not already contained in the calling DataFrame. Like an Excel VLOOKUP operation
  - **how**: {'left', 'right', 'outer', 'inner'}, default: ‘left’
    - How to handle the operation of the two objects.
      - left: use calling frame’s index (or column if on is specified)
      - right: use other frame’s index
• outer: form union of calling frame’s index (or column if on is specified) with other frame’s index, and sort it lexicographically
• inner: form intersection of calling frame’s index (or column if on is specified) with other frame’s index, preserving the order of the calling’s one

**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, the order of the join key depends on the join type (how keyword)

**Returns**

**joined** [DataFrame]

**See also:**  
*DataFrame.merge* For column(s)-on-column(s) operations

**Notes**

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

Support for specifying index levels as the on parameter was added in version 0.23.0

**Examples**

```python
>>> caller = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3', 'K4', 'K5'],
'  A': ['A0', 'A1', 'A2', 'A3', 'A4', 'A5']})

>>> caller
   A  key
0  A0 K0
1  A1 K1
2  A2 K2
3  A3 K3
4  A4 K4
5  A5 K5

>>> other = pd.DataFrame({'key': ['K0', 'K1', 'K2'],
'B': ['B0', 'B1', 'B2']})

>>> other
   B  key
0  B0 K0
1  B1 K1
2  B2 K2

Join DataFrames using their indexes.
```
If we want to join using the key columns, we need to set key to be the index in both caller and other. The joined DataFrame will have key as its index.

```python
>>> caller.set_index('key').join(other.set_index('key'))
```

```
   key     B
K0  A0  B0
K1  A1  B1
K2  A2  B2
K3  A3  NaN
K4  A4  NaN
K5  A5  NaN
```

Another option to join using the key columns is to use the on parameter. DataFrame.join always uses other’s index but we can use any column in the caller. This method preserves the original caller’s index in the result.

```python
>>> caller.join(other.set_index('key'), on='key')
```

```
   A key     B
0  A0  K0  B0
1  A1  K1  B1
2  A2  K2  B2
3  A3  K3  NaN
4  A4  K4  NaN
5  A5  K5  NaN
```

### 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 Fisher’s 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 when computing the result.

**level**: int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric_only**: boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **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 Fisher’s 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 when computing the result.

- **level**: int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

- **numeric_only**: boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **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, DateOffset, dateutil.relativedelta]

**Returns**

- **subset** [type of caller]

**Raises** **TypeError**

If the index is not a *DateTimeIndex*

**See also:**

---

34.4. **DataFrame**
**first**  Select initial periods of time series based on a date offset

**at_time**  Select values at a particular time of the day

**between_time**  Select values between particular times of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
    A
2018-04-09   1
2018-04-11   2
2018-04-13   3
2018-04-15   4

Get the rows for the last 3 days:
```
```python
>>> ts.last('3D')
    A
2018-04-13   3
2018-04-15   4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

**pandas.DataFrame.last_valid_index**

`DataFrame.last_valid_index()`

Return index for last non-NA/null value.

**Returns**

- scalar  [type of index]

**Notes**

If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

**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:

```python
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 when computing the result.
  
- **level** : int or level name, default None

  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

- **numeric_only** : boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **mad** [Series or DataFrame (if level specified)]
pandas.DataFrame.mask

DataFrame[mask](cond, other=None, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)

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, array-like, or callable

Where cond is False, keep the original value. Where True, replace with corresponding value from other. If cond is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as cond.

other : scalar, NDFrame, or callable

Entries where cond is True are replaced with corresponding value from other. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as other.

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]

errors : str, {'raise', 'ignore'}, default 'raise'

- raise: allow exceptions to be raised
- ignore: suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

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)

Deprecated since version 0.21.0.

Returns

wh [same type as caller]

See also:

DataFrame.where()
Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if cond is False the element is used; otherwise the corresponding element from the DataFrame other is used.

The signature for DataFrame.where() differs from numpy.where(). Roughly df1.where(m, df2) is equivalent to np.where(m, df1, df2).

For further details and examples see the mask documentation in indexing.

Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0  NaN
1  1.0
2  2.0
3  3.0
4  4.0

>>> s.mask(s > 0)
0  0.0
1  NaN
2  NaN
3  NaN
4  NaN

>>> s.where(s > 1, 10)
0  10.0
1  10.0
2  2.0
3  3.0
4  4.0

>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
      A   B
0   0  -1
1  -2   3
2 -14  -5
3   6  -7
4  -8   9

>>> df.where(m, -df) == np.where(m, df, -df)
      A   B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True

>>> df.where(m, -df) == df.mask(~m, -df)
      A   B
0  True  True
1  True  True
```

(continues on next page)
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 when computing the result.
level : int or level name, default None
    If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
numeric_only : boolean, default None
    Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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 when computing the result.
level : int or level name, default None
    If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
numeric_only : boolean, default None
    Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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 when computing the result.
- **level** : int or level name, default None
  - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
- **numeric_only** : boolean, default None
  - Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **median** [Series or DataFrame (if level specified)]

### pandas.DataFrame.melt

**DataFrame.melt** (*id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None*)

“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’.

New in version 0.20.0.

**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:

`melt`, `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

>>> df.melt(id_vars=['A'], value_vars=['B'])
   A    variable  value
0  a      B      1
1  b      B      3
2  c      B      5

>>> df.melt(id_vars=['A'], value_vars=['B', 'C'])
   A    variable  value
0  a      B      1
1  b      B      3
2  c      B      5
3  a      C      2
4  b      C      4
5  c      C      6

The names of `variable` and `value` columns can be customized:

```python
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'],
          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
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C
D  E  F
0  a  1  2
1  b  3  4
2  c  5  6

>>> df.melt(col_level=0, id_vars=['A'], value_vars=['B'])
   A    variable  value
0  a      B      1
1  b      B      3
2  c      B      5
```
pandas.DataFrame.memory_usage

DataFrame.memory_usage(index=True, deep=False)

Return the memory usage of each column in bytes.

The memory usage can optionally include the contribution of the index and elements of object dtype.

This value is displayed in DataFrame.info by default. This can be suppressed by setting pandas.options.display.memory_usage to False.

Parameters

index : bool, default True

Specifies whether to include the memory usage of the DataFrame’s index in returned Series. If index=True the memory usage of the index the first item in the output.

deep : bool, default False

If True, introspect the data deeply by interrogating object dtypes for system-level memory consumption, and include it in the returned values.

Returns

sizes : Series

A Series whose index is the original column names and whose values is the memory usage of each column in bytes.

See also:

numpy.ndarray.nbytes Total bytes consumed by the elements of an ndarray.

Series.memory_usage Bytes consumed by a Series.

pandas.Categorical Memory-efficient array for string values with many repeated values.

DataFrame.info Concise summary of a DataFrame.

Examples

```python
>>> dtypes = ['int64', 'float64', 'complex128', 'object', 'bool']
>>> data = dict([(t, np.ones(shape=5000).astype(t))
... for t in dtypes])
>>> df = pd.DataFrame(data)
>>> df.head()
   int64  float64  complex128  object  bool
0   1.0      1.0          1+0j     object   True
1   1.0      1.0          1+0j     object   True
2   1.0      1.0          1+0j     object   True
3   1.0      1.0          1+0j     object   True
4   1.0      1.0          1+0j     object   True
```
```python
>>> df.memory_usage()
Index  80
int64  40000
float64  40000
complex128  80000
object  40000
bool  5000
dtype: int64

>>> df.memory_usage(index=False)
int64  40000
float64  40000
complex128  80000
object  40000
bool  5000
dtype: int64

The memory footprint of object dtype columns is ignored by default:

>>> df.memory_usage(deep=True)
Index  80
int64  40000
float64  40000
complex128  80000
object  160000
bool  5000
dtype: int64

Use a Categorical for efficient storage of an object-dtype column with many repeated values.

>>> df['object'].astype('category').memory_usage(deep=True)
5168
```

**pandas.DataFrame.merge**

DataFrame.merge(right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('__x', '__y'), copy=True, indicator=False, validate=None)

Merge DataFrame 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, similar to a SQL left outer join; preserve key order
  - right: use only keys from right frame, similar to a SQL right outer join; preserve key order
  - outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically
inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys

**on** : label or list

Column or index level names to join on. These must be found in both DataFrames. If on is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

**left_on** : label or list, or array-like

Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

**right_on** : label or list, or array-like

Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

**left_index** : 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. If False, the order of the join keys depends on the join type (how keyword)

**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.

**validate** : string, default None

If specified, checks if merge is of specified type.

• “one_to_one” or “1:1”: check if merge keys are unique in both left and right datasets.

• “one_to_many” or “1:m”: check if merge keys are unique in left dataset.

• “many_to_one” or “m:1”: check if merge keys are unique in right dataset.
• “many_to_many” or “m:m”: allowed, but does not result in checks.

New in version 0.21.0.

**Returns** merged : DataFrame

The output type will the be same as ‘left’, if it is a subclass of DataFrame.

See also:

merge_ordered, merge_asof, DataFrame.join

**Notes**

Support for specifying index levels as the on, left_on, and right_on parameters was added in version 0.23.0

**Examples**

```python
>>> A
lkey  value
0     foo  1
1     bar  2
2     baz  3
3     foo  4

>>> B
value
0  foo  5
1  bar  6
2  qux  7
3  NaN
4  NaN
5  NaN

>>> A.merge(B, left_on='lkey', right_on='value', how='outer')
lkey  value_x  value_y
0    foo     1      5
1    bar     2      6
2    baz     3      7
3    foo     4      5
4    NaN     NaN    NaN
```

**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 when computing the result.
- **level** : int or level name, default None
  - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
- **numeric_only** : boolean, default None
  - Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
    Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.rmod

Notes

Mismatched indices will be unioned together

Examples

None

pandas.DataFrame.mode

DataFrame.mode (axis=0, numeric_only=False)

Gets the mode(s) of each element along the axis selected. 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

\textbf{numeric\_only} : boolean, default False
if True, only apply to numeric columns

Returns
\textbf{modes} [DataFrame (sorted)]

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})

>>> df.mode()
A
0 1
1 2
```

\textbf{pandas.DataFrame.mul}

\texttt{DataFrame.mul}\texttt{(\textit{other}, axis=’columns’, level=None, fill_value=None)}

Multiplication of dataframe and other, element-wise (binary operator \texttt{mul}).
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{level} : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level
\texttt{fill\_value} : None or float value, default None
Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

\textbf{result} [DataFrame]

See also:
\texttt{DataFrame.rmul}

Notes

Mismatched indices will be unioned together
Examples

None

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
level : int or name
   Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
   Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.rmul

Notes

Mismatched indices will be unioned together

Examples

None

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')
Return the first n rows ordered by columns in descending order.

Return the first n rows with the largest values in columns, in descending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to df.sort_values(columns, ascending=False).head(n), but more performant.

Parameters n : int
    Number of rows to return.

    columns : label or list of labels
        Column label(s) to order by.

    keep : {'first', 'last'}, default 'first'
        Where there are duplicate values:
        • first : prioritize the first occurrence(s)
        • last : prioritize the last occurrence(s)

Returns DataFrame
    The first n rows ordered by the given columns in descending order.

See also:

DataFrame.nsmallest Return the first n rows ordered by columns in ascending order.
DataFrame.sort_values Sort DataFrame by the values
DataFrame.head Return the first n rows without re-ordering.

Notes

This function cannot be used with all column types. For example, when specifying columns with object or category dtypes, TypeError is raised.

Examples

>>> df = pd.DataFrame({'a': [1, 10, 8, 10, -1],
...                    'b': list('abdce'),
...                    'c': [1.0, 2.0, np.nan, 3.0, 4.0]})
>>> df
   a  b  c
0  1  a  1.0
1 10  b  2.0
2  8  d  NaN
3 10  c  3.0
4 -1  e  4.0

In the following example, we will use nlargest to select the three rows having the largest values in column “a”.

```
>>> df.nlargest(3, 'a')
   a  b  c
0  1  8  d
1  3  10 2.0
2  2  10 3.0

When using `keep='last'`, ties are resolved in reverse order:
```
```
>>> df.nlargest(3, 'a', keep='last')
   a  b  c
0  3  10 3.0
1  1  10 2.0
2  2  8  NaN
```

To order by the largest values in column “a” and then “c”, we can specify multiple columns like in the next example.
```
>>> df.nlargest(3, ['a', 'c'])
   a  b  c
0  3  10 3.0
1  1  10 2.0
2  2  8  NaN
```

Attempting to use `nlargest` on non-numeric dtypes will raise a `TypeError`:
```
>>> df.nlargest(3, 'b')
Traceback (most recent call last):
  TypeError: Column 'b' has dtype object, cannot use method 'nlargest'
```

### pandas.DataFrame.notna

DataFrame.notna()  
Detect existing (non-missing) values.  
Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to False values.  
Returns DataFrame  
Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.  

See also:  
DataFrame.notnull alias of notna  
DataFrame.isna boolean inverse of notna  
DataFrame.dropna omit axes labels with missing values  
notna top-level notna

### Examples

Show which entries in a DataFrame are not NA.
```
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                    'name': ['Alfred', 'Batman', ''],
...                    'toy': [None, 'Batmobile', 'Joker']})

>>> df
          age   born           name      toy
0       5.0    NaT  Alfred          None
1       6.0 1939-05-27  Batman  Batmobile
2   NaN 1940-04-25    Joker

>>> df.notna()
          age   born           name      toy
0      True  False  True      False
1      True   True  True       True
2     False  True  True       True

Show which entries in a Series are not NA.

>>> ser = pd.Series([5, 6, np.NaN])

>>> ser
0    5.0
1    6.0
2   NaN
dtype: float64

>>> ser.notna()
0  True
1  True
2 False
dtype: bool
```

**pandas.DataFrame.notnull**

*DataFrame.notnull()*

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to `True`. Characters such as empty strings `'` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to `False` values.

**Returns** DataFrame

Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

**See also:**

- `DataFrame.notnull` alias of notna
- `DataFrame.isna` boolean inverse of notna
- `DataFrame.dropna` omit axes labels with missing values
- `notna` top-level notna
Examples

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
                             pd.Timestamp('1940-04-25')],
                    'name': ['Alfred', 'Batman', ''],
                    'toy': [None, 'Batmobile', 'Joker']})
```

```python
>>> df
   age  born    name   toy
0   5.0  NaT  Alfred  None
1   6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25     Joker
```

```python
>>> df.notna()
   age  born    name   toy
0  True False  True  False
1  True  True  True  True
2 False  True  True  True
```

Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.nan])
```

```python
>>> ser
0   5.0
1   6.0
2  NaN
dtype: float64
```

```python
>>> ser.notna()
0   True
1   True
2  False
dtype: bool
```

**pandas.DataFrame.nsmallest**

DataFrame.nsmallest \(n, columns, keep='first')\)

Get the rows of a DataFrame sorted by the \(n\) smallest values of \(columns\).

**Parameters**

- **n** : int
  Number of items to retrieve

- **columns** : list or str
  Column name or names to order by

- **keep** : {‘first’, ‘last’}, default ‘first’
  Where there are duplicate values: - first : take the first occurrence. - last : take the last occurrence.

**Returns**

DataFrame
Examples

```python
>>> df = pd.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
4  -1  e  4
2   8  d  NaN
0   1  a  1
```

**pandas.DataFrame.nunique**

`DataFrame.nunique (axis=0, dropna=True)`

Return Series with number of distinct observations over requested axis.

New in version 0.20.0.

**Parameters**

- `axis` [{0 or ‘index’, 1 or ‘columns’}, default 0]
- `dropna`: boolean, default True
  
  Don’t include NaN in the counts.

**Returns**

- `nunique` [Series]

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [1, 1, 1]})

>>> df.nunique()
    A  3
    B  1

>>> df.nunique(axis=1)
      0  1
    1  2  2
```

**pandas.DataFrame.pct_change**

`DataFrame.pct_change (periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

**Parameters**

- `periods` : int, default 1
  
  Periods to shift for forming percent change.
- `fill_method`: str, default ‘pad’
How to handle NAs before computing percent changes.

**limit**: int, default None
The number of consecutive NAs to fill before stopping.

**freq**: DateOffset, timedelta, or offset alias string, optional
Increment to use from time series API (e.g. ‘M’ or BDay()).

**kwargs**
Additional keyword arguments are passed into DataFrame.shift or Series.shift.

**Returns**

*chg*: Series or DataFrame
The same type as the calling object.

**See also:**

*Series.diff* Compute the difference of two elements in a Series.

*DataFrame.diff* Compute the difference of two elements in a DataFrame.

*Series.shift* Shift the index by some number of periods.

*DataFrame.shift* Shift the index by some number of periods.

**Examples**

**Series**

```python
>>> s = pd.Series([90, 91, None, 85])
>>> s
0  90
1  91
2  NaN
3  85
```

```python
>>> s.pct_change()
0   NaN
1  0.011111
2 -0.065934
```

```python
>>> s.pct_change(periods=2)
0   NaN
1   NaN
2 -0.055556
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```python
>>> s = pd.Series([90, 91, None, 85])
```

```python
>>> s
0  90.0
1  91.0
2  NaN
3  85.0
```

```python
>>> s.pct_change()
0   NaN
1  0.011111
2 -0.065934
```
```python
>>> s.pct_change(fill_method='ffill')
0    NaN
1  0.011111
2  0.000000
3 -0.065934
dtype: float64
```

**DataFrame**

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```python
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
...     'IT': [804.74, 810.01, 860.13],
...     index=['1980-01-01', '1980-02-01', '1980-03-01'])
```

```python
>>> df.pct_change()
               FR    GR    IT
1980-01-01  NaN  NaN  NaN
1980-02-01  0.0138  0.0137  0.0066
1980-03-01  0.0534  0.0593  0.0619
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```python
>>> df = pd.DataFrame({
...     '2016': [1769950, 30586265],
...     '2015': [1500923, 40912316],
...     '2014': [1371819, 41403351],
...     index=['GOOG', 'APPL'])
```

```python
>>> df.pct_change(axis='columns')
          GOOG     APPL
2016  NaN -0.1520
2015 -0.0860  0.3376
2014  0.0120  0.0120
```

**pandas.DataFrame.pipe**

DataFrame.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs)

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 : iterable, optional
    positional arguments passed into func.

kwargs : mapping, optional
    a dictionary of keyword arguments passed into func.

Returns

object [the return type of func.]

See also:
pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map

Notes

Use .pipe when chaining together functions that expect Series, DataFrames or GroupBy objects. 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)

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a “pivot” table) based on column values. Uses unique values from specified index / columns to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the User Guide for more on reshaping.

Parameters index : string or object, optional
    Column to use to make new frame’s index. If None, uses existing index.

columns : string or object
    Column to use to make new frame’s columns.

values : string, object or a list of the previous, optional
Column(s) to use for populating new frame’s values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

Changed in version 0.23.0: Also accept list of column names.

**Returns** DataFrame

Returns reshaped DataFrame.

**Raises** ValueError:

When there are any index, columns combinations with multiple values. `DataFrame.pivot_table` when you need to aggregate.

**See also:**

- `DataFrame.pivot_table` generalization of pivot that can handle duplicate values for one index/column pair.
- `DataFrame.unstack` pivot based on the index values instead of a column.

**Notes**

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

**Examples**

```python
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two', ...
                      'two'],
                      'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
                      'baz': [1, 2, 3, 4, 5, 6],
                      'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
   foo  bar  baz  zoo
0   one   A   1    x
1   one   B   2    y
2   one   C   3    z
3   two   A   4    q
4   two   B   5    w
5   two   C   6    t
```

```bash
>>> df.pivot(index='foo', columns='bar', values='baz')
bar  A  B  C
foo
one  1  2  3
two  4  5  6
```

```bash
>>> df.pivot(index='foo', columns='bar')['baz']
bar  A  B  C
foo
one  1  2  3
two  4  5  6
```
A ValueError is raised if there are any duplicates.

Notice that the first two rows are the same for our index and columns arguments.

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'two', 'two'], 'bar': ['A', 'A', 'B', 'C'], 'baz': [1, 2, 3, 4]})
```

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
  ... 
ValueError: Index contains duplicate entries, cannot reshape
```

```
pandas.DataFrame.pivot_table
```

DataFrame.pivot_table(values=None, index=None, columns=None, aggfunc=’mean’, fill_value=None, margins=False, dropna=True, margins_name='All')

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame

Parameters

values [column to aggregate, optional]

index : column, Grouper, array, or list of the previous

If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : column, Grouper, array, or list of the previous

If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, list of functions, dict, default numpy.mean

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions

fill_value : scalar, default None

Value to replace missing values with
**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

**margins_name** : string, default ‘All’
Name of the row / column that will contain the totals when margins is True.

**Returns**

- **table** : [DataFrame]

**See also:**

- **DataFrame.pivot** : pivot without aggregation that can handle non-numeric data

**Examples**

```python
>>> df = pd.DataFrame({'A': ['foo', 'foo', 'foo', 'foo', 'foo',
...                       'bar', 'bar', 'bar', 'bar'],
...                       'B': ['one', 'one', 'one', 'two', 'two',
...                       'one', 'one', 'two', 'two'],
...                       'C': ['small', 'large', 'large', 'small',
...                       'small', 'large', 'small', 'small',
...                       'large'],
...                       'D': [1, 2, 2, 3, 3, 4, 5, 6, 7]})
>>> 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
   C   large  small
   A  B
bar one  4.0  5.0
    two  7.0  6.0
foo one  4.0  1.0
    two  NaN  6.0

>>> table = pivot_table(df, values='D', index=['A', 'B'],
...                       columns=['C'], aggfunc=np.sum)
>>> table
   C   large  small
   A  B
bar one  4.0  5.0
```

(continues on next page)
two  7.0  6.0
foo one  4.0  1.0
two  NaN  6.0

```python
>>> table = pivot_table(df, values=['D', 'E'], index=['A', 'C'],
                        aggfunc={'D': np.mean,
                                'E': [min, max, np.mean]})

>>> table
   D     E
   A   C
  mean max median min
bar large 5.500000 16   14.5 13
  small 5.500000 15   14.5 14
foo large 2.000000 10   9.5   9
  small 2.333333 12  11.0   8
```

**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, position or list of label, positions, 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

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- `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 or list

  Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and `subplots` is True, print each item in the list above the corresponding subplot.

**grid** : 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)

**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.axes.Axes or numpy.ndarray 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.

Parameters item: str

    Column label to be popped

Returns

    popped [Series]

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
                     ('parrot', 'bird', 24.0),
                     ('lion', 'mammal', 80.5),
                     ('monkey', 'mammal', np.nan)],
                     columns=('name', 'class', 'max_speed'))
>>> df
   name    class  max_speed
0  falcon    bird     389.0
1  parrot    bird     24.0
2   lion  mammal     80.5
3  monkey  mammal      NaN

>>> df.pop('class')

0    bird
1    bird
2  mammal
3  mammal
Name: class, dtype: object

>>> df
   name  max_speed
0  falcon     389.0
1  parrot     24.0
2   lion     80.5
3  monkey      NaN
```
**pandas.DataFrame.pow**

DataFrame.pow(other, axis='columns', level=None, fill_value=None)

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
- **level** : int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level
- **fill_value** : None or float value, default None
  
  Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

**Returns**

- **result** [DataFrame]

**See also:**

DataFrame.rpow

**Notes**

Mismatched indices will be unioned together

**Examples**

None

**pandas.DataFrame.prod**

DataFrame.prod(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the product of the values for the requested axis

**Parameters**

- **axis** [{index (0), columns (1)}]
- **skipna** : boolean, default True
  
  Exclude NA/null values when computing the result.
- **level** : int or level name, default None
  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
numeric_only : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count : int, default 0

The required number of valid values to perform the operation. If fewer than
min_count non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of
an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

Returns

prod [Series or DataFrame (if level specified)]

Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the min_count parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the skipna parameter, min_count handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0

>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.DataFrame.product

DataFrame.product (axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the product of the values for the requested axis

Parameters

axis ([index (0), columns (1)])

skipna : boolean, default True

Exclude NA/null values when computing the result.

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
min_count : int, default 0

The required number of valid values to perform the operation. If fewer than
min_count non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of
an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

Returns

prod  [Series or DataFrame (if level specified)]

Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the min_count parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the skipna parameter, min_count handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.DataFrame.quantile

DataFrame.quantile (q=0.5, axis=0, numeric_only=True, interpolation='linear')

Return values at the given quantile over requested axis, 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

numeric_only : boolean, default True

If False, the quantile of datetime and timedelta data will be computed as well


New in version 0.18.0.

This optional parameter specifies the interpolation method to use, when the de-
sired quantile lies between two data points i and j:

- linear: $i + (j - i) \times fraction$, where fraction is the fractional part of the index
  surrounded by i and j.
- lower: $i$. 
• higher: $j$.
• nearest: $i$ or $j$ whichever is nearest.
• midpoint: $(i + j) / 2$.

Returns 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.

See also:
pandas.core.window.Rolling.quantile

Examples

```python
>>> df = pd.DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                     columns=['a', 'b'])
>>> df.quantile(.1)
a  1.3
b  3.7
dtype: float64
>>> df.quantile([.1, .5])
     a  b
0.1  1.3  3.7
0.5  2.5  55.0
```

Specifying numeric_only=False will also compute the quantile of datetime and timedelta data.

```python
>>> df = pd.DataFrame({'A': [1, 2],
                    'B': [pd.Timestamp('2010'),
                          pd.Timestamp('2011')],
                    'C': [pd.Timedelta('1 days'),
                          pd.Timedelta('2 days')]})
>>> df.quantile(0.5, numeric_only=False)
     A     B     C
Name: 0.5, dtype: object
```

pandas.DataFrame.query

DataFrame.query(expr, inplace=False, **kwargs)
Query the columns of a frame with a boolean expression.

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.

inplace: bool

Whether the query should modify the data in place or return a modified copy

New in version 0.18.0.
**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. Please note that Python keywords may not be used as identifiers.

For further details and examples see the `query` documentation in `indexing`.

**Examples**

```python
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> 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**

`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

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**fill_value**: None or float value, default None

Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

**Returns**

**result** [DataFrame]

**See also**:

*DataFrame.add*

**Notes**

Mismatched indices will be unioned together

**Examples**

```python
>>> a = pd.DataFrame([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'],
                     columns=['one'])
>>> a
  one
a 1.0
b 1.0
c 1.0
d NaN

>>> b = pd.DataFrame(dict(one=[1, np.nan, 1, np.nan],
                         two=[np.nan, 2, np.nan, 2]),
                    index=['a', 'b', 'd', 'e'])
>>> b
      one   two
a 1.0   NaN
b NaN  2.0
d 1.0   NaN
e NaN  2.0

>>> a.add(b, fill_value=0)
      one   two
a  2.0   NaN
b  1.0  2.0
c  1.0   NaN
d  1.0   NaN
e   NaN  2.0
```
**pandas.DataFrame.rank**

`DataFrame.rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)`

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values.

- **Parameters**
  - `axis`: {0 or ‘index’, 1 or ‘columns’}, default 0
    - index to direct ranking
  - `method`: {'average', 'min', 'max', 'first', 'dense'}
    - 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
  - `numeric_only`: boolean, default None
    - Include only float, int, boolean data. Valid only for DataFrame or Panel objects
  - `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` [same type as caller]

**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
  - `level`: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None

Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.truediv

Notes

Mismatched indices will be unioned together

Examples

None

pandas.DataFrame.reindex

DataFrame.reindex(labels=None, index=None, columns=None, axis=None, method=None, copy=True, level=None, fill_value=nan, limit=None, tolerance=None)

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 labels : array-like, optional

New labels / index to conform the axis specified by ‘axis’ to.

index, columns : array-like, optional (should be specified using keywords)

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : int or str, optional

Axis to target. Can be either the axis name (‘index’, ‘columns’) or number (0, 1).


method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

• 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.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

Returns

reindexed [DataFrame]

Examples

DataFrame.reindex supports two calling conventions

• (index=index_labels, columns=column_labels, ...)
• (labels, axis={'index', 'columns'}, ...)

We highly recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({
...   'http_status': [200, 200, 404, 404, 301],
...   'response_time': [0.04, 0.02, 0.07, 0.08, 1.0],
...   index=index)
```

```
<table>
<thead>
<tr>
<th>http_status</th>
<th>response_time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firefox</td>
<td>200</td>
</tr>
<tr>
<td>Chrome</td>
<td>200</td>
</tr>
<tr>
<td>Safari</td>
<td>404</td>
</tr>
<tr>
<td>IE10</td>
<td>404</td>
</tr>
<tr>
<td>Konqueror</td>
<td>301</td>
</tr>
</tbody>
</table>
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```
>>> new_index= ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...   'Chrome']
>>> df.reindex(new_index)
```

(continues on next page)
We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword `method` to fill the NaN values.

```
>>> df.reindex(new_index, fill_value=0)
  http_status  response_time
Safari       404.0       0.07
Iceweasel   NaN          NaN
Comodo Dragon NaN          NaN
IE10        404.0       0.08
Chrome      200.0       0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
  http_status  response_time
Safari       404          0.07
Iceweasel   missing      missing
Comodo Dragon missing      missing
IE10        404          0.08
Chrome      200          0.02
```

We can also reindex the columns.

```
>>> df.reindex(columns=["http_status", 'user_agent'])
  http_status user_agent
Firefox     200          NaN
Chrome      200          NaN
Safari      404          NaN
IE10        404          NaN
Konqueror   301          NaN
```

Or we can use “axis-style” keyword arguments

```
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
  http_status user_agent
Firefox     200          NaN
Chrome      200          NaN
Safari      404          NaN
IE10        404          NaN
Konqueror   301          NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame("
| prices: [100, 101, np.nan, 100, 89, 88] |
| index=date_index |...
| prices          |
2010-01-01       100
```

(continues on next page)
Suppose we decide to expand the dataframe to cover a wider date range.

```python
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
prices
2009-12-29 NaN
2009-12-30 NaN
2009-12-31 NaN
2010-01-01 100
2010-01-02 101
2010-01-03 NaN
2010-01-04 100
2010-01-05 89
2010-01-06 88
2010-01-07 NaN
```

The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with NaN. If desired, we can fill in the missing values using one of several options.

For example, to backpropagate the last valid value to fill the NaN values, pass bfill as an argument to the method keyword.

```python
>>> df2.reindex(date_index2, method='bfill')
prices
2009-12-29 100
2009-12-30 100
2009-12-31 100
2010-01-01 100
2010-01-02 101
2010-01-03 NaN
2010-01-04 100
2010-01-05 89
2010-01-06 88
2010-01-07 NaN
```

Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the fillna() method.

See the user guide for more.

**pandas.DataFrame.reindex_axis**

DataFrame.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=None)  
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 or ‘index’, 1 or ‘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.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

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. Can be list-like.
    New in version 0.21.0: (list-like tolerance)

Returns
    reindexed [same as input]

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.DataFrame.rename

DataFrame.rename(mapper=None, index=None, columns=None, axis=None, copy=True, inplace=False, level=None)

Alter axes labels.
Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.
Extra labels listed don’t throw an error.
See the user guide for more.

Parameters mapper, index, columns : dict-like or function, optional
    dict-like or functions transformations to apply to that axis’ values. Use either
    mapper and axis to specify the axis to target with mapper, or index and
    columns.
axis : int or str, optional
    Axis to target with mapper. Can be either the axis name (‘index’, ‘columns’) or
    number (0, 1). The default is ‘index’.
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.
level : int or level name, default None
    In case of a MultiIndex, only rename labels in the specified level.

Returns
    renamed [DataFrame]
See also:

pandas.DataFrame.rename_axis

Examples

DataFrame.rename supports two calling conventions

- (index=index_mapper, columns=columns_mapper, ...)
- (mapper, axis=('index', 'columns'), ...)

We highly recommend using keyword arguments to clarify your intent.

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename(index=str, columns={"A": "a", "B": "c"})
     a  c
0  1  4
1  2  5
2  3  6

>>> df.rename(index=str, columns={"A": "a", "C": "c"})
     a  B
0  1  4
1  2  5
2  3  6

Using axis-style parameters

```python
>>> df.rename(str.lower, axis='columns')
     a  b
0  1  4
1  2  5
2  3  6

>>> df.rename({1: 2, 2: 4}, axis='index')
     A  B
0  1  4
2  2  5
4  3  6
```

pandas.DataFrame.rename_axis

DataFrame.rename_axis (mapper, axis=0, copy=True, inplace=False)

Alter the name of the index or columns.

**Parameters**

- mapper : scalar, list-like, optional
  Value to set as the axis name attribute.
- axis : {0 or ‘index’, 1 or ‘columns’}, default 0
  The index or the name of the axis.
- copy : boolean, default True
  Also copy underlying data.
- inplace : boolean, default False
  Also copy underlying data.
Modifies the object directly, instead of creating a new Series or DataFrame.

**Returns** `renamed` : Series, DataFrame, or None

The same type as the caller or None if `inplace` is True.

**See also:**

- `pandas.Series.rename` Alter Series index labels or name
- `pandas.DataFrame.rename` Alter DataFrame index labels or name
- `pandas.Index.rename` Set new names on index

**Notes**

Prior to version 0.21.0, `rename_axis` could also be used to change the axis *labels* by passing a mapping or scalar. This behavior is deprecated and will be removed in a future version. Use `rename` instead.

**Examples**

**Series**

```python
>>> s = pd.Series([1, 2, 3])
>>> s.rename_axis("foo")
foo
0 1
1 2
2 3
dtype: int64
```

**DataFrame**

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename_axis("foo")
foo
A B
0 1 4
1 2 5
2 3 6

>>> df.rename_axis("bar", axis="columns")
bar A B
0 1 4
1 2 5
2 3 6
```

**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).
pandas: powerful Python data analysis toolkit, Release 0.23.1

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')
Replace values given in to_replace with value.

Values of the DataFrame are replaced with other values dynamically. This differs from updating with .loc or .iloc, which require you to specify a location to update with some value.

Parameters to_replace : str, regex, list, dict, Series, int, float, or None
How to find the values that will be replaced.

• numeric, str or regex:
  – numeric: numeric values equal to to_replace will be replaced with value
  – str: string exactly matching to_replace will be replaced with value
  – regex: regexs matching to_replace will be replaced with value
• list of str, regex, or numeric:
  – First, if to_replace and value are both lists, they must be the same length.
  – Second, if regex=True then all of the strings in both lists will be interpreted as regexs otherwise they will match directly. This doesn’t matter much for value since there are only a few possible substitution regexes you can use.
  – str, regex and numeric rules apply as above.
• dict:
  – Dicts can be used to specify different replacement values for different existing values. For example, {'a': 'b', 'y': 'z'} replaces the value ‘a’ with ‘b’ and ‘y’ with ‘z’. To use a dict in this way the value parameter should be None.
  – For a DataFrame a dict can specify that different values should be replaced in different columns. For example, {'a': 1, 'b': 'z'} looks for the value 1 in column ‘a’ and the value ‘z’ in column ‘b’ and replaces these values with whatever is specified in value. The value parameter should not be None in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
  – For a DataFrame nested dictionaries, e.g., {'a': {'b': np.nan}}, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The value parameter should be None to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
• None:
- This means that the regex argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If value is also None then this must be a nested dictionary or Series.

See the examples section for examples of each of these.

**value**: scalar, dict, list, str, regex, default None

Value to replace any values matching to_replace with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

**inplace**: boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

**limit**: int, default None

Maximum size gap to forward or backward fill.

**regex**: bool or same types as to_replace, default False

Whether to interpret to_replace and/or value as regular expressions. If this is True then to_replace must be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case to_replace must be None.

**method**: {'pad', 'ffill', 'bfill', None}

The method to use when for replacement, when to_replace is a scalar, list or tuple and value is None.

Changed in version 0.23.0: Added to DataFrame.

**Returns** DataFrame

Object after replacement.

**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.
- When replacing multiple bool or datetime64 objects and the arguments to to_replace does not match the type of the value being replaced

**ValueError**

- If a list or an ndarray is passed to to_replace and value but they are not the same length.

**See also**:

*DataFrame.fillna* Fill NA values

*DataFrame.where* Replace values based on boolean condition

*Series.str.replace* Simple string replacement.
Notes

• Regex substitution is performed under the hood with re.sub. The rules for substitution for re.sub are the same.

• Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers are strings, then you can do this.

• This method has a lot of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

• When dict is used as the to_replace value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar ‘to_replace‘ and ‘value‘

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0    5
1    1
2    2
3    3
4    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                    'B': [5, 6, 7, 8, 9],
...                    'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
     A  B  C
0   5  5  a
1   1  6  b
2   2  7  c
3   3  8  d
4   4  9  e
```

List-like ‘to_replace‘

```
>>> df.replace([0, 1, 2, 3], 4)
     A  B  C
0   4  5  a
1   4  6  b
2   4  7  c
3   4  8  d
4   4  9  e
```

```
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
     A  B  C
0   4  5  a
1   3  6  b
2   2  7  c
```
(continues on next page)
3 1 8 d
4 4 9 e

```python
>>> s.replace([1, 2], method='bfill')
0 0
1 3
2 3
3 3
4 4
dtype: int64
```

dict-like ‘to_replace’

```python
>>> df.replace({0: 10, 1: 100})
A  B  C
0  10 5  a
1 100 6  b
2  2 7  c
3  3 8  d
4  4 9  e
```

```python
>>> df.replace({'A': 0, 'B': 5}, 100)
A  B  C
0 100 100  a
1  1 6  b
2  2 7  c
3  3 8  d
4  4 9  e
```

```python
>>> df.replace({'A': {0: 100, 4: 400}})
A  B  C
0 100 5  a
1  1 6  b
2  2 7  c
3  3 8  d
4 400 9  e
```

Regular expression ‘to_replace’

```python
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'], 'B': ['abc', 'bar', 'xyz']})
... >>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
 A  B
0  new  abc
1   foo  new
2  bait  xyz
```

```python
>>> df.replace({'A': r'^ba.$'}, {'A': 'new', regex=True})
 A  B
0  new  abc
1   foo  bar
2  bait  xyz
```

```python
>>> df.replace(regex=r'^ba.$', value='new')
(continues on next page)
```

```
A  B
(continues on next page)
```
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(continued from previous page)

>>> df.replace(regex={r'^ba.$':'new', 'foo':'xyz'})
    A   B
0  new  abc
1   xyz  new
2  bait  xyz

Note that when replacing multiple bool or datetime64 objects, the data types in the to_replace parameter must match the data type of the value being replaced:

```python
>>> df = pd.DataFrame({'A': [True, False, True], 'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False})
Traceback (most recent call last):
  ...TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a TypeError because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the to_replace parameter:

```python
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the to_replace value, it is like the value(s) in the dict are equal to the value parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None):

```python
>>> s.replace({'a': None})
0   10
1  None
2  None
3    b
4  None
```

dtype: object

When `value=None` and to_replace is a scalar, list or tuple, replace uses the method parameter (default 'pad') to do the replacement. So this is why the 'a' values are being replaced by 10 in rows 1 and 2 and 'b' in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad'):

```python
>>> s.replace('a', None)
0   10
1   10
2   10
3    b
```

(continues on next page)
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, on=None, level=None)

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (DatetimeIndex, PeriodIndex, or TimedeltaIndex), or pass datetime-like values to the on or level keyword.

Parameters:

rule : string
    the offset string or object representing target conversion

axis : [int, optional, default 0]

closed : {'right', 'left'}
    Which side of bin interval is closed. The default is 'left' for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

label : {'right', 'left'}
    Which bin edge label to label bucket with. The default is 'left' for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of 'right'.

convention : {'start', 'end', 's', 'e'}
    For PeriodIndex only, controls whether to use the start or end of rule

kind : {'timestamp', 'period'}, optional
    Pass ‘timestamp’ to convert the resulting index to a DateTimeIndex or ‘period’ to convert it to a PeriodIndex. By default the input representation is retained.

loffset : timedelta
    Adjust the resampled time labels

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

on : string, optional
    For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.
    New in version 0.19.0.

level : string or int, optional
For a MultiIndex, level (name or number) to use for resampling. Level must be
datetime-like.

New in version 0.19.0.

Returns

Resampler object

See also:

`groupby` Group by mapping, function, label, or list of labels.

Notes

See the user guide for more.

To learn more about the offset strings, please see this link.

Examples

Start by creating a series with 9 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T').sum()
2000-01-01 00:00:00    3
2000-01-01 00:03:00   12
2000-01-01 00:06:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the
left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels.
For example, in the original series the bucket 2000-01-01 00:03:00 contains the value 3, but the
summed value in the resampled bucket with the label 2000-01-01 00:03:00 does not include 3 (if
it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval
as illustrated in the example below this one.

```python
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00    3
2000-01-01 00:06:00   12
2000-01-01 00:09:00   21
Freq: 3T, dtype: int64
```
Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00    0
2000-01-01 00:03:00    6
2000-01-01 00:06:00   15
2000-01-01 00:09:00   15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```python
>>> series.resample('30S').asfreq()[0:5] # select first 5 rows
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1.0
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```python
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
2000-01-01 00:01:00    1
2000-01-01 00:01:30    1
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```python
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    1
2000-01-01 00:01:00    1
2000-01-01 00:01:30    2
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00    8
2000-01-01 00:03:00   17
2000-01-01 00:06:00   26
Freq: 3T, dtype: int64
```
Resample by month using ‘start’ convention. Values are assigned to the first month of the period.

```python
>>> s.resample('M', convention='start').asfreq().head()
2012-01  1.0
2012-02  NaN
2012-03  NaN
2012-04  NaN
2012-05  NaN
Freq: M, dtype: float64
```

Resample by month using ‘end’ convention. Values are assigned to the last month of the period.

```python
>>> s.resample('M', convention='end').asfreq()
                          2012-12  1.0
2012-12  1.0
2013-01  NaN
2013-02  NaN
2013-03  NaN
2013-04  NaN
2013-05  NaN
2013-06  NaN
2013-07  NaN
2013-08  NaN
2013-09  NaN
2013-10  NaN
2013-11  NaN
2013-12  2.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword `on` can be used to specify the column instead of the index for resampling.

```python
>>> df = pd.DataFrame(data=9*[range(4)], columns=['a', 'b', 'c', 'd'])
>>> df['time'] = pd.date_range('1/1/2000', periods=9, freq='T')
>>> df.resample('3T', on='time').sum()
    a  b  c  d
time
2000-01-01 00:00:00  0  3  6  9
2000-01-01 00:03:00  0  3  6  9
2000-01-01 00:06:00  0  3  6  9
```

For a DataFrame with MultiIndex, the keyword `level` can be used to specify on level the resampling needs to take place.

```python
>>> time = pd.date_range('1/1/2000', periods=5, freq='T')
>>> df2 = pd.DataFrame(data=10*[range(4)],
                    columns=['a', 'b', 'c', 'd'],
                    index=pd.MultiIndex.from_product([time, [1, 2]])
                   )
>>> df2.resample('3T', level=0).sum()
          a  b  c  d
2000-01-01 00:00:00  0  6 12 18
2000-01-01 00:03:00  0  4  8 12
```
**DataFrame.reset_index**

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]

**Examples**

```python
>>> df = pd.DataFrame([['bird', 389.0],
                     ... ['bird', 24.0],
                     ... ['mammal', 80.5],
                     ... ['mammal', np.nan]],
                    index=['falcon', 'parrot', 'lion', 'monkey'],
                    columns=('class', 'max_speed'))

>>> df
   class  max_speed
falcon   bird     389.0
parrot   bird      24.0
lion   mammal     80.5
monkey  mammal       NaN
```

When we reset the index, the old index is added as a column, and a new sequential index is used:

```python
>>> df.reset_index()
   index    class  max_speed
0   falcon     bird     389.0
1   parrot     bird      24.0
2    lion  mammal     80.5
3   monkey  mammal       NaN
```

We can use the **drop** parameter to avoid the old index being added as a column:
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```python
>>> df.reset_index(drop=True)
class  max_speed
0  bird      389.0
1  bird       24.0
2 mammal    80.5
3 mammal     NaN

You can also use `reset_index` with `MultiIndex`.

```python
>>> index = pd.MultiIndex.from_tuples([('bird', 'falcon'), ...
... ('bird', 'parrot'), ...
... ('mammal', 'lion'), ...
... ('mammal', 'monkey')], names=['class', 'name'])
>>> columns = pd.MultiIndex.from_tuples([('speed', 'max'), ...
... ('species', 'type')])
>>> df = pd.DataFrame([(389.0, 'fly'), ...
... ( 24.0, 'fly'), ...
... ( 80.5, 'run'), ...
... (np.nan, 'jump')], index=index, columns=columns)
>>> df
speed species
max type
class name
bird falcon 389.0 fly
  parrot   24.0 fly
mammal lion 80.5 run
  monkey NaN jump

If the index has multiple levels, we can reset a subset of them:

```python
>>> df.reset_index(level='class')
class  speed species
max  type
name
falcon bird 389.0 fly
  parrot bird 24.0 fly
lion mammal 80.5 run
  monkey mammal NaN jump

If we are not dropping the index, by default, it is placed in the top level. We can place it in another level:

```python
>>> df.reset_index(level='class', col_level=1)
class  speed species
max  type
name
falcon bird 389.0 fly
  parrot bird 24.0 fly
lion mammal 80.5 run
  monkey mammal NaN jump

When the index is inserted under another level, we can specify under which one with the parameter `col_fill`:
If we specify a nonexistent level for `col_fill`, it is created:

```python
>>> df.reset_index(level='class', col_level=1, col_fill='genus')
```

<table>
<thead>
<tr>
<th>genus</th>
<th>speed</th>
<th>species</th>
</tr>
</thead>
<tbody>
<tr>
<td>class</td>
<td>max</td>
<td>type</td>
</tr>
<tr>
<td>name</td>
<td></td>
<td></td>
</tr>
<tr>
<td>falcon</td>
<td>bird</td>
<td>389.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fly</td>
</tr>
<tr>
<td>parrot</td>
<td>bird</td>
<td>24.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>fly</td>
</tr>
<tr>
<td>lion</td>
<td>mammal</td>
<td>80.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>run</td>
</tr>
<tr>
<td>monkey</td>
<td>mammal</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td></td>
<td>jump</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.rfloordiv**

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
- **level** : int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level
- **fill_value** : None or float value, default None
  - Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

**Returns**

- **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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
    Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.mod

Notes

Mismatched indices will be unioned together

Examples

None

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
level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
    Fill existing missing (NaN) values, and any new element needed for successful
    DataFrame alignment, with this value before computation. If data in both corre-
    sponding DataFrame locations is missing the result will be missing

Returns
    result [DataFrame]

See also:
    DataFrame.mul

Notes

Mismatched indices will be unioned together

Examples

None

pandas.DataFrame.rolling

DataFrame.rolling(window, min_periods=None, center=False, win_type=None, on=None,
                                    axis=0, closed=None)
    Provides rolling window calculations.
    New in version 0.18.0.

Parameters window : int, or offset
    Size of the moving window. This is the number of observations used for calculat-
    ing the statistic. Each window will be a fixed size.
    If its an offset then this will be the time period of each window. Each window will
    be a variable sized based on the observations included in the time-period. This is
    only valid for datetimelike indexes. This is new in 0.19.0

min_periods : int, default None
    Minimum number of observations in window required to have a value (otherwise
    result is NA). For a window that is specified by an offset, this will default to 1.

center : boolean, default False
    Set the labels at the center of the window.

win_type : string, default None
    Provide a window type. If None, all points are evenly weighted. See the notes
    below for further information.
on : string, optional

For a DataFrame, column on which to calculate the rolling window, rather than the index

closed : string, default None

Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’.

Remaining cases not implemented for fixed windows.

New in version 0.20.0.

axis [int or string, default 0]

Returns

a Window or Rolling sub-classed for the particular operation

See also:

expanding Provides expanding transformations.

ewm Provides exponential weighted functions

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting center=True.

To learn more about the center=False & frequency strings, please see this link.

The recognized win_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).

If win_type=None all points are evenly weighted. To learn more about different window types see scipy.signal window functions.
Examples

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
   B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0

Rolling sum with a window length of 2, using the 'triang' window type.

```python
>>> df.rolling(2, win_type='triang').sum()
   B
0  NaN
1  1.0
2  2.5
3  NaN
4  NaN

Rolling sum with a window length of 2, min_periods defaults to the window length.

```python
>>> df.rolling(2).sum()
   B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN

Same as above, but explicitly set the min_periods

```python
>>> df.rolling(2, min_periods=1).sum()
   B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                     index=[pd.Timestamp('20130101 09:00:00'),
                            pd.Timestamp('20130101 09:00:02'),
                            pd.Timestamp('20130101 09:00:03'),
                            pd.Timestamp('20130101 09:00:05'),
                            pd.Timestamp('20130101 09:00:06')])
>>> df
   B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```
Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```python
>>> df.rolling('2s').sum()
   B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

**pandas.DataFrame.round**

`DataFrame.round(decimals=0, *args, **kwargs)`

Round a DataFrame to a variable number of decimal places.

**Parameters**

- `decimals` : int, dict, Series
  
  Number of decimal places to round each column to. If an int is given, round each column to the same number of places. Otherwise dict and Series round to variable numbers of places. Column names should be in the keys if `decimals` is a dict-like, or in the index if `decimals` is a Series. Any columns not included in `decimals` will be left as is. Elements of `decimals` which are not columns of the input will be ignored.

**Returns**

- `DataFrame` object

**See also:**

- `numpy.around`
- `Series.round`

**Examples**

```python
>>> df = pd.DataFrame(np.random.random([3, 3]),
...                   columns=['A', 'B', 'C'], index=['first', 'second', 'third'])
```

```python
>>> 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
```

```python
>>> 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
```

```python
>>> df.round({'A': 1, 'C': 2})
   A         B         C
first  0.0    0.992815  0.173891
second 0.0    0.645646  0.577595
third  0.88    0.149370  0.491027
```

```python
>>> decimals = pd.Series([1, 0, 2], index=['A', 'B', 'C'])
>>> df.round(decimals)
   A         B         C
first  0.0  0.992815  0.173891
second 0.0  0.645646  0.577595
third  0.9  0.149370  0.491027
```

(continues on next page)
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
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level
fill_value : None or float value, default None
Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:
DataFrame.pow

Notes

Mismatched indices will be unioned together

Examples

None

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

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : None or float value, default None

Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.sub

Notes

Mismatched indices will be unioned together

Examples

```python
>>> a = pd.DataFrame([[2, 1, 1, np.nan], index=['a', 'b', 'c', 'd'],
                  columns=['one'])
>>> a
     one
a  2.0
b  1.0
c  1.0
d  NaN
```
```
>>> b = pd.DataFrame(dict(one=[1, np.nan, 1, np.nan],
                        two=[3, 2, np.nan, 2]),
                        index=['a', 'b', 'd', 'e'])
```
```
>>> a.sub(b, fill_value=0)
     one   two
a  1.0  -3.0
b  1.0  -2.0
c  1.0  NaN
d -1.0  NaN
e  NaN -2.0
```

pandas.DataFrame.rtruediv

DataFrame.rtruediv(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

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : None or float value, default None

Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns

result [DataFrame]

See also:

DataFrame.truediv

Notes

Mismatched indices will be unioned together

Examples

None

pandas.DataFrame.sample

DataFrame.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Return a random sample of items from an axis of object.

You can use random_state for reproducibility.

Parameters n : int, optional

Number of items from axis to return. Cannot be used with frac. Default = 1 if frac = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with n.

replace : 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.

**Examples**

Generate an example Series and DataFrame:

```python
>>> s = pd.Series(np.random.randn(50))
```

```python
0   -0.038497
1    1.820773
2    -0.972766
3    -1.598270
4    -1.095526
dtype: float64
```

```python
>>> df = pd.DataFrame(np.random.randn(50, 4), columns=list('ABCD'))
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 0.016443</td>
<td>-2.318952</td>
<td>-0.566372</td>
<td>-1.028078</td>
</tr>
<tr>
<td>1 -1.051921</td>
<td>0.438836</td>
<td>0.658280</td>
<td>-0.175797</td>
</tr>
<tr>
<td>2 -1.243569</td>
<td>-0.364626</td>
<td>-0.215065</td>
<td>0.057736</td>
</tr>
<tr>
<td>3 1.768216</td>
<td>0.404512</td>
<td>-0.385604</td>
<td>-1.457834</td>
</tr>
<tr>
<td>4 1.072446</td>
<td>-1.137172</td>
<td>0.314194</td>
<td>-0.046661</td>
</tr>
</tbody>
</table>

dtype: float64

Next extract a random sample from both of these objects...

3 random elements from the Series:

```python
>>> s.sample(n=3)
```

```python
27  -0.994689
55  -1.049016
67  -0.224565
dtype: float64
```

And a random 10% of the DataFrame with replacement:

```python
>>> df.sample(frac=0.1, replace=True)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>35 1.981780</td>
<td>0.142106</td>
<td>1.817165</td>
<td>-0.290805</td>
</tr>
</tbody>
</table>
```

(continues on next page)
You can use random state for reproducibility:

```python
In [9]: df.sample(random_state=1)
Out[9]:
   A         B         C        D
37  3.027662  0.103611  0.237496 -0.165867
43  0.259323 -0.583426  1.516140 -0.479118
12 -1.686325 -0.579510  0.985195 -0.460286
  8  1.167946  0.429082  1.215742 -1.636041
  9  1.197475 -0.864188  1.554031 -1.505264
```

### pandas.DataFrame.select

`DataFrame.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Depreciated since version 0.21.0: Use `df.loc[df.index.map(crit)]` to select via labels

**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 the DataFrame's columns based on the column dtypes.

**Parameters**

- **include**, **exclude**: scalar or list-like
  - A selection of dtypes or strings to be included/excluded. At least one of these parameters must be supplied.

**Returns**

- **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.
Notes

- To select all numeric types, use np.number or 'number'
- To select strings you must use the object dtype, but note that this will return all object dtype columns
- See the numpy dtype hierarchy
- To select datetimes, use np.datetime64, 'datetime' or 'datetime64'
- To select timedeltas, use np.timedelta64, 'timedelta' or 'timedelta64'
- To select Pandas categorical dtypes, use 'category'
- To select Pandas datetimetz dtypes, use 'datetimetz' (new in 0.20.0) or 'datetime64[ns, tz]'

Examples

```python
>>> df = pd.DataFrame({'a': [1, 2] * 3,
...                     'b': [True, False] * 3,
...                     'c': [1.0, 2.0] * 3})

>>> df
   a  b  c
0  1  True  1.0
1  2  False  2.0
2  1  True  1.0
3  2  False  2.0
4  1  True  1.0
5  2  False  2.0

>>> df.select_dtypes(include='bool')
   b
0  True
1  False
2  True
3  False
4  True
5  False

>>> df.select_dtypes(include=['float64'])
   c
0  1.0
1  2.0
2  1.0
3  2.0
4  1.0
5  2.0

>>> df.select_dtypes(exclude=['int'])
   b  c
0  True  1.0
1  False  2.0
2  True  1.0
3  False  2.0
```

(continues on next page)
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
- **ddof** : int, default 1
  
  Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** : boolean, default None
  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

- **sem** [Series or DataFrame (if level specified)]

pandas.DataFrame.set_axis

DataFrame.set_axis (labels, axis=0, inplace=None)

Assign desired index to given axis.

Indexes for column or row labels can be changed by assigning a list-like or Index.

Changed in version 0.21.0: The signature is now labels and axis, consistent with the rest of pandas API. Previously, the axis and labels arguments were respectively the first and second positional arguments.

Parameters **labels** : list-like, Index

  The values for the new index.

  **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0

  The axis to update. The value 0 identifies the rows, and 1 identifies the columns.

  **inplace** : boolean, default None

  Whether to return a new %(klass)s instance.
Warning: `inplace=None` currently falls back to `True`, but in a future version, will default to `False`. Use `inplace=True` explicitly rather than relying on the default.

Returns renamed: `%s` or `None`

An object of same type as caller if `inplace=False`, `None` otherwise.

See also:

`pandas.DataFrame.rename_axis` Alter the name of the index or columns.

Examples

Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0  1
1  2
2  3
dtype: int64
```

```python
>>> s.set_axis(['a', 'b', 'c'], axis=0, inplace=False)
a  1
b  2
c  3
dtype: int64
```

The original object is not modified.

```python
>>> s
0  1
1  2
2  3
dtype: int64
```

DataFrame

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})
```

Change the row labels.

```python
>>> df.set_axis(['a', 'b', 'c'], axis='index', inplace=False)
   A  B
a  1  4
b  2  5
c  3  6
```

Change the column labels.

```python
>>> df.set_axis(['I', 'II'], axis='columns', inplace=False)
   I  II
0  1  4
```

(continues on next page)
Now, update the labels inplace.

```python
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
```

```
>>> df
  i  ii
0 1  4
1 2  5
2 3  6
```

**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
>>> df = pd.DataFrame({'month': [1, 4, 7, 10],
...                    'year': [2012, 2014, 2013, 2014],
...                    'sale':[55, 40, 84, 31]})
```

<table>
<thead>
<tr>
<th>month</th>
<th>sale</th>
<th>year</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>55</td>
<td>2012</td>
</tr>
<tr>
<td>1</td>
<td>40</td>
<td>2014</td>
</tr>
<tr>
<td>2</td>
<td>84</td>
<td>2013</td>
</tr>
<tr>
<td>3</td>
<td>31</td>
<td>2014</td>
</tr>
</tbody>
</table>

Set the index to become the ‘month’ column:
```python
>>> df.set_index('month')

<table>
<thead>
<tr>
<th>month</th>
<th>sale</th>
<th>year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>55</td>
<td>2012</td>
</tr>
<tr>
<td>4</td>
<td>40</td>
<td>2014</td>
</tr>
<tr>
<td>7</td>
<td>84</td>
<td>2013</td>
</tr>
<tr>
<td>10</td>
<td>31</td>
<td>2014</td>
</tr>
</tbody>
</table>

Create a multi-index using columns ‘year’ and ‘month’:

```python
>>> df.set_index(['year', 'month'])

<table>
<thead>
<tr>
<th>year</th>
<th>month</th>
<th>sale</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>1</td>
<td>55</td>
</tr>
<tr>
<td>2014</td>
<td>4</td>
<td>40</td>
</tr>
<tr>
<td>2013</td>
<td>7</td>
<td>84</td>
</tr>
<tr>
<td>2014</td>
<td>10</td>
<td>31</td>
</tr>
</tbody>
</table>

Create a multi-index using a set of values and a column:

```python
>>> df.set_index([[1, 2, 3, 4], 'year'])

<table>
<thead>
<tr>
<th>month</th>
<th>sale</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2012</td>
</tr>
<tr>
<td>2</td>
<td>2014</td>
</tr>
<tr>
<td>3</td>
<td>2013</td>
</tr>
<tr>
<td>4</td>
<td>2014</td>
</tr>
</tbody>
</table>

pandas.DataFrame.set_value

DataFrame.set_value(index, col, value, takeable=False)

Put single value at passed column and index

Deprecated since version 0.21.0: Use .at[] or .iat[] accessors instead.

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 the tseries module or time rule (e.g. ‘EOM’). See Notes.

axis : [0 or ‘index’, 1 or ‘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 when computing the result.

level : int or level name, default None
       If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None
       Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

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_index

**DataFrame.sort_index**

```python
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, default False
  - if True, perform operation in-place
- `kind` : {'quicksort', 'mergesort', 'heapsort'}, default 'quicksort'
  - Choice of sorting algorithm. See also `ndarray.np.sort` for more information.
  - `mergesort` is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.
- `na_position` : {'first', 'last'}, default 'last'
  - `first` puts NaNs at the beginning, `last` puts NaNs at the end. Not implemented for MultiIndex.
- `sort_remaining` : bool, default True
  - if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

**Returns**

- `sorted_obj` [DataFrame]

### pandas.DataFrame.sort_values

**DataFrame.sort_values**

```python
DataFrame.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

Sort by the values along either axis

**Parameters**

- `by` : str or list of str
  - Name or list of names to sort by.
  - • if `axis` is 0 or `index` then `by` may contain index levels and/or column labels
  - • if `axis` is 1 or `columns` then `by` may contain column levels and/or index labels

  Changed in version 0.23.0: Allow specifying index or column level names.
- `axis` : {0 or ‘index’, 1 or ‘columns’}, default 0
Axis to be sorted

**ascending**: bool or list of bool, default True

Sort ascending vs. descending. Specify list for multiple sort orders. If this is a list of bools, must match the length of the by.

**inplace**: bool, default False

If True, perform operation in-place

**kind**: {'quicksort', 'mergesort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See also ndarray.np.sort for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na_position**: {'first', 'last'}, default 'last'

*first* puts NaNs at the beginning, *last* puts NaNs at the end

**Returns**

*sorted_obj* [DataFrame]

**Examples**

```python
def df = pd.DataFrame({
  'col1': ['A', 'A', 'B', np.nan, 'D', 'C'],
  'col2': [2, 1, 9, 8, 7, 4],
  'col3': [0, 1, 9, 4, 2, 3],
})
def df
  col1  col2  col3
  0   A    2    0
  1   A    1    1
  2   B    9    9
  3  NaN   8    4
  4   D    7    2
  5   C    4    3

Sort by col1

```python
def.sort_values(by=['col1'])
col1  col2  col3
  0   A    2    0
  1   A    1    1
  2   B    9    9
  3  NaN   8    4
  4   D    7    2
  5   C    4    3
```
Sort Descending

```python
>>> df.sort_values(by='col1', ascending=False)
   col1  col2  col3
4    D    7    2
5    C    4    3
2    B    9    9
1    A    1    1
3  NaN    8    4
```

Putting NAs first

```python
>>> df.sort_values(by='col1', ascending=False, na_position='first')
   col1  col2  col3
3  NaN    8    4
4    D    7    2
5    C    4    3
2    B    9    9
1    A    1    1
```

### 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).

Deprecated since version 0.20.0: Use `DataFrame.sort_index()`

**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** *(axis=None)*
Squeeze length 1 dimensions.

**Parameters**

**axis** : None, integer or string axis name, optional
The axis to squeeze if 1-sized.

New in version 0.20.0.

**Returns**

scalar if 1-sized, else original object

pandas.DataFrame.stack

Dataframe . **stack** *(level=-1, dropna=True)*
Stack the prescribed level(s) from columns to index.

Return a reshaped DataFrame or Series having a multi-level index with one or more new inner-most levels compared to the current DataFrame. The new inner-most levels are created by pivoting the columns of the current dataframe:

- if the columns have a single level, the output is a Series;
- if the columns have multiple levels, the new index level(s) is (are) taken from the prescribed level(s) and the output is a DataFrame.

The new index levels are sorted.

**Parameters**

**level** : int, str, list, default -1
Level(s) to stack from the column axis onto the index axis, defined as one index or label, or a list of indices or labels.

**dropna** : bool, default True
Whether to drop rows in the resulting Frame/Series with missing values. Stacking a column level onto the index axis can create combinations of index and column values that are missing from the original dataframe. See Examples section.

**Returns**

DataFrame or Series
Stacked dataframe or series.

See also:

*DataFrame.unstack* Unstack prescribed level(s) from index axis onto column axis.

*DataFrame.pivot* Reshape dataframe from long format to wide format.

*DataFrame.pivot_table* Create a spreadsheet-style pivot table as a DataFrame.

**Notes**

The function is named by analogy with a collection of books being re-organised from being side by side on a horizontal position (the columns of the dataframe) to being stacked vertically on top of of each other (in the index of the dataframe).
Examples

Single level columns

```python
>>> df_single_level_cols = pd.DataFrame([[0, 1], [2, 3]],
              index=['cat', 'dog'],
              columns=['weight', 'height'])
Stacking a dataframe with a single level column axis returns a Series:

```python
>>> df_single_level_cols
   weight  height
  cat    0      1
  dog    2      3
``` 

```python
>>> df_single_level_cols.stack()
cat weight  0
           height 1
  dog weight  2
           height 3
dtype: int64
``` 

Multi level columns: simple case

```python
>>> multicoll = pd.MultiIndex.from_tuples([('weight', 'kg'),
                                          ('weight', 'pounds')])
>>> df_multi_level_cols1 = pd.DataFrame([[1, 2], [2, 4]],
                                     index=['cat', 'dog'],
                                     columns=multicoll)
Stacking a dataframe with a multi-level column axis:

```python
>>> df_multi_level_cols1
   weight
  cat kg  1
          pounds  2
  dog kg  2
          pounds  4
``` 

```python
>>> df_multi_level_cols1.stack()
weight
  cat kg  1
           pounds  2
  dog kg  2
           pounds  4
``` 

Missing values

```python
>>> multicoll2 = pd.MultiIndex.from_tuples([('weight', 'kg'),
                                           ('height', 'm')])
>>> df_multi_level_cols2 = pd.DataFrame([[1.0, 2.0], [3.0, 4.0]],
                                        index=['cat', 'dog'],
                                        columns=multicoll2)
It is common to have missing values when stacking a dataframe with multi-level columns, as the stacked
dataframe typically has more values than the original dataframe. Missing values are filled with NaNs:

```python
>>> df_multi_level_cols2
   weight  height
   kg    m
``` (continues on next page)
Prescribing the level(s) to be stacked

The first parameter controls which level or levels are stacked:

```python
>>> df_multi_level_cols2.stack()
   height  weight
cat kg    NaN  1.0
   m    2.0  NaN
dog kg    NaN  3.0
   m    4.0  NaN
```

Dropping missing values

```python
>>> df_multi_level_cols3 = pd.DataFrame([[None, 1.0], [2.0, 3.0]],
                                      index=['cat', 'dog'],
                                      columns=multicol2)

>>> df_multi_level_cols3.stack(dropna=False)
   height  weight
cat kg    NaN  NaN
   m  1.0  NaN
dog kg    NaN  2.0
   m  3.0  NaN

>>> df_multi_level_cols3.stack(dropna=True)
   height  weight
cat m  1.0  NaN
dog kg  NaN  2.0
   m  3.0  NaN
```

pandas.DataFrame.std

DataFrame.std (axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)

Return sample standard deviation over requested axis.
Normalized by N-1 by default. This can be changed using the ddof argument

**Parameters**

- **axis**: [{index (0), columns (1)}]
- **skipna**: 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
- **ddof**: int, default 1
  - Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only**: boolean, default None
  - Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **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
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level
- **fill_value**: None or float value, default None
  - Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

**Returns**

- **result**: [DataFrame]

**See also:**

- `DataFrame.rsub`
Notes

Mismatched indices will be unioned together

Examples

```python
>>> a = pd.DataFrame([2, 1, 1, np.nan], index=['a', 'b', 'c', 'd'], columns=['one'])
>>> a
    one
a  2.0
b  1.0
c  1.0
d  NaN

>>> b = pd.DataFrame(dict(one=[1, np.nan, 1, np.nan],
                         two=[3, 2, np.nan, 2]),
                         index=['a', 'b', 'd', 'e'])
>>> b
     one  two
a  1.0  3.0
b  NaN  2.0
d  1.0  NaN
e  NaN  2.0

>>> a.sub(b, fill_value=0)
   one  two
a -1.0 -3.0
b  1.0 -2.0
c  1.0  NaN
d -1.0  NaN
e  NaN -2.0
```

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
- **level** : int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level
- **fill_value** : None or float value, default None
  Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

Returns
result [DataFrame]

See also:

`DataFrame.rsub`

Notes

Mismatched indices will be unioned together

Examples

```python
>>> a = pd.DataFrame([2, 1, 1, np.nan], index=['a', 'b', 'c', 'd'],
                   columns=['one'])
>>> a
  one
  a  2.0
  b  1.0
  c  1.0
  d  NaN

>>> b = pd.DataFrame(dict(one=[1, np.nan, 1, np.nan],
                         two=[3, 2, np.nan, 2]),
                   index=['a', 'b', 'd', 'e'])
>>> b
   one two
  a  1.0  3.0
  b  NaN  2.0
  d  1.0  NaN
  e  NaN  2.0

>>> a.sub(b, fill_value=0)
   one  two
  a  1.0 -3.0
  b  1.0 -2.0
  c  1.0  NaN
  d -1.0  NaN
  e  NaN -2.0
```

`pandas.DataFrame.sum`

`DataFrame.sum(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **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 when computing the result.
- **level** : int or level name, default None
  - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
- **numeric_only** : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

`min_count` : int, default 0

The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

`Returns`

`sum` [Series or DataFrame (if level specified)]

`Examples`

By default, the sum of an empty or all-NA Series is 0.

```python
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you’d like the sum of an empty series to be NaN, pass `min_count=1`.

```python
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).sum()
0.0
```

```python
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

**pandas.DataFrame.swapaxes**

`DataFrame.swapaxes(axis1, axis2, copy=True)`

Interchange axes and swap values axes appropriately

`Returns`

`y` [same as input]

**pandas.DataFrame.swaplevel**

`DataFrame.swaplevel(i=-2, j=-1, axis=0)`

Swap levels i and j in a MultiIndex on a particular axis

`Parameters i, j` : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

`Returns`

`swapped` [type of caller (new object)]
.. versionchanged:: 0.18.1

The indexes $i$ and $j$ are now optional, and default to the two innermost levels of the index.

**pandas.DataFrame.tail**

DataFrame.tail($n=5$)

Return the last $n$ rows.

This function returns last $n$ rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

**Parameters**

$n$ : int, default 5

Number of rows to select.

**Returns**

The last $n$ rows of the caller object.

**See also:**

pandas.DataFrame.head The first $n$ rows of the caller object.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion', ...
... 'monkey', 'parrot', 'shark', 'whale', 'zebra']})

Viewing the last 5 lines

```python
>>> df.tail()
   animal
0  alligator
1       bee
2  falcon
3      lion
4    monkey
5    parrot
6     shark
7      whale
8     zebra
```

Viewing the last $n$ lines (three in this case)

```python
>>> df.tail(3)
   animal
0  alligator
1       bee
2  falcon
```

(continues on next page)
pandas.DataFrame.take

DataFrame.take(indices, axis=0, convert=None, is_copy=True, **kwargs)

Return the elements in the given positional indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

Parameters
indices : array-like
    An array of ints indicating which positions to take.
axis : {0 or ‘index’, 1 or ‘columns’, None}, default 0
    The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.
convert : bool, default True
    Whether to convert negative indices into positive ones. For example, -1 would map to the len(axis) - 1. The conversions are similar to the behavior of indexing a regular Python list.
    Deprecated since version 0.21.0: In the future, negative indices will always be converted.
is_copy : bool, default True
    Whether to return a copy of the original object or not.

**kwargs
    For compatibility with numpy.take(). Has no effect on the output.

Returns
taken : type of caller
    An array-like containing the elements taken from the object.

See also:

DataFrame.loc Select a subset of a DataFrame by labels.

DataFrame.iloc Select a subset of a DataFrame by positions.

numpy.take Take elements from an array along an axis.

Examples

>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
                      ('parrot', 'bird', 24.0),
                      ('lion', 'mammal', 80.5),
                      ('monkey', 'mammal', np.nan),
                     columns=['name', 'class', 'max_speed'],
                     index=[0, 2, 3, 1])
>>> df
Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That’s because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```python
df.take([0, 3])
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```python
df.take([1, 2], axis=1)
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```python
df.take([-1, -2])
```

### pandas.DataFrame.to_clipboard

`DataFrame.to_clipboard` *(excel=True, sep=None, **kwargs)*

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

**Parameters**

- `excel`: bool, default True
  - True, use the provided separator, writing in a csv format for allowing easy pasting into excel.
  - False, write a string representation of the object to the clipboard.

- `sep`: str, default '\t'
  - Field delimiter.

**kwargs**

These parameters will be passed to DataFrame.to_csv.

**See also:**

- `DataFrame.to_csv` Write a DataFrame to a comma-separated values (csv) file.
pandas: powerful Python data analysis toolkit, Release 0.23.1

read_clipboard Read text from clipboard and pass to read_table.
Notes
Requirements for your platform.
• Linux : xclip, or xsel (with gtk or PyQt4 modules)
• Windows : none
• OS X : none
Examples
Copy the contents of a DataFrame to the clipboard.
>>>
>>>
...
...
...
...

df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
df.to_clipboard(sep=',')
# Wrote the following to the system clipboard:
# ,A,B,C
# 0,1,2,3
# 1,4,5,6

We can omit the the index by passing the keyword index and setting it to false.
>>>
...
...
...
...

df.to_clipboard(sep=',', index=False)
# Wrote the following to the system clipboard:
# A,B,C
# 1,2,3
# 4,5,6

pandas.DataFrame.to_csv
DataFrame.to_csv(path_or_buf=None, sep=’, ’, na_rep=”, float_format=None, columns=None,
header=True, index=True, index_label=None, mode=’w’, encoding=None,
compression=None, quoting=None, quotechar=’"’, line_terminator=’\n’,
chunksize=None, tupleize_cols=None, date_format=None, doublequote=True,
escapechar=None, decimal=’.’)
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

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Columns to write

**header** : boolean or list of string, default True

Write out the column names. If a list of strings is given it is assumed to be aliases for the column names

**index** : 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

**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.

**compression** : string, optional

A string representing the compression to use in the output file. Allowed values are ‘gzip’, ‘bz2’, ‘zip’, ‘xz’. This input is only used when the first argument is a filename.

**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. If you have set a float_format then floats are converted to strings and thus csv.QUOTE_NONNUMERIC will treat them as non-numeric

**quotechar** : 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

Deprecated since version 0.21.0: This argument will be removed and will always write each row of the multi-index as a separate row in the CSV file.

Write MultiIndex columns as a list of tuples (if True) or in the new, expanded format, where each MultiIndex column is a row in the CSV (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

**pandas.DataFrame.to_dense**

```python
DataFrame.to_dense()
```

Return dense representation of NDFrame (as opposed to sparse)

**pandas.DataFrame.to_dict**

```python
DataFrame.to_dict(orient='dict', into=<class 'dict'>)
```

Convert the DataFrame to a dictionary.

The type of the key-value pairs can be customized with the parameters (see below).

**Parameters**

- `orient`: str {'dict', 'list', 'series', 'split', 'records', 'index'}

  Determines the type of the values of the dictionary.

  - 'dict' (default): dict like {column -> {index -> value}}
  - 'list': dict like {column -> [values]}
  - 'series': dict like {column -> Series(values)}
  - 'split': dict like {'index' -> [index], 'columns' -> [columns], 'data' -> [values]}
  - 'records': list like [{column -> value}, . . . , {column -> value}]
  - 'index': dict like {index -> {column -> value}}

  Abbreviations are allowed. s indicates `series` and sp indicates `split`.

- `into`: class, default dict

  The collections.Mapping subclass used for all Mappings in the return value. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

  New in version 0.21.0.

**Returns**

- `result` [collections.Mapping like {column -> {index -> value}}]

**See also:**

- `DataFrame.from_dict` create a DataFrame from a dictionary
- `DataFrame.to_json` convert a DataFrame to JSON format

**Examples**
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```python
>>> df = pd.DataFrame({'col1': [1, 2],
...                    'col2': [0.5, 0.75]})
>>> df
     col1  col2
a    1.00  0.50
b    2.00  0.75
```

You can specify the return orientation.

```python
>>> df.to_dict('series')
{'col1': a 1
   b 2
   Name: col1, dtype: int64,
'col2': a 0.50
   b 0.75
   Name: col2, dtype: float64}
```

```python
>>> df.to_dict('split')
{'index': ['a', 'b'], 'columns': ['col1', 'col2'],
 'data': [[1.0, 0.5], [2.0, 0.75]]}
```

```python
>>> df.to_dict('records')
[{'col1': 1.0, 'col2': 0.5}, {'col1': 2.0, 'col2': 0.75}]
```

You can also specify the mapping type.

```python
>>> from collections import OrderedDict, defaultdict
>>> df.to_dict(into=OrderedDict)
OrderedDict([('col1', OrderedDict([('a', 1), ('b', 2)])), ('col2', OrderedDict([('a', 0.5), ('b', 0.75)]))]
```

If you want a `defaultdict`, you need to initialize it:

```python
>>> dd = defaultdict(list)
>>> df.to_dict('records', into=dd)
[defaultdict(<class 'list'>, {'col1': 1.0, 'col2': 0.5}),
  defaultdict(<class 'list'>, {'col1': 2.0, 'col2': 0.75})]
```

### pandas.DataFrame.to_excel

DataFrame.to_excel(excel_writer, sheet_name='Sheet1', na_rep=None, float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True, freeze_panes=None)

Write DataFrame to an 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 the column names. If a list of strings 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)

freeze_panes : tuple of integer (length 2), default None

Specifies the one-based bottommost row and rightmost column that is to be frozen

New in version 0.20.0.

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:
For compatibility with to_csv, to_excel serializes lists and dicts to strings before writing.

**pandas.DataFrame.to_feather**

DataFrame.to_feather (fname)
write out the binary feather-format for DataFrames
New in version 0.20.0.

Parameters fname : str
  string file path

**pandas.DataFrame.to_gbq**

DataFrame.to_gbq (destination_table, project_id, chunksize=None, verbose=None, reauth=False, if_exists='fail', private_key=None, auth_local_webserver=False, table_schema=None)
Write a DataFrame to a Google BigQuery table.
This function requires the pandas-gbq package.
Authentication to the Google BigQuery service is via OAuth 2.0.

- If private_key is provided, the library loads the JSON service account credentials and uses those to authenticate.
- If no private_key is provided, the library tries application default credentials.
- If application default credentials are not found or cannot be used with BigQuery, the library authenticates with user account credentials. In this case, you will be asked to grant permissions for product name ‘pandas GBQ’.

Parameters destination_table : str
  Name of table to be written, in the form ‘dataset.tablename’.

  project_id : str
    Google BigQuery Account project ID.

  chunksize : int, optional
    Number of rows to be inserted in each chunk from the dataframe. Set to None to load the whole dataframe at once.

  reauth : bool, default False
    Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

  if_exists : str, default ‘fail’
    Behavior when the destination table exists. Value can be one of:
    'fail' If table exists, do nothing.
'replace' If table exists, drop it, recreate it, and insert data.

'append' If table exists, insert data. Create if does not exist.

**private_key** : str, optional

Service account private key in JSON format. Can be file path or string contents. This is useful for remote server authentication (e.g., Jupyter/IPython notebook on remote host).

**auth_local_webserver** : bool, default False

Use the local webserver flow instead of the console flow when getting user credentials.

*New in version 0.2.0 of pandas-gbq.*

**table_schema** : list of dicts, optional

List of BigQuery table fields to which according DataFrame columns conform to, e.g. [{'name': 'col1', 'type': 'STRING'}, ...]. If schema is not provided, it will be generated according to dtypes of DataFrame columns. See BigQuery API documentation on available names of a field.

*New in version 0.3.1 of pandas-gbq.*

**verbose** : boolean, deprecated

*Deprecated in Pandas-GBQ 0.4.0.* Use the logging module to adjust verbosity instead.

See also:

- **pandas_gbq.to_gbq** This function in the pandas-gbq library.
- **pandas.read_gbq** Read a DataFrame from Google BigQuery.

**pandas.DataFrame.to_hdf**

**DataFrame.to_hdf**(path_or_buf, key, **kwargs)

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the user guide.

**Parameters**

- **path_or_buf** : str or pandas.HDFStore

  File path or HDFStore object.

- **key** : str

  Identifier for the group in the store.

- **mode** : {'a', 'w', 'r+'}, default 'a'

  Mode to open file:
• ‘w’: write, a new file is created (an existing file with the same name would be deleted).
• ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
• ‘r+’: similar to ‘a’, but the file must already exist.

**format**: {'fixed', 'table'}, default ‘fixed’

Possible values:
• ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

**append**: bool, default False

For Table formats, append the input data to the existing.

**data_columns**: list of columns or True, optional

List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See *Query via Data Columns*. Applicable only to format='table'.

**complevel**: {0-9}, optional

Specifies a compression level for data. A value of 0 disables compression.

**complib**: {'zlib', ‘lz4’, ‘bzip2’, ‘blosc’}, default ‘zlib’

Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {‘blosc:blosclz’, ‘blosc:lz4’, ‘blosc:lz4hc’, ‘blosc:snappy’, ‘blosc:zlib’, ‘blosc:zstd’}. Specifying a compression library which is not available issues a ValueError.

**fletcher32**: bool, default False

If applying compression use the fletcher32 checksum.

**dropna**: bool, default False

If true, ALL nan rows will not be written to store.

**errors**: str, default ‘strict’

Specifies how encoding and decoding errors are to be handled. See the errors argument for *open()* for a full list of options.

**See also:**

*DataFrame.read_hdf*  Read from HDF file.

*DataFrame.to_parquet*  Write a DataFrame to the binary parquet format.

*DataFrame.to_sql*  Write to a sql table.

*DataFrame.to_feather*  Write out feather-format for DataFrames.

*DataFrame.to_csv*  Write out to a csv file.
Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
    index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```python
>>> pd.read_hdf('data.h5', 'df')
A  B
a 1  4
b 2  5
c 3  6
```

```python
>>> pd.read_hdf('data.h5', 's')
0 1
1 2
2 3
3 4
dtype: int64
```

Deleting file with data:

```python
>>> import os
>>> os.remove('data.h5')
```

**pandas.DataFrame.to_html**

DataFrame.to_html(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, bold_rows=True, classes=None, escape=True, max_rows=None, max_cols=None, show_dimensions=False, notebook=False, decimal='.', border=None, table_id=None)

Render a DataFrame as an HTML table.

- **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.
- **decimal** [string, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe
  - New in version 0.18.0.
- **border** [int] A border=border attribute is included in the opening <table> tag. Default pd.options.html.border.
  - New in version 0.19.0.
table_id  [str, optional] A css id is included in the opening <table> tag if specified.

New in version 0.23.0.

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  

line_width : int, optional  

Width to wrap a line in characters, default no wrap  

table_id : str, optional  

id for the <table> element create by to_html  

New in version 0.23.0.  

justify : str, default None  

How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box. Valid values are  

• left  

• right  

• center
pandas.DataFrame.to_json

Convert the object to a JSON string.

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=None, double_precision=10, force_ascii=True, date_unit='ms', default_handler=None, lines=False, compression=None, index=True)

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 : string or file handle, optional
File path or object. If not specified, the result is returned as a string.

orient : string
Indication of expected JSON string format.

• 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
  – ‘table’ : dict like {'schema': {schema}, 'data': {data}} describing the data, and the data component is like orient='records'.

Changed in version 0.20.0.
**date_format** : {None, ‘epoch’, ‘iso’}

Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the *orient*. For *orient*='table', the default is ‘iso’. For all other orients, the default is ‘epoch’.

**double_precision** : int, default 10

The number of decimal places to use when encoding floating point values.

**force_ascii** : boolean, default True

Force encoded string to be ASCII.

**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.

**lines** : boolean, default False

If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

New in version 0.19.0.


A string representing the compression to use in the output file, only used when the first argument is a filename.

New in version 0.21.0.

**index** : boolean, default True

Whether to include the index values in the JSON string. Not including the index (index=False) is only supported when orient is ‘split’ or ‘table’.

New in version 0.23.0.

See also:

*pandas.read_json*

### Examples

```python
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                   index=['row 1', 'row 2'],
...                   columns=['col 1', 'col 2'])

>>> df.to_json(orient='split')
'{"columns": ["col 1", "col 2"],
  "index": ["row 1", "row 2"],
  "data": [["a", "b"], ["c", "d"]]}'
```

Encoding/decoding a Dataframe using ‘records’ formatted JSON. Note that index labels are not preserved with this encoding.
pandas: powerful Python data analysis toolkit, Release 0.23.1

>>> df.to_json(orient='records')
'[{"col 1":"a","col 2":"b"},{"col 1":"c","col 2":"d"}]'

Encoding/decoding a Dataframe using 'index' formatted JSON:
>>> df.to_json(orient='index')
'{"row 1":{"col 1":"a","col 2":"b"},"row 2":{"col 1":"c","col 2":"d"}}'

Encoding/decoding a Dataframe using 'columns' formatted JSON:
>>> df.to_json(orient='columns')
'{"col 1":{"row 1":"a","row 2":"c"},"col 2":{"row 1":"b","row 2":"d"}}'

Encoding/decoding a Dataframe using 'values' formatted JSON:
>>> df.to_json(orient='values')
'[["a","b"],["c","d"]]'

Encoding with Table Schema
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"},
{"name": "col 1", "type": "string"},
{"name": "col 2", "type": "string"}],
"primaryKey": "index",
"pandas_version": "0.20.0"},
"data": [{"index": "row 1", "col 1": "a", "col 2": "b"},
{"index": "row 2", "col 1": "c", "col 2": "d"}]}'

pandas.DataFrame.to_latex
DataFrame.to_latex(buf=None,
columns=None,
col_space=None,
header=True,
index=True, na_rep=’NaN’, formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=False, column_format=None,
longtable=None, escape=None, encoding=None, decimal=’.’, multicolumn=None, multicolumn_format=None, multirow=None)
Render an object to a tabular environment table. You can splice this into a LaTeX document. Requires
\usepackage{booktabs}.
Changed in version 0.20.2: Added to Series
to_latex-specific options:
bold_rows [boolean, default False] 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 will be read from the pandas config module] Default: False. Use a longtable
environment instead of tabular. Requires adding a \usepackage{longtable} to your LaTeX preamble.
escape [boolean, default will be read from the pandas config module] Default: True. When set to False
prevents from escaping latex special characters in column names.
encoding [str, default None] A string representing the encoding to use in the output file, defaults to ‘ascii’
on Python 2 and ‘utf-8’ on Python 3.

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decimal [string, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

New in version 0.18.0.

multicolumn [boolean, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

New in version 0.20.0.

multicolumn_format [str, default ‘l’] The alignment for multicolumns, similar to column_format. The default will be read from the config module.

New in version 0.20.0.

multirow [boolean, default False] Use multirow to enhance MultiIndex rows. Requires adding a \usepackage{multirow} to your LaTeX preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

New in version 0.20.0.

pandas.DataFrame.to_msgpack

DataFrame.to_msgpack(path_or_buf=None, encoding='utf-8', **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.

Deprecated since version 0.20.0.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns

- panel [Panel]

pandas.DataFrame.to_parquet

DataFrame.to_parquet(fname, engine='auto', compression='snappy', **kwargs)

Write a DataFrame to the binary parquet format.

New in version 0.21.0.
This function writes the dataframe as a parquet file. You can choose different parquet backends, and have the option of compression. See the user guide for more details.

**Parameters**

- **fname** : str
  
  String file path.

- **engine** : {'auto', 'pyarrow', 'fastparquet'}, default 'auto'
  
  Parquet library to use. If 'auto', then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try 'pyarrow', falling back to 'fastparquet' if 'pyarrow' is unavailable.

- **compression** : {'snappy', 'gzip', 'brotli', None}, default 'snappy'
  
  Name of the compression to use. Use None for no compression.

- **kwargs**
  
  Additional arguments passed to the parquet library. See pandas io for more details.

**See also:**

- `read_parquet` Read a parquet file.
- `DataFrame.to_csv` Write a csv file.
- `DataFrame.to_sql` Write to a sql table.
- `DataFrame.to_hdf` Write to hdf.

**Notes**

This function requires either the fastparquet or pyarrow library.

**Examples**

```python
>>> df = pd.DataFrame(data={'col1': [1, 2], 'col2': [3, 4]})
>>> df.to_parquet('df.parquet.gzip', compression='gzip')
>>> pd.read_parquet('df.parquet.gz')
<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
```

**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]
  
  The frequency.

- **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, compression='infer', protocol=4)

Pickle (serialize) object to file.

Parameters

path : str

File path where the pickled object will be stored.

compression : {'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'

A string representing the compression to use in the output file. By default, infers from the file extension in specified path.

New in version 0.20.0.

protocol : int

Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [R15] paragraph 12.1.2). The possible values for this parameter depend on the version of Python. For Python 2.x, possible values are 0, 1, 2. For Python >= 3.0, 3 is a valid value. For Python >= 3.4, 4 is a valid value. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

New in version 0.21.0.

See also:

read_pickle  Load pickled pandas object (or any object) from file.

DataFrame.to_hdf  Write DataFrame to an HDF5 file.

DataFrame.to_sql  Write DataFrame to a SQL database.

DataFrame.to_parquet  Write a DataFrame to the binary parquet format.

Examples

```python
>>> original_df = pd.DataFrame({'foo': range(5), 'bar': range(5, 10)})
>>> original_df
   foo  bar
0   0    5
1   1    6
2   2    7
3   3    8
4   4    9
>>> original_df.to_pickle('./dummy.pkl')
```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9

>>> import os
>>> os.remove("./dummy.pkl")

pandas.DataFrame.to_records

DataFrame.to_records(index=True, convert_datetime64=None)
Convert DataFrame to a NumPy 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 None
  Deprecated since version 0.23.0.
  Whether to convert the index to datetime.datetime if it is a DatetimeIndex.

Returns

- **y** [numpy.recarray]

See also:

- **DataFrame.from_records** convert structured or record ndarray to DataFrame.
- **numpy.recarray** ndarray that allows field access using attributes, analogous to typed columns in a spreadsheet.

Examples

```python
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0.5, 0.75]},
                    index=['a', 'b'])
>>> df
   A  B
a 1  0.5
b 2  0.75
```

The index can be excluded from the record array:

```python
>>> df.to_records(index=False)
rec.array([(1, 0.5), (2, 0.75)],
          dtype=[('A', '<i8'), ('B', '<f8')])
```
By default, timestamps are converted to `datetime.datetime`:

```python
>>> df.index = pd.date_range('2018-01-01 09:00', periods=2, freq='min')
>>> df
      A     B
2018-01-01 09:00:00 1 0.50
2018-01-01 09:01:00 2 0.75
```

```python
>>> df.to_records()
rec.array([(datetime.datetime(2018, 1, 1, 9, 0), 1, 0.5 ),
           (datetime.datetime(2018, 1, 1, 9, 1), 2, 0.75)],
          dtype=[('index', 'O'), ('A', '<i8'), ('B', '<f8')])
```

The timestamp conversion can be disabled so NumPy’s `datetime64` data type is used instead:

```python
>>> df.to_records(convert_datetime64=False)
rec.array([('2018-01-01T09:00:00.000000000', 1, 0.5 ),
           ('2018-01-01T09:01:00.000000000', 2, 0.75)],
          dtype=[('index', '<M8[ns]'), ('A', '<i8'), ('B', '<f8')])
```

**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_stata**

Dataframe.to_stata(fname, convert_dates=None, write_index=True, encoding='latin-1', byte-order=None, time_stamp=None, data_label=None, variable_labels=None, version=114, convert_strl=None)

Export Stata binary dta files.

**Parameters**

- fname : path (string), buffer or path object
  - string, path object (pathlib.Path or py._path.local.LocalPath) or object implementing a binary write() functions. If using a buffer then the buffer will not be automatically closed after the file data has been written.
- convert_dates : dict
  - Dictionary mapping columns containing datetime types to stata internal format to use when writing the dates. Options are ‘tc’, ‘td’, ‘tm’, ‘tw’, ‘th’, ‘tq’, ‘ty’. Column can be either an integer or a name. Datetime columns that do not have a conversion type specified will be converted to ‘tc’. Raises NotImplemetnedError if a datetime column has timezone information.
- write_index : bool
  - Write the index to Stata dataset.
encoding : str
    Default is latin-1. Unicode is not supported.

byteorder : str
    Can be “>”, “<”, “little”, or “big”. default is sys.byteorder.

time_stamp : datetime
    A datetime to use as file creation date. Default is the current time.

data_label : str
    A label for the data set. Must be 80 characters or smaller.

variable_labels : dict
    Dictionary containing columns as keys and variable labels as values. Each label
    must be 80 characters or smaller.

    New in version 0.19.0.

version : {114, 117}
    Version to use in the output dta file. Version 114 can be used read by Stata 10
    and later. Version 117 can be read by Stata 13 or later. Version 114 limits string
    variables to 244 characters or fewer while 117 allows strings with lengths up to
    2,000,000 characters.

    New in version 0.23.0.

convert_strl : list, optional
    List of column names to convert to string columns to Stata StrL format. Only
    available if version is 117. Storing strings in the StrL format can produce smaller
    dta files if strings have more than 8 characters and values are repeated.

    New in version 0.23.0.

Raises NotImplementedError
    • If datetimes contain timezone information
    • Column dtype is not representable in Stata

ValueError
    • Columns listed in convert_dates are neither datetime64[ns] or date-
      time.datetime
    • Column listed in convert_dates is not in DataFrame
    • Categorical label contains more than 32,000 characters

    New in version 0.19.0.

See also:

pandas.read_stata  Import Stata data files

pandas.io.stata.StataWriter  low-level writer for Stata data files

pandas.io.stata.StataWriter117  low-level writer for version 117 files
Examples

```python
>>> data.to_stata('./data_file.dta')
```

Or with dates

```python
>>> data.to_stata('./date_data_file.dta', {2 : 'tw'})
```

Alternatively you can create an instance of the StataWriter class

```python
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

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
  - Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names
- **index**: bool, optional
  - 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.
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**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

**line_width** : int, optional

Width to wrap a line in characters, default no wrap

**table_id** : str, optional

id for the `<table>` element create by to_html

New in version 0.23.0.

**justify** : str, default None

How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial
- unset

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_xarray

**DataFrame.to_xarray()**

Return an xarray object from the pandas object.

**Returns**

- a DataArray for a Series
- a Dataset for a DataFrame
- a DataArray for higher dims

**Notes**

See the xarray docs

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 1, 2], 'B': ['foo', 'bar', 'foo'], 'C': np.arange(4., 7)})

>>> df
  A B  C
0 1 foo 4.0
1 1 bar 5.0
2 2 foo 6.0

>>> df.to_xarray()
<xarray.Dataset>
Dimensions: (index: 3)
Coordinates:
  * index (index) int64 0 1 2
Data variables:
  A (index) int64 1 1 2
  B (index) object 'foo' 'bar' 'foo'
  C (index) float64 4.0 5.0 6.0

>>> df = pd.DataFrame({'A': [1, 1, 2], 'B': ['foo', 'bar', 'foo'], 'C': np.arange(4., 7)})

>>> df.set_index(['B','A'])

>>> df
  A B  C
foo 1 4.0
bar 1 5.0
foo 2 6.0
```
>>> df.to_xarray()
<xarray.Dataset>
Dimensions: (A: 2, B: 2)
Coordinates:
  * B (B) object 'bar' 'foo'
  * A (A) int64 1 2
Data variables:
  C (B, A) float64 5.0 nan 4.0 6.0

>>> p = pd.Panel(np.arange(24).reshape(4,3,2),
               items=list('ABCD'),
               major_axis=pd.date_range('20130101', periods=3),
               minor_axis=['first', 'second'])

>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: A to D
Major_axis axis: 2013-01-01 00:00:00 to 2013-01-03 00:00:00
Minor_axis axis: first to second

>>> p.to_xarray()
<xarray.DataArray (items: 4, major_axis: 3, minor_axis: 2)>
array([[[ 0,  1],
       [ 2,  3],
       [ 4,  5]],
       [[ 6,  7],
       [ 8,  9],
       [10, 11]],
       [[12, 13],
       [14, 15],
       [16, 17]],
       [[18, 19],
       [20, 21],
       [22, 23]])
Coordinates:
  * items (items) object 'A' 'B' 'C' 'D'
  * major_axis (major_axis) datetime64[ns] 2013-01-01 2013-01-02 2013-01-03
  * minor_axis (minor_axis) object 'first' 'second'

pandas.DataFrame.transform

DataFrame.transform(func, *args, **kwargs)
Call function producing a like-indexed NDFrame and return a NDFrame with the transformed values
New in version 0.20.0.

Parameters func : callable, string, dictionary, or list of string/callables
  To apply to column
  Accepted Combinations are:
  • string function name
  • function
  • list of functions
• dict of column names -> functions (or list of functions)

Returns

transformed [NDFrame]

See also:
pandas.NDFrame.aggregate, pandas.NDFrame.apply

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
                    index=pd.date_range('1/1/2000', periods=10))
>>> df.iloc[3:7] = np.nan

>>> df.transform(lambda x: (x - x.mean()) / x.std())
    A         B         C
2000-01-01  0.579457  1.236184  0.123424
2000-01-02  0.370357 -0.605875 -1.231325
2000-01-03  1.455756 -0.277446  0.288967
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 -0.498658  1.274522  1.642524
2000-01-09 -0.540524 -1.012676 -0.828968
2000-01-10 -1.366388 -0.614710  0.005378
```

pandas.DataFrame.transpose

DataFrame.transpose(*args, **kwargs)

Transpose index and columns.

Reflect the DataFrame over its main diagonal by writing rows as columns and vice-versa. The property $T$ is an accessor to the method `transpose()`.

Parameters

copy : bool, default False

If True, the underlying data is copied. Otherwise (default), no copy is made if possible.

*args, **kwargs

Additional keywords have no effect but might be accepted for compatibility with numpy.

Returns

DataFrame

The transposed DataFrame.

See also:

numpy.transpose  Permute the dimensions of a given array.
Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the `object` dtype. In such a case, a copy of the data is always made.

Examples

Square DataFrame with homogeneous dtype

```python
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
  col1  col2
0    1    3
1    2    4

>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
   0  1
col1 1 2
col2 3 4
```

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```python
>>> df1.dtypes
col1 int64
col2 int64
dtype: object

>>> df1_transposed.dtypes
0 int64
1 int64
dtype: object
```

Non-square DataFrame with mixed dtypes

```python
>>> d2 = {'name': ['Alice', 'Bob'], 'score': [9.5, 8], 'employed': [False, True], 'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
    name  score  employed  kids
0    Alice  9.5    False     0
1      Bob  8.0     True     0

>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
   0   1
name Alice Bob
score  9.5  8
employed False True
kids    0    0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the `object` dtype:
```python
>>> df2.dtypes
name  object
score  float64
employed  bool
kids   int64
dtype: object

>>> df2_transposed.dtypes
0  object
1  object
dtype: object
```

**pandas.DataFrame.truediv**

Dataframe.truediv(other, axis='columns', level=None, fill_value=None)
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
- **level**  int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level
- **fill_value**  : None or float value, default None
  - Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing

**Returns**
- **result**  [DataFrame]

**See also:**
- DataFrame.rtruediv

**Notes**

Mismatched indices will be unioned together

**Examples**

None
pandas.DataFrame.truncate

DataFrame.truncate(before=None, after=None, axis=None, copy=True)

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

**Parameters**

- **before**: date, string, int
  - Truncate all rows before this index value.

- **after**: date, string, int
  - Truncate all rows after this index value.

- **axis**: {0 or 'index', 1 or 'columns'}, optional
  - Axis to truncate. Truncates the index (rows) by default.

- **copy**: boolean, default is True,
  - Return a copy of the truncated section.

**Returns**

The truncated Series or DataFrame.

**See also:**

- **DataFrame.loc** Select a subset of a DataFrame by label.
- **DataFrame.iloc** Select a subset of a DataFrame by position.

**Notes**

If the index being truncated contains only datetime values, *before* and *after* may be specified as strings instead of Timestamps.

**Examples**

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                    'B': ['f', 'g', 'h', 'i', 'j'],
...                    'C': ['k', 'l', 'm', 'n', 'o'],
...                   'index':[1, 2, 3, 4, 5])
>>> df
   A  B  C
0  a  f  k
1  b  g  l
2  c  h  m
3  d  i  n
4  e  j  o
```

```python
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
```

The columns of a DataFrame can be truncated.
```python
>>> df.truncate(before="A", after="B", axis="columns")
   A   B
1  a  f
2  b  g
3  c  h
4  d  i
5  e  j
```

For Series, only rows can be truncated.

```python
>>> df["A"].truncate(before=2, after=4)
2  b
3  c
4  d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```python
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={"A": 1})
>>> df.tail()
          A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01  00:00:00  1
```

```python
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
               after=pd.Timestamp('2016-01-10')).tail()
          A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10  00:00:00  1
```

Because the index is a DatetimeIndex containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```python
>>> df.truncate('2016-01-05', '2016-01-10').tail()
          A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10  00:00:00  1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```python
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
          A
2016-01-10 23:59:55  1
2016-01-10 23:59:56  1
2016-01-10 23:59:57  1
```

(continues on next page)
pandas.DataFrame.tshift

DataFrame.tshift \( (\text{periods}=1, \text{freq}=None, \text{axis}=0) \)
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 the tseries 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 \( (\text{tz}, \text{axis}=0, \text{level}=None, \text{copy}=True) \)
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 \( (\text{tz}, \text{axis}=0, \text{level}=None, \text{copy}=True, \text{ambiguous}=\text{’raise’}) \)
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

Raises TypeError
    If the TimeSeries is tz-aware and tz is not None.

pandas.DataFrame.unstack

DataFrame.unstack(level=-1, fill_value=None)
    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
fill_value : replace NaN with this value if the unstack produces missing values
    New in version 0.18.0.

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
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'), ...
    ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one a 1.0
  b 2.0
two a 3.0
  b 4.0
dtype: float64

>>> s.unstack(level=-1)
   a  b
one 1.0 2.0
two 3.0 4.0

>>> s.unstack(level=0)
   one two
   a 1.0 3.0
   b 2.0 4.0

>>> df = s.unstack(level=0)
>>> df.unstack()
   one a 1.0
       b 2.0
two a 3.0
       b 4.0
dtype: float64

**pandas.DataFrame.update**

`DataFrame.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)`

Modify in place using non-NA values from another DataFrame.

Aligns on indices. There is no return value.

**Parameters**

- **other**: DataFrame, or object coercible into a DataFrame
  
  Should have at least one matching index/column label with the original DataFrame. If a Series is passed, its name attribute must be set, and that will be used as the column name to align with the original DataFrame.

- **join**: {'left'}, default ‘left’
  
  Only left join is implemented, keeping the index and columns of the original object.

- **overwrite**: bool, default True
  
  How to handle non-NA values for overlapping keys:

  - True: overwrite original DataFrame’s values with values from `other`.
  - False: only update values that are NA in the original DataFrame.

- **filter_func**: callable(1d-array) -> boolean 1d-array, optional
  
  Can choose to replace values other than NA. Return True for values that should be updated.
raise_conflict : bool, default False
If True, will raise a ValueError if the DataFrame and other both contain non-NA data in the same place.

Raises ValueError
When raise_conflict is True and there’s overlapping non-NA data.

See also:

dict.update  Similar method for dictionaries.

DataFrame.merge  For column(s)-on-column(s) operations.

Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3],
... 'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, 5, 6],
... 'C': [7, 8, 9]})
>>> df.update(new_df)
>>> df
   A  B
0  1  4
1  2  5
2  3  6
```

The DataFrame’s length does not increase as a result of the update, only values at matching index/column labels are updated.

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
... 'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e', 'f', 'g', 'h', 'i']})
>>> df.update(new_df)
>>> df
   A  B
0  a  d
1  b  e
2  c  f
```

For Series, it’s name attribute must be set.

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
... 'B': ['x', 'y', 'z']})
>>> new_column = pd.Series(['d', 'e'], name='B', index=[0, 2])
>>> df.update(new_column)
>>> df
   A  B
0  a  d
1  b  y
2  c  e
```

(continues on next page)
If `other` contains NaNs the corresponding values are not updated in the original dataframe.

```python
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                    'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, np.nan, 6]})
>>> df.update(new_df)
>>> df
   A    B
0  1  4.0
1  2 500.0
2  3  6.0
```

**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

- **ddof** : int, default 1

  Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

- **numeric_only** : boolean, default None

  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns:

- **var** [Series or DataFrame (if level specified)]

**pandas.DataFrame.where**

DataFrame.where (cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)  
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, array-like, or callable
Where \textit{cond} is True, keep the original value. Where False, replace with corresponding value from \textit{other}. If \textit{cond} is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as \textit{cond}.

\textbf{other :} scalar, NDFrame, or callable

Entries where \textit{cond} is False are replaced with corresponding value from \textit{other}. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as \textit{other}.

\textbf{inplace :} boolean, default False

Whether to perform the operation in place on the data

\textbf{axis :} [alignment axis if needed, default None]

\textbf{level :} [alignment level if needed, default None]

\textbf{errors :} str, \{‘raise’, ‘ignore’\}, default ‘raise’

- \textbf{raise :} allow exceptions to be raised
- \textbf{ignore :} suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

\textbf{try\_cast :} boolean, default False

try to cast the result back to the input type (if possible),

\textbf{raise\_on\_error :} boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Deprecated since version 0.21.0.

\textbf{Returns}

\textbf{wh} [same type as caller]

\textbf{See also:}

\textit{DataFrame.mask()}

\textbf{Notes}

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if \textit{cond} is True the element is used; otherwise the corresponding element from the DataFrame \textit{other} is used.

The signature for \textit{DataFrame.where()} differs from \textit{numpy.where()}. Roughly \textit{df1.where(m, df2)} is equivalent to \textit{np.where(m, df1, df2)}.

For further details and examples see the \textit{where} documentation in \textit{indexing}. 

---

1936 Chapter 34. API Reference
Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1     1.0
2     2.0
3     3.0
4     4.0

>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN

>>> s.where(s > 1, 10)
0    10.0
1    10.0
2     2.0
3     3.0
4     4.0

>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0 -1  0
1  3  1
2 -5  2
3 -7  3
4 -9  4

>>> df.where(m, -df) == np.where(m, df, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True

>>> df.where(m, -df) == df.mask(~m, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True
```

`pandas.DataFrame.xs`

**DataFrame.xs**(key, axis=0, level=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.

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 function-
ality, 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
a 4
   B
b 5
   C
c 2
Name: a

>>> df.xs('C', axis=1)
   a
   B
   2
   b
   9
   c
   3
Name: C

>>> df
   A  B  C  D
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)
   A  B  C  D
```

(continues on next page)
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

34.4.2 Attributes and underlying data

Axes

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.index</code></td>
<td>The index (row labels) of the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.columns</code></td>
<td>The column labels of the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.dtypes</code></td>
<td>Return the dtypes in the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.ftypes</code></td>
<td>Return the ftypes (indication of sparse/dense and dtype) in DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.get_dtypes()</code></td>
<td>Return counts of unique dtypes in this object.</td>
</tr>
<tr>
<td><code>DataFrame.get_ftypes()</code></td>
<td>(DEPRECATED) Return counts of unique ftypes in this object.</td>
</tr>
<tr>
<td><code>DataFrame.select_dtypes(include, exclude)</code></td>
<td>Return a subset of the DataFrame’s columns based on the column dtypes.</td>
</tr>
<tr>
<td><code>DataFrame.values</code></td>
<td>Return a Numpy representation of the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.get_values()</code></td>
<td>Return an ndarray after converting sparse values to dense.</td>
</tr>
<tr>
<td><code>DataFrame.axes</code></td>
<td>Return a list representing the axes of the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.ndim</code></td>
<td>Return an int representing the number of axes / array dimensions.</td>
</tr>
<tr>
<td><code>DataFrame.size</code></td>
<td>Return an int representing the number of elements in this object.</td>
</tr>
<tr>
<td><code>DataFrame.shape</code></td>
<td>Return a tuple representing the dimensionality of the DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.memory_usage(index, deep)</code></td>
<td>Return the memory usage of each column in bytes.</td>
</tr>
<tr>
<td><code>DataFrame.empty</code></td>
<td>Indicator whether DataFrame is empty.</td>
</tr>
<tr>
<td><code>DataFrame.is_copy</code></td>
<td></td>
</tr>
</tbody>
</table>

34.4.2.1 pandas.DataFrame.is_copy

`DataFrame.is_copy`

34.4.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.astype(dtype[, copy, errors])</code></td>
<td>Cast a pandas object to a specified dtype <code>dtype</code>.</td>
</tr>
<tr>
<td><code>DataFrame.convert_objects([convert_dates, ...])</code></td>
<td>(DEPRECATED) Attempt to infer better dtype for object columns.</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.infer_objects()</td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td>DataFrame.copy([deep])</td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td>DataFrame.isna()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td>DataFrame.notna()</td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td>DataFrame.bool()</td>
<td>Return the bool of a single element PandasObject.</td>
</tr>
</tbody>
</table>

### 34.4.4 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.head([n])</td>
<td>Return the first n rows.</td>
</tr>
<tr>
<td>DataFrame.at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>DataFrame.iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td>DataFrame.loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td>DataFrame.iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>DataFrame.insert(loc, column, value[, . . . ])</td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td>DataFrame.insert(loc, column, value[, . . . ])</td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td>DataFrame.<strong>iter</strong></td>
<td>Iterate over infor axis</td>
</tr>
<tr>
<td>DataFrame.items()</td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.keys()</td>
<td>Get the ‘info axis’ (see Indexing for more)</td>
</tr>
<tr>
<td>DataFrame.iteritems()</td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.iterrows()</td>
<td>Iterate over DataFrame rows as (index, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.iterrows()</td>
<td>Iterate over DataFrame rows as (index, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.lookup(row_labels, col_labels)</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>Return the last n rows.</td>
</tr>
<tr>
<td>DataFrame.xs(key[, axis, level, drop_level])</td>
<td>Returns a cross-section (row(s) or column(s)) from the Series/Object.</td>
</tr>
<tr>
<td>DataFrame.get(key[, default])</td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.).</td>
</tr>
<tr>
<td>DataFrame.isin(values)</td>
<td>Return boolean DataFrame showing whether each element in the DataFrame is contained in 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 self where cond is True and otherwise 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 self where cond is False and otherwise are from other.</td>
</tr>
<tr>
<td>DataFrame.query(expr[, inplace])</td>
<td>Query the columns of a frame with a boolean expression.</td>
</tr>
</tbody>
</table>

#### 34.4.4.1 pandas.DataFrame.__iter__

DataFrame.__iter__()  
Iterate over infor axis

For more information on .at, .iat, .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</code></td>
<td>Addition of dataframe and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td><code>DataFrame.sub</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td><code>DataFrame.mul</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td><code>DataFrame.div</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>DataFrame.truediv</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>DataFrame.floordiv</code></td>
<td>Integer division of dataframe and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td><code>DataFrame.mod</code></td>
<td>Modulo of dataframe and other, element-wise (binary operator mod).</td>
</tr>
<tr>
<td><code>DataFrame.pow</code></td>
<td>Exponential power of dataframe and other, element-wise (binary operator pow).</td>
</tr>
<tr>
<td><code>DataFrame.dot</code></td>
<td>Matrix multiplication with DataFrame or Series objects.</td>
</tr>
<tr>
<td><code>DataFrame.radd</code></td>
<td>Addition of dataframe and other, element-wise (binary operator radd).</td>
</tr>
<tr>
<td><code>DataFrame.rsub</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator rsub).</td>
</tr>
<tr>
<td><code>DataFrame.rmul</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator rmul).</td>
</tr>
<tr>
<td><code>DataFrame.rdiv</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td><code>DataFrame.rtruediv</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td><code>DataFrame.rfloordiv</code></td>
<td>Integer division of dataframe and other, element-wise (binary operator rfloordiv).</td>
</tr>
<tr>
<td><code>DataFrame.rmod</code></td>
<td>Modulo of dataframe and other, element-wise (binary operator rmod).</td>
</tr>
<tr>
<td><code>DataFrame.rpow</code></td>
<td>Exponential power of dataframe and other, element-wise (binary operator rpow).</td>
</tr>
<tr>
<td><code>DataFrame.lt</code></td>
<td>Wrapper for flexible comparison methods lt</td>
</tr>
<tr>
<td><code>DataFrame.gt</code></td>
<td>Wrapper for flexible comparison methods gt</td>
</tr>
<tr>
<td><code>DataFrame.le</code></td>
<td>Wrapper for flexible comparison methods le</td>
</tr>
<tr>
<td><code>DataFrame.ge</code></td>
<td>Wrapper for flexible comparison methods ge</td>
</tr>
<tr>
<td><code>DataFrame.ne</code></td>
<td>Wrapper for flexible comparison methods ne</td>
</tr>
<tr>
<td><code>DataFrame.eq</code></td>
<td>Wrapper for flexible comparison methods eq</td>
</tr>
<tr>
<td><code>DataFrame.combine</code></td>
<td>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)</td>
</tr>
<tr>
<td><code>DataFrame.combine_first</code></td>
<td>Combine two DataFrame objects and default to non-null values in frame calling the method.</td>
</tr>
<tr>
<td>Method</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>DataFrame.apply</td>
<td>Apply a function along an axis of the DataFrame.</td>
</tr>
<tr>
<td>DataFrame.applymap</td>
<td>Apply a function to a Dataframe elementwise.</td>
</tr>
<tr>
<td>DataFrame.pipe</td>
<td>Apply func(self, *args, **kwargs)</td>
</tr>
<tr>
<td>DataFrame.agg</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>DataFrame.aggregate</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>DataFrame.transform</td>
<td>Call function producing a like-indexed NDFrame and return a NDFrame with the transformed values</td>
</tr>
<tr>
<td>DataFrame.groupby</td>
<td>Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns.</td>
</tr>
<tr>
<td>DataFrame.rolling</td>
<td>Provides rolling window calculations.</td>
</tr>
<tr>
<td>DataFrame.expanding</td>
<td>Provides expanding transformations.</td>
</tr>
<tr>
<td>DataFrame.ewm</td>
<td>Provides exponential weighted functions</td>
</tr>
</tbody>
</table>

### 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 a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td>DataFrame.all</td>
<td>Return whether all elements are True over series or datafarme axis.</td>
</tr>
<tr>
<td>DataFrame.any</td>
<td>Return whether any element is True over requested axis.</td>
</tr>
<tr>
<td>DataFrame.clip</td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td>DataFrame.clip_lower</td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td>DataFrame.clip_upper</td>
<td>Return copy of input with values above given value(s) truncated.</td>
</tr>
<tr>
<td>DataFrame.compound</td>
<td>Return the compound percentage of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.corr</td>
<td>Compute pairwise correlation of columns, excluding NA/null values</td>
</tr>
<tr>
<td>DataFrame.corrwith</td>
<td>Compute pairwise correlation between rows or columns of two DataFrame objects.</td>
</tr>
<tr>
<td>DataFrame.count</td>
<td>Count non-NA cells for each column or row.</td>
</tr>
<tr>
<td>DataFrame.cov</td>
<td>Compute pairwise covariance of columns, excluding NA/null values.</td>
</tr>
<tr>
<td>DataFrame.cummax</td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>DataFrame.cummin</td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>DataFrame.cumprod</td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>DataFrame.cumsum</td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>DataFrame.describe</td>
<td>Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.</td>
</tr>
<tr>
<td>DataFrame.diff</td>
<td>First discrete difference of element.</td>
</tr>
</tbody>
</table>

Continued on next page
### DataFrame.eval(expr[, inplace])
Evaluate a string describing operations on DataFrame columns.

### DataFrame.kurt([axis, skipna, level, ...])
Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).

### DataFrame.kurtosis([axis, skipna, level, ...])
Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).

### DataFrame.max([axis, skipna, level, ...])
This method returns the maximum of the values for the requested axis.

### DataFrame.median([axis, skipna, level, ...])
Return the median of the values for the requested axis.

### DataFrame.min([axis, skipna, level, ...])
This method returns the minimum of the values in the object.

### DataFrame.mode([axis, numeric_only])
Gets the mode(s) of each element along the axis selected.

### DataFrame.pct_change([periods, fill_method, ...,])
Percentage change between the current and a prior element.

### DataFrame.prod([axis, skipna, level, ...])
Return the product of the values for the requested axis.

### DataFrame.product([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, method, numeric_only, ...])
Compute numerical data ranks (1 through n) along axis.

### DataFrame.round([decimals])
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 Normalized by N-1

### DataFrame.sum([axis, skipna, level, ...])
Return the sum of the values for the requested axis.

### DataFrame.std([axis, skipna, level, ddof, ...])
Return sample standard deviation over requested axis.

### DataFrame.var([axis, skipna, level, ddof, ...])
Return unbiased variance over requested axis.

### DataFrame.nunique([axis, dropna])
Return Series with number of distinct observations over requested axis.

#### 34.4.8 Reindexing / Selection / Label manipulation

- **DataFrame.add_prefix(prefix)**: Prefix labels with string prefix.
- **DataFrame.add_suffix(suffix)**: Suffix labels with string suffix.
- **DataFrame.align(other[, join, axis, level, ...])**: Align two objects on their axes with the specified join method for each axis Index
- **DataFrame.at_time(time[, asof])**: Select values at particular time of day (e.g. 9:00-9:30 AM).
- **DataFrame.between_time(start_time, end_time)**: Select values between particular times of the day (e.g., 9:00-9:30 AM).
- **DataFrame.drop([labels, axis, index, ...])**: Drop specified labels from rows or columns.
- **DataFrame.drop_duplicates([subset, keep, ...])**: Return DataFrame with duplicate rows removed, optionally only considering certain columns
### Table 69 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.duplicated([subset, keep])</td>
<td>Return boolean Series denoting duplicate rows, optionally only considering certain columns</td>
</tr>
<tr>
<td>DataFrame.equals(other)</td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td>DataFrame.filter([items, like, regex, axis])</td>
<td>Subset rows or columns of dataframe according to labels in the specified index.</td>
</tr>
<tr>
<td>DataFrame.first(offset)</td>
<td>Convenience method for subsetting initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td>DataFrame.head([n])</td>
<td>Return the first n rows.</td>
</tr>
<tr>
<td>DataFrame.idxmax([axis, skipna])</td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td>DataFrame.idxmin([axis, skipna])</td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
<tr>
<td>DataFrame.last(offset)</td>
<td>Convenience method for subsetting final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td>DataFrame.reindex([labels, index, columns, ...])</td>
<td>Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
<tr>
<td>DataFrame.reindex_axis(labels[, axis, ...])</td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
<tr>
<td>DataFrame.reindex_like(other[, method, ...])</td>
<td>Return an object with matching indices to myself.</td>
</tr>
<tr>
<td>DataFrame.rename([mapper, index, columns, ...])</td>
<td>Alter axes labels.</td>
</tr>
<tr>
<td>DataFrame.rename_axis(mapper[, axis, copy, ...])</td>
<td>Alter the name of the index or columns.</td>
</tr>
<tr>
<td>DataFrame.reset_index([level, drop, ...])</td>
<td>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.</td>
</tr>
<tr>
<td>DataFrame.sample([n, frac, replace, ...])</td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td>DataFrame.select(crit[, axis])</td>
<td>(DEPRECATED) Return data corresponding to axis labels matching criteria</td>
</tr>
<tr>
<td>DataFrame.set_axis(labels[, axis, inplace])</td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td>DataFrame.set_index(keys[, drop, append, ...])</td>
<td>Set the DataFrame index (row labels) using one or more existing columns.</td>
</tr>
<tr>
<td>DataFrame.tail([n])</td>
<td>Return the last n rows.</td>
</tr>
<tr>
<td>DataFrame.take(indices[, axis, convert, is_copy])</td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td>DataFrame.truncate([before, after, axis, copy])</td>
<td>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
</tbody>
</table>

### 34.4.9 Missing data handling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.dropna([axis, how, thresh, ...])</td>
<td>Remove missing values.</td>
</tr>
<tr>
<td>DataFrame.fillna([value, method, axis, ...])</td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td>DataFrame.replace([to_replace, value, ...])</td>
<td>Replace values given in to_replace with value.</td>
</tr>
<tr>
<td>DataFrame.interpolate([method, axis, limit, ...])</td>
<td>Interpolate values according to different methods.</td>
</tr>
</tbody>
</table>
34.4.10 Reshaping, sorting, transposing

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.pivot([index, columns, values])</code></td>
<td>Return reshaped DataFrame organized by given index / column values.</td>
</tr>
<tr>
<td><code>DataFrame.pivot_table([values, index, ...])</code></td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.reorder_levels(order[, axis])</code></td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td><code>DataFrame.sort_values(by[, axis, ascending, ...])</code></td>
<td>Sort by the values along either axis</td>
</tr>
<tr>
<td><code>DataFrame.sort_index([axis, level, ...])</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>DataFrame.nlargest(n, columns[, keep])</code></td>
<td>Return the first n rows ordered by columns in descending order.</td>
</tr>
<tr>
<td><code>DataFrame.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>DataFrame.swaplevel([i, j, axis])</code></td>
<td>Swap levels i and j in a MultiIndex on a particular axis.</td>
</tr>
<tr>
<td><code>DataFrame.stack([level, dropna])</code></td>
<td>Stack the prescribed level(s) from columns to index.</td>
</tr>
<tr>
<td><code>DataFrame.unstack([level, fill_value])</code></td>
<td>Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels.</td>
</tr>
<tr>
<td><code>DataFrame.swapaxes(axis1, axis2[, copy])</code></td>
<td>Interchange axes and swap values axes appropriately</td>
</tr>
<tr>
<td><code>DataFrame.melt([id_vars, value_vars, ...])</code></td>
<td>“Un pivots” a DataFrame from wide format to long format, optionally leaving identifier variables set.</td>
</tr>
<tr>
<td><code>DataFrame.squeeze([axis])</code></td>
<td>Squeeze length 1 dimensions.</td>
</tr>
<tr>
<td><code>DataFrame.to_panel()</code></td>
<td>(DEPRECATED) Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.</td>
</tr>
<tr>
<td><code>DataFrame.to_xarray()</code></td>
<td>Return an xarray object from the pandas object.</td>
</tr>
<tr>
<td><code>DataFrame.T</code></td>
<td>Transpose index and columns.</td>
</tr>
<tr>
<td><code>DataFrame.transpose(*args, **kwargs)</code></td>
<td>Transpose index and columns.</td>
</tr>
</tbody>
</table>

34.4.11 Combining / joining / merging

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.append(other[, ignore_index, ...])</code></td>
<td>Append rows of other to the end of this frame, returning a new object.</td>
</tr>
<tr>
<td><code>DataFrame.assign(**kwargs)</code></td>
<td>Assign new columns to a DataFrame, returning a new object (a copy) with the new columns added to the original ones.</td>
</tr>
<tr>
<td><code>DataFrame.join(other[, on, how, lsuffix, ...])</code></td>
<td>Join columns with other DataFrame either on index or on a key column.</td>
</tr>
<tr>
<td><code>DataFrame.merge(right[, how, on, left_on, ...])</code></td>
<td>Merge DataFrame objects by performing a database-style join operation by columns or indexes.</td>
</tr>
<tr>
<td><code>DataFrame.update(other[, join, overwrite, ...])</code></td>
<td>Modify in place using non-NA values from another DataFrame.</td>
</tr>
</tbody>
</table>

34.4.12 Time series-related

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.asfreq(freq[, method, how, ...])</code></td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td><code>DataFrame.asof(where[, subset])</code></td>
<td>The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)</td>
</tr>
</tbody>
</table>
### 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>`.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.plot(x=None, y=None,**kwds)</code></td>
<td>Area plot</td>
</tr>
<tr>
<td><code>DataFrame.plot.bar(x=None, y=None,**kwds)</code></td>
<td>Vertical bar plot</td>
</tr>
<tr>
<td><code>DataFrame.plot.barh(x=None, y=None,**kwds)</code></td>
<td>Make a horizontal bar plot.</td>
</tr>
<tr>
<td><code>DataFrame.plot.box(by,**kwds)</code></td>
<td>Make a box plot of the DataFrame columns.</td>
</tr>
<tr>
<td><code>DataFrame.plot.density(by,**kwds)</code></td>
<td>Generate Kernel Density Estimate plot using Gaussian kernels.</td>
</tr>
<tr>
<td><code>DataFrame.plot.hexbin(x, y,**kwds)</code></td>
<td>Generate a hexagonal binning plot.</td>
</tr>
<tr>
<td><code>DataFrame.plot.hist(by,**kwds)</code></td>
<td>Draw one histogram of the DataFrame’s columns.</td>
</tr>
<tr>
<td><code>DataFrame.plot.kde(by,**kwds)</code></td>
<td>Generate Kernel Density Estimate plot using Gaussian kernels.</td>
</tr>
<tr>
<td><code>DataFrame.plot.line(x=None, y=None,**kwds)</code></td>
<td>Plot DataFrame columns as lines.</td>
</tr>
<tr>
<td><code>DataFrame.plot.pie(y,**kwds)</code></td>
<td>Generate a pie plot.</td>
</tr>
<tr>
<td><code>DataFrame.plot.scatter(x, y,**kwds)</code></td>
<td>Create a scatter plot with varying marker point size and color.</td>
</tr>
</tbody>
</table>

#### 34.4.13.1 pandas.DataFrame.plot.area

`DataFrame.plot.area(x=None, y=None,**kwds)`  
Area plot

**Parameters**:  
- `x`, `y`: label or position, optional  
  Coordinates for each point.  
- `**kwds`: optional  
  Additional keyword arguments are documented in `pandas.DataFrame`.  

**Table 73 – continued from previous page**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.shift([periods, freq, axis])</code></td>
<td>Shift index by desired number of periods with an optional time freq</td>
</tr>
<tr>
<td><code>DataFrame.slice_shift([periods, axis])</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>DataFrame.tshift([periods, freq, axis])</code></td>
<td>Shift the time index, using the index’s frequency if available.</td>
</tr>
<tr>
<td><code>DataFrame.first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>DataFrame.last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
<tr>
<td><code>DataFrame.resample(rule[, how, axis, . . .])</code></td>
<td>Convenience method for frequency conversion and re-sampling of time series.</td>
</tr>
<tr>
<td><code>DataFrame.to_period([freq, axis, copy])</code></td>
<td>Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)</td>
</tr>
<tr>
<td><code>DataFrame.to_timestamp([freq, how, axis, copy])</code></td>
<td>Cast to DatetimeIndex of timestamps, at beginning of period</td>
</tr>
<tr>
<td><code>DataFrame.tz_convert(tz[, axis, level, copy])</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>DataFrame.tz_localize(tz[, axis, level, . . .])</code></td>
<td>Localize tz-naive TimeSeries to target time zone.</td>
</tr>
</tbody>
</table>
plot().

Returns

axes [matplotlib.axes.Axes or numpy.ndarray of them]

34.4.13.2 pandas.DataFrame.plot.bar

DataFrame.plot.bar(x=None, y=None, **kwds)
Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters x : label or position, optional
Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y : label or position, optional
Allows plotting of one column versus another. If not specified, all numerical columns are used.

**kwds
Additional keyword arguments are documented in pandas.DataFrame.plot().

Returns axes : matplotlib.axes.Axes or np.ndarray of them
An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:
pandas.DataFrame.plot.barh Horizontal bar plot.
pandas.DataFrame.plot Make plots of a DataFrame.
matplotlib.pyplot.bar Make a bar plot with matplotlib.

Examples

Basic plot.

```python
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant', ...
'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed, ...
'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)
```
Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a `numpy.ndarray` of `matplotlib.axes.Axes` are returned.

```python
>>> axes = df.plot.bar(rot=0, subplots=True)
>>> axes[1].legend(loc=2)
```

Plot a single column.

```python
>>> ax = df.plot.bar(y='speed', rot=0)
```

Plot only selected categories for the DataFrame.

```python
>>> ax = df.plot.bar(x='lifespan', rot=0)
```

### 34.4.13.3 pandas.DataFrame.plot.barh

**DataFrame.plot.barh**

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

**Parameters**

- **x**: label or position, default DataFrame.index
  - Column to be used for categories.
- **y**: label or position, default All numeric columns in dataframe
  - Columns to be plotted from the DataFrame.
- **kwds**: Keyword arguments to pass on to `pandas.DataFrame.plot()`.

**Returns**

- `axes` [`matplotlib.axes.Axes` or `numpy.ndarray` of them.]

**See also:**

- `pandas.DataFrame.plot.bar` Vertical bar plot.
- `pandas.DataFrame.plot` Make plots of DataFrame using `matplotlib`.
- `matplotlib.axes.Axes.bar` Plot a vertical bar plot using `matplotlib`.

**Examples**

**Basic example**

```python
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val':[10, 30, 20]})
>>> ax = df.plot.barh(x='lab', y='val')
```

Plot a whole DataFrame to a horizontal bar plot
Plot a column of the DataFrame to a horizontal bar plot

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
        ...
        'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
        ...
        'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(y='speed')
```

Plot DataFrame versus the desired column

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
        ...
        'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
        ...
        'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```

### 34.4.13.4 pandas.DataFrame.plot.box

DataFrame.plot.box(by=None, **kwds)

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia’s entry for boxplot.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

**Parameters**

by : string or sequence

Column in the DataFrame to group by.

**kwds** : optional

Additional keywords are documented in pandas.DataFrame.plot().

**Returns**

axes [matplotlib.axes.Axes or numpy.ndarray of them]

**See also:**

pandas.DataFrame.boxplot Another method to draw a box plot.

pandas.Series.plot.box Draw a box plot from a Series object.
matplotlib.pyplot.boxplot  Draw a box plot in matplotlib.

Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

34.4.13.5 pandas.DataFrame.plot.density

DataFrame.plot.density(bw_method=None, ind=None, **kwds)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

**Parameters**

**bw_method**: str, scalar or callable, optional

The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.

**ind**: NumPy array or integer, optional

Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

**kwds**: optional

Additional keyword arguments are documented in pandas.DataFrame.plot().

**Returns**

**axes**  [matplotlib.axes.Axes or numpy.ndarray of them]

See also:

scipy.stats.gaussian_kde  Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Series.plot.kde  Generate a KDE plot for a Series.

Examples

Given several Series of points randomly sampled from unknown distributions, estimate their PDFs using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
```
A scalar bandwidth can be specified. Using a small bandwidth value can lead to overfitting, while using a large bandwidth value may result in underfitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

### 34.4.13.6 pandas.DataFrame.plot.hexbin

`DataFrame.plot.hexbin(x, y, C=None, reduce_C_function=None, gridsize=None, **kwds)`

Generate a hexagonal binning plot.

Generate a hexagonal binning plot of `x` versus `y`. If `C` is `None` (the default), this is a histogram of the number of occurrences of the observations at `(x[i], y[i])`.

If `C` is specified, specifies values at given coordinates `(x[i], y[i])`. These values are accumulated for each hexagonal bin and then reduced according to `reduce_C_function`, having as default the NumPy's mean function (`numpy.mean()`). (If `C` is specified, it must also be a 1-D sequence of the same length as `x` and `y`, or a column label.)

**Parameters**  
- `x` : int or str  
The column label or position for `x` points.  
- `y` : int or str  
The column label or position for `y` points.  
- `C` : int or str, optional  
The column label or position for the value of `(x, y)` point.  
- `reduce_C_function` : callable, default `np.mean`  
Function of one argument that reduces all the values in a bin to a single number (e.g. `np.mean`, `np.max`, `np.sum`, `np.std`).  
- `gridsize` : int or tuple of (int, int), default 100  
The number of hexagons in the x-direction. The corresponding number of hexagons in the y-direction is chosen in a way that the hexagons are approximately regular. Alternatively, `gridsize` can be a tuple with two elements specifying the number of hexagons in the x-direction and the y-direction.

**Returns**  
- `matplotlib.AxesSubplot`  
The `Axes` on which the hexbin is plotted.
See also:

**DataFrame.plot** Make plots of a DataFrame.

**matplotlib.pyplot.hexbin** hexagonal binning plot using matplotlib, the matplotlib function that is used under the hood.

### Examples

The following examples are generated with random data from a normal distribution.

```python
>>> n = 10000
>>> df = pd.DataFrame({'x': np.random.randn(n),
...                    'y': np.random.randn(n)})
>>> ax = df.plot.hexbin(x='x', y='y', gridsize=20)
```

The next example uses `C` and `np.sum` as `reduce_C_function`. Note that `observations` values ranges from 1 to 5 but the result plot shows values up to more than 25. This is because of the `reduce_C_function`.

```python
>>> n = 500
>>> df = pd.DataFrame({
...                    'coord_x': np.random.uniform(-3, 3, size=n),
...                    'coord_y': np.random.uniform(30, 50, size=n),
...                    'observations': np.random.randint(1,5, size=n)
...                    })
>>> ax = df.plot.hexbin(x='coord_x',
...                      y='coord_y',
...                      C='observations',
...                      reduce_C_function=np.sum,
...                      gridsize=10,
...                      cmap="viridis")
```

#### 34.4.13.7 pandas.DataFrame.plot.hist

**DataFrame.plot.hist**(by=None, bins=10, **kwds)

Draw one histogram of the DataFrame's columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one `matplotlib.axes.Axes`. This is useful when the DataFrame's Series are in a similar scale.

**Parameters**

by : str or sequence, optional

Column in the DataFrame to group by.

bins : int, default 10

Number of histogram bins to be used.

**kwds**

Additional keyword arguments are documented in `pandas.DataFrame.plot()`.

**Returns**

axes [matplotlib.AxesSubplot histogram.]

See also:
**DataFrame.hist** Draw histograms per DataFrame’s Series.

**Series.hist** Draw a histogram with Series’ data.

### Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```python
>>> df = pd.DataFrame(
...     np.random.randint(1, 7, 6000),
...     columns = ['one'])

>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)

>>> ax = df.plot.hist(bins=12, alpha=0.5)
```

### 34.4.13.8 pandas.DataFrame.plot.kde

DataFrame.plot.kde(bw_method=None, ind=None, **kwds)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwith determination.

**Parameters**

bw_method : str, scalar or callable, optional

The method used to calculate the estimator bandwith. This can be `scott`, `silverman`, a scalar constant or a callable. If None (default), `scott` is used. See scipy.stats.gaussian_kde for more information.

ind : NumPy array or integer, optional

Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If `ind` is a NumPy array, the KDE is evaluated at the points passed. If `ind` is an integer, `ind` number of equally spaced points are used.

**kwds** : optional

Additional keyword arguments are documented in pandas.DataFrame.plot().

**Returns**

axes [matplotlib.axes.Axes or numpy.ndarray of them]

**See also:**

scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Series.plot.kde Generate a KDE plot for a Series.

### Examples

Given several Series of points randomly sampled from unknown distributions, estimate their PDFs using KDE with automatic bandwith determination and plot the results, evaluating them at 1000 equally spaced points (default):
A scalar bandwidth can be specified. Using a small bandwidth value can lead to overfitting, while using a large bandwidth value may result in underfitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)
```

```python
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

### 34.4.13.9 pandas.DataFrame.plot.line

`DataFrame.plot.line(x=None, y=None, **kwds)`

Plot DataFrame columns as lines.

This function is useful to plot lines using DataFrame’s values as coordinates.

**Parameters**

- `x`: int or str, optional
  Columns to use for the horizontal axis. Either the location or the label of the columns to be used. By default, it will use the DataFrame indices.

- `y`: int, str, or list of them, optional
  The values to be plotted. Either the location or the label of the columns to be used. By default, it will use the remaining DataFrame numeric columns.

- `**kwds`
  Keyword arguments to pass on to `pandas.DataFrame.plot()`.

**Returns**

- `axes`: matplotlib.axes.Axes or numpy.ndarray
  Returns an ndarray when `subplots=True`.

**See also:**

- **matplotlib.pyplot.plot**
  Plot y versus x as lines and/or markers.

**Examples**

The following example shows the populations for some animals over the years.

```python
>>> df = pd.DataFrame(
...     'pig': [20, 18, 489, 675, 1776],
...     'horse': [4, 25, 281, 600, 1900],
```

```python
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.
The following example shows the relationship between both populations.

```python
>>> lines = df.plot.line(x='pig', y='horse')
```

### 34.4.13.10 pandas.DataFrame.plot.pie

`DataFrame.plot.pie(y=None, **kwds)`

Generate a pie plot.

A pie plot is a proportional representation of the numerical data in a column. This function wraps `matplotlib.pyplot.pie()` for the specified column. If no column reference is passed and `subplots=True` a pie plot is drawn for each numerical column independently.

**Parameters**

- `y` : int or label, optional
  Label or position of the column to plot. If not provided, `subplots=True` argument must be passed.

**kwds**

Keyword arguments to pass on to `pandas.DataFrame.plot()`.

**Returns**

- `axes` : matplotlib.axes.Axes or np.ndarray of them.
  A NumPy array is returned when `subplots` is True.

See also:

- `Series.plot.pie` Generate a pie plot for a Series.
- `DataFrame.plot` Make plots of a DataFrame.

### Examples

In the example below we have a DataFrame with the information about planet’s mass and radius. We pass the ‘mass’ column to the pie function to get a pie plot.

```python
>>> df = pd.DataFrame({
...     'mass': [0.330, 4.87 , 5.97],
...     'radius': [2439.7, 6051.8, 6378.1]},
...     index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
>>> plot = df.plot.pie(subplots=True, figsize=(6, 3))
```

### 34.4.13.11 pandas.DataFrame.plot.scatter

`DataFrame.plot.scatter(x, y, s=None, c=None, **kwds)`

Create a scatter plot with varying marker point size and color.

The coordinates of each point are defined by two dataframe columns and filled circles are used to represent each point. This kind of plot is useful to see complex correlations between two variables. Points could be for instance
natural 2D coordinates like longitude and latitude in a map or, in general, any pair of metrics that can be plotted against each other.

**Parameters**

- **x**: int or str
  - The column name or column position to be used as horizontal coordinates for each point.

- **y**: int or str
  - The column name or column position to be used as vertical coordinates for each point.

- **s**: scalar or array_like, optional
  - The size of each point. Possible values are:
    - A single scalar so all points have the same size.
    - A sequence of scalars, which will be used for each point’s size recursively. For instance, when passing [2,14] all points size will be either 2 or 14, alternatively.

- **c**: str, int or array_like, optional
  - The color of each point. Possible values are:
    - A single color string referred to by name, RGB or RGBA code, for instance ‘red’ or ‘#a98d19’.
    - A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each point’s color recursively. For instance ['green','yellow'] all points will be filled in green or yellow, alternatively.
    - A column name or position whose values will be used to color the marker points according to a colormap.

- ****kwds**
  - Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

- **axes**: [matplotlib.axes.Axes or numpy.ndarray of them]

**See also:**

matplotlib.pyplot.scatter scatter plot using multiple input data formats.

**Examples**

Let’s see how to draw a scatter plot using coordinates from the values in a DataFrame’s columns.

```python
>>> df = pd.DataFrame([[5.1, 3.5, 0], [4.9, 3.0, 0], [7.0, 3.2, 1],
... [6.4, 3.2, 1], [5.9, 3.0, 2]],
... columns=['length', 'width', 'species'])
>>> ax1 = df.plot.scatter(x='length',
... y='width',
... c='DarkBlue')
```

And now with the color determined by a column as well.
>>> ax2 = df.plot.scatter(x='length',
... y='width',
... c='species',
... colormap='viridis')

**DataFrame.boxplot**([column, by, ax, ...])  
Make a box plot from DataFrame columns.

**DataFrame.hist**([column, by, grid, ...])  
Make a histogram of the DataFrame’s.

### 34.4.14 Serialization / IO / Conversion

**DataFrame.from_csv**(path[, header, sep, ...])  
(DEPRECATED) Read CSV file.

**DataFrame.from_dict**(data[, orient, dtype, ...])  
Construct DataFrame from dict of array-like or dicts.

**DataFrame.from_items**(items[, columns, orient])  
(DEPRECATED) Construct a dataframe from a list of tuples

**DataFrame.from_records**(data[, index, ...])  
Convert structured or record ndarray to DataFrame

**DataFrame.info**(verbose, buf, max_cols, ...)  
Print a concise summary of a DataFrame.

**DataFrame.to_parquet**(fname[, engine, ...])  
Write a DataFrame to the binary parquet format.

**DataFrame.to_pickle**(path[, compression, ...])  
Pickle (serialize) object to file.

**DataFrame.to_csv**([path_or_buf, sep, na_rep, ...])  
Write DataFrame to a comma-separated values (csv) file

**DataFrame.to_hdf**(path_or_buf, key, **kwargs)  
Write the contained data to an HDF5 file using HDFS-store.

**DataFrame.to_sql**(name, con[, schema, ...])  
Write records stored in a DataFrame to a SQL database.

**DataFrame.to_msgpack**)  
msgpack (serialize) object to input file path

**DataFrame.to_gbq**(destination_table, project_id)  
Write a DataFrame to a Google BigQuery table.

**DataFrame.to_records**([index, convert_datetime64])  
Convert DataFrame to a NumPy record array.

**DataFrame.to_sparse**([fill_value, kind])  
Convert to SparseDataFrame

**DataFrame.to_dense()**  
Return dense representation of NDFrame (as opposed to sparse)

**DataFrame.to_string**([buf, columns, ...])  
Render a DataFrame to a console-friendly tabular output.

**DataFrame.style**  
Property returning a Styler object containing methods for building a styled HTML representation for the DataFrame.

### 34.4.15 Sparse
34.4.15.1 pandas.SparseDataFrame.to_coo

SparseDataFrame.to_coo()

Return the contents of the frame as a sparse SciPy COO matrix.

New in version 0.20.0.

Returns coo_matrix : scipy.sparse.spmatrix

If the caller is heterogeneous and contains booleans or objects, the result will be of
dtype=object. See Notes.

Notes

The dtype will be the lowest-common-denominator type (implicit upcasting); that is to say if the dtypes (even
of numeric types) are mixed, the one that accommodates all will be chosen.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. By numpy.find_common_type conven-
tion, mixing int64 and and uint64 will result in a float64 dtype.

34.5 Panel

34.5.1 Constructor

Panel([data, items, major_axis, minor_axis, ...]) (DEPRECATED) Represents wide format panel data,
stored as 3-dimensional array

34.5.1.1 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

Deprecated since version 0.20.0: The recommended way to represent 3-D data are with a MultiIndex on a
DataFrame via the to_frame() method or with the xarray package. Pandas provides a to_xarray() method to automate this conversion.

Parameters data : ndarray (items x major x minor), or dict of DataFrames

items [Index or array-like] axis=0

major_axis [Index or array-like] axis=1

minor_axis [Index or array-like] axis=2

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>
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<tbody>
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<td>at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>axes</td>
<td>Return index label(s) of the internal NDFrame.</td>
</tr>
<tr>
<td>blocks</td>
<td>(DEPRECATED) Internal property, property synonym for as_blocks().</td>
</tr>
<tr>
<td>dtypes</td>
<td>Return the dtypes in the DataFrame.</td>
</tr>
<tr>
<td>empty</td>
<td>Indicator whether DataFrame is empty.</td>
</tr>
<tr>
<td>ftypes</td>
<td>Return the ftypes (indication of sparse/dense and dtype) in DataFrame.</td>
</tr>
<tr>
<td>iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td>ioc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>items</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td>major_axis</td>
<td></td>
</tr>
<tr>
<td>minor_axis</td>
<td></td>
</tr>
<tr>
<td>ndim</td>
<td>Return an int representing the 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>Return an int representing the number of elements in this object.</td>
</tr>
<tr>
<td>values</td>
<td>Return a Numpy representation of the DataFrame.</td>
</tr>
</tbody>
</table>

### pandas.Panel.at

Panel.at

Access a single value for a row/column label pair.

Similar to loc, in that both provide label-based lookups. Use at if you only need to get or set a single value in a DataFrame or Series.

**Raises** KeyError

When label does not exist in DataFrame

**See also:**

*DataFrame.iat* Access a single value for a row/column pair by integer position

*DataFrame.loc* Access a group of rows and columns by label(s)

*Series.at* Access a single value using a label

### Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
    ...   index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 0.23.1

```
A   B   C
4   0   2   3
5   0   4   1
6  10  20  30

Get value at specified row/column pair

```df.at[4, 'B']
2
```

Set value at specified row/column pair

```df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```df.loc[5].at['B']
4
```

**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()

Deprecated since version 0.21.0.
```

**pandas.Panel.dtypes**

```
Panel.dtypes

Return the dtypes in the DataFrame.

This returns a Series with the data type of each column. The result's index is the original DataFrame's columns. Columns with mixed types are stored with the object dtype. See the User Guide for more.

Returns pandas.Series

The data type of each column.

See also:

* **pandas.DataFrame.dtypes** dtypes and sparsity information.
Examples

```python
>>> df = pd.DataFrame({'float': [1.0],
...                    'int': [1],
...                    'datetime': [pd.Timestamp('20180310')],
...                    'string': ['foo'])
>>> df.dtypes
float float64
int   int64
datetime datetime64[ns]
string   object
dtype: object
```

**pandas.Panel.empty**

Panel.empty
Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

Returns bool
If DataFrame is empty, return True, if not return False.

See also:

*pandas.Series.dropna, pandas.DataFrame.dropna*

Notes
If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples
An example of an actual empty DataFrame. Notice the index is empty:

```python
>>> df_empty = pd.DataFrame({'A' : []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```python
>>> df = pd.DataFrame({'A' : [np.nan]})
>>> df
   A
0  NaN
>>> df.empty
False
>>> df.dropna().empty
True
```
pandas.Panel.ftypes

Panel.ftypes
Return the ftypes (indication of sparse/dense and dtype) in DataFrame.

This returns a Series with the data type of each column. The result’s index is the original DataFrame’s columns. Columns with mixed types are stored with the object dtype. See the User Guide for more.

Returns pandas.Series
The data type and indication of sparse/dense of each column.

See also:
pandas.DataFrame.dtypes Series with just dtype information.
pandas.SparseDataFrame Container for sparse tabular data.

Notes
Sparse data should have the same dtypes as its dense representation.

Examples

```python
>>> import numpy as np
>>> arr = np.random.RandomState(0).randn(100, 4)
>>> arr[arr < .8] = np.nan
>>> pd.DataFrame(arr).ftypes
0  float64:dense
1  float64:dense
2  float64:dense
3  float64:dense
dtype: object
```

```python
>>> pd.SparseDataFrame(arr).ftypes
0  float64:sparse
1  float64:sparse
2  float64:sparse
3  float64:sparse
dtype: object
```

pandas.Panel.iat

Panel.iat
Access a single value for a row/column pair by integer position.

Similar to iloc, in that both provide integer-based lookups. Use iat if you only need to get or set a single value in a DataFrame or Series.

Raises IndexError
When integer position is out of bounds

See also:
**DataFrame.at** Access a single value for a row/column label pair

**DataFrame.loc** Access a group of rows and columns by label(s)

**DataFrame.iloc** Access a group of rows and columns by integer position(s)

**Examples**

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
   columns=['A', 'B', 'C'])
>>> df
   A  B  C
0  0  2  3
1  0  4  1
2 10 20 30
```

Get value at specified row/column pair

```python
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```python
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```python
>>> df.loc[0].iat[1]
2
```

**pandas.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.
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above).

.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.items**

*Panel* *items*

**pandas.Panel.ix**

*Panel* *ix*

A primarily label-location based indexer, with integer position fallback.

Warning: Starting in 0.20.0, the .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers.

.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*

Access a group of rows and columns by label(s) or a boolean array.

.loc[] is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a label of the index, and never as an integer position along the index).
- A list or array of labels, e.g.['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, both the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. [True, False, True].
- A callable function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

See more at Selection by Label

**Raises** **KeyError:**

when any items are not found

See also:

*DataFrame.at* Access a single value for a row/column label pair

*DataFrame.iloc* Access group of rows and columns by integer position(s)

*DataFrame.xs* Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
Series.loc Access group of values using labels

Examples

Getting values

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=['cobra', 'viper', 'sidewinder'],
                   columns=['max_speed', 'shield'])
>>> df
  max_speed  shield
 cobra       1       2
viper        4       5
sidewinder   7       8

Single label. Note this returns the row as a Series.

>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64

List of labels. Note using [[]] returns a DataFrame.

>>> df.loc[['viper', 'sidewinder']]
  max_speed  shield
viper       4       5
sidewinder  7       8

Single label for row and column

>>> df.loc['cobra', 'shield']
2

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

>>> df.loc['cobra':'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64

Boolean list with the same length as the row axis

>>> df.loc[[False, False, True]]
  max_speed  shield
sidewinder  7       8

Conditional that returns a boolean Series

>>> df.loc[df['shield'] > 6]
  max_speed  shield
sidewinder  7       8

Conditional that returns a boolean Series with column labels specified

34.5. Panel
Callable that returns a boolean Series

```python
>>> df.loc[lambda df: df['shield'] == 8]
max_speed    shield
sidewinder    7  8
```

Setting values

Set value for all items matching the list of labels

```python
>>> df.loc[{'viper', 'sidewinder'}, ['shield']] = 50
```

Set value for an entire row

```python
>>> df.loc['cobra'] = 10
>>> df
max_speed    shield
cobra 10      10
viper 4      50
sidewinder 7  50
```

Set value for an entire column

```python
>>> df.loc[:, 'max_speed'] = 30
>>> df
max_speed    shield
cobra 30      10
viper 30      50
sidewinder 30  50
```

Set value for rows matching callable condition

```python
>>> df.loc[df['shield'] > 35] = 0
>>> df
max_speed    shield
cobra 30      10
viper 0       0
sidewinder 0   0
```

Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
max_speed    shield
7            1  2
```
Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```python
>>> df.loc[7:9]
   max_speed  shield
    7         1
    8         4
    9         7
```

**Getting values with a MultiIndex**

A number of examples using a DataFrame with a MultiIndex

```python
>>> tuples = [
    ... ('cobra', 'mark i'), ('cobra', 'mark ii'),
    ... ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
    ... ('viper', 'mark ii'), ('viper', 'mark iii')
    ... ]

>>> index = pd.MultiIndex.from_tuples(tuples)

>>> values = [[12, 2], [0, 4], [10, 20], ...
    ... [1, 4], [7, 1], [16, 36]]

>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
   max_speed  shield
    cobra mark i  12
              2
    mark ii  0
    sidewinder mark i  10
                20
    mark ii  1
    viper mark ii  7
              1
    mark iii  16
              36
```

Single label. Note this returns a DataFrame with a single index.

```python
>>> df.loc['cobra']
   max_speed  shield
    mark i  12
    mark ii  2
```

Single index tuple. Note this returns a Series.

```python
>>> df.loc[('cobra', 'mark ii')]
    max_speed  0
    shield    4
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```python
>>> df.loc['cobra', 'mark ii']
    max_speed  12
    shield    2
```

Single tuple. Note using [[]] returns a DataFrame.
>>> df.loc[['cobra', 'mark ii']]  
<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra mark ii</td>
<td>0</td>
<td>4</td>
</tr>
</tbody>
</table>

Single tuple for the index with a single label for the column

>>> df.loc[['cobra', 'mark i'], 'shield']  
2

Slice from index tuple to single label

>>> df.loc[['cobra', 'mark i']:'viper']  
<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra mark i</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>mark ii</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>sidewinder mark i</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>mark ii</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>viper mark ii</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>mark iii</td>
<td>16</td>
<td>36</td>
</tr>
</tbody>
</table>

Slice from index tuple to index tuple

>>> df.loc[['cobra', 'mark i']:'viper', 'mark ii']  
<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra mark i</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>mark ii</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>sidewinder mark i</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>mark ii</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>viper mark ii</td>
<td>7</td>
<td>1</td>
</tr>
</tbody>
</table>

**pandas.Panel.major_axis**

Panel.major_axis

**pandas.Panel.minor_axis**

Panel.minor_axis

**pandas.Panel.ndim**

Panel.ndim

Return an int representing the number of axes / array dimensions.

Return 1 if Series. Otherwise return 2 if DataFrame.

See also:

ndarray.ndim

**Examples**
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.ndim
1

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.ndim
2

pandas.Panel.shape

Panel.shape
Return a tuple of axis dimensions

pandas.Panel.size

Panel.size
Return an int representing the number of elements in this object.
Return the number of rows if Series. Otherwise return the number of rows times number of columns if DataFrame.

See also:
ndarray.size

Examples

>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.size
3

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.size
4

pandas.Panel.values

Panel.values
Return a Numpy representation of the DataFrame.
Only the values in the DataFrame will be returned, the axes labels will be removed.

Returns numpy.ndarray
The values of the DataFrame.

See also:

pandas.DataFrame.index Retrieve the index labels
pandas.DataFrame.columns Retrieving the column names
Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcast to int32. By numpy.find_common_type() convention, mixing int64 and uint64 will result in a float64 dtype.

Examples

A DataFrame where all columns are the same type (e.g., int64) results in an array of the same type.

```python
>>> df = pd.DataFrame({'age': [3, 29],
...                    'height': [94, 170],
...                    'weight': [31, 115]})
>>> df
  age  height  weight
0    3      94     31
1   29     170    115
```

```python
>>> df.dtypes
age    int64
height int64
weight int64
dtype: object
>>> df.values
array([[ 3, 94, 31],
       [29, 170, 115]], dtype=int64)
```

A DataFrame with mixed type columns (e.g., str/object, int64, float32) results in an ndarray of the broadest type that accommodates these mixed types (e.g., object).

```python
>>> df2 = pd.DataFrame([('parrot', 24.0, 'second'),
...                      ('lion', 80.5, 1),
...                      ('monkey', np.nan, None)],
...                     columns=('name', 'max_speed', 'rank'))
>>> df2.dtypes
name          object
max_speed      float64
rank           object
dtype: object
>>> df2.values
array([['parrot', 24.0, 'second'],
       ['lion', 80.5, 1],
       ['monkey', nan, None]], dtype=object)
```

Methods
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs()</td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td>add(other[, axis])</td>
<td>Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>add_prefix(prefix)</td>
<td>Prefix labels with string prefix.</td>
</tr>
<tr>
<td>add_suffix(suffix)</td>
<td>Suffix labels with string suffix.</td>
</tr>
<tr>
<td>align(other, **kwargs)</td>
<td>Align two objects on their axes with the specified join method for each axis Index</td>
</tr>
<tr>
<td>all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True over series or dataframe 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 axis (or axes) of the Panel</td>
</tr>
<tr>
<td>as_blocks([copy])</td>
<td>(DEPRECATED) Convert the frame to a dict of dtype -&gt; Constructor Types that each has a homogenous dtype.</td>
</tr>
<tr>
<td>as_matrix()</td>
<td>Convert the frame to its Numpy-array representation.</td>
</tr>
<tr>
<td>asfreq(freq[, method, how, normalize, ...])</td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td>asof(where[, subset])</td>
<td>The last row without any NaN is taken (or the last row without NaN considering only the subset of columns in the case of a DataFrame)</td>
</tr>
<tr>
<td>astype(dtype, copy, errors)</td>
<td>Cast a pandas object to a specified dtype dtype.</td>
</tr>
<tr>
<td>at_time(time[, asof])</td>
<td>Select values at particular time of day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td>between_time(start_time, end_time[, ...])</td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td>bfill([axis, inplace, limit, downcast])</td>
<td>Synonym for DataFrame.fillna(method='bfill')</td>
</tr>
<tr>
<td>bool()</td>
<td>Return the bool of a single element PandasObject.</td>
</tr>
<tr>
<td>clip([lower, upper, axis, inplace])</td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td>clip_lower(threshold[, axis, inplace])</td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td>clip_upper(threshold[, axis, inplace])</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([inplace])</td>
<td>(DEPRECATED) Compute NDFrame with &quot;consolidated&quot; internals (data of each dtype grouped together in a single ndarray).</td>
</tr>
<tr>
<td>convert_objects([convert_dates,...])</td>
<td>(DEPRECATED) Attempt to infer better dtype for object columns.</td>
</tr>
<tr>
<td>copy([deep])</td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td>count(axis)</td>
<td>Return number of observations over requested axis.</td>
</tr>
<tr>
<td>cummax([axis, skipna])</td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>cummin([axis, skipna])</td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>cumprod([axis, skipna])</td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>cumsum</code></td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>describe</code></td>
<td>Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.</td>
</tr>
<tr>
<td><code>div(other, axis)</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>divide(other, axis)</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>dropna(axis, how, inplace)</code></td>
<td>Drop 2D from panel, holding passed axis constant</td>
</tr>
<tr>
<td><code>eq(other, axis)</code></td>
<td>Wrapper for comparison method <code>eq</code>.</td>
</tr>
<tr>
<td><code>equals(other)</code></td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>ffill(axis, inplace, limit, downcast)</code></td>
<td>Synonym for <code>DataFrame.fillna(method='ffill')</code>.</td>
</tr>
<tr>
<td><code>fillna(value, method, axis, inplace, ...)</code></td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td><code>filter(items, like, regex, axis)</code></td>
<td>Subset rows or columns of dataframe according to labels in the specified index.</td>
</tr>
<tr>
<td><code>first(offset)</code></td>
<td>Convenience method for subsetting initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>floordiv(other, axis)</code></td>
<td>Integer division of series and other, element-wise (binary operator <code>floordiv</code>).</td>
</tr>
<tr>
<td><code>fromDict(data[, intersect, orient, dtype])</code></td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td><code>from_dict(data[, intersect, orient, dtype])</code></td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td><code>ge(other, axis)</code></td>
<td>Wrapper for comparison method <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 counts of unique dtypes in this object.</td>
</tr>
<tr>
<td><code>get_ftype_counts()</code></td>
<td>(DEPRECATED) Return counts of unique ftypes in this object.</td>
</tr>
<tr>
<td><code>get_value(*args, **kwargs)</code></td>
<td>(DEPRECATED) Quickly retrieve single value at (item, major, minor) location</td>
</tr>
<tr>
<td><code>get_values()</code></td>
<td>Return an ndarray after converting sparse values to dense.</td>
</tr>
<tr>
<td><code>groupby(function[, axis])</code></td>
<td>Group data on given axis, returning GroupBy object</td>
</tr>
<tr>
<td><code>gt(other, axis)</code></td>
<td>Wrapper for comparison method <code>gt</code>.</td>
</tr>
<tr>
<td><code>head(n)</code></td>
<td>Return the first n rows.</td>
</tr>
<tr>
<td><code>infer_objects()</code></td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td><code>interpolate([method, axis, limit, inplace, ...])</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>isnull()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>iteritems()</code></td>
<td>Iterate over (label, values) on info axis</td>
</tr>
<tr>
<td><code>join(other[, how, lsuffix, rsuffix])</code></td>
<td>Join items with other Panel either on major or minor axes 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 Fisher’s definition of kurtosis (kurtosis of normal == 0.0).</td>
</tr>
</tbody>
</table>
Table 81 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>kurtosis([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0).</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Convenience method for subsetting final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
<tr>
<td><code>le(other[, axis])</code></td>
<td>Wrapper for comparison method le</td>
</tr>
<tr>
<td><code>lt(other[, axis])</code></td>
<td>Wrapper for comparison method lt</td>
</tr>
<tr>
<td><code>mad([axis, skipna, level])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>major_xs(key)</code></td>
<td>Return slice of panel along major axis</td>
</tr>
<tr>
<td><code>mask(cond[, other, inplace, axis, level, ...])</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.</td>
</tr>
<tr>
<td><code>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>mean([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>median([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>min([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>minor_xs(key)</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 mod).</td>
</tr>
<tr>
<td><code>mul(other[, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator mul).</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[, axis])</code></td>
<td>Wrapper for comparison method ne</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>pct_change([periods, fill_method, limit, freq])</code></td>
<td>Percentage change between the current and a prior element.</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>rank([axis, method, numeric_only, ...])</code></td>
<td>Compute numerical data ranks (1 through n) along axis.</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(*args, **kwargs)</code></td>
<td>Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>reindex_axis</code></td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
<tr>
<td><code>reindex_like</code></td>
<td>Return an object with matching indices to myself.</td>
</tr>
<tr>
<td><code>rename</code></td>
<td>Alter axes input function or functions.</td>
</tr>
<tr>
<td><code>rename_axis</code></td>
<td>Alter the name of the index or columns.</td>
</tr>
<tr>
<td><code>replace</code></td>
<td>Replace values given in <code>to_replace</code> with <code>value</code>.</td>
</tr>
<tr>
<td><code>resample</code></td>
<td>Convenience method for frequency conversion and resampling of time series.</td>
</tr>
<tr>
<td><code>rdiv</code></td>
<td>Integer division of series and other, element-wise (binary operator <code>rdiv</code>).</td>
</tr>
<tr>
<td><code>rmod</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
<tr>
<td><code>rmul</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>round</code></td>
<td>Round each value in Panel to a specified number of decimal places.</td>
</tr>
<tr>
<td><code>rpow</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>rsub</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>rtruediv</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>sample</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>select</code></td>
<td>(DEPRECATED) Return data corresponding to axis labels matching criteria.</td>
</tr>
<tr>
<td><code>sem</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>set_axis</code></td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td><code>set_value</code></td>
<td>(DEPRECATED) Quickly set single value at (item, major, minor) location</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 Normalized by N-1.</td>
</tr>
<tr>
<td><code>slice_shift</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>sort_index</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>sort_values</code></td>
<td>NOT IMPLEMENTED: do not call this method, as sorting values is not supported for Panel objects and will raise an error.</td>
</tr>
<tr>
<td><code>squeeze</code></td>
<td>Squeeze length 1 dimensions.</td>
</tr>
<tr>
<td><code>std</code></td>
<td>Return sample standard deviation over requested axis.</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>
</tbody>
</table>

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### Table 81 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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>Return the last n rows.</td>
</tr>
<tr>
<td><code>take(indices[, axis, convert, is_copy])</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>to_clipboard([excel, sep])</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>to_dense()</code></td>
<td>Return dense representation of NDFrame (as opposed to sparse)</td>
</tr>
<tr>
<td><code>to_excel(path[, na_rep, engine])</code></td>
<td>Write each DataFrame in Panel to a separate excel sheet</td>
</tr>
<tr>
<td><code>to_frame([filter_observations])</code></td>
<td>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.</td>
</tr>
<tr>
<td><code>to_hdf(path_or_buf, key, **kwargs)</code></td>
<td>Write the contained data to an HDF5 file using HDF-Store.</td>
</tr>
<tr>
<td><code>to_json([path_or_buf, orient, date_format, . . .])</code></td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td><code>to_latex([buf, columns, col_space, header, . . .])</code></td>
<td>Render an object to a tabular environment table.</td>
</tr>
<tr>
<td><code>to_msgpack([path_or_buf, encoding])</code></td>
<td>msgpack (serialize) object to input file path.</td>
</tr>
<tr>
<td><code>to_pickle(path[, compression, protocol])</code></td>
<td>Pickle (serialize) object to file.</td>
</tr>
<tr>
<td><code>to_sparse(*args, **kwargs)</code></td>
<td>NOT IMPLEMENTED: do not call this method, as sparsifying is not supported for Panel objects and will raise an error.</td>
</tr>
<tr>
<td><code>to_sql(name, con[, schema, if_exists, . . .])</code></td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td><code>to_xarray()</code></td>
<td>Return an xarray object from the pandas object.</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>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
<tr>
<td><code>tz_shift([periods, freq, axis])</code></td>
<td>Shift the time index, using the index’s frequency if available.</td>
</tr>
<tr>
<td><code>tz_convert(tz[, axis, level, copy])</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>tz_localize(tz[, axis, level, copy, ambiguous])</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 self where cond is True and otherwise are from other.</td>
</tr>
<tr>
<td><code>xs(key[, axis])</code></td>
<td>Return slice of panel along selected axis</td>
</tr>
</tbody>
</table>

#### pandas.Panel.abs

`Panel.abs()`

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

**Returns abs**

Series/DataFrame containing the absolute value of each element.
See also:

numpy.abs

Notes

For complex inputs, $1.2 + 1j$, the absolute value is $\sqrt{a^2 + b^2}$.

Examples

Absolute numeric values in a Series.

```python
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0   1.10
1   2.00
2   3.33
3   4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```python
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```python
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0   1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```python
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
   a  b  c
0  4  10 100
1  5  20  50
2  6  30 -30
3  7  40 -50
>>> df.loc[(df.c - 43).abs().argsort()]
   a  b  c
0  5  20  50
1  4  10 100
2  6  30 -30
3  7  40 -50
```
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.add_prefix

Panel.add_prefix(prefix)
Prefix labels with string prefix.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

Parameters prefix : str
The string to add before each label.

Returns Series or DataFrame
New Series or DataFrame with updated labels.

See also:
Series.add_suffix Suffix row labels with string suffix.
DataFrame.add_suffix Suffix column labels with string suffix.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0 1
1 2
2 3
3 4
dtype: int64

>>> s.add_prefix('item_')
item_0 1
item_1 2
item_2 3
item_3 4
dtype: int64
```
```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```python
>>> df.add_prefix('col_')
   col_A  col_B
0     1     3
1     2     4
2     3     5
3     4     6
```

**pandas.Panel.add_suffix**

Panel.add_suffix(suffix)

Suffix labels with string suffix.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

**Parameters**

suffix : str

The string to add after each label.

**Returns**

Series or DataFrame

New Series or DataFrame with updated labels.

**See also:**

Series.add_prefix Prefix row labels with string prefix.

DataFrame.add_prefix Prefix column labels with string prefix.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```python
>>> s.add_suffix('_item')
   0_item  1_item  2_item  3_item
0     1     2     3     4
```

```python
>>> df = pd.DataFrame({
    'A': [1, 2, 3, 4],
    'B': [3, 4, 5, 6]
})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6

>>> df.add_suffix('_col')
   A_col  B_col
0     1     3
1     2     4
2     3     5
3     4     6
```

### pandas.Panel.align

`Panel.align(other, **kwargs)`

Align two objects 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
  - Filling axis, method and limit
- `broadcast_axis`: int or labels for object, default None
  - Broadcast values along this axis, if aligning two objects of different dimensions

**Returns** `(left, right)` (NDFrame, type of other)

Aligned objects
pandas.Panel.all

Panel.all (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether all elements are True over series or dataframe axis.

Returns True if all elements within a series or along a dataframe axis are non-zero, not-empty or not-False.

Parameters

axis : int, default 0
Select the axis which can be 0 for indices and 1 for columns.

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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**kwargs : any, default None
Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

all [DataFrame or Panel (if level specified)]

See also:

pandas.Series.all Return True if all elements are True
pandas.DataFrame.any Return True if one (or more) elements are True

Examples

Series

```python
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
```

Dataframes

Create a dataframe from a dictionary.

```python
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1   col2
0   True   True
1   True   False
```

Default behaviour checks if column-wise values all return True.
Adding axis=1 argument will check if row-wise values all return True.

```python
donf.all(axis=1)
 0 True
 1 False
dtype: bool
```

### pandas.Panel.any

Panel.any (axis=None, bool_only=None, skipna=None, level=None, **kwargs)

Return whether any element is True over requested axis.

Unlike DataFrame.all(), this performs an or operation. If any of the values along the specified axis is True, this will return True.

**Parameters**

- **axis**: int, default 0
  - Select the axis which can be 0 for indices and 1 for columns.

- **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 columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**kwargs**: any, default None

- Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- any [DataFrame or Panel (if level specified)]

**See also:**

- pandas.DataFrame.all Return whether all elements are True.

### Examples

**Series**

For Series input, the output is a scalar indicating whether any element is True.

```python
>>> pd.Series([True, False]).any()
True
```
DataFrame

Whether each column contains at least one True element (the default).

```python
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0, 2], 'C': [0, 0]})
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```python
>>> df.any()
A   True
B   True
C  False
dtype: bool
```

Aggregating over the columns.

```python
>>> df = pd.DataFrame({'A': [True, False], 'B': [1, 2]})
>>> df
   A  B
0  True  1
1  False  2
```

```python
>>> df.any(axis='columns')
0  True
1  True
dtype: bool
```

```python
>>> df = pd.DataFrame({'A': [True, False], 'B': [1, 0]})
>>> df
   A  B
0  True  1
1  False  0
```

```python
>>> df.any(axis='columns')
0  True
1  False
dtype: bool
```

*any* for an empty DataFrame is an empty Series.

```python
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

**pandas.Panel.apply**

Panel.apply(func, axis='major', **kwargs)

Applies function along axis (or axes) of the Panel

**Parameters**

- **func**: function

  Function to apply to each combination of ‘other’ axes e.g. if axis = ‘items’, the combination of major_axis/minor_axis will each be passed as a Series; if axis = (‘items’, ‘major’), DataFrames of items & major axis will be passed

- **axis**: {'items', 'minor', 'major'}, or {0, 1, 2}, or a tuple with two
axes

Additional keyword arguments will be passed as keywords to the function

Returns

result [Panel, DataFrame, or Series]

Examples

Returns a Panel with the square root of each element

```python
>>> p = pd.Panel(np.random.rand(4,3,2))
>>> p.apply(np.sqrt)
```

Equivalent to p.sum(1), returning a DataFrame

```python
>>> p.apply(lambda x: x.sum(), axis=1)
```

Equivalent to previous:

```python
>>> p.apply(lambda x: x.sum(), axis='major')
```

Return the shapes of each DataFrame over axis 2 (i.e the shapes of items x major), as a Series

```python
>>> p.apply(lambda x: x.shape, axis=(0,1))
```

**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.

Deprecated since version 0.21.0.

**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()`

Convert the frame to its Numpy-array representation.

Deprecated since version 0.23.0: Use `DataFrame.values()` instead.

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. By numpy.find_common_type convention, mixing int64 and uint64 will result in a float64 dtype.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

pandas.Panel.asfreq

Panel.asfreq(freq=None, method=None, how=None, normalize=False, fill_value=None)

Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. resample is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

Parameters

freq [DateOffset object, or string]

method : {'backfill'/'bfill', 'pad'/'ffill'}, default None

Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):

• 'pad' / 'ffill': propagate last valid observation forward to next valid

• 'backfill' / 'bfill': use NEXT valid observation to fill

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

fill_value: scalar, optional

Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

New in version 0.20.0.

Returns

converted [type of caller]
See also:

reindex

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
                                    s
2000-01-01 00:00:00  0.0
2000-01-01 00:01:00  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:03:00  3.0
```

Upsample the series into 30 second bins.

```
>>> df.asfreq(freq='30S')
                                    s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  NaN
2000-01-01 00:03:00  3.0
```

Upsample again, providing a fill value.

```
>>> df.asfreq(freq='30S', fill_value=9.0)
                                    s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  9.0
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  9.0
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  9.0
2000-01-01 00:03:00  3.0
```

Upsample again, providing a method.

```
>>> df.asfreq(freq='30S', method='bfill')
                                    s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  2.0
2000-01-01 00:02:00  2.0
```

(continues on next page)
pandas.Panel.asof

Panel.asof(where, subset=None)
The last row without any NaN is taken (or the last row without NaN considering only the subset of
columns in the case of a DataFrame)

New in version 0.19.0: For DataFrame

If there is no good value, NaN is returned for a Series a Series of NaN values for a DataFrame

Parameters

where [date or array of dates]
subset : string or list of strings, default None
    if not None use these columns for NaN propagation

Returns where is scalar

• value or NaN if input is Series
• Series if input is DataFrame

where is Index: same shape object as input

See also:
merge_asof

Notes

Dates are assumed to be sorted Raises if this is not the case

pandas.Panel.astype

Panel.astype(dtype, copy=True, errors='raise', **kwargs)
Cast a pandas object to a specified dtype dtype.

Parameters dtype : data type, or dict of column name -> data type

Use a numpy.dtype or Python type to cast entire pandas object to the same type.
Alternatively, use {col: dtype, ...}, where col is a column label and dtype is a
numpy.dtype or Python type to cast one or more of the DataFrame’s columns to
column-specific types.
copy : bool, default True.
    Return a copy when copy=True (be very careful setting copy=False as
    changes to values then may propagate to other pandas objects).

errors : {'raise', 'ignore'}, default 'raise'.
    Control raising of exceptions on invalid data for provided dtype.
• `raise`: allow exceptions to be raised
• `ignore`: suppress exceptions. On error return original object

New in version 0.20.0.

`raise_on_error`: raise on invalid input

Deprecated since version 0.20.0: Use `errors` instead

`kwargs` [keyword arguments to pass on to the constructor]

Returns

`casted` [type of caller]

See also:

`pandas.to_datetime` Convert argument to datetime.

`pandas.to_timedelta` Convert argument to timedelta.

`pandas.to_numeric` Convert argument to a numeric type.

`numpy.ndarray.astype` Cast a numpy array to a specified type.

Examples

```python
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```python
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```python
>>> ser.astype('category', ordered=True, categories=[2, 1])
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```python
>>> s1 = pd.Series([1,2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
```

(continues on next page)
>>> s1  # note that s1[0] has changed too
0  10
1   2
dtype: int64

**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]

**Raises** TypeError
If the index is not a DatetimeIndex

**See also:**

- **between_time** Select values between particular times of the day
- **first** Select initial periods of time series based on a date offset
- **last** Select final periods of time series based on a date offset
- **DatetimeIndex.indexer_at_time** Get just the index locations for values at particular time of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4

>>> ts.at_time('12:00')
A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```

**pandas.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).
By setting `start_time` to be later than `end_time`, you can get the times that are *not* between the two times.

**Parameters**

- `start_time` [datetime.time or string]
- `end_time` [datetime.time or string]
- `include_start` [boolean, default True]
- `include_end` [boolean, default True]

**Returns**

- `values_between_time` [type of caller]

**Raises** `TypeError`

If the index is not a `DatetimeIndex`

**See also:**

- `at_time` Select values at a particular time of the day
- `first` Select initial periods of time series based on a date offset
- `last` Select final periods of time series based on a date offset
- `DatetimeIndex.indexer_between_time` Get just the index locations for values between particular times of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
          A
2018-04-09  00:00:00  1
2018-04-10  00:20:00  2
2018-04-11  00:40:00  3
2018-04-12  01:00:00  4

>>> ts.between_time('0:15', '0:45')
          A
2018-04-10  00:20:00  2
2018-04-11  00:40:00  3
```

You get the times that are *not* between two times by setting `start_time` later than `end_time`:

```python
>>> ts.between_time('0:45', '0:15')
          A
2018-04-09  00:00:00  1
2018-04-12  01:00:00  4
```

**pandas.Panel.bfill**

`Panel.bfill` *(axis=None, inplace=False, limit=None, downcast=None)*

Syonym for `DataFrame.fillna(method='bfill')`
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**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, axis=None, inplace=False, *args, **kwargs)

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

**Parameters**

- **lower**: float or array_like, default None
  
  Minimum threshold value. All values below this threshold will be set to it.

- **upper**: float or array_like, default None

  Maximum threshold value. All values above this threshold will be set to it.

- **axis**: int or string axis name, optional

  Align object with lower and upper along the given axis.

- **inplace**: boolean, default False

  Whether to perform the operation in place on the data.

  New in version 0.21.0.

- ***args, **kwargs**

  Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

Series or DataFrame

Same type as calling object with the values outside the clip boundaries replaced.

**See also**

- **clip_lower** Clip values below specified threshold(s).

- **clip_upper** Clip values above specified threshold(s).

**Examples**

```python
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
  col_0  col_1
0     9   -2
1    -3   -7
2     0    6
3    -1    8
4     5   -5
```
Clips per column using lower and upper thresholds:

```python
>>> df.clip(-4, 6)
col_0  col_1
 0   6  -2
 1  -3  -4
 2   0   6
 3  -1   6
 4   5  -4
```

Clips using specific lower and upper thresholds per column element:

```python
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0   2
1  -4
2  -1
3   6
4   3
dtype: int64

>>> df.clip(t, t + 4, axis=0)
col_0  col_1
 0   6   2
 1  -3  -4
 2   0   3
 3   6   8
 4   5   3
```

**pandas.Panel.clip_lower**

Panel.clip_lower(threshold, axis=None, inplace=False)

Return copy of the input with values below a threshold truncated.

**Parameters**

- **threshold**: numeric or array-like
  - Minimum value allowed. All values below threshold will be set to this value.
  - float: every value is compared to `threshold`.
  - array-like: The shape of `threshold` should match the object it’s compared to. When `self` is a Series, `threshold` should be the length. When `self` is a DataFrame, `threshold` should 2-D and the same shape as `self` for `axis=None`, or 1-D and the same length as the axis being compared.

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  - Align `self` with `threshold` along the given axis.

- **inplace**: boolean, default False
  - Whether to perform the operation in place on the data.

**Returns**

- clipped [same type as input]

**See also**:

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Series.clip Return copy of input with values below and above thresholds truncated.
Series.clip_upper Return copy of input with values above threshold truncated.
Examples
Series single threshold clipping:
>>> s = pd.Series([5, 6, 7, 8, 9])
>>> s.clip_lower(8)
0
8
1
8
2
8
3
8
4
9
dtype: int64

Series clipping element-wise using an array of thresholds. threshold should be the same length as the
Series.
>>> elemwise_thresholds = [4, 8, 7, 2, 5]
>>> s.clip_lower(elemwise_thresholds)
0
5
1
8
2
7
3
8
4
9
dtype: int64

DataFrames can be compared to a scalar.
>>> df = pd.DataFrame({"A": [1, 3, 5], "B": [2, 4, 6]})
>>> df
A B
0 1 2
1 3 4
2 5 6
>>> df.clip_lower(3)
A B
0 3 3
1 3 4
2 5 6

Or to an array of values. By default, threshold should be the same shape as the DataFrame.
>>> df.clip_lower(np.array([[3, 4], [2, 2], [6, 2]]))
A B
0 3 4
1 3 4
2 6 6

Control how threshold is broadcast with axis. In this case threshold should be the same length as the axis
specified by axis.

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```python
>>> df.clip_lower(np.array([3, 3, 5]), axis='index')
   A  B
0  3  3
1  3  4
2  5  6

>>> df.clip_lower(np.array([4, 5]), axis='columns')
   A  B
0  4  5
1  4  5
2  5  6
```

**pandas.Panel.clip_upper**

Panel.clip_upper(threshold, axis=None, inplace=False)  
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.
- **inplace** : boolean, default False  
  Whether to perform the operation in place on the data  
  New in version 0.21.0.

**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 when computing the result.
- **level** : int or level name, default None  
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame
- **numeric_only** : boolean, default None  
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
Returns

**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).

Deprecated since version 0.20.0: Consolidate will be an internal implementation only.

**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.

Deprecated since version 0.21.0.

**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]
See also:

**pandas.to_datetime** Convert argument to datetime.

**pandas.to_timedelta** Convert argument to timedelta.

**pandas.to_numeric** Return a fixed frequency timedelta index, with day as the default.

Pandas.Panel.copy

Panel.copy (deep=True)

Make a copy of this object’s indices and data.

When deep=True (default), a new object will be created with a copy of the calling object’s data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When deep=False, a new object will be created without copying the calling object’s data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

Parameters deep : bool, default True

Make a deep copy, including a copy of the data and the indices. With deep=False neither the indices nor the data are copied.

Returns copy : Series, DataFrame or Panel

Object type matches caller.

Notes

When deep=True, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to copy.deepcopy in the Standard Library, which recursively copies object data (see examples below).

While Index objects are copied when deep=True, the underlying numpy array is not copied for performance reasons. Since Index is immutable, the underlying data can be safely shared and a copy is not needed.

Examples

```python
>>> s = pd.Series([1, 2], index=["a", "b"])
```

```plaintext
a  1
b  2
dtype: int64
```

```python
>>> s_copy = s.copy()
```

```plaintext
a  1
b  2
dtype: int64
```

Shallow copy versus default (deep) copy:
shallow = s.copy(deep=False)

Shallow copy shares data and index with original.

Deep copy has own copy of data and index.

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

pandas.Panel.count

Panel.count (axis='major')

Return number of observations over requested axis.

Parameters
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axis [{‘items’, ‘major’, ‘minor’} or {0, 1, 2}]

Returns
count [DataFrame]

pandas.Panel.cummax

Panel.cummax (axis=None, skipna=True, *args, **kwargs)
Return cumulative maximum over a DataFrame or Series axis.
Returns a DataFrame or Series of the same size containing the cumulative maximum.
Parameters axis : {0 or ‘index’, 1 or ‘columns’}, default 0
The index or the name of the axis. 0 is equivalent to None or ‘index’.
skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA.
*args, **kwargs :
Additional keywords have no effect but might be accepted for compatibility with NumPy.
Returns
cummax [DataFrame or Panel]
See also:
pandas.core.window.Expanding.max Similar functionality but ignores NaN values.
Panel.max Return the maximum over Panel axis.
Panel.cummax Return cumulative maximum over Panel axis.
Panel.cummin Return cumulative minimum over Panel axis.
Panel.cumsum Return cumulative sum over Panel axis.
Panel.cumprod Return cumulative product over Panel axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0  2.0
1  NaN
2  5.0
3 -1.0
4  0.0
dtype: float64

By default, NA values are ignored.
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

```python
>>> s.cummax()
0   2.0
1   NaN
2   5.0
3   5.0
4   5.0
dtype: float64

To include NA values in the operation, use `skipna=False`

```python
>>> s.cummax(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

**DataFrame**

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                   columns=list('AB'))

>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cummax()
   A  B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```python
>>> df.cummax(axis=1)
   A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

**pandas.Panel.cummin**

Panel.cummin(\( axis=None, \) \( skipna=True, \) *\( \)args, **\( \)kwargs)\)

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

**Parameters**

- **axis**: \{0 or ‘index’, 1 or ‘columns’\}, default 0
  - The index or the name of the axis. 0 is equivalent to None or ‘index’.
skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs :

Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

cummin [DataFrame or Panel]

See also:

pandas.core.window.Expanding.min Similar functionality but ignores NaN values.

Panel.min Return the minimum over Panel axis.

Panel.cummax Return cumulative maximum over Panel axis.

Panel.cummin Return cumulative minimum over Panel axis.

Panel.cumsum Return cumulative sum over Panel axis.

Panel.cumprod Return cumulative product over Panel axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0   2.0
1   NaN
2   5.0
3  -1.0
4   0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cummin()
0   2.0
1  NaN
2   2.0
3  -1.0
4  -1.0
dtype: float64
```

To include NA values in the operation, use skipna=False

```python
>>> s.cummin(skipna=False)
0   2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64
```

DataFrame
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [np.nan, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  NaN NaN
2  1.0  0.0

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

>>> df.cummin()
   A  B
0  2.0  1.0
1  2.0 NaN
2  1.0  0.0

To iterate over columns and find the minimum in each row, use `axis=1`

>>> df.cummin(axis=1)
   A  B
0  2.0  1.0
1  3.0 NaN
2  1.0  0.0

pandas.Panel.cumprod

Panel.cumprod(axis=None, skipna=True, *args, **kwargs)
Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

Parameters

- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  The index or the name of the axis. 0 is equivalent to None or ‘index’.
- **skipna** : boolean, default True
  Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs :
Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

cumprod [DataFrame or Panel]

See also:

- pandas.core.window.Expanding.prod Similar functionality but ignores NaN values.
- Panel.prod Return the product over Panel axis.
- Panel.cummax Return cumulative maximum over Panel axis.
- Panel.cummin Return cumulative minimum over Panel axis.
**Panel.cumsum** Return cumulative sum over Panel axis.

**Panel.cumprod** Return cumulative product over Panel axis.

### Examples

#### Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])

>>> s
0    2.0
1   NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cumprod()
0    2.0
1   NaN
2   10.0
3  -10.0
4    0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumprod(skipna=False)
0    2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

#### DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],...[3.0, np.nan],...[1.0, 0.0]],...columns=list('AB'))

>>> df
   A   B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumprod()
   A   B
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```
To iterate over columns and find the product in each row, use `axis=1`:

```python
>>> df.cumprod(axis=1)
   A  B
0  2.0 2.0
1  3.0 NaN
2  1.0 0.0
```

### pandas.Panel.cumsum

`Panel.cumsum(axis=None, skipna=True, *args, **kwargs)`

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

**Parameters**

- `axis` : {0 or ‘index’, 1 or ‘columns’}, default 0
  
  The index or the name of the axis. 0 is equivalent to None or ‘index’.

- `skipna` : boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA.

- `*args, **kwargs` :
  
  Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- `cumsum` [DataFrame or Panel]

**See also:**

- `pandas.core.window.Expanding.sum` Similar functionality but ignores NaN values.
- `Panel.sum` Return the sum over Panel axis.
- `Panel.cummax` Return cumulative maximum over Panel axis.
- `Panel.cummin` Return cumulative minimum over Panel axis.
- `Panel.cumsum` Return cumulative sum over Panel axis.
- `Panel.cumprod` Return cumulative product over Panel axis.

### Examples

#### Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
 0  2.0
 1  NaN
 2  5.0
 3 -1.0
 4  0.0
dtype: float64
```

By default, NA values are ignored.
To include NA values in the operation, use `skipna=False`

```python
>>> s.cumsum(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64
```

**DataFrame**

```python
>>> df = pd.DataFrame([[2.0, 1.0], ...
...
... [3.0, np.nan],
...
... [1.0, 0.0]],
...
... columns=list('AB'))

>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumsum()
   A  B
0  2.0  3.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```python
>>> df.cumsum(axis=1)
   A  B
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0
```

**pandas.Panel.describe**

The `pandas.Panel.describe()` function generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

**Parameters**

- `percentiles`: list-like of numbers, optional
The percentiles to include in the output. All should fall between 0 and 1. The default is \([.25, .5, .75]\), which returns the 25th, 50th, and 75th percentiles.

**include**: ‘all’, list-like of dtypes or None (default), optional

A white list of data types to include in the result. Ignored for Series. Here are the options:

- ‘all’: All columns of the input will be included in the output.
- A list-like of dtypes: Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use ‘category’
- None (default): The result will include all numeric columns.

**exclude**: list-like of dtypes or None (default), optional,

A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes: Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use ‘category’
- None (default): The result will exclude nothing.

**Returns**

- summary: Series/DataFrame of summary statistics

**See also:**

`DataFrame.count`, `DataFrame.max`, `DataFrame.min`, `DataFrame.mean`, `DataFrame.std`, `DataFrame.select_dtypes`

**Notes**

For numeric data, the result’s index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value’s frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`. 

---

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Examples

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
  count  3.0
  mean  2.0
  std  1.0
  min  1.0
  25%  1.5
  50%  2.0
  75%  2.5
  max  3.0
```

Describing a categorical Series.

```python
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
  count  4
  unique  3
  top  a
  freq  2
dtype: object
```

Describing a timestamp Series.

```python
>>> s = pd.Series([np.datetime64("2000-01-01"),
... np.datetime64("2010-01-01"),
... np.datetime64("2010-01-01")
...])
>>> s.describe()
  count  3
  unique  2
  top  2010-01-01 00:00:00
  freq  2
  first  2000-01-01 00:00:00
  last  2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({ 'object': ['a', 'b', 'c'],
... 'numeric': [1, 2, 3],
... 'categorical': pd.Categorical(['d', 'e', 'f'])
... })
>>> df.describe()
    numeric
  count  3.0
  mean  2.0
  std  1.0
  min  1.0
  25%  1.5
  50%  2.0
  75%  2.5
  max  3.0
```
Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
categorical  numeric  object
   count    3      3.0     3
  unique    3    NaN      3
   top     f       NaN    c
   freq    1    NaN      1
  mean   NaN     2.0   NaN
  std    NaN     1.0   NaN
  min   NaN     1.0   NaN
25%    NaN     1.5   NaN
50%    NaN     2.0   NaN
75%    NaN     2.5   NaN
 max   NaN     3.0   NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()
count  3.0
 mean  2.0
  std  1.0
  min  1.0
25%   1.5
50%   2.0
75%   2.5
 max  3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
   numeric
   count  3.0
    mean  2.0
     std  1.0
     min  1.0
25%     1.5
50%     2.0
75%     2.5
 max     3.0
```

Including only string columns in a DataFrame description.

```python
>>> df.describe(include=[np.object])
   object
   count  3
 unique  3
    top  c
   freq  1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
    categorical
   count  3
 unique  3
```
Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
    categorical          object
count       3          3
unique      3          3
top         f          c
freq        1          1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.object])
        categorical      numeric
count    3          3.0
unique   3          NaN
top      f          NaN
freq     1          NaN
mean     NaN          2.0
std      NaN          1.0
min      NaN          1.0
25%      NaN          1.5
50%      NaN          2.0
75%      NaN          2.5
max      NaN          3.0
```

`pandas.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]

Axis to broadcast over

Returns

Panel

See also:

Panel.rtruediv

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, axis=None)

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 DataFrame.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'}]

- **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. Must be greater than 0 if not None.

- **downcast**: dict, default is None
  - A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns

- **filled** [Panel]

See also:

- **interpolate** Fill NaN values using interpolation.
- **reindex, asfreq**

Examples

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                   columns=list('ABCD'))
>>> df
          A     B     C     D
0  NaN     2  NaN    0.0
1   3.0   4.0  NaN    1.0
2  NaN  NaN  NaN    5.0
3  NaN   3.0  NaN    4.0
```
Replace all NaN elements with 0s.

```python
>>> df.fillna(0)
   A   B   C   D
0  0.0  2.0  0.0  0.0
1  3.0  4.0  0.0  1.0
2  0.0  0.0  0.0  5.0
3  0.0  3.0  0.0  4.0
```

We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
   A   B   C   D
0  NaN  2.0  NaN  0.0
1  3.0  4.0  NaN  1.0
2  3.0  4.0  NaN  5.0
3  3.0  3.0  NaN  4.0
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}

>>> df.fillna(value=values)
   A   B   C   D
0  0.0  2.0  2.0  0.0
1  3.0  4.0  2.0  1.0
2  0.0  1.0  2.0  5.0
3  0.0  3.0  2.0  4.0
```

Only replace the first NaN element.

```python
>>> df.fillna(value=values, limit=1)
   A   B   C   D
0  0.0  2.0  2.0  0.0
1  3.0  4.0  NaN  1.0
2  NaN  1.0  NaN  5.0
3  NaN  3.0  NaN  4.0
```

**pandas.Panel.filter**

Panel.filter(items=None, like=None, regex=None, axis=None)

Subset rows or columns of dataframe according to labels in the specified index.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

**Parameters**

- **items**: list-like
  
  List of info axis to restrict to (must not all be present)

- **like**: string
  
  Keep info axis where “arg in col == True”

---

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regex : string (regular expression)
        Keep info axis with re.search(regex, col) == True

axis : int or string axis name
        The axis to filter on. By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame

Returns
        same type as input object

See also:
        pandas.DataFrame.loc

Notes
        The items, like, and regex parameters are enforced to be mutually exclusive.
        axis defaults to the info axis that is used when indexing with [].

Examples

```python
>>> df
  one   two   three
mouse  1  2  3
rabbit 4  5  6

>>> # select columns by name
>>> df.filter(items=['one', 'three'])
  one   three
mouse  1  3
rabbit 4  6

>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
  one   three
mouse  1  3
rabbit 4  6

>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
  one   two   three
rabbit 4  5  6
```

pandas.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]

Raises TypeError

If the index is not a `DatetimeIndex`

See also:

- `last` Select final periods of time series based on a date offset
- `at_time` Select values at a particular time of the day
- `between_time` Select values between particular times of the day

Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
   A
2018-04-09    1
2018-04-11    2
2018-04-13    3
2018-04-15    4

Get the rows for the first 3 days:

```python
>>> ts.first('3D')
   A
2018-04-09    1
2018-04-11    2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

### pandas.Panel.first_valid_index

Panel`first_valid_index`()

Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

### 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, axis=None)
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 counts of unique dtypes in this object.

Returns dtypes: Series
Series with the count of columns with each dtype.

See also:
dtypes Return the dtypes in this object.

Examples

```python
>>> a = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
>>> df = pd.DataFrame(a, columns=['str', 'int', 'float'])
>>> df
     str  int  float
0    a  1.0  1.0
1    b  2.0  2.0
2    c  3.0  3.0

>>> df.get_dtype_counts()
float64  1
int64    1
object   1
dtype: int64
```
pandas.Panel.get_ftype_counts

Panel.get_ftype_counts()
Return counts of unique ftypes in this object.
Deprecated since version 0.23.0.
This is useful for SparseDataFrame or for DataFrames containing sparse arrays.

Returns dtype: Series
Series with the count of columns with each type and sparsity (dense/sparse)

See also:
ftypes Return ftypes (indication of sparse/dense and dtype) in this object.

Examples

```python
da = [['a', 1, 1.0], ['b', 2, 2.0], ['c', 3, 3.0]]
df = pd.DataFrame(a, columns=['str', 'int', 'float'])
df
str  int  float
0  a   1  1.0
1  b   2  2.0
2  c   3  3.0

>>> df.get_ftype_counts()
floating:dense 1
int64:dense   1
object:dense  1
dtype: int64
```

pandas.Panel.get_value

Panel.get_value(*args, **kwargs)
Quickly retrieve single value at (item, major, minor) location
Deprecated since version 0.21.0.
Please use .at[] or .iat[] accessors.

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()
Return an ndarray after converting sparse values to dense.
This is the same as .values for non-sparse data. For sparse data contained in a pandas.SparseArray, the data are first converted to a dense representation.

Returns numpy.ndarray
Numpy representation of DataFrame

See also:
values Numpy representation of DataFrame.
pandas.SparseArray Container for sparse data.

Examples

```python
>>> df = pd.DataFrame({
'a': [1, 2], 'b': [True, False],
... 'c': [1.0, 2.0])
>>> df
   a   b    c
0  1  True  1.0
1  2  False 2.0

>>> df.get_values()
array([[1, True, 1.0], [2, False, 2.0]], dtype=object)
```

```python
>>> df = pd.DataFrame({'a': pd.SparseArray([1, None, None]),
... 'c': [1.0, 2.0, 3.0])
>>> df
   a   c
0  1.0  1.0
1  NaN  2.0
2  NaN  3.0

>>> df.get_values()
array([[ 1., 1.],
       [nan, 2.],
       [nan, 3.]]
```

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, axis=None)
Wrapper for comparison method gt

**pandas.Panel.head**

Panel.head(n=5)
Return the first n rows.
This function returns the first n rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

**Parameters**
- n : int, default 5
  Number of rows to select.

**Returns**
- obj_head : type of caller
  The first n rows of the caller object.

See also:

**pandas.DataFrame.tail** Returns the last n rows.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion', ...
                      'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
   animal
0  alligator
1       bee
2   falcon
3       lion
4  monkey
5   parrot
6    shark
7     whale
8     zebra

Viewing the first 5 lines

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```python
>>> df.head()
   animal
0  alligator
1       bee
2   falcon
3       lion
4  monkey

Viewing the first n lines (three in this case)

```
pandas: powerful Python data analysis toolkit, Release 0.23.1

>>> df.head(3)
   animal
0  alligator
1     bee
2    falcon

pandas.Panel.infer_objects

Panel.infer_objects()

Attempt to infer better dtypes for object columns.
Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

New in version 0.21.0.

Returns

converted [same type as input object]

See also:

pandas.to_datetime Convert argument to datetime.
pandas.to_timedelta Convert argument to timedelta.
pandas.to_numeric Convert argument to numeric typeR

Examples

>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
   A
0  1
1  2
2  3

>>> df.dtypes
A object
dtype: object

>>> df.infer_objects().dtypes
A int64
dtype: object

pandas.Panel.interpolate

Panel.interpolate(method='linear', axis=0, limit=None, inplace=False,
                  limit_direction='forward', limit_area=None, downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

Parameters method : {'linear', 'time', 'index', 'values', 'nearest', 'zero',}
• ‘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’, ‘linear’, ‘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’, ‘pchip’ and ‘akima’ are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. For more information on their behavior, see the scipy documentation and tutorial documentation
• ‘from_derivatives’ refers to BPoly.from_derivatives which replaces ‘piecewise_polynomial’ interpolation method in scipy 0.18

New in version 0.18.1: Added support for the ‘akima’ method Added interpolate method ‘from_derivatives’ which replaces ‘piecewise_polynomial’ in scipy 0.18; backwards-compatible with scipy < 0.18

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. Must be greater than 0.

limit_direction : [{'forward', 'backward', 'both'}, default ‘forward’]

limit_area : {'inside', 'outside'}, default None
  • None: (default) no fill restriction
  • ‘inside’ Only fill NaNs surrounded by valid values (interpolate).
  • ‘outside’ Only fill NaNs outside valid values (extrapolate).

If limit is specified, consecutive NaNs will be filled in this direction.

New in version 0.21.0.

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.Panel.isna

Panel.isna()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

Returns

NDFrame

Mask of bool values for each element in NDFrame that indicates whether an element is not an NA value.

See also:

NDFrame.isnull alias of isna
NDFrame.notna boolean inverse of isna
NDFrame.dropna omit axes labels with missing values

isna top-level isna

Examples

Show which entries in a DataFrame are NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                    'name': ['Alfred', 'Batman', ''],
...                    'toy': [None, 'Batmobile', 'Joker']})
```

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0 5.0  NaT  Alfred  None
1 6.0 1939-05-27 Batman  Batmobile
2 NaN 1940-04-25 Joker

```python
>>> df.isna()
age  born  name  toy
0  False  True  False  True
1  False  False  False  False
2  True  False  False  False
```

Show which entries in a Series are NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
```

```python
>>> ser
0 5.0
1 6.0
2 NaN
dtype: float64
```

```python
>>> ser.isna()
0  False
1  False
2   True
dtype: bool
```

**pandas.PanelisNull**

Panel.isnull()  
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.nan, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

Returns

NDFrame

Mask of bool values for each element in NDFrame that indicates whether an element is not an NA value.

See also:

NDFrame.isnull alias of isna

NDFrame.notna boolean inverse of isna

NDFrame.dropna omit axes labels with missing values

isna top-level isna

Examples

Show which entries in a DataFrame are NA.
```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                   'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                            pd.Timestamp('1940-04-25')],
...                   'name': ['Alfred', 'Batman', ''],
...                   'toy': [None, 'Batmobile', 'Joker']})

>>> df
   age   born                name   toy
0   5.0  NaT  Alfred        None
1   6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25    Joker

>>> df.isna()
   age   born    name   toy
0  False  True  False  True
1  False  False  False  False
2  True   False  False  False

Show which entries in a Series are NA.

>>> ser = pd.Series([5, 6, np.NaN])

>>> ser
0    5.0
1    6.0
2   NaN
dtype: float64

>>> ser.isna()
0  False
1  False
2  True
dtype: bool

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.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

\texttt{rsuffix} : string

Suffix to use from right frame’s overlapping columns

Returns

\texttt{joined} [Panel]

\texttt{pandas.Panel.keys}

\texttt{Panel.keys}()

Get the ‘info axis’ (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

\texttt{pandas.Panel.kurt}

\texttt{Panel.kurt} (axis=\texttt{None}, skipna=\texttt{None}, level=\texttt{None}, numeric\_only=\texttt{None}, **\texttt{kwargs})

Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

\texttt{axis} [{\texttt{items (0), major\_axis (1), minor\_axis (2)}]}

\texttt{skipna} : boolean, default True

Exclude NA/null values when computing the result.

\texttt{level} : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

\texttt{numeric\_only} : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

\texttt{kurt} [DataFrame or Panel (if level specified)]

\texttt{pandas.Panel.kurtosis}

\texttt{Panel.kurtosis} (axis=\texttt{None}, skipna=\texttt{None}, level=\texttt{None}, numeric\_only=\texttt{None}, **\texttt{kwargs})

Return unbiased kurtosis over requested axis using Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

\texttt{axis} [{\texttt{items (0), major\_axis (1), minor\_axis (2)}]}

\texttt{skipna} : boolean, default True

Exclude NA/null values when computing the result.

\texttt{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 columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**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]

**Raises** TypeError

If the index is not a `DatetimeIndex`

**See also:**

**first** Select initial periods of time series based on a date offset

**at_time** Select values at a particular time of the day

**between_time** Select values between particular times of the day

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ta = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ta
   A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the last 3 days:

```python
>>> ts.last('3D')
   A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.
**pandas.Panel.last_valid_index**

Panel.last_valid_index()  
Return index for last non-NA/null value.

**Returns**

scalar [type of index]

**Notes**

If all elements are non-NA/null, returns None. Also returns None for empty NDFrame.

**pandas.Panel.le**

Panel.le(other, axis=None)  
Wrapper for comparison method le

**pandas.Panel.lt**

Panel.lt(other, axis=None)  
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 when computing the result.  
level : int or level name, default None  
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame  
numeric_only : boolean, default None  
Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

mad [DataFrame or Panel (if level specified)]

**pandas.Panel.major_xs**

Panel.major_xs(key)  
Return slice of panel along major axis
Parameters key: object

Major axis label

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 and is a superset of major_xs functionality, see MultiIndex Slicers

pandas.Panel.mask

Panel.mask(cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)

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, array-like, or callable

Where cond is False, keep the original value. Where True, replace with corresponding value from other. If cond is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as cond.

other: scalar, NDFrame, or callable

Entries where cond is True are replaced with corresponding value from other. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as other.

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]

errors: str, {‘raise’, ‘ignore’}, default ‘raise’

• raise: allow exceptions to be raised
• ignore: suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

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)

Deprecated since version 0.21.0.

Returns

\[\text{wh} \quad \text{[same type as caller]}\]

See also:

\[\text{DataFrame.where()}\]

Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if \(\text{cond}\) is False the element is used; otherwise the corresponding element from the DataFrame \(\text{other}\) is used.

The signature for \texttt{DataFrame.where()} differs from \texttt{numpy.where()}. Roughly \texttt{df1.where(m, df2)} is equivalent to \texttt{np.where(m, df1, df2)}.

For further details and examples see the mask documentation in \texttt{indexing}.

Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0  NaN
1  1.0
2  2.0
3  3.0
4  4.0
```

```python
>>> s.mask(s > 0)
0  0.0
1  NaN
2  NaN
3  NaN
4  NaN
```

```python
>>> s.where(s > 1, 10)
0  10.0
1  10.0
2  2.0
3  3.0
4  4.0
```

```python
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0  -1
1 -2   3
2 -4  -5
3  6  -7
4 -8   9
```

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```python
>>> df.where(m, -df) == np.where(m, df, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True
>>> df.where(m, -df) == df.mask(~m, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True
```

**pandas.Panel.max**

`Panel.max(\text{axis}=\text{None}, \text{skipna}=\text{None}, \text{level}=\text{None}, \text{numeric_only}=\text{None}, **\text{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` \{\text{items (0), major_axis (1), minor_axis (2)}\}
- `skipna`: boolean, default True
  Excluding NA/null values when computing the result.
- `level`: int or level name, default None
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame
- `numeric_only`: boolean, default None
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- `max` [DataFrame or Panel (if level specified)]

**pandas.Panel.mean**

`Panel.mean(\text{axis}=\text{None}, \text{skipna}=\text{None}, \text{level}=\text{None}, \text{numeric_only}=\text{None}, **\text{kwargs})`  

Return the mean of the values for the requested axis.

**Parameters**

- `axis` \{\text{items (0), major_axis (1), minor_axis (2)}\}
- `skipna`: boolean, default True
  Excluding NA/null values when computing the result.
- `level`: int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

**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 when computing the result.

**level** : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

**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 when computing the result.

**level** : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
Returns

\texttt{min} [DataFrame or Panel (if level specified)]

\texttt{pandas.Panel.minor_xs}

Panel.\texttt{minor_xs}(key)

Return slice of panel along minor axis

**Parameters**

- **key** : object
  
  Minor axis label

**Returns**

- **y** : DataFrame
  
  index -> major axis, columns -> items

Notes

\texttt{minor_xs} is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels and is a superset of \texttt{minor_xs} functionality, see \textit{MultiIndex Slicers}

\texttt{pandas.Panel.mod}

Panel.\texttt{mod}(other, axis=0)

Modulo of series and other, element-wise (binary operator \texttt{mod}). Equivalent to \texttt{panel \% other}.

**Parameters**

- **other** [DataFrame or Panel]

  \texttt{axis} : {items, major_axis, minor_axis}

  Axis to broadcast over

**Returns**

Panel

See also:

\texttt{Panel.rmod}

\texttt{pandas.Panel.mul}

Panel.\texttt{mul}(other, axis=0)

Multiplication of series and other, element-wise (binary operator \texttt{mul}). Equivalent to \texttt{panel * other}.

**Parameters**

- **other** [DataFrame or Panel]

  \texttt{axis} : {items, major_axis, minor_axis}

  Axis to broadcast over

**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}

   Axis to broadcast over

Returns

Panel

See also:

   Panel.rmul

pandas.Panel.ne

Panel.ne(other, axis=None)

Wrapper for comparison method ne

pandas.Panel.notna

Panel.notna()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns NDFrame

   Mask of bool values for each element in NDFrame that indicates whether an element is not an NA value.

See also:

   NDFrame.notnull alias of notna

   NDFrame.isna boolean inverse of notna

   NDFrame.dropna omit axes labels with missing values

   notna top-level notna
Examples

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                            pd.Timestamp('1940-04-25')],
...                    'name': ['Alfred', 'Batman', ''],
...                    'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age    born      name  toy
0   5.0  NaT    Alfred  None
1   6.0 1939-05-27  Batman  Batmobile
2  NaN  1940-04-25    Joker  

>>> df.notna()
   age   born      name   toy
0  True  False  True  False
1  True   True  True  True
2 False  True  True  True
```

Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64

>>> ser.notna()
0   True
1   True
2  False
dtype: bool
```

pandas.Panel.notnull

Panel.notnull()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns NDFrame

Mask of bool values for each element in NDFrame that indicates whether an element is not an NA value.

See also:

NDFrame.notnull alias of notna
NDFrame.isna boolean inverse of notna
**NDFrame.dropna**  omit axes labels with missing values

**notna**  top-level notna

### Examples

Show which entries in a DataFrame are not NA.

```python
def = pd.DataFrame({'age': [5, 6, np.NaN],
              pd.Timestamp('1940-04-25')],
    'name': ['Alfred', 'Batman', ''],
    'toy': [None, 'Batmobile', 'Joker']})

def
age   born   name  toy
0  5.0     NaT   Alfred  None
1  6.0  1939-05-27  Batman  Batmobile
2  NaN   1940-04-25   Joker

def.notna()
   age   born   name  toy
0   True  False  True  False
1   True   True  True   True
2  False  True  True   True
```

Show which entries in a Series are not NA.

```python
ser = pd.Series([5, 6, np.NaN])

ser
0  5.0
1  6.0
2  NaN
dtype: float64

ser.notna()
0  True
1  True
2  False
dtype: bool
```

**pandas.Panel.pct_change**

Panel.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percentage change between the current and a prior element. Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

- **Parameters**
  - **periods**: int, default 1
    - Periods to shift for forming percent change.
  - **fill_method**: str, default ‘pad’
    - How to handle NAs before computing percent changes.
  - **limit**: int, default None
The number of consecutive NAs to fill before stopping.

**freq** : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. ‘M’ or BDay()).

**kwargs

Additional keyword arguments are passed into DataFrame.shift or Series.shift.

**Returns** chg: Series or DataFrame

The same type as the calling object.

See also:

**Series.diff** Compute the difference of two elements in a Series.

**Dataframe.diff** Compute the difference of two elements in a DataFrame.

**Series.shift** Shift the index by some number of periods.

**Dataframe.shift** Shift the index by some number of periods.

**Examples**

Series

```python
>>> s = pd.Series([90, 91, 85])
>>> s
0  90
1  91
2  85
dtype: int64
```

```python
>>> s.pct_change()  
0  NaN
1  0.011111
2 -0.065934
dtype: float64
```

```python
>>> s.pct_change(periods=2)  
0  NaN
1  NaN
2 -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```python
>>> s = pd.Series([90, 91, None, 85])
>>> s
0  90.0
1  91.0
2  NaN
3  85.0

dtype: float64
```
DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```python
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
...     'IT': [804.74, 810.01, 860.13],
...     'index': ['1980-01-01', '1980-02-01', '1980-03-01']
... })
>>> df
     FR     GR     IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13
```

```python
>>> df.pct_change()
      FR   GR   IT
1980-01-01 NaN NaN NaN
1980-02-01  0.013810  0.013684  0.006549
1980-03-01  0.053365  0.059318  0.061876
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```python
>>> df = pd.DataFrame({
...     '2016': [1769950, 30586265],
...     '2015': [1500923, 40912316],
...     '2014': [1371819, 41403351],
...     'index': ['GOOG', 'APPL']
... })
>>> df
     2016  2015  2014
GOOG  1769950  1500923  1371819
APPL  30586265  40912316  41403351
```

```python
>>> df.pct_change(axis='columns')
    2016  2015  2014
GOOG  NaN -0.151997 -0.086016
APPL  NaN  0.337604  0.012002
```

**pandas.Panel.pipe**

Panel.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs)

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**: iterable, optional
positiona l arguments passed into func.

**kwargs**: mapping, optional
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 Series, DataFrames or GroupBy objects. 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.

**Parameters item**: str
Column label to be popped

**Returns**

**popped** [Series]

**Examples**
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```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
... ('parrot', 'bird', 24.0),
... ('lion', 'mammal', 80.5),
... ('monkey', 'mammal', np.nan)],
... columns=('name', 'class', 'max_speed'))

>>> df
   name  class max_speed
0  falcon    bird       389.0
1  parrot    bird        24.0
2    lion  mammal        80.5
3   monkey  mammal         NaN

>>> df.pop('class')

0  bird
1  bird
2  mammal
3  mammal
Name: class, dtype: object

>>> df
   name  max_speed
0  falcon       389.0
1  parrot       24.0
2    lion       80.5
3   monkey     NaN
```

**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, min_count=0, **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 when computing the result.

**level**: int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame.

**numeric_only**: boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min_count**: int, default 0

The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**Returns**

**prod** [DataFrame or Panel (if level specified)]

**Examples**

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the min_count parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the skipna parameter, min_count handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

**pandas.Panel.product**

*Panel.product*(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the product of the values for the requested axis

**Parameters**

- **axis**: [[items (0), major_axis (1), minor_axis (2)]]
- **skipna**: boolean, default True
  - Exclude NA/null values when computing the result.
- **level**: int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only**: boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min_count**: int, default 0

The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

**Examples**

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

**pandas.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.rank

Panel.rank(axis=0, method='average', numeric_only=None, 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
  - index to direct ranking
- **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
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. Valid only for DataFrame or Panel objects
- **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** [same type as caller]

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(*args, **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 (should be specified using keywords)
- New labels / index to conform to. Preferably an Index object to avoid duplicating data

- method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.
  - 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 \( \text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance} \).
- Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.
- New in version 0.21.0: (list-like tolerance)

**Returns**

`reindexed` [Panel]
Examples

DataFrame.reindex supports two calling conventions

- (index=index_labels, columns=column_labels, ...)
- (labels, axis={"index", "columns"}, ...)

We highly recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```python
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({
...     'http_status': [200, 200, 404, 404, 301],
...     'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...     index=index)
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```python
>>> new_index= ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10', 'Chrome']
```

```python
>>> df.reindex(new_index)
```

```python
http_status  response_time
Safari        404.0         0.07
Iceweasel     NaN           NaN
Comodo Dragon NaN           NaN
IE10          404.0         0.08
Chrome        200.0         0.02
```

We can fill in the missing values by passing a value to the keyword fill_value. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword method to fill the NaN values.

```python
>>> df.reindex(new_index, fill_value=0)
```

```python
http_status  response_time
Safari        404           0.07
Iceweasel     0             0.00
Comodo Dragon 0             0.00
IE10          404           0.08
Chrome        200           0.02
```

```python
>>> df.reindex(new_index, fill_value='missing')
```

```python
http_status  response_time
Safari        404           0.07
Iceweasel     missing      missing
Comodo Dragon  missing      missing
IE10          404           0.08
Chrome        200           0.02
```

We can also reindex the columns.
>>> df.reindex(columns=['http_status', 'user_agent'])

<table>
<thead>
<tr>
<th></th>
<th>http_status</th>
<th>user_agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firefox</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Chrome</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Safari</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>IE10</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>Konqueror</td>
<td>301</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Or we can use “axis-style” keyword arguments

>>> df.reindex(['http_status', 'user_agent'], axis="columns")

<table>
<thead>
<tr>
<th></th>
<th>http_status</th>
<th>user_agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firefox</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Chrome</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Safari</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>IE10</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>Konqueror</td>
<td>301</td>
<td>NaN</td>
</tr>
</tbody>
</table>

To further illustrate the filling functionality in reindex, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```python
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]},
... index=date_index)
>>> df2
   prices
2010-01-01    100
2010-01-02    101
2010-01-03     NaN
2010-01-04    100
2010-01-05     89
2010-01-06     88
```

Suppose we decide to expand the dataframe to cover a wider date range.

```python
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
   prices
2009-12-29     NaN
2009-12-30     NaN
2009-12-31     NaN
2010-01-01    100
2010-01-02    101
2010-01-03     NaN
2010-01-04    100
2010-01-05     89
2010-01-06     88
```

The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with NaN. If desired, we can fill in the missing values using one of several options.

For example, to backpropagate the last valid value to fill the NaN values, pass bfill as an argument to the method keyword.

```python
>>> df2.reindex(date_index2, method='bfill')
   prices
2009-12-29     NaN
2009-12-30     NaN
2009-12-31     NaN
2010-01-01    100
2010-01-02    101
2010-01-03     NaN
2010-01-04    100
2010-01-05     89
2010-01-06     88
2010-01-07     NaN
```
Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the fillna() method.

See the user guide for more.

**pandas.Panel.reindex_axis**

Panel.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 \( \text{abs(index[indexer] - target)} \leq \text{tolerance} \).

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

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=None, 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. Can be list-like.

New in version 0.21.0: (list-like tolerance)

Returns

reindexed [same as input]

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)
pandas: powerful Python data analysis toolkit, Release 0.23.1

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. Extra labels listed don’t throw an error. Alternatively, change Series.name with a scalar value (Series only).

Parameters  
- **items**, **major_axis**, **minor_axis**: scalar, list-like, dict-like or function, optional
  - Scalar or list-like will alter the Series.name attribute, and raise on DataFrame or Panel. dict-like or functions are transformations 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.
- **level**: int or level name, default None
  - In case of a MultiIndex, only rename labels in the specified level.

Returns

renamed [Panel (new object)]

See also:

pandas.NDFrame.rename_axis

Examples

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0 1  
1 2   
2 3  
dtype: int64
>>> s.rename("my_name") # scalar, changes Series.name
0 1  
1 2   
2 3  
Name: my_name, dtype: int64
>>> s.rename(lambda x: x ** 2) # function, changes labels
0 1  
1 4   
2 9  
dtype: int64
>>> s.rename({1: 3, 2: 5}) # mapping, changes labels
0 1  
3 2   
5 3  
dtype: int64
```

Since DataFrame doesn’t have a .name attribute, only mapping-type arguments are allowed.
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})
>>> df.rename(2)
Traceback (most recent call last):
...
TypeError: 'int' object is not callable

DataFrame.rename supports two calling conventions

- (index=index_mapper, columns=columns_mapper, ...)
- (mapper, axis={'index', 'columns'}, ...)

We highly recommend using keyword arguments to clarify your intent.

>>> df.rename(index=str, columns={'A': 'a', 'B': 'c'})
   a  c
0  1  4
1  2  5
2  3  6

>>> df.rename(index=str, columns={'A': 'a', 'C': 'c'})
   a  B
0  1  4
1  2  5
2  3  6

Using axis-style parameters

>>> df.rename(str.lower, axis='columns')
   a  b
0  1  4
1  2  5
2  3  6

>>> df.rename({1: 2, 2: 4}, axis='index')
   A  B
0  1  4
1  2  5
2  4  6

See the user guide for more.

pandas.Panel.rename_axis

Panel.rename_axis (mapper, axis=0, copy=True, inplace=False)
Alter the name of the index or columns.

Parameters mapper : scalar, list-like, optional
    Value to set as the axis name attribute.

    axis : {0 or ‘index’, 1 or ‘columns’}, default 0
    The index or the name of the axis.

    copy : boolean, default True
    Also copy underlying data.
inplace : boolean, default False

Modifies the object directly, instead of creating a new Series or DataFrame.

Returns renamed : Series, DataFrame, or None

The same type as the caller or None if inplace is True.

See also:

- `pandas.Series.rename` Alter Series index labels or name
- `pandas.DataFrame.rename` Alter DataFrame index labels or name
- `pandas.Index.rename` Set new names on index

Notes

Prior to version 0.21.0, rename_axis could also be used to change the axis labels by passing a mapping or scalar. This behavior is deprecated and will be removed in a future version. Use rename instead.

Examples

Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s.rename_axis("foo")
foo
0 1
1 2
2 3
dtype: int64
```

DataFrame

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename_axis("foo")
A  B
foo
0 1 4
1 2 5
2 3 6
```

```python
>>> df.rename_axis("bar", axis="columns")
bar  A  B
0   1  4
1   2  5
2   3  6
```

**pandas.Panel.replace**

Panel.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')

Replace values given in to_replace with value.
Values of the NDFrame are replaced with other values dynamically. This differs from updating with `.loc` or `.iloc`, which require you to specify a location to update with some value.

**Parameters**  
`to_replace` : str, regex, list, dict, Series, int, float, or None

How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to `to_replace` will be replaced with `value`
  - str: string exactly matching `to_replace` will be replaced with `value`
  - regex: regexs matching `to_replace` will be replaced with `value`

- list of str, regex, or numeric:
  - First, if `to_replace` and `value` are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in both lists will be interpreted as regexs otherwise they will match directly. This doesn’t matter much for `value` since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.

- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, `{‘a’: ‘b’, ‘y’: ‘z’}` replaces the value ‘a’ with ‘b’ and ‘y’ with ‘z’. To use a dict in this way the `value` parameter should be `None`.
  - For a DataFrame a dict can specify that different values should be replaced in different columns. For example, `{‘a’: 1, ‘b’: ‘z’}` looks for the value 1 in column ‘a’ and the value ‘z’ in column ‘b’ and replaces these values with whatever is specified in `value`. The `value` parameter should not be `None` in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
  - For a DataFrame nested dictionaries, e.g., `{‘a’: {‘b’: np.nan}}`, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The `value` parameter should be `None` to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.

- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If `value` is also `None` then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

**value** : scalar, dict, list, str, regex, default None

Value to replace any values matching `to_replace` with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular 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 from a DataFrame). Returns the caller if this is True.

**limit** : int, default None

Maximum size gap to forward or backward fill.

**regex** : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* must be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case *to_replace* must be None.

**method** : {'pad', 'ffill', 'bfill', None}

The method to use when for replacement, when *to_replace* is a scalar, list or tuple and *value* is None.

Changed in version 0.23.0: Added to DataFrame.

**Returns** **NDFrame**

Object after replacement.

**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.
- When replacing multiple bool or datetime64 objects and the arguments to *to_replace* does not match the type of the value being replaced

**ValueError**

- If a list or an ndarray is passed to *to_replace* and *value* but they are not the same length.

**See also:**

NDFrame.fillna Fill NA values

NDFrame.where Replace values based on boolean condition

Series.str.replace Simple string replacement.

**Notes**

- Regex substitution is performed under the hood with re.sub. The rules for substitution for re.sub are the same.

- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers are strings, then you can do this.

- This method has a lot of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
- When dict is used as the `to_replace` value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

**Examples**

**Scalar ‘to_replace‘ and ‘value’**

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0  5
1  1
2  2
3  3
4  4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
                     'B': [5, 6, 7, 8, 9],
                     'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

**List-like ‘to_replace‘**

```python
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```

```python
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```python
>>> s.replace([1, 2], method='bfill')
0  0
1  3
2  3
3  3
4  4
dtype: int64
```

**dict-like ‘to_replace‘**
>>> df.replace({0: 10, 1: 100})
   A   B  C
0   10  5  a
1  100  6  b
2   2  7  c
3   3  8  d
4   4  9  e

>>> df.replace({'A': 0, 'B': 5}, 100)
   A   B  C
0  100  100  a
1    1   6  b
2    2   7  c
3    3   8  d
4    4  9  e

>>> df.replace({'A': {0: 100, 4: 400}})
   A   B  C
0  100   5  a
1    1   6  b
2    2   7  c
3    3   8  d
4  400   9  e

Regular expression 'to_replace'

>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                     'B': ['abc', 'bar', 'xyz']})
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
   A   B
0  new abc
1   foo new
2  bait xyz

>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
   A   B
0  new abc
1   foo bar
2  bait xyz

>>> df.replace(regex=r'^ba.$', value='new')
   A   B
0  new abc
1   foo new
2  bait xyz

>>> df.replace(regex={r'^ba.$': 'new', 'foo': 'xyz'})
   A   B
0  new abc
1   xyz new
2  bait xyz

>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
   A   B
0  new abc
(continues on next page)
Note that when replacing multiple bool or datetime64 objects, the data types in the to_replace parameter must match the data type of the value being replaced:

```python
>>> df = pd.DataFrame({'A': [True, False, True],
                    'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False})  # raises
Traceback (most recent call last):
  ...TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a TypeError because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the to_replace parameter:

```python
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the to_replace value, it is like the value(s) in the dict are equal to the value parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None):

```python
>>> s.replace({'a': None})
0  10
1  None
2  None
3   b
4  None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the method parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad'):

```python
>>> s.replace('a', None)
0  10
1  10
2   b
3   b
dtype: object
```

### pandas.Panel.resample

`pandas.Panel.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0, on=None, level=None)`

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (DatetimeIndex, PeriodIndex, or TimedeltaIndex), or pass datetime-like values to the on or level keyword.

**Parameters**

- `rule`: string
the offset string or object representing target conversion

**axis** [int, optional, default 0]

**closed**: {'right', 'left'}

Which side of bin interval is closed. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**label**: {'right', 'left'}

Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**convention**: {'start', 'end', 's', 'e'}

For PeriodIndex only, controls whether to use the start or end of rule

**kind**: {'timestamp', 'period'}, optional

Pass ‘timestamp’ to convert the resulting index to a DateTimeIndex or ‘period’ to convert it to a PeriodIndex. By default the input representation is retained.

**loffset**: timedelta

Adjust the resampled time labels

**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

**on**: string, optional

For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

New in version 0.19.0.

**level**: string or int, optional

For a MultiIndex, level (name or number) to use for resampling. Level must be datetime-like.

New in version 0.19.0.

**Returns**

Resampler object

**See also:**

groupby Group by mapping, function, label, or list of labels.

**Notes**

See the user guide for more.

To learn more about the offset strings, please see this link.
Examples

Start by creating a series with 9 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series

2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T').sum()
2000-01-01 00:00:00    3
2000-01-01 00:03:00   12
2000-01-01 00:06:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket `2000-01-01 00:03:00` contains the value 3, but the summed value in the resampled bucket with the label `2000-01-01 00:03:00` does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```python
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00    3
2000-01-01 00:06:00   12
2000-01-01 00:09:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00    0
2000-01-01 00:03:00    6
2000-01-01 00:06:00   15
2000-01-01 00:09:00   15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```python
>>> series.resample('30S').asfreq()[0:5] #select first 5 rows
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00    1.0
2000-01-01 00:01:30  NaN
2000-01-01 00:02:00    2.0
Freq: 30S, dtype: float64
```
Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 0
2000-01-01 00:01:00 1
2000-01-01 00:01:30 1
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the bfill method.

```python
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 1
2000-01-01 00:01:00 1
2000-01-01 00:01:30 2
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Pass a custom function via apply

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00 8
2000-01-01 00:03:00 17
2000-01-01 00:06:00 26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword `convention` can be used to control whether to use the start or end of `rule`.

```python
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
               freq='A',
               periods=2))

>>> s
2012    1
2013    2
Freq: A-DEC, dtype: int64

Resample by month using ‘start’ `convention`. Values are assigned to the first month of the period.

```python
>>> s.resample('M', convention='start').asfreq().head()
2012-01 1.0
2012-02 NaN
2012-03 NaN
2012-04 NaN
2012-05 NaN
Freq: M, dtype: float64
```

Resample by month using ‘end’ `convention`. Values are assigned to the last month of the period.

```python
>>> s.resample('M', convention='end').asfreq()
2012-12 1.0
2013-01 NaN
```

pandas: powerful Python data analysis toolkit, Release 0.23.1

(continued from previous page)

<table>
<thead>
<tr>
<th>Year-Month</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-02</td>
<td>NaN</td>
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<tr>
<td>2013-11</td>
<td>NaN</td>
</tr>
<tr>
<td>2013-12</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Freq: M, dtype: float64

For DataFrame objects, the keyword `on` can be used to specify the column instead of the index for resampling.

```python
>>> df = pd.DataFrame(data=9*range(4), columns=['a', 'b', 'c', 'd'])
>>> df['time'] = pd.date_range('1/1/2000', periods=9, freq='T')
>>> df.resample('3T', on='time').sum()
   a  b  c  d
time
2000-01-01 00:00:00  0  3  6  9
2000-01-01 00:03:00  0  3  6  9
2000-01-01 00:06:00  0  3  6  9
```

For a DataFrame with MultiIndex, the keyword `level` can be used to specify on level the resampling needs to take place.

```python
>>> time = pd.date_range('1/1/2000', periods=5, freq='T')
>>> df2 = pd.DataFrame(data=10*range(4), columns=['a', 'b', 'c', 'd'],
                     index=pd.MultiIndex.from_product([time, [1, 2]])
                     )
>>> df2.resample('3T', level=0).sum()
   a  b  c  d
2000-01-01 00:00:00  0  6 12 18
2000-01-01 00:03:00  0  4  8 12
```

### 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.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.round**

Panel.round(decimals=0, *args, **kwargs)

Round each value in Panel to a specified number of decimal places.

New in version 0.18.0.

**Parameters**

decimals : int

Number of decimal places to round to (default: 0). If decimals is negative, it specifies the number of positions to the left of the decimal point.

**Returns**

Panel object
See also:

`numpy.around`

**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.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)

Return a random sample of items from an axis of object.

You can use random_state for reproducibility.

Parameters n : int, optional

    Number of items from axis to return. Cannot be used with frac. Default = 1 if frac = None.

frac : float, optional

    Fraction of axis items to return. Cannot be used with n.

replace : 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.

Examples

Generate an example Series and DataFrame:

```python
>>> s = pd.Series(np.random.randn(50))
>>> s.head()
0   -0.038497
1    1.820773
2   -0.972766
3   -1.598270
4   -1.598270
```
Next extract a random sample from both of these objects...

3 random elements from the Series:

```python
>>> s.sample(n=3)
27    -0.994689
55    -1.049016
67    -0.224565
dtype: float64
```

And a random 10% of the DataFrame with replacement:

```python
>>> df.sample(frac=0.1, replace=True)
A        B         C         D
35  1.981780   0.142106   1.817165  -0.290805
49  -1.336199  -0.448634  -0.789640   0.217116
40   0.823173  -0.078816   1.009536   1.015108
15   1.421154  -0.055301  -1.922594  -0.019696
  6  -0.148339   0.832938   1.787600  -1.383767
```

You can use random state for reproducibility:

```python
>>> df.sample(random_state=1)
A        B         C         D
37  -2.027662  0.103611   0.237496  -0.165867
43  -0.259323  -0.583426   1.516140  -0.479118
12  -1.686325  -0.579510   0.985195  -0.460286
  8   1.167946   0.429082  -1.215742  -1.636041
  9   1.197475  -0.864188   1.554031  -1.505264
```

### pandas.Panel.select

`Panel.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Deprecated since version 0.21.0: Use `df.loc[df.index.map(crit)]` to select via labels

**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
- **ddof** : int, default 1
  - Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** : boolean, default None
  - Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **sem** [DataFrame or Panel (if level specified)]

pandas.Panel.set_axis

**Panel.set_axis** *(labels, axis=0, inplace=None)*

Assign desired index to given axis.

Indexes for column or row labels can be changed by assigning a list-like or Index.

Changed in version 0.21.0: The signature is now *labels* and *axis*, consistent with the rest of pandas API. Previously, the *axis* and *labels* arguments were respectively the first and second positional arguments.

**Parameters**

- **labels** : list-like, Index
  - The values for the new index.
- **axis** : {0 or ‘index’, 1 or ‘columns’}, default 0
  - The axis to update. The value 0 identifies the rows, and 1 identifies the columns.
- **inplace** : boolean, default None
  - Whether to return a new %(klass)s instance.

**Warning:** inplace=None currently falls back to True, but in a future version, will default to False. Use inplace=True explicitly rather than relying on the default.

**Returns**

- **renamed** : %(klass)s or None
An object of same type as caller if inplace=False, None otherwise.

See also:

`pandas.DataFrame.rename_axis` Alter the name of the index or columns.

Examples

Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0  1
1  2
2  3
dtype: int64

>>> s.set_axis(['a', 'b', 'c'], axis=0, inplace=False)
a  1
b  2
c  3
dtype: int64
```

The original object is not modified.

```python
>>> s
0  1
1  2
2  3
dtype: int64
```

DataFrame

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})

Change the row labels.

```python
>>> df.set_axis(['a', 'b', 'c'], axis='index', inplace=False)
     A  B
a  1  4
b  2  5
c  3  6
```

Change the column labels.

```python
>>> df.set_axis(['I', 'II'], axis='columns', inplace=False)
     I  II
0  1  4
1  2  5
2  3  6
```

Now, update the labels inplace.

```python
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
>>> df
      i  ii
0   1   4
1   2   5
2   3   6
```
pandas.DataFrame

DataFrame.set_value

DataFrame.set_value(*args, **kwargs)
Quickly set single value at (item, major, minor) location

Deprecation since version 0.21.0.
Please use .at[] or .iat[] accessors.

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.DataFrame.shift

DataFrame.shift(periods=1, freq=None, axis='major')
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.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 [{‘items (0), major_axis (1), minor_axis (2)}]
**skipna** : boolean, default True

Exclude NA/null values when computing the result.

**level** : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

**skew** [DataFrame or Panel (if level specified)]

**pandas.Panel.slice_shift**

Panel.slice_shift \( (\text{periods}=1, \text{axis}=0) \)

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 \( (\text{axis}=0, \text{level}=\text{None}, \text{ascending}=\text{True}, \text{inplace}=\text{False}, \text{kind}=\text{‘quicksort’}, \text{na_position}=\text{‘last’}, \text{sort_remaining}=\text{True}) \)

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, default False

if True, perform operation in-place

**kind** : [‘quicksort’, ‘mergesort’, ‘heapsort’], default ‘quicksort’
Choice of sorting algorithm. See also ndarray.np.sort for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na_position**: {'first', 'last'}, default 'last'

*first* puts NaNs at the beginning, *last* puts NaNs at the end. Not implemented for MultiIndex.

**sort_remaining**: bool, default True

If true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.

**Returns**

sorted_obj [NDFrame]

```
pandas.Panel.sort_values

Panel.sort_values(by=None, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

NOT IMPLEMENTED: do not call this method, as sorting values is not supported for Panel objects and will raise an error.

```
pandas.Panel.squeeze

Panel.squeeze(axis=None)
```

Squeeze length 1 dimensions.

**Parameters**

axis: None, integer or string axis name, optional

The axis to squeeze if 1-sized.

New in version 0.20.0.

**Returns**

scalar if 1-sized, else original object

```
pandas.Panel.std

Panel.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)
```

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument.

**Parameters**

axis: [{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

ddof: int, default 1
Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

std [DataFrame or Panel (if level specified)]

pandas.Panel.sub

Panel.\texttt{sub}(\texttt{other, axis=0})

Subtraction of series and other, element-wise (binary operator \texttt{sub}). Equivalent to \texttt{panel - other}.

Parameters

\texttt{other} [DataFrame or Panel]

\texttt{axis} : [items, major_axis, minor_axis]

Axis to broadcast over

Returns

Panel

See also:

\texttt{Panel.rsub}

pandas.Panel.subtract

Panel.\texttt{subtract}(\texttt{other, axis=0})

Subtraction of series and other, element-wise (binary operator \texttt{sub}). Equivalent to \texttt{panel - other}.

Parameters

\texttt{other} [DataFrame or Panel]

\texttt{axis} : [items, major_axis, minor_axis]

Axis to broadcast over

Returns

Panel

See also:

\texttt{Panel.rsub}

pandas.Panel.sum

Panel.\texttt{sum}(\texttt{axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs})

Return the sum of the values for the requested axis

Parameters

\texttt{axis} [{items (0), major_axis (1), minor_axis (2)}]
skipna : boolean, default True

Exclude NA/null values when computing the result.

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count : int, default 0

The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

Returns

sum  [DataFrame or Panel (if level specified)]

Examples

By default, the sum of an empty or all-NA Series is 0.

```python
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the min_count parameter. For example, if you’d like the sum of an empty series to be NaN, pass min_count=1.

```python
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the skipna parameter, min_count handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).sum()
0.0
```

```python
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

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=-2, j=-1, 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)

.. versionchanged:: 0.18.1

The indexes i and j are now optional, and default to the two innermost levels of the index.

pandas.Panel.tail

`Panel.tail(n=5)`
Return the last n rows.

This function returns last n rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

**Parameters** n : int, default 5
Number of rows to select.

**Returns** type of caller
The last n rows of the caller object.

See also:

*pandas.DataFrame.head* The first n rows of the caller object.

Examples

```python
>>> df = pd.DataFrame({'animal':['alligator', 'bee', 'falcon', 'lion',
                                  'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
                      animal
0            alligator
1              bee
2           falcon
3             lion
4         monkey
5          parrot
6            shark
7            whale
8            zebra
```

Viewing the last 5 lines
Viewing the last \( n \) lines (three in this case)

```python
>>> df.tail(3)
animal
6  shark
7  whale
8  zebra
```

**pandas.Panel.take**

The `take` method of `pandas.Panel` takes the elements in the given positional indices along an axis. This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

- **Parameters**
  - `indices`: array-like
    - An array of ints indicating which positions to take.
  - `axis`: {0 or ‘index’, 1 or ‘columns’, None}, default 0
    - The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.
  - `convert`: bool, default True
    - Whether to convert negative indices into positive ones. For example, -1 would map to the len(axis) - 1. The conversions are similar to the behavior of indexing a regular Python list.
    - Deprecated since version 0.21.0: In the future, negative indices will always be converted.
  - `is_copy`: bool, default True
    - Whether to return a copy of the original object or not.
  - `**kwargs`
    - For compatibility with `numpy.take()`. Has no effect on the output.

- **Returns**
  - `taken`: type of caller
    - An array-like containing the elements taken from the object.

**See also:**

- `DataFrame.loc` Select a subset of a DataFrame by labels.
- `DataFrame.iloc` Select a subset of a DataFrame by positions.
- `numpy.take` Take elements from an array along an axis.
Examples

```python
>>> df = pd.DataFrame({'falcon': 'bird', 389.0),
... ('parrot', 'bird', 24.0),
... ('lion', 'mammal', 80.5),
... ('monkey', 'mammal', np.nan),
... columns=['name', 'class', 'max_speed'],
... index=[0, 2, 3, 1])
>>> df

name    class    max_speed
0  falcon   bird      389.0
2  parrot   bird       24.0
3   lion   mammal     80.5
1  monkey   mammal      NaN

Take elements at positions 0 and 3 along the axis 0 (default).
Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```python
>>> df.take([0, 3])

name    class    max_speed
0  falcon   bird      389.0
1  monkey   mammal      NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```python
>>> df.take([1, 2], axis=1)

class    max_speed
0   bird      389.0
2   bird       24.0
3  mammal     80.5
1  mammal      NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```python
>>> df.take([-1, -2])

name    class    max_speed
1  monkey   mammal      NaN
3   lion   mammal     80.5
```

```python
pandas.Panel.to_clipboard

Panel.to_clipboard(excel=True, sep=None, **kwargs)
Copy object to the system clipboard.
Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

Parameters excel : bool, default True

- True, use the provided separator, writing in a csv format for allowing easy pasting into excel.
- False, write a string representation of the object to the clipboard.

sep : str, default '\t'
```
Field delimiter

**kwargs

These parameters will be passed to DataFrame.to_csv.

See also:

**DataFrame.to_csv** Write a DataFrame to a comma-separated values (csv) file.

**read_clipboard** Read text from clipboard and pass to read_table.

Notes

Requirements for your platform.

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

Examples

Copy the contents of a DataFrame to the clipboard.

```python
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the the index by passing the keyword `index` and setting it to false.

```python
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```

**pandas.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** : 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`.

**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)

Write the contained data to an HDF5 file using HDFStore.
Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different key.

For more information see the user guide.

**Parameters**

path_or_buf : str or pandas.HDFStore
    File path or HDFStore object.

key : str
    Identifier for the group in the store.

mode : {'a', 'w', 'r+'}, default ‘a’
    Mode to open file:
    • ‘w’: write, a new file is created (an existing file with the same name would be deleted).
    • ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
    • ‘r+’: similar to ‘a’, but the file must already exist.

format : {'fixed', 'table'}, default ‘fixed’
    Possible values:
    • ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

append : bool, default False
    For Table formats, append the input data to the existing.

data_columns : list of columns or True, optional
    List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See Query via Data Columns. Applicable only to format='table'.

complevel : {0-9}, optional
    Specifies a compression level for data. A value of 0 disables compression.

complib : {'zlib', 'lzo', 'bzip2', 'blosc'}, default ‘zlib’
    Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {'blosc:blosclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd'}. Specifying a compression library which is not available issues a ValueError.

fletcher32 : bool, default False
    If applying compression use the fletcher32 checksum.

dropna : bool, default False
If true, ALL nan rows will not be written to store.

**errors**: str, default ‘strict’

Specifies how encoding and decoding errors are to be handled. See the errors argument for open() for a full list of options.

See also:

- **DataFrame.read_hdf** Read from HDF file.
- **DataFrame.to_parquet** Write a DataFrame to the binary parquet format.
- **DataFrame.to_sql** Write to a sql table.
- **DataFrame.to_feather** Write out feather-format for DataFrames.
- **DataFrame.to_csv** Write out to a csv file.

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
...                     index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')

We can add another object to the same file:

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```python
>>> pd.read_hdf('data.h5', 'df')
A   B
a  1  4
b  2  5
c  3  6

>>> pd.read_hdf('data.h5', 's')
0  1
1  2
2  3
3  4
dtype: int64
```

Deleting file with data:

```python
>>> import os
>>> os.remove('data.h5')
```

**pandas.Panel.to_json**

Panel.to_json(path_or_buf=None, orient=None, date_format=None, double_precision=10,
force_ascii=True, date_unit='ms', default_handler=None, lines=False, compression=None, index=True)

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**: string or file handle, optional

File path or object. If not specified, the result is returned as a string.

**orient**: string

Indication of expected JSON string format.

- **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
  - ‘table’ : dict like {‘schema’: {schema}, ‘data’: {data}} describing the data, and the data component is like orient='records'.

  Changed in version 0.20.0.

**date_format**: {None, ‘epoch’, ‘iso’}

Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the **orient**. For orient='table', the default is ‘iso’. For all other orients, the default is ‘epoch’.

**double_precision**: int, default 10

The number of decimal places to use when encoding floating point values.

**force_ascii**: boolean, default True

Force encoded string to be ASCII.

**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.

**lines**: boolean, default False
pandas: powerful Python data analysis toolkit, Release 0.23.1

If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError
if incorrect ‘orient’ since others are not list like.
New in version 0.19.0.
A string representing the compression to use in the output file, only used when
the first argument is a filename.
New in version 0.21.0.
index : boolean, default True
Whether to include the index values in the JSON string. Not including the index
(index=False) is only supported when orient is ‘split’ or ‘table’.
New in version 0.23.0.
See also:
pandas.read_json
Examples
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...
index=['row 1', 'row 2'],
...
columns=['col 1', 'col 2'])
>>> df.to_json(orient='split')
'{"columns":["col 1","col 2"],
"index":["row 1","row 2"],
"data":[["a","b"],["c","d"]]}'

Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved with this encoding.
>>> df.to_json(orient='records')
'[{"col 1":"a","col 2":"b"},{"col 1":"c","col 2":"d"}]'

Encoding/decoding a Dataframe using 'index' formatted JSON:
>>> df.to_json(orient='index')
'{"row 1":{"col 1":"a","col 2":"b"},"row 2":{"col 1":"c","col 2":"d"}}'

Encoding/decoding a Dataframe using 'columns' formatted JSON:
>>> df.to_json(orient='columns')
'{"col 1":{"row 1":"a","row 2":"c"},"col 2":{"row 1":"b","row 2":"d"}}'

Encoding/decoding a Dataframe using 'values' formatted JSON:
>>> df.to_json(orient='values')
'[["a","b"],["c","d"]]'

Encoding with Table Schema
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"},
{"name": "col 1", "type": "string"},
(continues on next page)

34.5. Panel

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Panel.to_latex

Panel.to_latex(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparse=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal='. ')

Render an object to a tabular environment table. You can splice this into a LaTeX document. Requires \usepackage{booktabs}.

Changed in version 0.20.2: Added to Series

to_latex-specific options:

bold_rows [boolean, default False] 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 will be read from the pandas config module] Default: False. Use a longtable environment instead of tabular. Requires adding a \usepackage{longtable} to your LaTeX preamble.

escape [boolean, default will be read from the pandas config module] Default: True. When set to False prevents from escaping latex special characters in column names.

encoding [str, default None] A string representing the encoding to use in the output file, defaults to ‘ascii’ on Python 2 and ‘utf-8’ on Python 3.

decimal [string, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

New in version 0.18.0.

multicolumn [boolean, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

New in version 0.20.0.

multicolumn_format [str, default ‘l’] The alignment for multicolumns, similar to column_format The default will be read from the config module.

New in version 0.20.0.

multirow [boolean, default False] Use multirow to enhance MultiIndex rows. Requires adding a \usepackage{multirow} to your LaTeX preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

New in version 0.20.0.
pandas.Panel.to_msgpack

Panel.to_msgpack(path_or_buf=None, encoding='utf-8', **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, compression='infer', protocol=4)

Pickle (serialize) object to file.

**Parameters**

- **path**: str
  
  File path where the pickled object will be stored.

  
  A string representing the compression to use in the output file. By default, infers from the file extension in specified path.

  New in version 0.20.0.

- **protocol**: int
  
  Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [R21] paragraph 12.1.2). The possible values for this parameter depend on the version of Python. For Python 2.x, possible values are 0, 1, 2. For Python>=3.0, 3 is a valid value. For Python >= 3.4, 4 is a valid value.

  A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

  New in version 0.21.0.

**See also:**

- **read_pickle** Load pickled pandas object (or any object) from file.

- **DataFrame.to_hdf** Write DataFrame to an HDF5 file.

- **DataFrame.to_sql** Write DataFrame to a SQL database.

- **DataFrame.to_parquet** Write a DataFrame to the binary parquet format.

**Examples**
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9

>>> original_df.to_pickle("./dummy.pkl")

>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9

>>> import os
>>> os.remove("./dummy.pkl")

**pandas.Panel.to_sparse**

Panel.to_sparse(*args, **kwargs)

NOT IMPLEMENTED: do not call this method, as sparsifying is not supported for Panel objects and will raise an error.

Convert to SparsePanel

**pandas.Panel.to_sql**

Panel.to_sql(name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [*R22*] are supported. Tables can be newly created, appended to, or overwritten.

**Parameters**

name : string
    Name of SQL table.

con : sqlalchemy.engine.Engine or sqlite3.Connection
    Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects.

schema : string, optional
    Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default ‘fail’
    How to behave if the table already exists.
    * fail: Raise a ValueError.
• replace: Drop the table before inserting new values.
• append: Insert new values to the existing table.

index : boolean, default True
    Write DataFrame index as a column. Uses index_label as the column name in the
table.

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, optional
    Rows will be written in batches of this size at a time. By default, all rows will be
written at once.

dtype : dict, optional
    Specifying the datatype for columns. The keys should be the column names
and the values should be the SQLAlchemy types or strings for the sqlite3 legacy
mode.

Raises ValueError
    When the table already exists and if_exists is ‘fail’ (the default).

See also:
pandas.read_sql read a DataFrame from a table

References

[R22], [R23]

Examples

Create an in-memory SQLite database.

```python
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```python
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
    name
0  User 1
1  User 2
2  User 3

>>> df.to_sql('users', con=engine)
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```
```python
>>> df1 = pd.DataFrame({'name': ['User 4', 'User 5']})
>>> df1.to_sql('users', con=engine, if_exists='append')
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),
 (0, 'User 4'), (1, 'User 5')]

Overwrite the table with just df1.
```
```python
>>> df1.to_sql('users', con=engine, if_exists='replace',
...     index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 4'), (1, 'User 5')]
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```python
>>> df = pd.DataFrame({'A': [1, None, 2]})
>>> df
   A
0  1.0
1  NaN
2  2.0
```
```python
>>> from sqlalchemy.types import Integer

>>> df.to_sql('integers', con=engine, index=False,
...     dtype={'A': Integer()})
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

### pandas.DataFrame.to_xarray

```
Panel.to_xarray()
```

Return an xarray object from the pandas object.

- **Returns**
  - a DataArray for a Series
  - a Dataset for a DataFrame
  - a DataArray for higher dims

### Notes

See the xarray docs

### Examples

```python
>>> df = pd.DataFrame({'A': [1, 1, 2],
...     'B': ['foo', 'bar', 'foo'],
...     'C': [True, False, True]})
>>> df
   A   B   C
0  1.0  foo  True
1  1.0  bar False
2  2.0  foo  True
```

```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
```python
>>> df.to_xarray()
```
>> df
  A  B  C
0  1  foo  4.0
1  1  bar  5.0
2  2  foo  6.0

>> df.to_xarray()
<xarray.Dataset>
Dimensions: (index: 3)
Coordinates:
  * index (index) int64 0 1 2
Data variables:
  A (index) int64 1 1 2
  B (index) object 'foo' 'bar' 'foo'
  C (index) float64 4.0 5.0 6.0

>> df = pd.DataFrame({'A': [1, 1, 2],
                     'B': ['foo', 'bar', 'foo'],
                     'C': np.arange(4., 7)}).
.set_index(['B', 'A'])

>> df
    C
   B A
foo 1 4.0
bar 1 5.0
foo 2 6.0

>> df.to_xarray()
<xarray.Dataset>
Dimensions: (A: 2, B: 2)
Coordinates:
  * B (B) object 'bar' 'foo'
  * A (A) int64 1 2
Data variables:
  C (B, A) float64 5.0 nan 4.0 6.0

>> p = pd.Panel(np.arange(24).reshape(4, 3, 2),
               items=list('ABCD'),
               major_axis=pd.date_range('20130101', periods=3),
               minor_axis=['first', 'second'])

>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: A to D
Major_axis axis: 2013-01-01 00:00:00 to 2013-01-03 00:00:00
Minor_axis axis: first to second

>> p.to_xarray()
<xarray.DataArray (items: 4, major_axis: 3, minor_axis: 2)>
array([[[ 0, 1],
        [ 2, 3],
        [ 4, 5]],
       [[ 6, 7],
        [ 8, 9],
        [ 9, 10]]])
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.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)

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

- **before**: date, string, int
  Truncate all rows before this index value.
- **after**: date, string, int
  Truncate all rows after this index value.
- **axis**: {0 or ‘index’, 1 or ‘columns’}, optional
  Axis to truncate. Truncates the index (rows) by default.
- **copy**: boolean, default is True,
  Return a copy of the truncated section.

Returns

type of caller

The truncated Series or DataFrame.

See also:

DataFrame.loc Select a subset of a DataFrame by label.

DataFrame.iloc Select a subset of a DataFrame by position.

Notes

If the index being truncated contains only datetime values, before and after may be specified as strings instead of Timestamps.

Examples

```python
def = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
                   'B': ['f', 'g', 'h', 'i', 'j'],
                   'C': ['k', 'l', 'm', 'n', 'o'],
                   index=[1, 2, 3, 4, 5])
def
A B C
1 a f k
2 b g l
3 c h m
4 d i n
5 e j o```
The columns of a DataFrame can be truncated.

```python
>>> df.truncate(before=2, after=4)
A   B   C
2   b   g   l
3   c   h   m
4   d   i   n
```

For Series, only rows can be truncated.

```python
>>> df['A'].truncate(before=2, after=4)
2   b
3   c
4   d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```python
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
    A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01 00:00:00  1
```

```python
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
               after=pd.Timestamp('2016-01-10')).tail()
    A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Because the index is a DatetimeIndex containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```python
>>> df.truncate('2016-01-05', '2016-01-10').tail()
    A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.
```python
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
      A
2016-01-10 23:59:55  1
2016-01-10 23:59:56  1
2016-01-10 23:59:57  1
2016-01-10 23:59:58  1
2016-01-10 23:59:59  1
```

**pandas.Panel.tshift**

Panel.tshift *(periods=1, freq=None, axis='major')*

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 the tseries 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.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 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.Panel.tz_localize

Panel.tz_localize(tz, axis=0, level=None, copy=True, ambiguous='raise')
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

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
- **ddof** : int, default 1
  Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** : boolean, default None
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- **var** [DataFrame or Panel (if level specified)]

**pandas.Panel.where**

Panel.where (cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False, raise_on_error=None)

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, array-like, or callable
  Where cond is True, keep the original value. Where False, replace with corresponding value from other. If cond is callable, it is computed on the NDFrame and should return boolean NDFrame or array. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as cond.

- **other** : scalar, NDFrame, or callable
  Entries where cond is False are replaced with corresponding value from other. If other is callable, it is computed on the NDFrame and should return scalar or NDFrame. The callable must not change input NDFrame (though pandas doesn’t check it).

New in version 0.18.1: A callable can be used as other.

- **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]

**errors** : str, {'raise', 'ignore'}, default 'raise'
- **raise**: allow exceptions to be raised
- **ignore**: suppress exceptions. On error return original object

Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

**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)

Deprecated since version 0.21.0.

**Returns**

wh [same type as caller]

**See also:**
*DataFrame.mask()*

**Notes**

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if \( \text{cond} \) is True the element is used; otherwise the corresponding element from the DataFrame \( \text{other} \) is used.

The signature for \( \text{DataFrame.where()} \) differs from \( \text{numpy.where()} \). Roughly \( \text{df1.where(m, df2)} \) is equivalent to \( \text{np.where(m, df1, df2)} \).

For further details and examples see the where documentation in \textit{indexing}.

**Examples**

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
```

```python
>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
```
>>> s.where(s > 1, 10)
 0   10.0
 1   10.0
 2    2.0
 3    3.0
 4    4.0

>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0 -1 3
1 -5
2 0 6
3 -9
4 -8 9

>>> df.where(m, -df) == np.where(m, df, -df)
   A  B
0 True True
1 True True
2 True True
3 True True
4 True True

>>> df.where(m, -df) == df.mask(~m, -df)
   A  B
0 True True
1 True True
2 True True
3 True True
4 True True

pandas.Panel.xs

Panel.xs(key, axis=1)
  Return slice of panel along selected axis

Parameters  
  key : object
    Label
  axis : {'items', 'major', 'minor'}, default 1/major

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 and is a superset of xs functionality, see MultiIndex 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

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.values</code></td>
<td>Return a Numpy representation of the DataFrame.</td>
</tr>
<tr>
<td><code>Panel.axes</code></td>
<td>Return index label(s) of the internal NDFrame.</td>
</tr>
<tr>
<td><code>Panel.ndim</code></td>
<td>Return an int representing the number of axes / array dimensions.</td>
</tr>
<tr>
<td><code>Panel.size</code></td>
<td>Return an int representing the number of elements in this object.</td>
</tr>
<tr>
<td><code>Panel.shape</code></td>
<td>Return a tuple of axis dimensions.</td>
</tr>
<tr>
<td><code>Panel.dtypes</code></td>
<td>Return the dtypes in the DataFrame.</td>
</tr>
<tr>
<td><code>Panel.ftypes</code></td>
<td>Return the ftypes (indication of sparse/dense and dtype) in DataFrame.</td>
</tr>
<tr>
<td><code>Panel.get_dtype_counts()</code></td>
<td>Return counts of unique dtypes in this object.</td>
</tr>
<tr>
<td><code>Panel.get_ftype_counts()</code></td>
<td>(DEPRECATED) Return counts of unique ftypes in this object.</td>
</tr>
</tbody>
</table>

34.5.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.astype()</code></td>
<td>Cast a pandas object to a specified dtype <code>dtype</code>.</td>
</tr>
<tr>
<td><code>Panel.copy()</code></td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td><code>Panel.isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>Panel.notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
</tbody>
</table>

34.5.4 Getting and setting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.get_value(*args, **kwargs)</code></td>
<td>(DEPRECATED) Quickly retrieve single value at (item, major, minor) location</td>
</tr>
<tr>
<td><code>Panel.set_value(*args, **kwargs)</code></td>
<td>(DEPRECATED) Quickly set single value at (item, major, minor) location</td>
</tr>
</tbody>
</table>

34.5.5 Indexing, iteration, slicing

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.at</code></td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td><code>Panel.iat</code></td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
</tbody>
</table>
Panel.loc
Access a group of rows and columns by label(s) or a boolean array.

Panel.iloc
Purely integer-location based indexing for selection by position.

Panel.__iter__()
Iterate over info axis

Panel.iteritems()
Iterate over (label, values) on info axis

Panel.pop(item)
Return item and drop from frame.

Panel.xs(key[, axis])
Return slice of panel along selected axis

Panel.major_xs(key)
Return slice of panel along major axis

Panel.minor_xs(key)
Return slice of panel along minor axis

34.5.5.1 pandas.Panel.__iter__
Panel.__iter__()
Iterate over info axis

For more information on .at, .iat, .loc, and .iloc, see the indexing documentation.

34.5.6 Binary operator functions

Panel.add(other[, axis])
Addition of series and other, element-wise (binary operator add).

Panel.sub(other[, axis])
Subtraction of series and other, element-wise (binary operator sub).

Panel.mul(other[, axis])
Multiplication of series and other, element-wise (binary operator mul).

Panel.div(other[, axis])
Floating division of series and other, element-wise (binary operator truediv).

Panel.truediv(other[, axis])
Floating division of series and other, element-wise (binary operator truediv).

Panel.floordiv(other[, axis])
Integer division of series and other, element-wise (binary operator floordiv).

Panel.mod(other[, axis])
Modulo of series and other, element-wise (binary operator mod).

Panel.pow(other[, axis])
Exponential power of series and other, element-wise (binary operator pow).

Panel.radd(other[, axis])
Addition of series and other, element-wise (binary operator radd).

Panel.rsub(other[, axis])
Subtraction of series and other, element-wise (binary operator rsub).

Panel.rmul(other[, axis])
Multiplication of series and other, element-wise (binary operator rmul).

Panel.rdiv(other[, axis])
Floating division of series and other, element-wise (binary operator rtruediv).

Panel.rtruediv(other[, axis])
Floating division of series and other, element-wise (binary operator rtruediv).

Panel.rfloordiv(other[, axis])
Integer division of series and other, element-wise (binary operator rfloordiv).

Panel.rmod(other[, axis])
Modulo of series and other, element-wise (binary operator rmod).

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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.rpow(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>Panel.lt(other[, axis])</code></td>
<td>Wrapper for comparison method <code>lt</code>.</td>
</tr>
<tr>
<td><code>Panel.gt(other[, axis])</code></td>
<td>Wrapper for comparison method <code>gt</code>.</td>
</tr>
<tr>
<td><code>Panel.le(other[, axis])</code></td>
<td>Wrapper for comparison method <code>le</code>.</td>
</tr>
<tr>
<td><code>Panel.ge(other[, axis])</code></td>
<td>Wrapper for comparison method <code>ge</code>.</td>
</tr>
<tr>
<td><code>Panel.ne(other[, axis])</code></td>
<td>Wrapper for comparison method <code>ne</code>.</td>
</tr>
<tr>
<td><code>Panel.eq(other[, axis])</code></td>
<td>Wrapper for comparison method <code>eq</code>.</td>
</tr>
</tbody>
</table>

### 34.5.7 Function application, GroupBy

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.apply(func[, axis])</code></td>
<td>Applies function along axis (or axes) of the Panel.</td>
</tr>
<tr>
<td><code>Panel.groupby(function[, axis])</code></td>
<td>Group data on given axis, returning GroupBy object.</td>
</tr>
</tbody>
</table>

### 34.5.8 Computations / Descriptive Stats

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.abs()</code></td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td><code>Panel.clip([lower, upper, axis, inplace])</code></td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td><code>Panel.clip_lower(threshold[, axis, inplace])</code></td>
<td>Return copy of the input with values below a threshold truncated.</td>
</tr>
<tr>
<td><code>Panel.clip_upper(threshold[, axis, inplace])</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.cummmax([axis, skipna])</code></td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Panel.cummin([axis, skipna])</code></td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Panel.cumprod([axis, skipna])</code></td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>Panel.cumsum([axis, skipna])</code></td>
<td>Return cumulative sum over a DataFrame or Series 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.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 for the requested axis.</td>
</tr>
<tr>
<td><code>Panel.pct_change([periods, fill_method, ...])</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>Panel.prod([axis, skipna, level, ...])</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 Normalized by N-1</td>
</tr>
<tr>
<td><code>Panel.sum([axis, skipna, level, ...])</code></td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td><code>Panel.std([axis, skipna, level, ddof, ...])</code></td>
<td>Return sample standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>Panel.var([axis, skipna, level, ddof, ...])</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
</tbody>
</table>
### 34.5.9 Reindexing / Selection / Label manipulation

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.add_prefix(prefix)</code></td>
<td>Prefix labels with string <code>prefix</code>.</td>
</tr>
<tr>
<td><code>Panel.add_suffix(suffix)</code></td>
<td>Suffix labels with string <code>suffix</code>.</td>
</tr>
<tr>
<td><code>Panel.drop([labels, axis, index, columns, ...])</code></td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>Panel.equals(other)</code></td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>Panel.filter([items, like, regex, axis])</code></td>
<td>Subset rows or columns of dataframe according to labels in the specified index.</td>
</tr>
<tr>
<td><code>Panel.first(offset)</code></td>
<td>Convenience method for subsetting initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>Panel.last(offset)</code></td>
<td>Convenience method for subsetting final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>Panel.reindex(*args, **kwargs)</code></td>
<td>Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
<tr>
<td><code>Panel.reindex_axis(labels[, axis, method, ...])</code></td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index.</td>
</tr>
<tr>
<td><code>Panel.reindex_like(other[, method, copy, ...])</code></td>
<td>Return an object with matching indices to myself.</td>
</tr>
<tr>
<td><code>Panel.rename([items, major_axis, minor_axis])</code></td>
<td>Alter axes input function or functions.</td>
</tr>
<tr>
<td><code>Panel.sample([n, frac, replace, weights, ...])</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>Panel.select(crit[, axis])</code></td>
<td>(DEPRECATED) Return data corresponding to axis labels matching criteria</td>
</tr>
<tr>
<td><code>Panel.take(indices[, axis, convert, is_copy])</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>Panel.truncate([before, after, axis, copy])</code></td>
<td>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
</tbody>
</table>

#### 34.5.9.1 pandas.Panel.drop

**Function:** `Panel.drop(labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')`

**Description:** Drop 2D from panel, holding passed axis constant.

### 34.5.10 Missing data handling

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.dropna([axis, how, inplace])</code></td>
<td>Drop 2D from panel, holding passed axis constant</td>
</tr>
</tbody>
</table>

### 34.5.11 Reshaping, sorting, transposing

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.sort_index( axis, level, ascending, ...)</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>Panel.swaplevel([i, j, axis])</code></td>
<td>Swap levels i and j in a MultiIndex on a particular axis</td>
</tr>
<tr>
<td><code>Panel.transpose(*args, **kwargs)</code></td>
<td>Permute the dimensions of the Panel</td>
</tr>
<tr>
<td><code>Panel.swapaxes(axis1, axis2[, copy])</code></td>
<td>Interchange axes and swap values axes appropriately</td>
</tr>
<tr>
<td><code>Panel.conform(frame[, axis])</code></td>
<td>Conform input DataFrame to align with chosen axis pair.</td>
</tr>
</tbody>
</table>
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 Panel.

34.5.13 Time series-related

Panel.asfreq(freq[, method, how, normalize, ...])  
Convert TimeSeries to specified frequency.

Panel.shift([periods, freq, axis])  
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 time series.

Panel.tz_convert(tz[, axis, level, copy])  
Convert tz-aware axis to target time zone.

Panel.tz_localize(tz[, axis, level, copy, ...])  
Localize tz-naive TimeSeries to target time zone.

34.5.14 Serialization / IO / Conversion

Panel.from_dict(data[, intersect, orient, dtype])  
Construct Panel from dict of DataFrame objects

Panel.to_pickle(path[, compression, protocol])  
Pickle (serialize) object to file.

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)  
Write the contained data to an HDF5 file using HDFStore.

Panel.to_sparse(*args, **kwargs)  
NOT IMPLEMENTED: do not call this method, as sparsifying is not supported for Panel objects and will raise an error.

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])  
Copy object to the system clipboard.

34.6 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.

34.6.1 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

See also:

RangeIndex Index implementing a monotonic integer range
CategoricalIndex Index of Categoricals.
MultiIndex A multi-level, or hierarchical, Index
IntervalIndex an Index of Intervals.

DatetimeIndex, TimedeltaIndex, PeriodIndex, Int64Index, UInt64Index,
Float64Index

Notes

An Index instance can only contain hashable objects

Examples

```python
>>> pd.Index([3, 2, 3])
Int64Index([1, 2, 3], dtype='int64')

>>> pd.Index(list('abc'))
Index(['a', 'b', 'c'], dtype='object')
```

Attributes

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td>base</td>
<td>return the base object if the memory of the underlying data is shared</td>
</tr>
<tr>
<td>data</td>
<td>return the data pointer of the underlying data</td>
</tr>
<tr>
<td>dtype</td>
<td>return the dtype object of the underlying data</td>
</tr>
<tr>
<td>dtype_str</td>
<td>return the dtype str of the underlying data</td>
</tr>
<tr>
<td>flags</td>
<td></td>
</tr>
<tr>
<td>hasnans</td>
<td>return if I have any nans; enables various perf speedups</td>
</tr>
<tr>
<td>inferred_type</td>
<td>return a string of the type inferred from the values</td>
</tr>
<tr>
<td>is_monotonic</td>
<td>alias for is_monotonic_increasing (deprecated)</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_monotonic_decreasing</td>
<td>return if the index is monotonic decreasing (only equal or decreasing) values.</td>
</tr>
<tr>
<td>is_monotonic_increasing</td>
<td>return if the index is monotonic increasing (only equal or increasing) values.</td>
</tr>
<tr>
<td>is_unique</td>
<td>return if the index has unique values</td>
</tr>
<tr>
<td>itemsize</td>
<td>return the size of the dtype of the item of the underlying data</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>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>

34.6.1 pandas.Index.T

Index.T

return the transpose, which is by definition self

34.6.1.2 pandas.Index.base

Index.base

return the base object if the memory of the underlying data is shared

34.6.1.3 pandas.Index.data

Index.data

return the data pointer of the underlying data

34.6.1.4 pandas.Index.dtype

Index.dtype

return the dtype object of the underlying data

34.6.1.5 pandas.Index.dtype_str

Index.dtype_str

return the dtype str of the underlying data

34.6.1.6 pandas.Index.flags

Index.flags

34.6.1.7 pandas.Index.hasnans

Index.hasnans

return if I have any nans; enables various perf speedups
34.6.1.8 pandas.Index.inferred_type

Index.inferred_type
return a string of the type inferred from the values

34.6.1.9 pandas.Index.is_monotonic

Index.is_monotonic
alias for is_monotonic_increasing (deprecated)

34.6.1.10 pandas.Index.is_monotonic_decreasing

Index.is_monotonic_decreasing
return if the index is monotonic decreasing (only equal or decreasing) values.

Examples

>>> Index([3, 2, 1]).is_monotonic_decreasing
True
>>> Index([3, 2, 2]).is_monotonic_decreasing
True
>>> Index([3, 1, 2]).is_monotonic_decreasing
False

34.6.1.11 pandas.Index.is_monotonic_increasing

Index.is_monotonic_increasing
return if the index is monotonic increasing (only equal or increasing) values.

Examples

>>> Index([1, 2, 3]).is_monotonic_increasing
True
>>> Index([1, 2, 2]).is_monotonic_increasing
True
>>> Index([1, 3, 2]).is_monotonic_increasing
False

34.6.1.12 pandas.Index.is_unique

Index.is_unique
return if the index has unique values

34.6.1.13 pandas.Index.itemsize

Index.itemsize
return the size of the dtype of the item of the underlying data
34.6.1.14 pandas.Index.nbytes

Index.nbytes
return the number of bytes in the underlying data

34.6.1.15 pandas.Index.ndim

Index.ndim
return the number of dimensions of the underlying data, by definition 1

34.6.1.16 pandas.Index.shape

Index.shape
return a tuple of the shape of the underlying data

34.6.1.17 pandas.Index.size

Index.size
return the number of elements in the underlying data

34.6.1.18 pandas.Index.strides

Index.strides
return the strides of the underlying data

34.6.1.19 pandas.Index.values

Index.values
return the underlying data as an ndarray

<table>
<thead>
<tr>
<th>asi8</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>empty</td>
<td></td>
</tr>
<tr>
<td>has_duplicates</td>
<td></td>
</tr>
<tr>
<td>is_all_dates</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>names</td>
<td></td>
</tr>
<tr>
<td>nlevels</td>
<td></td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th>all(*args, **kwargs)</th>
<th>Return whether all elements are True.</th>
</tr>
</thead>
<tbody>
<tr>
<td>any(*args, **kwargs)</td>
<td>Return whether any element is True.</td>
</tr>
<tr>
<td>append(other)</td>
<td>Append a collection of Index options together</td>
</tr>
<tr>
<td>argmax([axis])</td>
<td>return a ndarray of the maximum argument indexer</td>
</tr>
<tr>
<td>argmin([axis])</td>
<td>return a ndarray of the minimum argument indexer</td>
</tr>
<tr>
<td>argsort(*args, **kwargs)</td>
<td>Return the integer indicies that would sort the index.</td>
</tr>
</tbody>
</table>

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### Table 97 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>asof</code>(label)</td>
<td>For a sorted index, return the most recent label up to and including the passed label.</td>
</tr>
<tr>
<td><code>asof_locs</code>(where, mask)</td>
<td>where : array of timestamps mask : array of booleans where data is not NA</td>
</tr>
<tr>
<td><code>astype</code>(dtype[, copy])</td>
<td>Create an Index with values cast to dtypes.</td>
</tr>
<tr>
<td><code>contains</code>(key)</td>
<td>return a boolean if this key is in the index</td>
</tr>
<tr>
<td><code>copy</code>([name, deep, dtype])</td>
<td>Make a copy of this object.</td>
</tr>
<tr>
<td><code>delete</code>(loc)</td>
<td>Make new Index with passed location(-s) deleted</td>
</tr>
<tr>
<td><code>difference</code>(other)</td>
<td>Return a new Index with elements from the index that are not in other.</td>
</tr>
<tr>
<td><code>drop</code>(labels[, errors])</td>
<td>Make new Index with passed list of labels deleted</td>
</tr>
<tr>
<td><code>drop_duplicates</code>([keep])</td>
<td>Return Index with duplicate values removed.</td>
</tr>
<tr>
<td><code>dropna</code>([how])</td>
<td>Return Index without NA/NaN values</td>
</tr>
<tr>
<td><code>duplicated</code>([keep])</td>
<td>Indicate duplicate index values.</td>
</tr>
<tr>
<td><code>equals</code>(other)</td>
<td>Determines if two Index objects contain the same elements.</td>
</tr>
<tr>
<td><code>factorize</code>([sort, na_sentinel])</td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td><code>fillna</code>([value, downcast])</td>
<td>Fill NA/NaN values with the specified value</td>
</tr>
<tr>
<td><code>format</code>([name, formatter])</td>
<td>Render a string representation of the Index</td>
</tr>
<tr>
<td><code>get_duplicates</code>()</td>
<td>(DEPRECATED) Extract duplicated index elements.</td>
</tr>
<tr>
<td><code>get_indexer</code>(target[, method, limit, tolerance])</td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>get_indexer_for</code>(target, **kwargs)</td>
<td>guaranteed return of an indexer even when non-unique This dispatches to get_indexer or get_indexer_nonunique as appropriate</td>
</tr>
<tr>
<td><code>get_indexer_non_unique</code>(target)</td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>get_level_values</code>(level)</td>
<td>Return an Index of values for requested level, equal to the length of the index.</td>
</tr>
<tr>
<td><code>get_loc</code>(key[, method, tolerance])</td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
<tr>
<td><code>get_slice_bound</code>(label, side, kind)</td>
<td>Calculate slice bound that corresponds to given label.</td>
</tr>
<tr>
<td><code>get_values</code>()</td>
<td>Return Index data as an numpy.ndarray.</td>
</tr>
<tr>
<td><code>groupby</code>(values)</td>
<td>Group the index labels by a given array of values.</td>
</tr>
<tr>
<td><code>identical</code>(other)</td>
<td>Similar to equals, but check that other comparable attributes are also equal</td>
</tr>
<tr>
<td><code>insert</code>(loc, item)</td>
<td>Make new Index inserting new item at location.</td>
</tr>
<tr>
<td><code>intersection</code>(other)</td>
<td>Form the intersection of two Index objects.</td>
</tr>
<tr>
<td><code>is</code>(other)</td>
<td>More flexible, faster check like <code>is</code> but that works through views</td>
</tr>
<tr>
<td><code>is_categorical</code>()</td>
<td>Check if the Index holds categorical data.</td>
</tr>
<tr>
<td><code>isin</code>(values[, level])</td>
<td>Return a boolean array where the index values are in values.</td>
</tr>
<tr>
<td><code>isna</code>()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>isnull</code>()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>item</code>()</td>
<td>return the first element of the underlying data as a python scalar</td>
</tr>
<tr>
<td><code>join</code>(other[, how, level, return_indexers, sort])</td>
<td><em>this is an internal non-public method</em></td>
</tr>
</tbody>
</table>

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Table 97 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>map(mapper[, na_action])</code></td>
<td>Map values using input correspondence (a dict, Series, or function).</td>
</tr>
<tr>
<td><code>max()</code></td>
<td>Return the maximum value of the Index.</td>
</tr>
<tr>
<td><code>memory_usage([deep])</code></td>
<td>Memory usage of the values.</td>
</tr>
<tr>
<td><code>min()</code></td>
<td>Return the minimum value of the Index.</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nunique([dropna])</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>putmask(mask, value)</code></td>
<td>return a new Index of the values set with the mask</td>
</tr>
<tr>
<td><code>ravel([order])</code></td>
<td>return an ndarray of the flattened values of the underlying data</td>
</tr>
<tr>
<td><code>reindex(target[, method, level, limit, ...])</code></td>
<td>Create index with target’s values (move/add/delete values as necessary)</td>
</tr>
<tr>
<td><code>rename(name[, inplace])</code></td>
<td>Set new names on index.</td>
</tr>
<tr>
<td><code>repeat(repeats, *args, **kwargs)</code></td>
<td>Repeat elements of an Index.</td>
</tr>
<tr>
<td><code>searchsorted(value[, side, sorter])</code></td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>set_names(names[, level, inplace])</code></td>
<td>Set new names on index.</td>
</tr>
<tr>
<td><code>set_value(arr, key, value)</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>shift([periods, freq])</code></td>
<td>Shift index by desired number of time frequency increments.</td>
</tr>
<tr>
<td><code>slice_indexer([start, end, step, kind])</code></td>
<td>For an ordered or unique index, compute the slice indexer for input labels and step.</td>
</tr>
<tr>
<td><code>slice_locs([start, end, step, kind])</code></td>
<td>Compute slice locations for input labels.</td>
</tr>
<tr>
<td><code>sort_values([return_indexer, ascending])</code></td>
<td>For internal compatibility with with the Index API</td>
</tr>
<tr>
<td><code>str</code></td>
<td>alias of pandas.core.strings.StringMethods</td>
</tr>
<tr>
<td><code>summary([name])</code></td>
<td>(DEPRECATED) Return a summarized representation ..</td>
</tr>
<tr>
<td><code>symmetric_difference(other[, result_name])</code></td>
<td>Compute the symmetric difference of two Index objects.</td>
</tr>
<tr>
<td><code>take(indices[, axis, allow_fill, fill_value])</code></td>
<td>return a new Index of the values selected by the indices</td>
</tr>
<tr>
<td><code>to_frame([index])</code></td>
<td>Create a DataFrame with a column containing the index.</td>
</tr>
<tr>
<td><code>to_native_types([slicer])</code></td>
<td>Format specified values of self and return them.</td>
</tr>
<tr>
<td><code>to_series([index, name])</code></td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index</td>
</tr>
<tr>
<td><code>tolist()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>transpose(*args, **kwargs)</code></td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td><code>union(other)</code></td>
<td>Form the union of two Index objects and sorts if possible.</td>
</tr>
<tr>
<td><code>unique([level])</code></td>
<td>Return unique values in the index.</td>
</tr>
<tr>
<td><code>value_counts([normalize, sort, ascending, ...])</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
<tr>
<td><code>where(cond[, other])</code></td>
<td>Return whether all elements are True.</td>
</tr>
</tbody>
</table>

34.6.1.20 pandas.Index.all

`Index.all(*args, **kwargs)`

Return whether all elements are True.
Parameters *args
These parameters will be passed to numpy.all.

**kwargs
These parameters will be passed to numpy.all.

Returns all : bool or array_like (if axis is specified)
A single element array_like may be converted to bool.

See also:

pandas.Index.any Return whether any element in an Index is True.
pandas.Series.any Return whether any element in a Series is True.
pandas.Series.all Return whether all elements in a Series are True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

all
True, because nonzero integers are considered True.

```python
>>> pd.Index([1, 2, 3]).all()
True
```
False, because 0 is considered False.

```python
>>> pd.Index([0, 1, 2]).all()
False
```

any
True, because 1 is considered True.

```python
>>> pd.Index([0, 0, 1]).any()
True
```
False, because 0 is considered False.

```python
>>> pd.Index([0, 0, 0]).any()
False
```

34.6.1.21 pandas.Index.any

Index.any (*args, **kwargs)
Return whether any element is True.

Parameters *args
These parameters will be passed to numpy.any.

**kwargs
These parameters will be passed to numpy.any.

**Returns** any : bool or array_like (if axis is specified)
A single element array_like may be converted to bool.

See also:

*pandas.Index.all* Return whether all elements are True.
*pandas.Series.all* Return whether all elements are True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

```
>>> index = pd.Index([0, 1, 2])
>>> index.any()
True

>>> index = pd.Index([0, 0, 0])
>>> index.any()
False
```

### 34.6.1.22 pandas.Index.append

Index.append(other)
Append a collection of Index options together

**Parameters**

other [Index or list/tuple of indices]

**Returns**

appended [Index]

### 34.6.1.23 pandas.Index.argmax

Index.argmax(axis=None)
return a ndarray of the maximum argument indexer

See also:

numpy.ndarray.argmax
34.6.1.24 pandas.Index.argmin

Index.argmin(axis=None)
return a ndarray of the minimum argument indexer

See also:

numpy.ndarray.argmin

34.6.1.25 pandas.Index.argsort

Index.argsort(*args, **kwargs)
Return the integer indicies that would sort the index.

Parameters

*args
Passed to numpy.ndarray.argsort.

**kwargs
Passed to numpy.ndarray.argsort.

Returns

numpy.ndarray
Integer indicies that would sort the index if used as an indexer.

See also:

numpy.argsort Similar method for NumPy arrays.

Index.sort_values Return sorted copy of Index.

Examples

```python
>>> idx = pd.Index(['b', 'a', 'd', 'c'])
>>> idx
Index(['b', 'a', 'd', 'c'], dtype='object')

>>> order = idx.argsort()
>>> order
array([1, 0, 3, 2])

>>> idx[order]
Index(['a', 'b', 'c', 'd'], dtype='object')
```

34.6.1.26 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'
34.6.1.27 pandas.Index.asof_locs

Index.asof_locs(where, mask)
where : array of timestamps mask : array of booleans where data is not NA

34.6.1.28 pandas.Index.astype

Index.astype(dtype, copy=True)
Create an Index with values cast to dtypes. The class of a new Index is determined by dtype. When conversion is impossible, a ValueError exception is raised.

Parameters

dtype [numpy dtype or pandas type]
copy : bool, default True
By default, astype always returns a newly allocated object. If copy is set to False and internal requirements on dtype are satisfied, the original data is used to create a new Index or the original Index is returned.

New in version 0.19.0.

34.6.1.29 pandas.Index.contains

Index.contains(key)
return a boolean if this key is IN the index

Parameters

key [object]

Returns

boolean

34.6.1.30 pandas.Index.copy

Index.copy(name=None, deep=False, dtype=None, **kwargs)
Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters

name [string, optional]
deep [boolean, default False]
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.
34.6.1.31 pandas.Index.delete

```
Index.delete(loc)
```

Make new Index with passed location(-s) deleted

**Returns**

```
new_index [Index]
```

34.6.1.32 pandas.Index.difference

```
Index.difference(other)
```

Return a new Index with elements from the index that are not in other.

This is the set difference of two Index objects. It’s sorted if sorting is possible.

**Parameters**

```
other [Index or array-like]
```

**Returns**

```
difference [Index]
```

**Examples**

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.difference(idx2)
Int64Index([1, 2], dtype='int64')
```

34.6.1.33 pandas.Index.drop

```
Index.drop(labels, errors='raise')
```

Make new Index with passed list of labels deleted

**Parameters**

```
labels [array-like]
errors: {'ignore', 'raise'}, default 'raise'
```

If ‘ignore’, suppress error and existing labels are dropped.

**Returns**

```
dropped [Index]
```

**Raises** KeyError

If none of the labels are found in the selected axis

34.6.1.34 pandas.Index.drop_duplicates

```
Index.drop_duplicates(keep='first')
```

Return Index with duplicate values removed.

**Parameters**

```
keep: {'first', 'last', False}, default ‘first’
```
• ‘first’ : Drop duplicates except for the first occurrence.
• ‘last’ : Drop duplicates except for the last occurrence.
• False : Drop all duplicates.

Returns
deduplicated [Index]

See also:
Series.drop_duplicates equivalent method on Series
DataFrame.drop_duplicates equivalent method on DataFrame
Index.duplicated related method on Index, indicating duplicate Index values.

Examples

Generate an pandas.Index with duplicate values.

```python
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'])
```

The keep parameter controls which duplicate values are removed. The value ‘first’ keeps the first occurrence for each set of duplicated entries. The default value of keep is ‘first’.

```python
>>> idx.drop_duplicates(keep='first')
Index(['lama', 'cow', 'beetle', 'hippo'], dtype='object')
```

The value ‘last’ keeps the last occurrence for each set of duplicated entries.

```python
>>> idx.drop_duplicates(keep='last')
Index(['cow', 'beetle', 'lama', 'hippo'], dtype='object')
```

The value False discards all sets of duplicated entries.

```python
>>> idx.drop_duplicates(keep=False)
Index(['cow', 'beetle', 'hippo'], dtype='object')
```

34.6.1.35 pandas.Index.dropna

Index.dropna (how='any')
Return Index without NA/NaN values

Parameters how : {'any', 'all'}, default ‘any’
    If the Index is a MultiIndex, drop the value when any or all levels are NaN.

Returns
valid [Index]

34.6.1.36 pandas.Index.duplicated

Index.duplicated (keep='first')
Indicate duplicate index values.
Duplicated values are indicated as True values in the resulting array. Either all duplicates, all except the first, or all except the last occurrence of duplicates can be indicated.

Parameters keep : {'first', 'last', False}, default 'first'

The value or values in a set of duplicates to mark as missing.
- 'first' : Mark duplicates as True except for the first occurrence.
- 'last' : Mark duplicates as True except for the last occurrence.
- False : Mark all duplicates as True.

Returns
numpy.ndarray

See also:
pandas.Series.duplicated  Equivalent method on pandas.Series
pandas.DataFrame.duplicated  Equivalent method on pandas.DataFrame
pandas.Index.drop_duplicates  Remove duplicate values from Index

Examples

By default, for each set of duplicated values, the first occurrence is set to False and all others to True:

```python
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> idx.duplicated()
array([False, False, True, False, True])
```

which is equivalent to

```python
>>> idx.duplicated(keep='first')
array([False, False, True, False, True])
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True:

```python
>>> idx.duplicated(keep='last')
array([ True, False, True, False, False])
```

By setting keep on False, all duplicates are True:

```python
>>> idx.duplicated(keep=False)
array([ True, False, True, False, True])
```
This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

**Parameters**

- **sort**: boolean, default False
  Sort `uniques` and shuffle `labels` to maintain the relationship.

- **na_sentinel**: int, default -1
  Value to mark “not found”.

**Returns**

- **labels**: ndarray
  An integer ndarray that’s an indexer into `uniques`. `uniques.take(labels)` will have the same values as `values`.

- **uniques**: ndarray, Index, or Categorical
  The unique valid values. When `values` is Categorical, `uniques` is a Categorical. When `values` is some other pandas object, an Index is returned. Otherwise, a 1-D ndarray is returned.

**Note:** Even if there’s a missing value in `values`, `uniques` will *not* contain an entry for it.

**See also:**

- `pandas.cut` Discretize continuous-valued array.
- `pandas.unique` Find the unique value in an array.

**Examples**

These examples all show `factorize` as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> labels
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the `uniques` will be sorted, and `labels` will be shuffled so that the relationship is maintained.

```python
>>> labels, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> labels
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in `labels` with `na_sentinel` (-1 by default). Note that missing values are never included in `uniques`. 
>>> labels, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> labels
array([ 0, -1, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of uniques will differ. For Categoricals, a Categorical is returned.

>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]

Notice that 'b' is in uniques.categories, despite not being present in cat.values.

For all other pandas objects, an Index of the appropriate type is returned.

>>> cat = pd.Series(['a', 'a', 'c'])
>>> labels, uniques = pd.factorize(cat)
>>> labels
array([0, 0, 1])
>>> uniques
Index(['a', 'c'], dtype='object')

34.6.1.39 pandas.Index.fillna

Index.fillna (value=None, downcast=None)
Fill NA/NaN values with the specified value

Parameters
value : scalar
Scalar value to use to fill holes (e.g. 0). This value cannot be a list-likes.

downcast : dict, default is None
a dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns
filled [%(klass)s]

34.6.1.40 pandas.Index.format

Index.format (name=False, formatter=None, **kwargs)
Render a string representation of the Index

34.6.1.41 pandas.Index.get_duplicates

Index.get_duplicates ()
Extract duplicated index elements.

Returns a sorted list of index elements which appear more than once in the index.
Deprecated since version 0.23.0: Use idx[idx.duplicated()].unique() instead

**Returns** array-like

List of duplicated indexes.

**See also:**

*Index.duplicated* Return boolean array denoting duplicates.

*Index.drop_duplicates* Return Index with duplicates removed.

**Examples**

Works on different Index of types.

```python
>>> pd.Index([1, 2, 2, 3, 3, 3, 4]).get_duplicates()
[2, 3]
```

```python
>>> pd.Index([1., 2., 2., 3., 3., 3., 4.]).get_duplicates()
[2.0, 3.0]
```

```python
>>> pd.Index(['a', 'b', 'b', 'c', 'c', 'c', 'd']).get_duplicates()
['b', 'c']
```

Note that for a DatetimeIndex, it does not return a list but a new DatetimeIndex:

```python
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-02', '2018-01-03', ...
'2018-01-04'], format='%Y-%m-%d')
>>> pd.Index(dates).get_duplicates()
DatetimeIndex(['2018-01-03', '2018-01-04'], dtype='datetime64[ns]', freq=None)
```

Sorts duplicated elements even when indexes are unordered.

```python
>>> pd.Index([1, 2, 3, 2, 3, 4, 3]).get_duplicates()
[2, 3]
```

Return empty array-like structure when all elements are unique.

```python
>>> pd.Index([1, 2, 3, 4]).get_duplicates()
[]
```

```python
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-02', '2018-01-03', ...
    format='%Y-%m-%d'])
>>> pd.Index(dates).get_duplicates()
DatetimeIndex([], dtype='datetime64[ns]', freq=None)
```

**34.6.1.42 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`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like 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)
```

### 34.6.1.43 pandas.Index.get_indexer_for

`Index.get_indexer_for(target, **kwargs)`

Guaranteed return of an indexer even when non-unique. This dispatches to `get_indexer` or `get_indexer_nonunique` as appropriate.

### 34.6.1.44 pandas.Index.get_indexer_non_unique

`Index.get_indexer_non_unique(target)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

**Parameters**

- **target** [Index]

**Returns** `indexer` : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

- **missing** : ndarray of int
An indexer into the target of the values not found. These correspond to the -1 in the indexer array

### 34.6.1.45 pandas.Index.get_level_values

`Index.get_level_values(level)`

Return an Index of values for requested level, equal to the length of the index.

**Parameters**

- **level**: int or str
  - level is either the integer position of the level in the MultiIndex, or the name of the level.

**Returns**

- **values**: Index
  - self, as there is only one level in the Index.

**See also:**

- `pandas.MultiIndex.get_level_values` get values for a level of a MultiIndex

### 34.6.1.46 pandas.Index.get_loc

`Index.get_loc(key, method=None, tolerance=None)`

Get integer location, slice or boolean mask for requested label.

**Parameters**

- **key** [label]
- **method**: {None, ‘pad’/’ffill’, ‘backfill’/’bfill’, ‘nearest’}, optional
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
- **tolerance**: optional
  - Maximum distance from index value for inexact matches. The value of the index at the matching location most satisfy the equation \( \text{abs(index[loc] - key)} \leq \text{tolerance} \).
  - Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.
  - New in version 0.21.0: (list-like tolerance)

**Returns**

- **loc**: [int if unique index, slice if monotonic index, else mask]
Examples

```python
>>> unique_index = pd.Index(list('abc'))
>>> unique_index.get_loc('b')
1

>>> monotonic_index = pd.Index(list('abbc'))
>>> monotonic_index.get_loc('b')
slice(1, 3, None)

>>> non_monotonic_index = pd.Index(list('abcb'))
>>> non_monotonic_index.get_loc('b')
array([False,  True, False,  True], dtype=bool)
```

34.6.1.47 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**: ['ix', 'loc', 'getitem']

34.6.1.48 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

34.6.1.49 pandas.Index.get_values

Index.get_values()

Return Index data as an numpy.ndarray.

Returns numpy.ndarray

A one-dimensional numpy array of the Index values.

See also:

- Index.values The attribute that get_values wraps.

Examples

Getting the Index values of a DataFrame:
```python
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6], [7, 8, 9]],
                   index=['a', 'b', 'c'], columns=['A', 'B', 'C'])
>>> df
     A  B  C
a  1  2  3
b  4  5  6
c  7  8  9
>>> df.index.get_values()
array(['a', 'b', 'c'], dtype=object)

Standalone `Index` values:

```python
>>> idx = pd.Index(['1', '2', '3'])
>>> idx.get_values()
array(['1', '2', '3'], dtype=object)

`MultiIndex` arrays also have only one dimension:

```python
>>> midx = pd.MultiIndex.from_arrays([[1, 2, 3], ['a', 'b', 'c']],
                                  names=('number', 'letter'))
>>> midx.get_values()
array([(1, 'a'), (2, 'b'), (3, 'c')], dtype=object)
>>> midx.get_values().ndim
1
```

#### 34.6.1.50 `pandas.Index.groupby`

`Index.groupby(values)`

Group the index labels by a given array of values.

- **Parameters**
  - `values`: array
    - Values used to determine the groups.
  - `groups`: dict
    - `{group name -> group labels}`

#### 34.6.1.51 `pandas.Index.identical`

`Index.identical(other)`

Similar to equals, but check that other comparable attributes are also equal.

#### 34.6.1.52 `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]
### 34.6.1.53 pandas.Index.intersection

**Index.intersection(other)**

Form the intersection of two Index objects.

This returns a new Index with elements common to the index and other, preserving the order of the calling index.

**Parameters**

- **other** [Index or array-like]

**Returns**

- **intersection** [Index]

**Examples**

```python
generate_example_code()
```

### 34.6.1.54 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

**Returns**

- True if both have same underlying data, False otherwise [bool]

### 34.6.1.55 pandas.Index.is_categorical

**Index.is_categorical()**

Check if the Index holds categorical data.

**Returns**

- boolean

True if the Index is categorical.

**See also:**

- `CategoricalIndex` Index for categorical data.

**Examples**

```python
generate_example_code()
```
>>> idx = pd.Index(["Watermelon", "Orange", "Apple", ...
"Watermelon"]).astype("category")
>>> idx.is_categorical()
True

>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_categorical()
False

>>> s = pd.Series(["Peter", "Victor", "Elisabeth", "Mar"])
>>> s
0 Peter
1 Victor
2 Elisabeth
3 Mar
dtype: object

>>> s.index.is_categorical()
False

34.6.1.56 pandas.Index.isin

Index.isin(values, level=None)
Return a boolean array where the index values are in values.

Compute boolean array of whether each index value is found in the passed set of values. The length of the returned boolean array matches the length of the index.

Parameters values : set or list-like
Sought values.

New in version 0.18.1: Support for values as a set.

level : str or int, optional
Name or position of the index level to use (if the index is a MultiIndex).

Returns is_contained : ndarray
NumPy array of boolean values.

See also:

Series.isin Same for Series.

DataFrame.isin Same method for DataFrames.

Notes

In the case of MultiIndex you must either specify values as a list-like object containing tuples that are the same length as the number of levels, or specify level. Otherwise it will raise a ValueError.

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.
Examples

```python
>>> idx = pd.Index([1, 2, 3])
>>> idx
Int64Index([1, 2, 3], dtype='int64')
```

Check whether each index value in a list of values.

```python
>>> idx.isin([1, 4])
array([True, False, False])
```

```python
>>> midx = pd.MultiIndex.from_arrays([[[1, 2, 3],
... ['red', 'blue', 'green']],
... names=('number', 'color'))
>>> midx
MultiIndex(levels=[[1, 2, 3], ['blue', 'green', 'red']],
labels=[[0, 1, 2], [2, 0, 1]],
names=['number', 'color'])
```

Check whether the strings in the ‘color’ level of the MultiIndex are in a list of colors.

```python
>>> midx.isin(['red', 'orange', 'yellow'], level='color')
array([True, False, False])
```

To check across the levels of a MultiIndex, pass a list of tuples:

```python
>>> midx.isin([(1, 'red'), (3, 'red')])
array([True, False, False])
```

For a DatetimeIndex, string values in `values` are converted to Timestamps.

```python
>>> dates = ['2000-03-11', '2000-03-12', '2000-03-13']
>>> dti = pd.to_datetime(dates)
>>> dti
DatetimeIndex(['2000-03-11', '2000-03-12', '2000-03-13'],
dtype='datetime64[ns]', freq=None)
```

```python
>>> dti.isin(['2000-03-11'])
array([True, False, False])
```

### 34.6.1.57 pandas.Index.isna

*Index.isna()*

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None, numpy.NaN or pd.NaT, get mapped to True values. Everything else get mapped to False values. Characters such as empty strings ‘’ or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

New in version 0.20.0.

**Returns** numpy.ndarray

A boolean array of whether my values are NA

**See also:**

*pandas.Index.notna* boolean inverse of isna.
**pandas.Index.dropna** omit entries with missing values.

**pandas.isna** top-level isna.

**Series.isna** detect missing values in Series object.

**Examples**

Show which entries in a pandas.Index are NA. The result is an array.

```python
g >>> idx = pd.Index([5.2, 6.0, np.NaN])
g >>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
g >>> idx.isna()
g array([False, False, True], dtype=bool)
```

Empty strings are not considered NA values. None is considered an NA value.

```python
g >>> idx = pd.Index(['black', '', 'red', None])
g >>> idx
Index(['black', '', 'red', None], dtype='object')
g >>> idx.isna()
g array([False, False, False, True], dtype=bool)
```

For datetimes, `NaT` (Not a Time) is considered as an NA value.

```python
g >>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
... pd.Timestamp(''), None, pd.NaT])
g >>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
... dtype='datetime64[ns]', freq=None)
g >>> idx.isna()
g array([False, True, True, True], dtype=bool)
```

### 34.6.1.58 pandas.Index.isnull

**Index.isnull()**

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as `None`, `numpy.NaN` or `pd.NaT`, get mapped to `True` values. Everything else get mapped to `False` values. Characters such as empty strings `' '` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

New in version 0.20.0.

**Returns** numpy.ndarray

A boolean array of whether my values are NA

**See also:**

**pandas.Index.notna** boolean inverse of isna.

**pandas.Index.dropna** omit entries with missing values.

**pandas.isna** top-level isna.

**Series.isna** detect missing values in Series object.
Examples

Show which entries in a pandas.Index are NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False, True], dtype=bool)
```

Empty strings are not considered NA values. None is considered an NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False, True], dtype=bool)
```

For datetimes, NaT (Not a Time) is considered as an NA value.

```python
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),...
                        pd.Timestamp(''), None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
               dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False, True, True, True], dtype=bool)
```

34.6.1.59 pandas.Index.item

`Index.item()`

return the first element of the underlying data as a python scalar

34.6.1.60 pandas.Index.join

`Index.join(other, how='left', level=None, return_indexers=False, sort=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]
- `sort` : boolean, default False

Sort the join keys lexicographically in the result Index. If False, the order of the join keys depends on the join type (how keyword)

New in version 0.20.0.

Returns
join_index, (left_indexer, right_indexer)

### 34.6.1.61 pandas.Index.map

**Index.map** *(mapper, na_action=None)*

Map values using input correspondence (a dict, Series, or function).

- **Parameters**
  - **mapper**: function, dict, or Series
    - Mapping correspondence.
  - **na_action**: {None, ‘ignore’}
    - If ‘ignore’, propagate NA values, without passing them to the mapping correspondence.

- **Returns**
  - **applied**: Union[Index, MultiIndex], inferred
    - The output of the mapping function applied to the index. If the function returns a tuple with more than one element a MultiIndex will be returned.

### 34.6.1.62 pandas.Index.max

**Index.max**

Return the maximum value of the Index.

- **Returns**
  - **scalar**: Maximum value.

- **See also**
  - **Index.min** Return the minimum value in an Index.
  - **Series.max** Return the maximum value in a Series.
  - **DataFrame.max** Return the maximum values in a DataFrame.

### Examples

```python
>>> idx = pd.Index([3, 2, 1])
>>> idx.max()
3
```

```python
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.max()
'c'
```

For a MultiIndex, the maximum is determined lexicographically.

```python
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.max()
('b', 2)
```
### 34.6.1.63 pandas.Index.memory_usage

**Index.memory_usage**(deep=False)

Memory usage of the values

**Parameters**

- **deep** : bool
  - Introspect the data deeply, interrogate object dtypes for system-level memory consumption

**Returns**

- bytes used

**See also:**

- numpy.ndarray.nbytes

**Notes**

Memory usage does not include memory consumed by elements that are not components of the array if deep=False or if used on PyPy

### 34.6.1.64 pandas.Index.min

**Index.min()**

Return the minimum value of the Index.

**Returns**

- scalar

  Minimum value.

**See also:**

- **Index.max** Return the maximum value of the object.
- **Series.min** Return the minimum value in a Series.
- **DataFrame.min** Return the minimum values in a DataFrame.

**Examples**

```python
>>> idx = pd.Index([3, 2, 1])
>>> idx.min()
1
```

```python
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.min()
'a'
```

For a MultiIndex, the minimum is determined lexicographically.

```python
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.min()
('a', 1)
```
### pandas.Index.notna

**Index.notna()**

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to `True`. Characters such as empty strings `' '` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to `False` values.

New in version 0.20.0.

**Returns** `numpy.ndarray`

Boolean array to indicate which entries are not NA.

**See also:**

- `Index.notnull` alias of `notna`
- `Index.isna` inverse of `notna`
- `pandas.notna` top-level `notna`

**Examples**

Show which entries in an Index are not NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True, True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True, True, True, False])
```

### pandas.Index.notnull

**Index.notnull()**

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to `True`. Characters such as empty strings `' '` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to `False` values.

New in version 0.20.0.

**Returns** `numpy.ndarray`

Boolean array to indicate which entries are not NA.

**See also:**
Index.notnull  alias of notna
Index.isna  inverse of notna
pandas.notna  top-level notna

Examples

Show which entries in an Index are not NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True, True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True, True, True, False])
```

34.6.1.67 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]

34.6.1.68 pandas.Index.putmask

Index.putmask (mask, value)

return a new Index of the values set with the mask

See also:

numpy.ndarray.putmask

34.6.1.69 pandas.Index.ravel

Index.ravel (order='C')

return an ndarray of the flattened values of the underlying data

See also:

numpy.ndarray.ravel
34.6.1.70 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

34.6.1.71 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]

34.6.1.72 pandas.Index.repeat

Index.repeat (repeats, *args, **kwargs)
Repeat elements of an Index.

Returns a new index where each element of the current index is repeated consecutively a given number of times.

Parameters repeats : int
    The number of repetitions for each element.

**kwargs
    Additional keywords have no effect but might be accepted for compatibility with numpy.

Returns pandas.Index
    Newly created Index with repeated elements.

See also:

Series.repeat  Equivalent function for Series

numpy.repeat  Underlying implementation
Examples

```python
>>> idx = pd.Index([1, 2, 3])
>>> idx
Int64Index([1, 2, 3], dtype='int64')
>>> idx.repeat(2)
Int64Index([1, 1, 2, 2, 3, 3], dtype='int64')
>>> idx.repeat(3)
Int64Index([1, 1, 1, 2, 2, 2, 3, 3, 3], dtype='int64')
```

34.6.1.73 pandas.Index.searchsorted

Index.searchsorted(value, side='left', sorter=None)

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted IndexOpsMixin `self` such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

**Parameters**

- **value**: array_like
  
  Values to insert into `self`.

- **side**: {'left', 'right'}, optional
  
  If `left`, the index of the first suitable location found is given. If `right`, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of `self`).

- **sorter**: 1-D array_like, optional
  
  Optional array of integer indices that sort `self` into ascending order. They are typically the result of np.argsort.

**Returns**

- **indices**: array of ints

  Array of insertion points with the same shape as `value`.

See also:

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 = pd.Categorical(['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True)

Categories (4, object): [apple < bread < cheese < milk]

>>> x.searchsorted('bread')
array([1]) # Note: an array, not a scalar

>>> x.searchsorted(['bread'], side='right')
array([3])

34.6.1.74 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, 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', name='foo')

>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64', name='foo')

>>> 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'])
34.6.1.75 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.

34.6.1.76 pandas.Index.shift

Index.shift(periods=1, freq=None)

Shift index by desired number of time frequency increments.

This method is for shifting the values of datetime-like indexes by a specified time increment a given number of times.

Parameters

- **periods**: int, default 1
  - Number of periods (or increments) to shift by, can be positive or negative.

- **freq**: pandas.DateOffset, pandas.Timedelta or string, optional
  - Frequency increment to shift by. If None, the index is shifted by its own freq attribute. Offset aliases are valid strings, e.g., ‘D’, ‘W’, ‘M’ etc.

Returns

- pandas.Index
  - shifted index

See also:

- **Series.shift** Shift values of Series.

Notes

This method is only implemented for datetime-like index classes, i.e., DatetimeIndex, PeriodIndex and TimedeltaIndex.

Examples

Put the first 5 month starts of 2011 into an index.

```python
>>> month_starts = pd.date_range('1/1/2011', periods=5, freq='MS')
>>> month_starts
              dtype='datetime64[ns]', freq='MS')
```

Shift the index by 10 days.

```python
...```
The default value of \textit{freq} is the \textit{freq} attribute of the index, which is ‘MS’ (month start) in this example.

```
>>> month_starts.shift(10)
DatetimeIndex(['2011-11-01', '2011-12-01', '2012-01-01', '2012-02-01',
               '2012-03-01'],
              dtype='datetime64[ns]', freq='MS')
```

### 34.6.1.77 pandas.Index.slice_indexer

\texttt{Index.slice_indexer(\texttt{start}=None, \texttt{end}=None, \texttt{step}=None, \texttt{kind}=None)}

For an ordered or unique index, compute the slice indexer for input labels and step.

- **Parameters**
  - \texttt{start} : label, default None
    - If None, defaults to the beginning
  - \texttt{end} : label, default None
    - If None, defaults to the end
  - \texttt{step} : int, default None
  - \texttt{kind} : string, default None

- **Returns**
  - \texttt{indexer} : slice

- ** Raises \texttt{KeyError}** : If key does not exist, or key is not unique and index is not ordered.

**Notes**

This function assumes that the data is sorted, so use at your own peril

**Examples**

This is a method on all index types. For example you can do:

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_indexer(start='b', end='c')
slice(1, 3)
```

```
>>> idx = pd.MultiIndex.from_arrays([list('abcd'), list('efgh')])
>>> idx.slice_indexer(start='b', end=('c', 'g'))
slice(1, 3)
```
34.6.1.78 pandas.Index.slice_locs

`Index.slice_locs(start=None, end=None, step=None, kind=None)`

Compute slice locations for input labels.

**Parameters**

- **start**: label, default None
  If None, defaults to the beginning
- **end**: label, default None
  If None, defaults to the end
- **step**: int, defaults None
  If None, defaults to 1
- **kind**: {'ix', 'loc', 'getitem'} or None

**Returns**

- **start, end**: [int]

**See also:**

*Index.get_loc* Get location for a single label

**Notes**

This method only works if the index is monotonic or unique.

**Examples**

```python
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_locs(start='b', end='c')
(1, 3)
```

34.6.1.79 pandas.Index.sort_values

`Index.sort_values(return_indexer=False, ascending=True)`

Return a sorted copy of the index.

Return a sorted copy of the index, and optionally return the indices that sorted the index itself.

**Parameters**

- **return_indexer**: bool, default False
  Should the indices that would sort the index be returned.
- **ascending**: bool, default True
  Should the index values be sorted in an ascending order.

**Returns**

- **sorted_index**: pandas.Index
  Sorted copy of the index.
- **indexer**: numpy.ndarray, optional
  The indices that the index itself was sorted by.
See also:

- `pandas.Series.sort_values` Sort values of a Series.
- `pandas.DataFrame.sort_values` Sort values in a DataFrame.

**Examples**

```python
>>> idx = pd.Index([10, 100, 1, 1000])
>>> idx
Int64Index([10, 100, 1, 1000], dtype='int64')

Sort values in ascending order (default behavior).

```python
>>> idx.sort_values()
Int64Index([1, 10, 100, 1000], dtype='int64')
```  
Sort values in descending order, and also get the indices `idx` was sorted by.

```python
>>> idx.sort_values(ascending=False, return_indexer=True)
(Int64Index([1000, 100, 10, 1], dtype='int64'), array([3, 1, 0, 2]))
```

### 34.6.1.80 pandas.Index.sortlevel

`Index.sortlevel(level=None, ascending=True, sort_remaining=None)`

For internal compatibility with the Index API

Sort the Index. This is for compat with MultiIndex

**Parameters**

- `ascending : boolean, default True`
  - False to sort in descending order

**Returns**

- `sorted_index` [Index]

### 34.6.1.81 pandas.Index.str

`Index.str()`

Vectorized string functions for Series and Index. NAs stay NA unless handled otherwise by a particular method. Patterned after Python’s string methods, with some inspiration from R’s stringr package.

**Examples**

```python
>>> s.str.split('_')
>>> s.str.replace('_', '')
```
### 34.6.1.82 pandas.Index.summary

Index.summary(name=None)
Return a summarized representation. deprecated:: 0.23.0

### 34.6.1.83 pandas.Index.symmetric_difference

Index.symmetric_difference(other, result_name=None)
Compute the symmetric difference of two Index objects. It’s sorted if sorting is possible.

**Parameters**
- **other** [Index or array-like]
- **result_name** [str]

**Returns**
- **symmetric_difference** [Index]

**Notes**

symmetric_difference contains elements that appear in either idx1 or idx2 but not both. Equivalent to the Index created by idx1.difference(idx2) | idx2.difference(idx1) with duplicates dropped.

**Examples**

```python
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.symmetric_difference(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```python
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

### 34.6.1.84 pandas.Index.take

Index.take(indices, axis=0, allow_fill=True, fill_value=None, **kwargs)
return a new Index of the values selected by the indices

For internal compatibility with numpy arrays.

**Parameters**
- **indices** : list
  Indices to be taken
- **axis** : int, optional
  The axis over which to select values, always 0.
- **allow_fill** [bool, default True]
fill_value : bool, default None

If allow_fill=True and fill_value is not None, indices specified by -1 is regarded as NA. If Index doesn’t hold NA, raise ValueError

See also:
numpy.ndarray.take

34.6.1.85 pandas.Index.to_frame

Index.to_frame(index=True)

Create a DataFrame with a column containing the Index.

New in version 0.21.0.

Parameters index : boolean, default True

Set the index of the returned DataFrame as the original Index.

Returns DataFrame

DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.

Series.to_frame Convert Series to DataFrame.

Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
   animal
      animal
     Ant    Ant
    Bear    Bear
   Cow     Cow
```

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
   animal
0   Ant
1  Bear
2  Cow
```

34.6.1.86 pandas.Index.to_native_types

Index.to_native_types(slicer=None, **kwargs)

Format specified values of self and return them.

Parameters slicer : int, array-like

An indexer into self that specifies which values are used in the formatting process.

kwargs : dict
Options for specifying how the values should be formatted. These options include the following:

1. **na_rep** [str] The value that serves as a placeholder for NULL values
2. **quoting** [bool or None] Whether or not there are quoted values in *self*
3. **date_format** [str] The format used to represent date-like values

### 34.6.1.87 pandas.Index.to_series

**Index.to_series** (*index=None, name=None*)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

**Parameters**

- **index** : Index, optional
  
  Index of resulting Series. If None, defaults to original index

- **name** : string, optional
  
  Name of resulting Series. If None, defaults to name of original index

**Returns**

- **Series** [dtype will be based on the type of the Index values.]

### 34.6.1.88 pandas.Index.tolist

**Index.tolist**()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

**See also:**

numpy.ndarray.tolist

### 34.6.1.89 pandas.Index.transpose

**Index.transpose** (*args, **kwargs*)

Return the transpose, which is by definition self

### 34.6.1.90 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]
Examples

```python
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.union(idx2)
Int64Index([1, 2, 3, 4, 5, 6], dtype='int64')
```

### 34.6.1.91 pandas.Index.unique

`Index.unique(level=None)`

Return unique values in the index. Uniques are returned in order of appearance, this does NOT sort.

**Parameters**
- `level` : int or str, optional, default None
  - Only return values from specified level (for MultiIndex)
  - New in version 0.23.0.

**Returns**
- Index without duplicates

**See also:**
- `unique`, `Series.unique`

### 34.6.1.92 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]
34.6.1.93 pandas.Index.where

Index.where (cond, other=None)
New in version 0.19.0.

Return an Index of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters

- **cond** [boolean array-like with the same length as self]
- **other** [scalar, or array-like]

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<td>is_boolean</td>
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<td>is_floating</td>
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34.6.2 Attributes

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<td>return if the index is monotonic increasing</td>
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<td>(only equal or increasing) values.</td>
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<td>Index.is_monotonic_decreasing</td>
<td>return if the index is monotonic decreasing</td>
</tr>
<tr>
<td></td>
<td>(only equal or decreasing) values.</td>
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<tr>
<td>Index.is_unique</td>
<td>return if the index has unique values</td>
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<tr>
<td>Index.has_duplicates</td>
<td>return if I have any nans; enables various perf</td>
</tr>
<tr>
<td></td>
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<tr>
<td>Index.hasnans</td>
<td>return the dtype object of the underlying data</td>
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<tr>
<td>Index.dtype</td>
<td>return the dtype str of the underlying data</td>
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<tr>
<td>Index.inferred_type</td>
<td>return a string of the type inferred from the</td>
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<td>Index.shape</td>
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</tr>
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<tr>
<td>Index.nbytes</td>
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<td>Index.ndim</td>
<td>return the number of dimensions of the underlying</td>
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<td>Memory usage of the values</td>
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### 34.6.2.1 pandas.Index.has_duplicates

`Index.has_duplicates`

### 34.6.2.2 pandas.Index.is_all_dates

`Index.is_all_dates`

### 34.6.2.3 pandas.Index.name

`Index.name = None`

### 34.6.2.4 pandas.Index.names

`Index.names`

### 34.6.2.5 pandas.Index.empty

`Index.empty`

### 34.6.3 Modifying and Computations

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<th>Description</th>
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<td><code>Index.all(*args, **kwargs)</code></td>
<td>Return whether all elements are True.</td>
</tr>
<tr>
<td><code>Index.any(*args, **kwargs)</code></td>
<td>Return whether any element is True.</td>
</tr>
<tr>
<td><code>Index.argmin(axis)</code></td>
<td>return a ndarray of the minimum argument indexer</td>
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<tr>
<td><code>Index.argmax(axis)</code></td>
<td>return a ndarray of the maximum argument indexer</td>
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<td><code>Index.copy(name, deep, dtype)</code></td>
<td>Make a copy of this object.</td>
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<tr>
<td><code>Index.delete(loc)</code></td>
<td>Make new Index with passed location(-s) deleted</td>
</tr>
<tr>
<td><code>Index.drop(labels[, errors])</code></td>
<td>Make new Index with passed list of labels deleted</td>
</tr>
<tr>
<td><code>Index.drop_duplicates([keep])</code></td>
<td>Return Index with duplicate values removed.</td>
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<tr>
<td><code>Index.duplicated([keep])</code></td>
<td>Indicate duplicate index values.</td>
</tr>
<tr>
<td><code>Index.equals(other)</code></td>
<td>Determines if two Index objects contain the same elements.</td>
</tr>
<tr>
<td><code>Index.factorize([sort, na_sentinel])</code></td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td><code>Index.identical(other)</code></td>
<td>Similar to equals, but check that other comparable attributes are also equal</td>
</tr>
<tr>
<td><code>Index.insert(loc, item)</code></td>
<td>Make new Index inserting new item at location.</td>
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<td><code>Index.is_(other)</code></td>
<td>More flexible, faster check like <code>is</code> but that works through views</td>
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### pandas.Index.is_boolean

Index.is_boolean()

### pandas.Index.is_floating

Index.is_floating()

### pandas.Index.is_integer

Index.is_integer()

### pandas.Index.is_interval

Index.is_interval()

### 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.min

Index.min()

### pandas.Index.max

Index.max()

### pandas.Index.reindex

Index.reindex(target[, method, level, ...])

### pandas.Index.rename

Index.rename(name[, inplace])

### pandas.Index.repeat

Index.repeat(repeats, *args, **kwargs)

### pandas.Index.where

Index.where(cond[, other])

### pandas.Index.take

Index.take(indices[, axis, allow_fill, ...])

### pandas.Index.putmask

Index.putmask(mask, value)

### pandas.Index.set_names

Index.set_names(names[, level, inplace])

### pandas.Index.unique

Index.unique([level])

### pandas.Index.value_counts

Index.value_counts([normalize, sort, ...])

---

**34.6.3.1 pandas.Index.is_boolean**

Index.is_boolean()

**34.6.3.2 pandas.Index.is_floating**

Index.is_floating()

**34.6.3.3 pandas.Index.is_integer**

Index.is_integer()

**34.6.3.4 pandas.Index.is_interval**

Index.is_interval()

**34.6.3.5 pandas.Index.is_lexsorted_for_tuple**

Index.is_lexsorted_for_tuple(tup)

**34.6.3.6 pandas.Index.is_mixed**

Index.is_mixed()
34.6.3.7 pandas.Index.is_numeric

Index.is_numeric()

34.6.3.8 pandas.Index.is_object

Index.is_object()

34.6.4 Missing Values

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.fillna(value, downcast)</td>
<td>Fill NA/NaN values with the specified value</td>
</tr>
<tr>
<td>Index.dropna(how)</td>
<td>Return Index without NA/NaN values</td>
</tr>
<tr>
<td>Index.isna()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td>Index.notna()</td>
<td>Detect existing (non-missing) values.</td>
</tr>
</tbody>
</table>

34.6.5 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.astype(dtype[, copy])</td>
<td>Create an Index with values cast to dtypes.</td>
</tr>
<tr>
<td>Index.item()</td>
<td>return the first element of the underlying data as a python scalar</td>
</tr>
<tr>
<td>Index.map(mapper[, na_action])</td>
<td>Map values using input correspondence (a dict, Series, or function).</td>
</tr>
<tr>
<td>Index.ravel([order])</td>
<td>return an ndarray of the flattened values of the underlying data</td>
</tr>
<tr>
<td>Index.tolist()</td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td>Index.to_native_types([slicer])</td>
<td>Format specified values of self and return them.</td>
</tr>
<tr>
<td>Index.to_series([index, name])</td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index</td>
</tr>
<tr>
<td>Index.to_frame([index])</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
<tr>
<td>Index.view([cls])</td>
<td></td>
</tr>
</tbody>
</table>

34.6.5.1 pandas.Index.view

Index.view(cls=None)

34.6.6 Sorting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.argsort(*args, **kwargs)</td>
<td>Return the integer indices that would sort the index.</td>
</tr>
<tr>
<td>Index.searchsorted(value[, side, sorter])</td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td>Index.sort_values([return_indexer, ascending])</td>
<td>Return a sorted copy of the index.</td>
</tr>
</tbody>
</table>

34.6.7 Time-specific operations
### 34.6.8 Combining / joining / set operations

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.shift([periods, freq])</code></td>
<td>Shift index by desired number of time frequency increments.</td>
</tr>
<tr>
<td><code>Index.append(other)</code></td>
<td>Append a collection of Index options together</td>
</tr>
<tr>
<td><code>Index.join(other[, how, level, ...])</code></td>
<td>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>Return a new Index with elements from the index that are not in <code>other</code>.</td>
</tr>
<tr>
<td><code>Index.symmetric_difference(other[, result_name])</code></td>
<td>Compute the symmetric difference of two Index objects.</td>
</tr>
</tbody>
</table>

### 34.6.9 Selecting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.asof(label)</code></td>
<td>For a sorted index, return the most recent label up to and including the passed label.</td>
</tr>
<tr>
<td><code>Index.asof_locs(where, mask)</code></td>
<td>Where : array of timestamps Mask : array of booleans where data is not NA</td>
</tr>
<tr>
<td><code>Index.contains(key)</code></td>
<td>Return a boolean if this key is IN the index</td>
</tr>
<tr>
<td><code>Index.get_duplicates()</code></td>
<td>(DEPRECATED) Extract duplicated index elements.</td>
</tr>
<tr>
<td><code>Index.get_indexer(target[, method, limit, ...])</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>Index.get_indexer_non_unique(target)</code></td>
<td>Guaranteed return of an indexer even when non-unique. This dispatches to get_indexer or get_indexer_nonunique as appropriate</td>
</tr>
<tr>
<td><code>Index.get_level_values(level)</code></td>
<td>Return an Index of values for requested level, equal to the length of the index.</td>
</tr>
<tr>
<td><code>Index.get_loc(key[, method, tolerance])</code></td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
<tr>
<td><code>Index.get_slice_bound(label, side, kind)</code></td>
<td>Calculate slice bound that corresponds to given label.</td>
</tr>
<tr>
<td><code>Index.get_value(series, key)</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>Index.get_values()</code></td>
<td>Return Index data as an numpy.ndarray.</td>
</tr>
<tr>
<td><code>Index.set_value(arr, key, value)</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>Index.isin(values[, level])</code></td>
<td>Return a boolean array where the index values are in <code>values</code>.</td>
</tr>
<tr>
<td><code>Index.slice_indexer([start, end, step, kind])</code></td>
<td>For an ordered or unique index, compute the slice indexer for input labels and step.</td>
</tr>
<tr>
<td><code>Index.slice_locs([start, end, step, kind])</code></td>
<td>Compute slice locations for input labels.</td>
</tr>
</tbody>
</table>

### 34.7 Numeric Index
### pandas.RangeIndex

**class** pandas.RangeIndex

Immutable Index implementing a monotonic integer range.

RangeIndex is a memory-saving special case of Int64Index limited to representing monotonic ranges. Using RangeIndex may in some instances improve computing speed.

This is the default index type used by DataFrame and Series when no explicit index is provided by the user.

**Parameters**

- **start**: int (default: 0), or other RangeIndex instance. 
  - If int and “stop” is not given, interpreted as “stop” instead.
- **stop** [int (default: 0)]
- **step** [int (default: 1)]
- **name**: object, optional
  - Name to be stored in the index
- **copy**: bool, default False
  - Unused, accepted for homogeneity with other index types.

**See also:**

- **Index**: The base pandas Index type
- **Int64Index**: Index of int64 data

**Attributes**

None

**Methods**

- **from_range**(data[, name, dtype])
  - create RangeIndex from a range (py3), or xrange (py2) object
34.7.1.1 pandas.RangeIndex.from_range

classmethod `RangeIndex.from_range` *(data, name=None, dtype=None, **kwargs)*
create RangeIndex from a range (py3), or xrange (py2) object

34.7.2 pandas.Int64Index

class `pandas.Int64Index`
Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. Int64Index is a special case of `Index` with purely integer labels.

**Parameters**

- `data` [array-like (1-dimensional)]
- `dtype` [NumPy dtype (default: int64)]
- `copy` : bool
  Make a copy of input ndarray
- `name` : object
  Name to be stored in the index

**See also:**

- `Index` The base pandas Index type

**Notes**

An Index instance can only contain hashable objects.

**Attributes**

None

**Methods**

None

34.7.3 pandas.UInt64Index

class `pandas.UInt64Index`
Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. UInt64Index is a special case of `Index` with purely unsigned integer labels.

**Parameters**

- `data` [array-like (1-dimensional)]
- `dtype` [NumPy dtype (default: uint64)]
copy : bool
   Make a copy of input ndarray
name : object
   Name to be stored in the index

See also:

Index  The base pandas Index type

Notes

An Index instance can only contain hashable objects.

Attributes

None

Methods

None

34.7.4 pandas.Float64Index

class pandas.Float64Index
   Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas
   objects. Float64Index is a special case of Index with purely float labels.

   Parameters

   data [array-like (1-dimensional)]
   dtype [NumPy dtype (default: float64)]
   copy : bool
      Make a copy of input ndarray
   name : object
      Name to be stored in the index

   See also:

   Index  The base pandas Index type

   Notes

   An Index instance can only contain hashable objects.
Attributes

RangeIndex.from_range(data[, name, dtype]) create RangeIndex from a range (py3), or xrange (py2) object

34.8 CategoricalIndex

CategoricalIndex

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.

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

See also:
Categorical, Index

Attributes
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>rename_categories(*args, **kwargs)</td>
<td>Renames categories.</td>
</tr>
<tr>
<td>reorder_categories(*args, **kwargs)</td>
<td>Reorders categories as specified in new_categories.</td>
</tr>
<tr>
<td>add_categories(*args, **kwargs)</td>
<td>Add new categories.</td>
</tr>
<tr>
<td>remove_categories(*args, **kwargs)</td>
<td>Removes the specified categories.</td>
</tr>
<tr>
<td>remove_unused_categories(*args, **kwargs)</td>
<td>Removes categories which are not used.</td>
</tr>
<tr>
<td>set_categories(*args, **kwargs)</td>
<td>Sets the categories to the specified new_categories.</td>
</tr>
<tr>
<td>as_ordered(*args, **kwargs)</td>
<td>Sets the Categorical to be ordered.</td>
</tr>
<tr>
<td>as_unordered(*args, **kwargs)</td>
<td>Sets the Categorical to be unordered.</td>
</tr>
<tr>
<td>map(mapper)</td>
<td>Map values using input correspondence (a dict, Series, or function).</td>
</tr>
</tbody>
</table>

34.8.1.1 pandas.CategoricalIndex.rename_categories

CategoricalIndex.rename_categories(*args, **kwargs)

Renames categories.

**Parameters**

- new_categories : list-like, dict-like or callable
  - list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
  - dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
    New in version 0.21.0.
  - callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.
    New in version 0.23.0.

**Warning:** Currently, Series are considered list like. In a future version of pandas they’ll be considered dict-like.

- 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 or None

  With inplace=False, the new categorical is returned. With inplace=True, there is no return value.

**Raises**

ValueError

If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

**See also:**

reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories
Examples

```python
>>> c = Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]

For dict-like new_categories, extra keys are ignored and categories not in the dictionary are passed through

```python
>>> c.rename_categories({'a': 'A', 'c': 'C'})
[A, A, b]
Categories (2, object): [A, b]
```

You may also provide a callable to create the new categories

```python
>>> c.rename_categories(lambda x: x.upper())
[A, A, b]
Categories (2, object): [A, b]
```

34.8.1.2 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

34.8.1.3 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

### 34.8.1.4 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

### 34.8.1.5 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

34.8.1.6 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 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

34.8.1.7 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

### 34.8.1.8 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

### 34.8.1.9 pandas.CategoricalIndex.map

CategoricalIndex.map(mapper)

Map values using input correspondence (a dict, Series, or function).

Maps the values (their categories, not the codes) of the index to new categories. If the mapping correspondence is one-to-one the result is a CategoricalIndex which has the same order property as the original, otherwise an Index is returned.

If a dict or Series is used any unmapped category is mapped to NaN. Note that if this happens an Index will be returned.

**Parameters** mapper : function, dict, or Series

Mapping correspondence.

**Returns** pandas.CategoricalIndex or pandas.Index

Mapped index.

See also:

*Index.map* Apply a mapping correspondence on an Index.

*Series.map* Apply a mapping correspondence on a Series.

*Series.apply* Apply more complex functions on a Series.

Examples

```python
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'])
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'], ordered=False, dtype='category')
>>> idx.map(lambda x: x.upper())
CategoricalIndex(['A', 'B', 'C'], categories=['A', 'B', 'C'], ordered=False, dtype='category')
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'third'})
CategoricalIndex(['first', 'second', 'third'], categories=['first', 'second', 'third'], ordered=False, dtype='category')
```

If the mapping is one-to-one the ordering of the categories is preserved:
CategoricalComponents

CategoricalIndex.codes
CategoricalIndex.categories
CategoricalIndex.ordered
CategoricalIndex.rename_categories(*args,...)
   Renames categories.
CategoricalIndex.reorder_categories(*args,...)
   Reorders categories as specified in new_categories.
CategoricalIndex.add_categories(*args,**kwargs)
   Add new categories.
CategoricalIndex.remove_categories(*args,...)
   Removes the specified categories.
CategoricalIndex.remove_unused_categories(...)
   Removes categories which are not used.
CategoricalIndex.set_categories(*args,**kwargs)
   Sets the categories to the specified new_categories.
CategoricalIndex.as_ordered(*args,**kwargs)
   Sets the Categorical to be ordered
CategoricalIndex.as_unordered(*args,**kwargs)
   Sets the Categorical to be unordered
CategoricalIndex.map(mapper)
   Map values using input correspondence (a dict, Series, or function).

34.8.2.1 pandas.CategoricalIndex.codes

CategoricalIndex.codes

34.8.2.2 pandas.CategoricalIndex.categories

CategoricalIndex.categories
34.8.2.3 pandas.CategoricalIndex.ordered

CategoricalIndex.ordered

34.9 IntervalIndex

| IntervalIndex | Immutable Index implementing an ordered, sliceable set. |

34.9.1 pandas.IntervalIndex

class pandas.IntervalIndex

Immutable Index implementing an ordered, sliceable set. IntervalIndex represents an Index of Interval objects that are all closed on the same side.

New in version 0.20.0.

**Warning:** The indexing behaviors are provisional and may change in a future version of pandas.

**Parameters**

data : array-like (1-dimensional)

Array-like containing Interval objects from which to build the IntervalIndex

closed : {'left', 'right', 'both', 'neither'}, default 'right'

Whether the intervals are closed on the left-side, right-side, both or neither.

name : object, optional

Name to be stored in the index.

copy : boolean, default False

Copy the meta-data

dtype : dtype or None, default None

If None, dtype will be inferred

.. versionadded:: 0.23.0

**See also:**

Index The base pandas Index type

Interval A bounded slice-like interval; the elements of an IntervalIndex

interval_range Function to create a fixed frequency IntervalIndex

cut, qcut

**Notes**

See the user guide for more.
Examples

A new `IntervalIndex` is typically constructed using `interval_range()`:

```python
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
closed='right', dtype='interval[int64]')
```

It may also be constructed using one of the constructor methods: `IntervalIndex.from_arrays()`, `IntervalIndex.from_breaks()`, and `IntervalIndex.from_tuples()`.

See further examples in the doc strings of `interval_range` and the mentioned constructor methods.

Attributes

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<th>Attribute</th>
<th>Description</th>
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<tbody>
<tr>
<td><code>closed</code></td>
<td>Whether the intervals are closed on the left-side, right-side, both or neither</td>
</tr>
<tr>
<td><code>is_non_overlapping_monotonic</code></td>
<td>Return True if the IntervalIndex is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False</td>
</tr>
<tr>
<td><code>left</code></td>
<td>Return the left endpoints of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>length</code></td>
<td>Return an Index with entries denoting the length of each Interval in the IntervalIndex</td>
</tr>
<tr>
<td><code>mid</code></td>
<td>Return the midpoint of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>right</code></td>
<td>Return the right endpoints of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>values</code></td>
<td>Return the IntervalIndex’s data as a numpy array of Interval objects (with dtype='object')</td>
</tr>
</tbody>
</table>

34.9.1.1 pandas.IntervalIndex.closed

`IntervalIndex.closed`  
Whether the intervals are closed on the left-side, right-side, both or neither

34.9.1.2 pandas.IntervalIndex.is_non_overlapping_monotonic

`IntervalIndex.is_non_overlapping_monotonic`  
Return True if the IntervalIndex is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False

34.9.1.3 pandas.IntervalIndex.left

`IntervalIndex.left`  
Return the left endpoints of each Interval in the IntervalIndex as an Index
34.9.1.4 pandas.IntervalIndex.length

IntervalIndex.length
Return an Index with entries denoting the length of each Interval in the IntervalIndex

34.9.1.5 pandas.IntervalIndex.mid

IntervalIndex.mid
Return the midpoint of each Interval in the IntervalIndex as an Index

34.9.1.6 pandas.IntervalIndex.right

IntervalIndex.right
Return the right endpoints of each Interval in the IntervalIndex as an Index

34.9.1.7 pandas.IntervalIndex.values

IntervalIndex.values
Return the IntervalIndex’s data as a numpy array of Interval objects (with dtype=’object’)

Methods

<table>
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<tr>
<th>Method</th>
<th>Description</th>
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<tbody>
<tr>
<td>contains(key)</td>
<td>Return a boolean indicating if the key is IN the index</td>
</tr>
<tr>
<td>from_arrays</td>
<td>Construct from two arrays defining the left and right bounds.</td>
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<tr>
<td>from_breaks</td>
<td>Construct an IntervalIndex from an array of splits</td>
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<tr>
<td>from_tuples</td>
<td>Construct an IntervalIndex from a list/array of tuples</td>
</tr>
<tr>
<td>get_indexer</td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td>get_loc(key[, method])</td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
</tbody>
</table>

34.9.1.8 pandas.IntervalIndex.contains

IntervalIndex.contains(key)
Return a boolean indicating if the key is IN the index

We accept / allow keys to be not just actual objects.

Parameters

key [int, float, Interval]

Returns

boolean
34.9.1.9 pandas.IntervalIndex.from_arrays

```
classmethod IntervalIndex.from_arrays(
    left, right, closed='right', name=None,
    copy=False, dtype=None)
```

Construct from two arrays defining the left and right bounds.

Parameters:
- **left**: array-like (1-dimensional)
  - Left bounds for each interval.
- **right**: array-like (1-dimensional)
  - Right bounds for each interval.
- **closed**: {'left', 'right', 'both', 'neither'}, default 'right'
  - Whether the intervals are closed on the left-side, right-side, both or neither.
- **name**: object, optional
  - Name to be stored in the index.
- **copy**: boolean, default False
  - Copy the data.
- **dtype**: dtype, optional
  - If None, dtype will be inferred.

Returns:
- **index**: [IntervalIndex]

Raises **ValueError**

- When a value is missing in only one of `left` or `right`. When a value in `left` is greater than the corresponding value in `right`.

See also:

- `interval_range` Function to create a fixed frequency IntervalIndex.
- `IntervalIndex.from_breaks` Construct an IntervalIndex from an array of splits.
- `IntervalIndex.from_tuples` Construct an IntervalIndex from a list/array of tuples.

Notes

Each element of `left` must be less than or equal to the `right` element at the same position. If an element is missing, it must be missing in both `left` and `right`. A TypeError is raised when using an unsupported type for `left` or `right`. At the moment, ‘category’, ‘object’, and ‘string’ subtypes are not supported.

Examples

```python
>>> pd.IntervalIndex.from_arrays([[0, 1, 2], [1, 2, 3]], closed='right', dtype='interval[int64]')
```
If you want to segment different groups of people based on ages, you can apply the method as follows:

```python
>>> ages = pd.IntervalIndex.from_arrays([0, 2, 13],
... [2, 13, 19], closed='left')
>>> ages
IntervalIndex([[0, 2), [2, 13), [13, 19))
     closed='left',
      dtype='interval[int64]')
>>> s = pd.Series(['baby', 'kid', 'teen'], ages)
>>> s
[0, 2)   baby
[2, 13)  kid
[13, 19) teen
dtype: object
```

Values may be missing, but they must be missing in both arrays.

```python
>>> pd.IntervalIndex.from_arrays([0, np.nan, 13],
... [2, np.nan, 19])
IntervalIndex([(0.0, 2.0], nan, (13.0, 19.0)])
     closed='right',
      dtype='interval[float64]')
```

### 34.9.1.10 pandas.IntervalIndex.from_breaks

**classmethod** IntervalIndex.from_breaks(breaks, closed='right', name=None, copy=False, dtype=None)

Construct an IntervalIndex from an array of splits

**Parameters**

- **breaks** : array-like (1-dimensional)
  - Left and right bounds for each interval.
- **closed** : ['left', 'right', 'both', 'neither'], default 'right'
  - Whether the intervals are closed on the left-side, right-side, both or neither.
- **name** : object, optional
  - Name to be stored in the index.
- **copy** : boolean, default False
  - copy the data
- **dtype** : dtype or None, default None
  - If None, dtype will be inferred

**See also:**

- `interval_range` Function to create a fixed frequency IntervalIndex
- `IntervalIndex.from_arrays` Construct an IntervalIndex from a left and right array
- `IntervalIndex.from_tuples` Construct an IntervalIndex from a list/array of tuples
Examples

```python
>>> pd.IntervalIndex.from_breaks([0, 1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]
    closed='right',
    dtype='interval[int64]')
```

34.9.1.11 pandas.IntervalIndex.from_tuples

**classmethod** `IntervalIndex.from_tuples(data, closed='right', name=None, copy=False, dtype=None)`

Construct an IntervalIndex from a list/array of tuples

**Parameters**

- `data` : array-like (1-dimensional)
  Array of tuples

- `closed` : {'left', 'right', 'both', 'neither'}, default 'right'
  Whether the intervals are closed on the left-side, right-side, both or neither.

- `name` : object, optional
  Name to be stored in the index.

- `copy` : boolean, default False
  by-default copy the data, this is compat only and ignored

- `dtype` : dtype or None, default None
  If None, dtype will be inferred

**See also:**

- `interval_range` Function to create a fixed frequency IntervalIndex
- `IntervalIndex.from_arrays` Construct an IntervalIndex from a left and right array
- `IntervalIndex.from_breaks` Construct an IntervalIndex from an array of splits

Examples

```python
>>> pd.IntervalIndex.from_tuples([(0, 1), (1, 2)])
IntervalIndex([(0, 1], (1, 2]
    closed='right', dtype='interval[int64]')
```

34.9.1.12 pandas.IntervalIndex.get_indexer

`IntervalIndex.get_indexer(target, method=None, limit=None, tolerance=None)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**

- `target` [IntervalIndex or list of Intervals]
method : {None, ‘pad’/’ffill’, ‘backfill’/’bfill’, ‘nearest’}, optional

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit : int, optional

Maximum number of consecutive labels in target to match for inexact matches.

tolerance : optional

Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation
\[ \text{abs(index[indexer]} - \text{target) } \leq \text{tolerance}. \]

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like 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)
```

34.9.1.13 pandas.IntervalIndex.get_loc

IntervalIndex.get_loc(key, method=None)

Get integer location, slice or boolean mask for requested label.

Parameters

key [label]

method : {None}, optional

- default: matches where the label is within an interval only.

Returns

loc [int if unique index, slice if monotonic index, else mask]
Examples

```python
>>> i1, i2 = pd.Interval(0, 1), pd.Interval(1, 2)
>>> index = pd.IntervalIndex([i1, i2])
>>> index.get_loc(1)
0

You can also supply an interval or an location for a point inside an interval.

```python
>>> index.get_loc(pd.Interval(0, 2))
array([0, 1], dtype=int64)
>>> index.get_loc(1.5)
1

If a label is in several intervals, you get the locations of all the relevant intervals.

```python
>>> i3 = pd.Interval(0, 2)
>>> overlapping_index = pd.IntervalIndex([i2, i3])
>>> overlapping_index.get_loc(1.5)
array([0, 1], dtype=int64)
```

34.9.2 IntervalIndex Components

<table>
<thead>
<tr>
<th>Method Name</th>
<th>Description</th>
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<tbody>
<tr>
<td><code>IntervalIndex.from_arrays(left, right[, ...])</code></td>
<td>Construct from two arrays defining the left and right bounds.</td>
</tr>
<tr>
<td><code>IntervalIndex.from_tuples(data[, closed, ...])</code></td>
<td>Construct an IntervalIndex from a list/array of tuples</td>
</tr>
<tr>
<td><code>IntervalIndex.from_breaks(breaks[, closed, ...])</code></td>
<td>Construct an IntervalIndex from an array of splits</td>
</tr>
<tr>
<td><code>IntervalIndex.contains(key)</code></td>
<td>Return a boolean indicating if the key is IN the index</td>
</tr>
<tr>
<td><code>IntervalIndex.left</code></td>
<td>Return the left endpoints of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>IntervalIndex.right</code></td>
<td>Return the right endpoints of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>IntervalIndex.mid</code></td>
<td>Return the midpoint of each Interval in the IntervalIndex as an Index</td>
</tr>
<tr>
<td><code>IntervalIndex.closed</code></td>
<td>Whether the intervals are closed on the left-side, right-side, both or neither</td>
</tr>
<tr>
<td><code>IntervalIndex.length</code></td>
<td>Return an Index with entries denoting the length of each Interval in the IntervalIndex</td>
</tr>
<tr>
<td><code>IntervalIndex.values</code></td>
<td>Return the IntervalIndex’s data as a numpy array of Interval objects (with dtype=’object’)</td>
</tr>
<tr>
<td><code>IntervalIndex.is_non_overlapping_monotonic</code></td>
<td>Return True if the IntervalIndex is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False</td>
</tr>
<tr>
<td><code>IntervalIndex.get_loc(key[, method])</code></td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
<tr>
<td><code>IntervalIndex.get_indexer(target[, method, ...])</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
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34.10 MultiIndex

MultiIndex

A multi-level, or hierarchical, index object for pandas objects

34.10.1 pandas.MultiIndex

class pandas.MultiIndex

A multi-level, or hierarchical, index object for pandas objects

Parameters

levels : sequence of arrays

The unique labels for each level

labels : sequence of arrays

Integers for each level designating which label at each location

sortorder : optional int

Level of sortedness (must be lexicographically sorted by that level)

names : optional sequence of objects

Names for each of the index levels. (name is accepted for compat)

copy : boolean, default False

Copy the meta-data

verify_integrity : boolean, default True

Check that the levels/labels are consistent and valid

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex

MultiIndex.from_product Create a MultiIndex from the cartesian product of iterables

MultiIndex.from_tuples Convert list of tuples to a MultiIndex

Index The base pandas Index type

Notes

See the user guide for more.

Examples

A new MultiIndex is typically constructed using one of the helper methods MultiIndex.from_arrays(), MultiIndex.from_product() and MultiIndex.from_tuples(). For example (using .from_arrays):

```python
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex(levels=[[1, 2], ['blue', 'red']], 
(continues on next page)
labels=[[0, 0, 1, 1], [1, 0, 1, 0]],
names=['number', 'color'])

See further examples for how to construct a MultiIndex in the doc strings of the mentioned helper methods.

### Attributes

<table>
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<tbody>
<tr>
<td>names</td>
<td>Names of levels in MultiIndex</td>
</tr>
<tr>
<td>nlevels</td>
<td>Integer number of levels in this MultiIndex.</td>
</tr>
<tr>
<td>levshape</td>
<td>A tuple with the length of each level.</td>
</tr>
</tbody>
</table>

#### 34.10.1.1 pandas.MultiIndex.names

MultiIndex.names
Names of levels in MultiIndex

#### 34.10.1.2 pandas.MultiIndex.nlevels

MultiIndex.nlevels
Integer number of levels in this MultiIndex.

#### 34.10.1.3 pandas.MultiIndex.levshape

MultiIndex.levshape
A tuple with the length of each level.

### Methods

- **from_arrays**
  - Convert arrays to MultiIndex

- **from_tuples**
  - Convert list of tuples to MultiIndex

- **from_product**
  - Make a MultiIndex from the cartesian product of multiple iterables

- **set_levels**
  - Set new levels on MultiIndex.

- **set_labels**
  - Set new labels on MultiIndex.

- **to_hierarchical**
  - Return a MultiIndex reshaped to conform to the shapes given by n_repeat and n_shuffle.

- **to_frame**
  - Create a DataFrame with the levels of the MultiIndex as columns.

- **is_lexsorted**
  - Return True if the labels are lexicographically sorted

- **sortlevel**
  - Sort MultiIndex at the requested level.

- **droplevel**
  - Return Index with requested level removed.

- **swaplevel**
  - Swap level i with level j.

- **reorder_levels**
  - Rearrange levels using input order.
remove_unused_levels() create a new MultiIndex from the current that re-
moving unused levels, meaning that they are not ex-
pressed in the labels

34.10.1.4 pandas.MultiIndex.from_arrays

classmethod MultiIndex.from_arrays(arrays, sortorder=None, names=None)
Convert arrays to MultiIndex

Parameters arrays : list / sequence of array-likes
Each array-like gives one level’s value for each data point. len(arrays) is the
number of levels.

sortorder : int or None
Level of sortedness (must be lexicographically sorted by that level)

Returns

index [MultiIndex]

See also:

MultiIndex.from_tuples Convert list of tuples to MultiIndex
MultiIndex.from_product Make a MultiIndex from cartesian product of iterables

Examples

>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> MultiIndex.from_arrays(arrays, names=('number', 'color'))

34.10.1.5 pandas.MultiIndex.from_tuples

classmethod MultiIndex.from_tuples(tuples, sortorder=None, names=None)
Convert list of tuples to MultiIndex

Parameters tuples : list / sequence of tuple-likes
Each tuple is the index of one row/column.

sortorder : int or None
Level of sortedness (must be lexicographically sorted by that level)

Returns

index [MultiIndex]

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex
MultiIndex.from_product Make a MultiIndex from cartesian product of iterables
Examples

```python
>>> tuples = [(1, u'red'), (1, u'blue'),
            (2, u'red'), (2, u'blue')]
>>> MultiIndex.from_tuples(tuples, names=('number', 'color'))
```

### 34.10.1.6 pandas.MultiIndex.from_product

classmethod `MultiIndex.from_product`(iterables, sortorder=None, names=None)

Make a MultiIndex from the cartesian product of multiple iterables

**Parameters**
- `iterables` : list / sequence of iterables
  Each iterable has unique labels for each level of the index.
- `sortorder` : int or None
  Level of sortedness (must be lexicographically sorted by that level).
- `names` : list / sequence of strings or None
  Names for the levels in the index.

**Returns**
- `index` [MultiIndex]

**See also:**

- `MultiIndex.from_arrays` Convert list of arrays to MultiIndex
- `MultiIndex.from_tuples` Convert list of tuples to MultiIndex

### Examples

```python
>>> numbers = [0, 1, 2]
>>> colors = [u'green', u'purple']
>>> MultiIndex.from_product([numbers, colors],
                           names=['number', 'color'])
MultiIndex(levels=[[0, 1, 2], [u'green', u'purple']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=['number', 'color'])
```

### 34.10.1.7 pandas.MultiIndex.set_levels

`MultiIndex.set_levels`(levels, level=None, inplace=False, verify_integrity=True)

Set new levels on MultiIndex. Defaults to returning new index.

**Parameters**
- `levels` : sequence or list of sequence
  new level(s) to apply
- `level` : int, level name, or sequence of int/level names (default None)
  level(s) to set (None for all levels)
- `inplace` : bool
if True, mutates in place

**verify_integrity** : bool (default True)

if True, checks that levels and labels are compatible

**Returns**

new index (of same type and class... etc)

**Examples**

```python
>>> idx = MultiIndex.from_tuples([(1, 'one'), (1, 'two'),
                               (2, 'one'), (2, 'two')],
                               names=['foo', 'bar'])
```

```python
>>> idx.set_levels(['a','b'], [1,2])
MultiIndex(levels=[['a', 'b'], [1, 2]],
          labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
          names=['foo', 'bar'])
```

```python
>>> idx.set_levels(['a','b'], level=0)
MultiIndex(levels=[['a', 'b'], ['one', 'two']],
          labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
          names=['foo', 'bar'])
```

```python
>>> idx.set_levels(['a','b'], level='bar')
MultiIndex(levels=[[1, 2], ['a', 'b']],
          labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
          names=['foo', 'bar'])
```

```python
>>> idx.set_levels([['a','b'], [1,2]], level=[0,1])
MultiIndex(levels=[['a', 'b'], [1, 2]],
          labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
          names=['foo', 'bar'])
```

### 34.10.1.8 pandas.MultiIndex.set_labels

**MultiIndex.set_labels** *(labels, level=None, inplace=False, verify_integrity=True)*

Set new labels on MultiIndex. Defaults to returning new index.

**Parameters**

- **labels** : sequence or list of sequence
  
  new labels to apply

- **level** : int, level name, or sequence of int/level names (default None)
  
  level(s) to set (None for all levels)

- **inplace** : bool
  
  if True, mutates in place

- **verify_integrity** : bool (default True)
  
  if True, checks that levels and labels are compatible

**Returns**

new index (of same type and class... etc)
Examples

```python
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])
>>> idx.set_labels(((1, 0, 1, 0), [0, 0, 1, 1]),
                 MultiIndex(levels=[[1, 2], [u'one', u'two']],
                          labels=[[1, 0, 1, 0], [0, 0, 1, 1]],
                          names=['foo', 'bar']))
>>> idx.set_labels([1, 0, 1, 0], level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
          labels=[[1, 0, 1, 0], [0, 1, 0, 1]],
          names=['foo', 'bar'])
>>> idx.set_labels([0, 0, 1, 1], level='bar')
MultiIndex(levels=[[1, 2], [u'one', u'two']],
          labels=[[0, 0, 1, 1], [0, 0, 1, 1]],
          names=['foo', 'bar'])
>>> idx.set_labels(((1, 0, 1, 0), [0, 0, 1, 1]), level=[0, 1])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
          labels=[[0, 0, 1, 1], [0, 0, 1, 1]],
          names=['foo', 'bar'])
```

34.10.1.9 pandas.MultiIndex.to_hierarchical

MultiIndex.to_hierarchical(n_repeat, n_shuffle=1)

Return a MultiIndex reshaped to conform to the shapes given by n_repeat and n_shuffle.

Useful to replicate and rearrange a MultiIndex for combination with another Index with n_repeat items.

Parameters

- **n_repeat**: int
  Number of times to repeat the labels on self

- **n_shuffle**: int
  Controls the reordering of the labels. If the result is going to be an inner level in a MultiIndex, n_shuffle will need to be greater than one. The size of each label must be divisible by n_shuffle.

Returns

- MultiIndex

Examples

```python
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')])
>>> idx.to_hierarchical(3)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
          labels=[[0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1],
                  [0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1]])
```
34.10.1.10 pandas.MultiIndex.to_frame

MultiIndex.to_frame(index=True)
Create a DataFrame with the levels of the MultiIndex as columns.

New in version 0.20.0.

Parameters index : boolean, default True
Set the index of the returned DataFrame as the original MultiIndex.

Returns

 DataFrame [a DataFrame containing the original MultiIndex data.]

34.10.1.11 pandas.MultiIndex.is_lexsorted

MultiIndex.is_lexsorted()
Return True if the labels are lexicographically sorted

34.10.1.12 pandas.MultiIndex.sortlevel

MultiIndex.sortlevel(level=0, ascending=True, sort_remaining=True)
Sort MultiIndex at the requested level. The result will respect the original ordering of the associated factor at that level.

Parameters level : list-like, int or str, default 0
If a string is given, must be a name of the level If list-like must be names or ints of levels.

ascending : boolean, default True
False to sort in descending order Can also be a list to specify a directed ordering

sort_remaining : [sort by the remaining levels after level.]

Returns sorted_index : pd.MultiIndex
Resulting index

indexer : np.ndarray
Indices of output values in original index

34.10.1.13 pandas.MultiIndex.droplevel

MultiIndex.droplevel(level=0)
Return Index with requested level removed. If MultiIndex has only 2 levels, the result will be of Index type not MultiIndex.

Parameters

 level [int/level name or list thereof]

Returns

 index [Index or MultiIndex]
Notes

Does not check if result index is unique or not

34.10.1.14 pandas.MultiIndex.swaplevel

MultiIndex.swaplevel \((i=-2, j=-1)\)

Swap level \(i\) with level \(j\).

Calling this method does not change the ordering of the values.

**Parameters**

\(i\) : int, str, default -2

First level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.

\(j\) : int, str, default -1

Second level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.

**Returns** MultiIndex

A new MultiIndex

.. versionchanged:: 0.18.1

The indexes \(i\) and \(j\) are now optional, and default to the two innermost levels of the index.

**See also:**

*Series.swaplevel* Swap levels \(i\) and \(j\) in a MultiIndex

*Dataframe.swaplevel* Swap levels \(i\) and \(j\) in a MultiIndex on a particular axis

**Examples**

```python
>>> mi = pd.MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
                         labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
>>> mi
MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
        labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
>>> mi.swaplevel(0, 1)
MultiIndex(levels=[['bb', 'aa'], ['a', 'b']],
        labels=[[0, 1, 0, 1], [0, 0, 1, 1]])
```

34.10.1.15 pandas.MultiIndex.reorder_levels

MultiIndex.reorder_levels \((order)\)

Rearrange levels using input order. May not drop or duplicate levels
34.10.1.16 pandas.MultiIndex.remove_unused_levels

MultiIndex.remove_unused_levels()
create a new MultiIndex from the current that removing unused levels, meaning that they are not expressed
in the labels
The resulting MultiIndex will have the same outward appearance, meaning the same .values and ordering.
It will also be .equals() to the original.
New in version 0.20.0.

Returns
MultiIndex

Examples

```python
>>> i = pd.MultiIndex.from_product([range(2), list('ab')])
MultiIndex(levels=[[0, 1], ['a', 'b']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

```python
>>> i[2:]
MultiIndex(levels=[[0, 1], ['a', 'b']],
           labels=[[1, 1], [0, 1]])
```

The 0 from the first level is not represented and can be removed

```python
>>> i[2:].remove_unused_levels()
MultiIndex(levels=[[1], ['a', 'b']],
           labels=[[0, 0], [0, 1]])
```

IndexSlice
Create an object to more easily perform multi-index slicing

34.10.2 pandas.IndexSlice

pandas.IndexSlice = <pandas.core.indexing._IndexSlice object>
Create an object to more easily perform multi-index slicing

Examples

```python
>>> midx = pd.MultiIndex.from_product([['A0','A1'], ['B0','B1','B2','B3']])
>>> columns = ['foo', 'bar']
>>> dfmi = pd.DataFrame(np.arange(16).reshape((len(midx), len(columns))),
                        index=midx, columns=columns)
```

Using the default slice command:

```python
>>> dfmi.loc[(slice(None), slice('B0', 'B1')), :]
foo  bar
A0   B0   0  1
    B1   2  3
```
(continues on next page)
Using the IndexSlice class for a more intuitive command:

```python
>>> idx = pd.IndexSlice
>>> dfmi.loc[idx[:, 'B0':'B1'], :]
foo    bar
A0  B0  0  1
    B1  2  3
A1  B0  8  9
    B1 10 11
```

### 34.10.3 MultiIndex Constructors

- **MultiIndex.from_arrays**
  - `arrays[, sortorder, ...]` Convert arrays to MultiIndex
- **MultiIndex.from_tuples**
  - `tuples[, sortorder, ...]` Convert list of tuples to MultiIndex
- **MultiIndex.from_product**
  - `iterables[, ...]` Make a MultiIndex from the cartesian product of multiple iterables

### 34.10.4 MultiIndex Attributes

- **MultiIndex.names** Names of levels in MultiIndex
- **MultiIndex.levels**
- **MultiIndex.labels**
- **MultiIndex.nlevels** Integer number of levels in this MultiIndex.
- **MultiIndex.levshape** A tuple with the length of each level.

### 34.10.4.1 pandas.MultiIndex.levels

MultiIndex.**levels**

### 34.10.4.2 pandas.MultiIndex.labels

MultiIndex.**labels**

### 34.10.5 MultiIndex Components

- **MultiIndex.set_levels**
  - `levels[, level, ...]` Set new levels on MultiIndex.
- **MultiIndex.set_labels**
  - `labels[, level, ...]` Set new labels on MultiIndex.
- **MultiIndex.to_hierarchical**
  - `n_repeat[n_shuffle]` Return a MultiIndex reshaped to conform to the shapes given by n_repeat and n_shuffle.
- **MultiIndex.to_frame**
  - `index` Create a DataFrame with the levels of the MultiIndex as columns.

Continued on next page
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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>MultiIndex.is_lexsorted()</code></td>
<td>Return True if the labels are lexicographically sorted</td>
</tr>
<tr>
<td><code>MultiIndex.sortlevel([level, ascending, ...])</code></td>
<td>Sort MultiIndex at the requested level.</td>
</tr>
<tr>
<td><code>MultiIndex.droplevel([level])</code></td>
<td>Return Index with requested level removed.</td>
</tr>
<tr>
<td><code>MultiIndex.swaplevel([i, j])</code></td>
<td>Swap level i with level j.</td>
</tr>
<tr>
<td><code>MultiIndex.reorder_levels(order)</code></td>
<td>Rearrange levels using input order.</td>
</tr>
<tr>
<td><code>MultiIndex.remove_unused_levels()</code></td>
<td>create a new MultiIndex from the current that removing unused levels, meaning that they are not expressed in the labels</td>
</tr>
<tr>
<td><code>MultiIndex.unique([level])</code></td>
<td>Return unique values in the index.</td>
</tr>
</tbody>
</table>

### 34.10.5.1 pandas.MultiIndex.unique

`MultiIndex.unique(level=None)`

Return unique values in the index. Uniques are returned in order of appearance, this does NOT sort.

**Parameters**

- **level** : int or str, optional, default None
  - Only return values from specified level (for MultiIndex)
  - New in version 0.23.0.

**Returns**

- Index without duplicates

**See also:**

- unique, Series.unique

### 34.10.6 MultiIndex Selecting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>MultiIndex.get_loc(key[, method])</code></td>
<td>Get location for a label or a tuple of labels as an integer, slice or boolean mask.</td>
</tr>
<tr>
<td><code>MultiIndex.get_indexer(target[, method, ...])</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>MultiIndex.get_level_values(level)</code></td>
<td>Return vector of label values for requested level, equal to the length of the index.</td>
</tr>
</tbody>
</table>

### 34.10.6.1 pandas.MultiIndex.get_loc

`MultiIndex.get_loc(key, method=None)`

Get location for a label or a tuple of labels as an integer, slice or boolean mask.

**Parameters**

- **key** : [label or tuple of labels (one for each level)]
- **method** : [None]

**Returns**

- **loc** : int, slice object or boolean mask
  - If the key is past the lexsort depth, the return may be a boolean mask array, otherwise it is always a slice or int.

**See also:**

- Index.get_loc get_loc method for (single-level) index.
**MultiIndex.slice_locs** Get slice location given start label(s) and end label(s).

**MultiIndex.get_locs** Get location for a label/slice/list/mask or a sequence of such.

**Notes**

The key cannot be a slice, list of same-level labels, a boolean mask, or a sequence of such. If you want to use those, use MultiIndex.get_locs() instead.

**Examples**

```python
def pd.MultiIndex.from_arrays([list('abb'), list('def')])

>>> mi.get_loc('b')
slice(1, 3, None)

>>> mi.get_loc(('b', 'e'))
1
```

### 34.10.6.2 pandas.MultiIndex.get_indexer

**MultiIndex.get_indexer** *(target, method=None, limit=None, tolerance=None)*

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**

- **target** [MultiIndex or list of tuples]
- **method** : {None, ‘pad’/’ffill’, ‘backfill’/’bfill’, ‘nearest’}, optional
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match.
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
- **limit** : int, optional
  - Maximum number of consecutive labels in target to match for inexact matches.
- **tolerance** : optional
  - Maximum distance between original and new labels for inexact matches.
    The values of the index at the matching locations most satisfy the equation \( \text{abs(index[indexer] - target)} \leq \text{tolerance} \).
    Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.
    New in version 0.21.0: (list-like 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)
```

34.10.6.3 pandas.MultiIndex.get_level_values

`MultiIndex.get_level_values(level)`
Return vector of label values for requested level, equal to the length of the index.

**Parameters**
- `level` : int or str
  - level is either the integer position of the level in the MultiIndex, or the name of the level.

**Returns**
- `values` : Index
  - values is a level of this MultiIndex converted to a single `Index` (or subclass thereof).

Examples

Create a MultiIndex:

```python
>>> mi = pd.MultiIndex.from_arrays((list('abc'), list('def')))
>>> mi.names = ['level_1', 'level_2']
```

Get level values by supplying level as either integer or name:

```python
>>> mi.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object', name='level_1')
>>> mi.get_level_values('level_2')
Index(['d', 'e', 'f'], dtype='object', name='level_2')
```

34.11 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.

34.11.1 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
    - 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

**name** : object
    Name to be stored in the index

**dayfirst** : bool, default False
    If True, parse dates in data with the day first order

**yearfirst** : bool, default False
    If True parse dates in data with the year first order

See also:

- **Index** The base pandas Index type
- **TimedeltaIndex** Index of timedelta64 data
- **PeriodIndex** Index of Period data
- **pandas.to_datetime** Convert argument to datetime

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Notes

To learn more about the frequency strings, please see this link.

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>year</code></td>
<td>The year of the datetime</td>
</tr>
<tr>
<td><code>month</code></td>
<td>The month as January=1, December=12</td>
</tr>
<tr>
<td><code>day</code></td>
<td>The days of the datetime</td>
</tr>
<tr>
<td><code>hour</code></td>
<td>The hours of the datetime</td>
</tr>
<tr>
<td><code>minute</code></td>
<td>The minutes of the datetime</td>
</tr>
<tr>
<td><code>second</code></td>
<td>The seconds of the datetime</td>
</tr>
<tr>
<td><code>microsecond</code></td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td><code>nanosecond</code></td>
<td>The nanoseconds of the datetime</td>
</tr>
<tr>
<td><code>date</code></td>
<td>Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).</td>
</tr>
<tr>
<td><code>time</code></td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td><code>dayofyear</code></td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td><code>weekofyear</code></td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td><code>week</code></td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td><code>dayofweek</code></td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td><code>weekday</code></td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td><code>quarter</code></td>
<td>The quarter of the date</td>
</tr>
<tr>
<td><code>freq</code></td>
<td>Return the frequency object if it is set, otherwise None</td>
</tr>
<tr>
<td><code>freqstr</code></td>
<td>Return the frequency object as a string if it is 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>Indicator for whether the date is the last day of the month.</td>
</tr>
<tr>
<td><code>is_quarter_start</code></td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td><code>is_quarter_end</code></td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td><code>is_year_start</code></td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td><code>is_year_end</code></td>
<td>Indicate whether the date is the last day of the year.</td>
</tr>
<tr>
<td><code>is_leap_year</code></td>
<td>Boolean indicator if the date belongs to a leap year.</td>
</tr>
<tr>
<td><code>inferred_freq</code></td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

**34.11.1.1 pandas.DatetimeIndex.year**

`DatetimeIndex.year`

The year of the datetime
34.11.1.2 pandas.DatetimeIndex.month

DatetimeIndex.month
The month as January=1, December=12

34.11.1.3 pandas.DatetimeIndex.day

DatetimeIndex.day
The days of the datetime

34.11.1.4 pandas.DatetimeIndex.hour

DatetimeIndex.hour
The hours of the datetime

34.11.1.5 pandas.DatetimeIndex.minute

DatetimeIndex.minute
The minutes of the datetime

34.11.1.6 pandas.DatetimeIndex.second

DatetimeIndex.second
The seconds of the datetime

34.11.1.7 pandas.DatetimeIndex.microsecond

DatetimeIndex.microsecond
The microseconds of the datetime

34.11.1.8 pandas.DatetimeIndex.nanosecond

DatetimeIndex.nanosecond
The nanoseconds of the datetime

34.11.1.9 pandas.DatetimeIndex.date

DatetimeIndex.date
Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without time-zone information).

34.11.1.10 pandas.DatetimeIndex.time

DatetimeIndex.time
Returns numpy array of datetime.time. The time part of the Timestamps.
34.11.1.11 pandas.DatetimeIndex.dayofyear

DatetimeIndex.dayofyear
   The ordinal day of the year

34.11.1.12 pandas.DatetimeIndex.weekofyear

DatetimeIndex.weekofyear
   The week ordinal of the year

34.11.1.13 pandas.DatetimeIndex.week

DatetimeIndex.week
   The week ordinal of the year

34.11.1.14 pandas.DatetimeIndex.dayofweek

DatetimeIndex.dayofweek
   The day of the week with Monday=0, Sunday=6

34.11.1.15 pandas.DatetimeIndex.weekday

DatetimeIndex.weekday
   The day of the week with Monday=0, Sunday=6

34.11.1.16 pandas.DatetimeIndex.quarter

DatetimeIndex.quarter
   The quarter of the date

34.11.1.17 pandas.DatetimeIndex.freq

DatetimeIndex.freq
   Return the frequency object if it is set, otherwise None

34.11.1.18 pandas.DatetimeIndex.freqstr

DatetimeIndex.freqstr
   Return the frequency object as a string if it is set, otherwise None

34.11.1.19 pandas.DatetimeIndex.is_month_start

DatetimeIndex.is_month_start
   Logical indicating if first day of month (defined by frequency)
34.11.1.20 pandas.DatetimeIndex.is_month_end

DatetimeIndex.is_month_end
Indicator for whether the date is the last day of the month.

Returns Series or array
For Series, returns a Series with boolean values. For DatetimeIndex, returns a
boolean array.

See also:

is_month_start Indicator for whether the date is the first day of the month.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on Date-
timeIndex.

```python
>>> dates = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> dates
dt: datetime64[ns]
0 2018-02-27
1 2018-02-28
2 2018-03-01
dtype: datetime64[ns]
>>> dates.dt.is_month_end
dtype: bool
0 False
1 True
2 False
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_end
array([False, True, False], dtype=bool)
```

34.11.1.21 pandas.DatetimeIndex.is_quarter_start

DatetimeIndex.is_quarter_start
Indicator for whether the date is the first day of a quarter.

Returns is_quarter_start : Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same
name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.

is_quarter_end Similar property for indicating the quarter start.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on Date-
timeIndex.
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", 
... periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter, 
... is_quarter_start=df.dates.dt.is_quarter_start)

<table>
<thead>
<tr>
<th>dates</th>
<th>quarter</th>
<th>is_quarter_start</th>
</tr>
</thead>
<tbody>
<tr>
<td>2017-03-30</td>
<td>1</td>
<td>False</td>
</tr>
<tr>
<td>2017-03-31</td>
<td>1</td>
<td>False</td>
</tr>
<tr>
<td>2017-04-01</td>
<td>2</td>
<td>True</td>
</tr>
<tr>
<td>2017-04-02</td>
<td>2</td>
<td>False</td>
</tr>
</tbody>
</table>

>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
dtype='datetime64[ns]', freq='D')

>>> idx.is_quarter_start
array([False, False, True, False])

34.11.1.22 pandas.DatetimeIndex.is_quarter_end

DatetimeIndex.is_quarter_end
Indicator for whether the date is the last day of a quarter.

Returns is_quarter_end : Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.
is_quarter_start Similar property indicating the quarter start.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", 
... periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter, 
... is_quarter_end=df.dates.dt.is_quarter_end)

<table>
<thead>
<tr>
<th>dates</th>
<th>quarter</th>
<th>is_quarter_end</th>
</tr>
</thead>
<tbody>
<tr>
<td>2017-03-30</td>
<td>1</td>
<td>False</td>
</tr>
<tr>
<td>2017-03-31</td>
<td>1</td>
<td>True</td>
</tr>
<tr>
<td>2017-04-01</td>
<td>2</td>
<td>False</td>
</tr>
<tr>
<td>2017-04-02</td>
<td>2</td>
<td>False</td>
</tr>
</tbody>
</table>

>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
dtype='datetime64[ns]', freq='D')
>>> idx.is_quarter_end
array([False, True, False, False])

34.11.1.23 pandas.DatetimeIndex.is_year_start

DatetimeIndex.is_year_start
Indicate whether the date is the first day of a year.

Returns Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_end Similar property indicating the last day of the year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0 2017-12-30
1 2017-12-31
2 2018-01-01
dtype: datetime64[ns]

>>> dates.dt.is_year_start
0 False
1 False
2 True
dtype: bool
```

```python
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
dtype='datetime64[ns]', freq='D')
```

```python
>>> idx.is_year_start
array([False, False, True])
```

34.11.1.24 pandas.DatetimeIndex.is_year_end

DatetimeIndex.is_year_end
Indicate whether the date is the last day of the year.

Returns Series or DatetimeIndex
The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:
is_year_start  Similar property indicating the start of the year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0 2017-12-30
1 2017-12-31
2 2018-01-01
dtype: datetime64[ns]

>>> dates.dt.is_year_end
0 False
1  True
2 False
dtype: bool
```

```python
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')

>>> idx.is_year_end
array([False,  True, False])
```

34.11.1.25 pandas.DatetimeIndex.is_leap_year

DatetimeIndex.is_leap_year

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary
day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not
by 400.

Returns  Series or ndarray

Booleans indicating if dates belong to a leap year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(["2012-12-31", '2013-12-31', '2014-12-31'],
               dtype='datetime64[ns]', freq='A-DEC')

>>> idx.is_leap_year
array([ True, False, False], dtype=bool)
```
>>> dates = pd.Series(idx)
>>> dates_series
0  2012-12-31
1  2013-12-31
2  2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
0   True
1  False
2  False
dtype: bool

34.11.1.26 pandas.DatetimeIndex.inferred_freq

DatetimeIndex.inferred_freq
Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can’t autodetect the frequency.

Methods

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<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>normalize()</td>
<td>Convert times to midnight.</td>
</tr>
<tr>
<td>strftime(date_format)</td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td>snap(freq)</td>
<td>Snap time stamps to nearest occurring frequency</td>
</tr>
<tr>
<td>tz_convert(tz)</td>
<td>Convert tz-aware DatetimeIndex from one time zone to another.</td>
</tr>
<tr>
<td>tz_localize(tz[, ambiguous, errors])</td>
<td>Localize tz-naive DatetimeIndex to tz-aware DatetimeIndex.</td>
</tr>
<tr>
<td>round(freq, *args, **kwargs)</td>
<td>round the data to the specified freq.</td>
</tr>
<tr>
<td>floor(freq)</td>
<td>floor the data to the specified freq.</td>
</tr>
<tr>
<td>ceil(freq)</td>
<td>ceil the data to the specified freq.</td>
</tr>
<tr>
<td>to_period(freq)</td>
<td>Cast to PeriodIndex at a particular frequency.</td>
</tr>
<tr>
<td>to_perioddelta(freq)</td>
<td>Calculate TimedeltaIndex of difference between index values and index converted to periodIndex at specified freq.</td>
</tr>
<tr>
<td>to_pydatetime()</td>
<td>Return DatetimeIndex as object ndarray of datetime.datetime objects</td>
</tr>
<tr>
<td>to_series([keep_tz, index, name])</td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index</td>
</tr>
<tr>
<td>to_frame([index])</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
<tr>
<td>month_name([locale])</td>
<td>Return the month names of the DateTimeIndex with specified locale.</td>
</tr>
<tr>
<td>day_name([locale])</td>
<td>Return the day names of the DateTimeIndex with specified locale.</td>
</tr>
</tbody>
</table>
34.11.1.27 pandas.DatetimeIndex.normalize

DatetimeIndex.normalize()
Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

Returns DatetimeIndex or Series

The same type as the original data. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

floor Floor the datetimes to the specified freq.
ceil Ceil the datetimes to the specified freq.
round Round the datetimes to the specified freq.

Examples

```python
>>> idx = pd.DatetimeIndex(start='2014-08-01 10:00', freq='H',
... periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
'2014-08-01 11:00:00+05:30',
'2014-08-01 12:00:00+05:30'],
dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
'2014-08-01 00:00:00+05:30',
'2014-08-01 00:00:00+05:30'],
dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

34.11.1.28 pandas.DatetimeIndex.strftime

DatetimeIndex.strftime(date_format)
Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

Parameters date_format : str

Date format string (e.g. “%Y-%m-%d”).

Returns Index

Index of formatted strings

See also:

pandas.to_datetime Convert the given argument to datetime
**DatetimeIndex.normalize**  Return DatetimeIndex with times to midnight.

**DatetimeIndex.round**  Round the DatetimeIndex to the specified freq.

**DatetimeIndex.floor**  Floor the DatetimeIndex to the specified freq.

**Examples**

```python
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...          periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(["March 10, 2018, 09:00:00 AM", 'March 10, 2018, 09:00:01 AM',
      'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

---

**34.11.1.29 pandas.DatetimeIndex.snap**

**DatetimeIndex.snap**(freq='S')

Snap time stamps to nearest occurring frequency

---

**34.11.1.30 pandas.DatetimeIndex.tz_convert**

**DatetimeIndex.tz_convert**(tz)

Convert tz-aware DatetimeIndex from one time zone to another.

**Parameters**

- **tz**: string, pytz timezone, dateutil.tzfile or None

  Time zone for time. Corresponding timestamps would be converted to this time
  zone of the DatetimeIndex. A tz of None will convert to UTC and remove the
  timezone information.

**Returns**

- **normalized**: [Datet imeIndex]

**Raises**

- **TypeError**

  If DatetimeIndex is tz-naive.

**See also:**

- **DatetimeIndex.tz**  A timezone that has a variable offset from UTC

- **DatetimeIndex.tz_localize**  Localize tz-naive DatetimeIndex to a given time zone, or remove
  timezone from a tz-aware DatetimeIndex.

**Examples**

With the `tz` parameter, we can change the DatetimeIndex to other time zones:

```python
>>> dti = pd.DatetimeIndex(start='2014-08-01 09:00',
...          freq='H', periods=3, tz='Europe/Berlin')
```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')

>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
               dtype='datetime64[ns, US/Central]', freq='H')

With the tz=None, we can remove the timezone (after converting to UTC if necessary):

```python
>>> dti = pd.DatetimeIndex(start='2014-08-01 09:00', freq='H',
                         periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```python
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
               '2014-08-01 08:00:00',
               '2014-08-01 09:00:00'],
               dtype='datetime64[ns]', freq='H')
```

### 34.11.1.31 pandas.DatetimeIndex.tz_localize

**DatetimeIndex.tz_localize**(tz, ambiguous='raise', errors='raise')

Localize tz-naive DatetimeIndex to tz-aware DatetimeIndex.

This method takes a time zone (tz) naive DatetimeIndex object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

**Parameters**

- **tz**: string, pytz.timezone, dateutil.tz.tzfile or None
  - Time zone to convert timestamps to. Passing None will remove the time zone information preserving local time.

- **ambiguous**: str {‘infer’, ‘NaT’, ‘raise’} or bool array, 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

- **errors**: {‘raise’, ‘coerce’}, default ‘raise’
  - ‘raise’ will raise a NonExistentTimeError if a timestamp is not valid in the specified time zone (e.g. due to a transition from or to DST time)
• ‘coerce’ will return NaT if the timestamp can not be converted to the specified time zone

New in version 0.19.0.

Returns DatetimeIndex

Index converted to the specified time zone.

Raises TypeError

If the DatetimeIndex is tz-aware and tz is not None.

See also:

DatetimeIndex.tz_convert Convert tz-aware DatetimeIndex from one time zone to another.

Examples

```
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
```
```
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'], dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
```
```
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
               dtype='datetime64[ns, US/Eastern]', freq='D')
```

With the tz=None, we can remove the time zone information while keeping the local time (not converted to UTC):

```
>>> tz_aware.tz_localize(None)
```
```
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'], dtype='datetime64[ns]', freq='D')
```

34.11.1.32 pandas.DatetimeIndex.round

DatetimexIndex.round(freq, *args, **kwargs)

round the data to the specified freq.

Parameters freq : str or Offset

The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

Returns DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises
ValueError if the ‘freq’ cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
   '2018-01-01 12:01:00'],
   dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
   '2018-01-01 12:00:00'],
   dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.round("H")
0 2018-01-01 12:00:00
1 2018-01-01 12:00:00
2 2018-01-01 12:00:00
dtype: datetime64[ns]
```

34.11.1.33 pandas.DatetimeIndex.floor

`DatetimeIndex.floor(freq)`

floor the data to the specified `freq`.

Parameters

 freq : str or Offset

The frequency level to floor the index to. Must be a fixed frequency like ‘S’
(second) not ‘ME’ (month end). See `frequency aliases` for a list of possible `freq`
values.

Returns

 DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with
the same index for a Series.

Raises

 ValueError if the ‘freq’ cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
   '2018-01-01 12:01:00'],
   dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
   '2018-01-01 12:00:00'],
   dtype='datetime64[ns]', freq=None)
```
Series

```python
>>> pd.Series(rng).dt.floor("H")
0  2018-01-01 11:00:00
1  2018-01-01 12:00:00
2  2018-01-01 12:00:00
dtype: datetime64[ns]
```

34.11.1.34 pandas.DatetimeIndex.ceil

```
DatetimeIndex.ceil(freq)
```

ceil the data to the specified `freq`.

**Parameters**

- `freq`: str or Offset
  - The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible `freq` values.

**Returns**

- DatetimeIndex, TimedeltaIndex, or Series
  - Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**

- ValueError if the ‘freq’ cannot be converted.

**Examples**

Datetimexd

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
  '2018-01-01 12:01:00'],
  dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
  '2018-01-01 13:00:00'],
  dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 13:00:00
dtype: datetime64[ns]
```
34.11.1.35 pandas.DatetimeIndex.to_period

DatetimeIndex.to_period(freq=None)
Cast to PeriodIndex at a particular frequency.

Converting DatetimeIndex to PeriodIndex.

Parameters freq : string or Offset, optional
One of pandas’ offset strings or an Offset object. Will be inferred by default.

Returns
PeriodIndex

 Raises ValueError
When converting a DatetimeIndex with non-regular values, so that a frequency
cannot be inferred.

See also:
pandas.PeriodIndex Immutable ndarray holding ordinal values
pandas.DatetimeIndex.to_pydatetime Return DatetimeIndex as object

Examples

```python
>>> df = pd.DataFrame({"y": [1, 2, 3]},
                    index=pd.to_datetime(["2000-03-31 00:00:00",
                                          "2000-05-31 00:00:00",
                                          "2000-08-31 00:00:00"]))
>>> df.index.to_period("M")
PeriodIndex(['2000-03', '2000-05', '2000-08'],
dtype='period[M]', freq='M')

Infer the daily frequency

```python
>>> idx = pd.date_range("2017-01-01", periods=2)
```python
>>> idx.to_period()
PeriodIndex(['2017-01-01', '2017-01-02'],
dtype='period[D]', freq='D')
```

34.11.1.36 pandas.DatetimeIndex.to_perioddelta

DatetimeIndex.to_perioddelta(freq)
Calculate TimedeltaIndex of difference between index values and index converted to periodIndex at specified freq. Used for vectorized offsets

Parameters

freq: Period frequency

Returns

y: TimedeltaIndex
34.11.1.37 pandas.DatetimeIndex.to_pydatetime

DatetimeIndex.to_pydatetime()  
Return DatetimeIndex as object ndarray of datetime.datetime objects

Returns

datetimes [ndarray]

34.11.1.38 pandas.DatetimeIndex.to_series

DatetimeIndex.to_series(keep_tz=False, index=None, name=None)  
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Parameters keep_tz : optional, defaults 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.

index : Index, optional
  index of resulting Series. If None, defaults to original index

name : string, optional
  name of resulting Series. If None, defaults to name of original index

Returns

Series

34.11.1.39 pandas.DatetimeIndex.to_frame

DatetimeIndex.to_frame(index=True)  
Create a DataFrame with a column containing the Index.

New in version 0.21.0.

Parameters index : boolean, default True
  Set the index of the returned DataFrame as the original Index.

Returns DataFrame
  DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.
Series.to_frame Convert Series to DataFrame.
Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
    animal
   Ant  Ant
  Bear  Bear
   Cow  Cow
```

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
     animal
0   Ant
1   Bear
2   Cow
```

### 34.11.1.40 `pandas.DatetimeIndex.month_name`

`DatetimeIndex.month_name` *(locale=None)*

Return the month names of the `DateTimeIndex` with specified locale.

**Parameters**

- `locale` : string, default None (English locale)

  locale determining the language in which to return the month name

**Returns**

- `month_names` : Index

  Index of month names

.. versionadded:: 0.23.0

### 34.11.1.41 `pandas.DatetimeIndex.day_name`

`DatetimeIndex.day_name` *(locale=None)*

Return the day names of the `DateTimeIndex` with specified locale.

**Parameters**

- `locale` : string, default None (English locale)

  locale determining the language in which to return the day name

**Returns**

- `month_names` : Index

  Index of day names

.. versionadded:: 0.23.0

### 34.11.2 Time/Date Components

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DatetimeIndex.year</code></td>
<td>The year of the datetime</td>
</tr>
<tr>
<td><code>DatetimeIndex.month</code></td>
<td>The month as January=1, December=12</td>
</tr>
<tr>
<td><code>DatetimeIndex.day</code></td>
<td>The days of the datetime</td>
</tr>
<tr>
<td><code>DatetimeIndex.hour</code></td>
<td>The hours of the datetime</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>DatetimeIndex.minute</th>
<th>The minutes of the datetime</th>
</tr>
</thead>
<tbody>
<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 python datetime.date objects (namely, the date part of Timestamps without timezone information).</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>DatetimeIndex.freq</td>
</tr>
<tr>
<td>DatetimeIndex.freqstr</td>
<td>Return the frequency object as a string if it is set, otherwise None</td>
</tr>
<tr>
<td>DatetimeIndex.is_month_start</td>
<td>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td>DatetimeIndex.is_month_end</td>
<td>Indicator for whether the date is the last day of the month.</td>
</tr>
<tr>
<td>DatetimeIndex.is_quarter_start</td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td>DatetimeIndex.is_quarter_end</td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td>DatetimeIndex.is_year_start</td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td>DatetimeIndex.is_year_end</td>
<td>Indicate whether the date is the last day of the year.</td>
</tr>
<tr>
<td>DatetimeIndex.is_leap_year</td>
<td>Boolean indicator if the date belongs to a leap year.</td>
</tr>
<tr>
<td>DatetimeIndex.inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

### 34.11.2.1 pandas.DatetimeIndex.tz

**DatetimeIndex.tz**

### 34.11.3 Selecting

**DatetimeIndex.indexer_at_time(time[, asof])**

Returns index locations of index values at particular time of day (e.g. 9:30AM).

**DatetimeIndex.indexer_between_time(...)**

Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

#### 34.11.3.1 pandas.DatetimeIndex.indexer_at_time

**DatetimeIndex.indexer_at_time(time, asof=False)**

Returns index locations of index values at particular time of day (e.g. 9:30AM).

**Parameters**

- **time**: datetime.time or string
  - datetime.time or string in appropriate format (“%H:%M”, “%H%M”, “%I:%M%p”, “%I%M%p”, “%H:%M:%S”, “%H%M%S”, “%I:%M:%S%p”, “%I%M%S%p”).

**Returns**
values_at_time  [array of integers]

See also:

indexer_between_time, DataFrame.at_time

34.11.3.2  pandas.DatetimeIndex.indexer_between_time

DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)

Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

Parameters start_time, end_time : datetime.time, str
datetime.time or string in appropriate format (“%H:%M”, “%H%M”, “%I:%M%p”,
“%I%M%p”, “%H:%M:%S”, “%H%M%S”, “%I:%M:%S%p”, “%I%M%S%p”).

include_start [boolean, default True]
include_end [boolean, default True]

Returns

values_between_time  [array of integers]

See also:

indexer_at_time, DataFrame.between_time

34.11.4  Time-specific operations

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.normalize()</td>
<td>Convert times to midnight.</td>
</tr>
<tr>
<td>DatetimeIndex.strftime(date_format)</td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td>DatetimeIndex.snap(freq)</td>
<td>Snap time stamps to nearest occurring frequency.</td>
</tr>
<tr>
<td>DatetimeIndex.tz_convert(tz)</td>
<td>Convert tz-aware DatetimeIndex from one time zone to another.</td>
</tr>
<tr>
<td>DatetimeIndex.tz_localize([tz], ambiguous, ...)</td>
<td>Localize tz-naive DatetimeIndex to tz-aware DatetimeIndex.</td>
</tr>
<tr>
<td>DatetimeIndex.round(freq, *args, **kwargs)</td>
<td>round the data to the specified freq.</td>
</tr>
<tr>
<td>DatetimeIndex.floor(freq)</td>
<td>floor the data to the specified freq.</td>
</tr>
<tr>
<td>DatetimeIndex.ceil(freq)</td>
<td>ceil the data to the specified freq.</td>
</tr>
<tr>
<td>DatetimeIndex.month_name([locale])</td>
<td>Return the month names of the DateTimeIndex with specified locale.</td>
</tr>
<tr>
<td>DatetimeIndex.day_name([locale])</td>
<td>Return the day names of the DateTimeIndex with specified locale.</td>
</tr>
</tbody>
</table>

34.11.5  Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.to_period([freq])</td>
<td>Cast to PeriodIndex at a particular frequency.</td>
</tr>
<tr>
<td>DatetimeIndex.to_period(delta)</td>
<td>Calculate TimedeltaIndex of difference between index values and index converted to periodIndex at specified freq.</td>
</tr>
</tbody>
</table>

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### 34.12 TimedeltaIndex

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DatetimeIndex.to_pydatetime()</code></td>
<td>Return DatetimeIndex as object ndarray of datetime.datetime objects</td>
</tr>
<tr>
<td><code>DatetimeIndex.to_series([keep_tz, name])</code></td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index</td>
</tr>
<tr>
<td><code>DatetimeIndex.to_frame([index])</code></td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
</tbody>
</table>

### 34.12.1 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

**See also:**
Index The base pandas Index type

Timedelta Represents a duration between two dates or times.

DatetimeIndex Index of datetime64 data

PeriodIndex Index of Period data

Notes

To learn more about the frequency strings, please see this link.

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>days</td>
<td>Number of days for each element.</td>
</tr>
<tr>
<td>seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</td>
</tr>
<tr>
<td>microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) for each element.</td>
</tr>
<tr>
<td>nanoseconds</td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td>components</td>
<td>Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.</td>
</tr>
<tr>
<td>inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

34.12.1.1 pandas.TimedeltaIndex.days

TimedeltaIndex.days Number of days for each element.

34.12.1.2 pandas.TimedeltaIndex.seconds

TimedeltaIndex.seconds Number of seconds (>= 0 and less than 1 day) for each element.

34.12.1.3 pandas.TimedeltaIndex.microseconds

TimedeltaIndex.microseconds Number of microseconds (>= 0 and less than 1 second) for each element.

34.12.1.4 pandas.TimedeltaIndex.nanoseconds

TimedeltaIndex.nanoseconds Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
34.12.1.5 pandas.TimedeltaIndex.components

TimedeltaIndex.components

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns

a DataFrame

34.12.1.6 pandas.TimedeltaIndex.inferred_freq

TimedeltaIndex.inferred_freq

Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can’t autodetect the frequency.

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>to_pytimedelta()</td>
<td>Return TimedeltaIndex as object ndarray of datetime.timedelta objects</td>
</tr>
<tr>
<td>to_series([index, name])</td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index</td>
</tr>
<tr>
<td>round(freq, *args, **kwargs)</td>
<td>round the data to the specified freq.</td>
</tr>
<tr>
<td>floor(freq)</td>
<td>floor the data to the specified freq.</td>
</tr>
<tr>
<td>ceil(freq)</td>
<td>ceil the data to the specified freq.</td>
</tr>
<tr>
<td>to_frame([index])</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
</tbody>
</table>

34.12.1.7 pandas.TimedeltaIndex.to_pytimedelta

TimedeltaIndex.to_pytimedelta()

Return TimedeltaIndex as object ndarray of datetime.timedelta objects

Returns

datetimes [ndarray]

34.12.1.8 pandas.TimedeltaIndex.to_series

TimedeltaIndex.to_series(index=None, name=None)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Parameters

index : Index, optional

index of resulting Series. If None, defaults to original index

name : string, optional

name of resulting Series. If None, defaults to name of original index

Returns

Series [dtype will be based on the type of the Index values.]
34.12.1.9 pandas.TimedeltaIndex.round

TimedeltaIndex.round(freq, *args, **kwargs)
round the data to the specified freq.

**Parameters**

freq : str or Offset

The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See *frequency aliases* for a list of possible freq values.

**Returns**

DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**

ValueError if the ‘freq’ cannot be converted.

**Examples**

**DatetimeIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')

>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

**Series**

```python
>>> pd.Series(rng).dt.round("H")
0 2018-01-01 12:00:00
1 2018-01-01 12:00:00
2 2018-01-01 12:00:00
dtype: datetime64[ns]
```

34.12.1.10 pandas.TimedeltaIndex.floor

TimedeltaIndex.floor(freq)
floor the data to the specified freq.

**Parameters**

freq : str or Offset

The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See *frequency aliases* for a list of possible freq values.

**Returns**

DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**

ValueError if the ‘freq’ cannot be converted.
ValueError if the ‘freq’ cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
```
```
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
               dtype='datetime64[ns]', freq='T')
```
```
>>> rng.floor('H')
```
```
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
               dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.floor("H")
```
```
0   2018-01-01 11:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

34.12.1.11 pandas.TimedeltaIndex.ceil

TimedeltaIndex.ceil(freq)

Ceil the data to the specified freq.

Parameters freq : str or Offset

The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

Returns DatetimeIndex, TimedeltaIndex, or Series

Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises ValueError if the ‘freq’ cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
```
```
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
               dtype='datetime64[ns]', freq='T')
```
```
>>> rng.ceil('H')
```
```
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
               dtype='datetime64[ns]', freq=None)
```
Series

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 13:00:00
dtype: datetime64[ns]
```

34.12.12 pandas.TimedeltaIndex.to_frame

TimedeltaIndex.to_frame(index=True)

Create a DataFrame with a column containing the Index.

New in version 0.21.0.

Parameters

- **index**: boolean, default True
  Set the index of the returned DataFrame as the original Index.

Returns

DataFrame

DataFrame containing the original Index data.

See also:

- **Index.to_series** Convert an Index to a Series.
- **Series.to_frame** Convert Series to DataFrame.

Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
    animal
   animal
   Ant    Ant
   Bear   Bear
   Cow    Cow
```

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
     animal
    animal
   0    Ant
   1    Bear
   2    Cow
```

34.12.2 Components
The following table describes the methods available for the `TimedeltaIndex` class:

<table>
<thead>
<tr>
<th>Method Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>days</code></td>
<td>Number of days for each element.</td>
</tr>
<tr>
<td><code>seconds</code></td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</td>
</tr>
<tr>
<td><code>microseconds</code></td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) for each element.</td>
</tr>
<tr>
<td><code>nanoseconds</code></td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td><code>components</code></td>
<td>Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.</td>
</tr>
<tr>
<td><code>inferred_freq</code></td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

### 34.12.3 Conversion

- `to_pytimedelta()`: Return TimedeltaIndex as object ndarray of date-time.timedelta objects.
- `to_series([index, name])`: Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.
- `round(freq, *args, **kwargs)`: Round the data to the specified freq.
- `floor(freq)`: Floor the data to the specified freq.
- `ceil(freq)`: Ceil the data to the specified freq.
- `to_frame([index])`: Create a DataFrame with a column containing the Index.

### 34.13 PeriodIndex

**PeriodIndex**

Immutable ndarray holding ordinal values indicating regular periods in time such as particular years, quarters, months, etc.

### 34.13.1 pandas.PeriodIndex

The `PeriodIndex` class represents an immutable ndarray holding ordinal values indicating regular periods in time such as particular years, quarters, months, etc.

Index keys are boxed to Period objects which carry the metadata (e.g., frequency information).

**Parameters**

- `data` : array-like (1-dimensional), optional
  Optional period-like data to construct index with
  - `copy` : bool
    - Make a copy of input ndarray
  - `freq` : string or period object, optional
    - One of pandas period strings or corresponding objects
  - `start` : starting value, period-like, optional
    - If data is None, used as the start point in generating regular period data.
periods : int, optional, > 0
    Number of periods to generate, if generating index. Takes precedence over end argument
end : end value, period-like, optional
    If periods is none, generated index will extend to first conforming period on or just past end argument
year [int, array, or Series, default None]
month [int, array, or Series, default None]
quarter [int, array, or Series, default None]
day [int, array, or Series, default None]
hour [int, array, or Series, default None]
minute [int, array, or Series, default None]
second [int, array, or Series, default None]
tz : object, default None
    Timezone for converting datetime64 data to Periods
dtype [str or PeriodDtype, default None]

See also:
Index The base pandas Index type
Period Represents a period of time
DatetimeIndex Index with datetime64 data
TimedeltaIndex Index of timedelta64 data

Examples

```python
>>> idx = PeriodIndex(year=year_arr, quarter=q_arr)

>>> idx2 = PeriodIndex(start='2000', end='2010', freq='A')
```

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>day</td>
<td>The days of the period</td>
</tr>
<tr>
<td>dayofweek</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>dayofyear</td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td>days_in_month</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>daysinmonth</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>freq</td>
<td>Return the frequency object if it is set, otherwise None</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>freqstr</th>
<th>Return the frequency object as a string if it is set, otherwise None</th>
</tr>
</thead>
<tbody>
<tr>
<td>hour</td>
<td>The hour of the period</td>
</tr>
<tr>
<td>is_leap_year</td>
<td>Logical indicating if the date belongs to a leap year</td>
</tr>
<tr>
<td>minute</td>
<td>The minute of the period</td>
</tr>
<tr>
<td>month</td>
<td>The month as January=1, December=12</td>
</tr>
<tr>
<td>quarter</td>
<td>The quarter of the date</td>
</tr>
<tr>
<td>second</td>
<td>The second of the period</td>
</tr>
<tr>
<td>week</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>weekofyear</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>year</td>
<td>The year of the period</td>
</tr>
</tbody>
</table>

34.13.1.1 pandas.PeriodIndex.day

PeriodIndex.day
The days of the period

34.13.1.2 pandas.PeriodIndex.dayofweek

PeriodIndex.dayofweek
The day of the week with Monday=0, Sunday=6

34.13.1.3 pandas.PeriodIndex.dayofyear

PeriodIndex.dayofyear
The ordinal day of the year

34.13.1.4 pandas.PeriodIndex.days_in_month

PeriodIndex.days_in_month
The number of days in the month

34.13.1.5 pandas.PeriodIndex.daysinmonth

PeriodIndex.daysinmonth
The number of days in the month

34.13.1.6 pandas.PeriodIndex.freq

PeriodIndex.freq
Return the frequency object if it is set, otherwise None

34.13.1.7 pandas.PeriodIndex.freqstr

PeriodIndex.freqstr
Return the frequency object as a string if it is set, otherwise None
34.13.1.8 pandas.PeriodIndex.hour

PeriodIndex.hour
The hour of the period

34.13.1.9 pandas.PeriodIndex.is_leap_year

PeriodIndex.is_leap_year
Logical indicating if the date belongs to a leap year

34.13.1.10 pandas.PeriodIndex.minute

PeriodIndex.minute
The minute of the period

34.13.1.11 pandas.PeriodIndex.month

PeriodIndex.month
The month as January=1, December=12

34.13.1.12 pandas.PeriodIndex.quarter

PeriodIndex.quarter
The quarter of the date

34.13.1.13 pandas.PeriodIndex.second

PeriodIndex.second
The second of the period

34.13.1.14 pandas.PeriodIndex.week

PeriodIndex.week
The week ordinal of the year

34.13.1.15 pandas.PeriodIndex.weekday

PeriodIndex.weekday
The day of the week with Monday=0, Sunday=6

34.13.1.16 pandas.PeriodIndex.weekofyear

PeriodIndex.weekofyear
The week ordinal of the year
34.13.1.17 pandas.PeriodIndex.year

PeriodIndex.year
The year of the period

<table>
<thead>
<tr>
<th>end_time</th>
</tr>
</thead>
<tbody>
<tr>
<td>qyear</td>
</tr>
<tr>
<td>start_time</td>
</tr>
</tbody>
</table>

Methods

- **asfreq**([freq, how])
  Convert the PeriodIndex to the specified frequency freq.
  
  Parameters **freq** : str
  
  a frequency
  
  **how** : str {'E', 'S'}
  
  ‘E’, ‘END’, or ‘FINISH’ for end, ‘S’, ‘START’, or ‘BEGIN’ for start. Whether the elements should be aligned to the end or start within a period. January 31st (‘END’) vs. January 1st (‘START’) for example.
  
  Returns
  
  new [PeriodIndex with the new frequency]

Examples

```python
>>> pidx = pd.period_range('2010-01-01', '2015-01-01', freq='A')
>>> pidx
<class 'pandas.core.indexes.period.PeriodIndex'>
[2010, ..., 2015]
Length: 6, Freq: A-DEC

>>> pidx.asfreq('M')
<class 'pandas.core.indexes.period.PeriodIndex'>
[2010-12, ..., 2015-12]
Length: 6, Freq: M
```
>>> pidx.asfreq('M', how='S')
<class 'pandas.core.indexes.period.PeriodIndex'>
[2010-01, ..., 2015-01]
Length: 6, Freq: M

34.13.1.19 pandas.PeriodIndex.strftime

PeriodIndex.strftime(date_format)
Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as
the python standard library. Details of the string format can be found in python string format doc

Parameters date_format : str
  Date format string (e.g. “%Y-%m-%d”).

Returns Index
  Index of formatted strings

See also:
pandas.to_datetime  Convert the given argument to datetime
DatetimeIndex.normalize Return DatetimeIndex with times to midnight.
DatetimeIndex.round Round the DatetimeIndex to the specified freq.
DatetimeIndex.floor  Floor the DatetimeIndex to the specified freq.

Examples

>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
  ... periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(["March 10, 2018, 09:00:00 AM", 'March 10, 2018, 09:00:01 AM',
  'March 10, 2018, 09:00:02 AM'],
dtype='object')

34.13.1.20 pandas.PeriodIndex.to_timestamp

PeriodIndex.to_timestamp(freq=None, how='start')
Cast to DatetimeIndex

Parameters freq : string or DateOffset, optional
  Target frequency. The default is ‘D’ for week or longer, ‘S’ otherwise

  how [{'s', 'e', 'start', 'end'}]

Returns
  DatetimeIndex
34.13.1.21 pandas.PeriodIndex.tz_convert

PeriodIndex.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]

Notes

Not currently implemented for PeriodIndex

34.13.1.22 pandas.PeriodIndex.tz_localize

PeriodIndex.tz_localize(tz, ambiguous='raise')
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.

Returns

localized [DatetimeIndex]

Notes

Not currently implemented for PeriodIndex

34.13.2 Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PeriodIndex.day</td>
<td>The days of the period</td>
</tr>
<tr>
<td>PeriodIndex.dayofweek</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>PeriodIndex.dayofyear</td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td>PeriodIndex.days_in_month</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>PeriodIndex.daysinmonth</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>PeriodIndex.end_time</td>
<td></td>
</tr>
<tr>
<td>PeriodIndex.freq</td>
<td>Return the frequency object if it is set, otherwise None</td>
</tr>
<tr>
<td>PeriodIndex freqstr</td>
<td>Return the frequency object as a string if it is set, otherwise None</td>
</tr>
<tr>
<td>PeriodIndex.hour</td>
<td>The hour of the period</td>
</tr>
<tr>
<td>PeriodIndex.is_leap_year</td>
<td>Logical indicating if the date belongs to a leap year</td>
</tr>
<tr>
<td>PeriodIndex.minute</td>
<td>The minute of the period</td>
</tr>
<tr>
<td>PeriodIndex.month</td>
<td>The month as January=1, December=12</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PeriodIndex.quarter</td>
<td>The quarter of the date</td>
</tr>
<tr>
<td>PeriodIndex.qyear</td>
<td>The year of the period</td>
</tr>
<tr>
<td>PeriodIndex.second</td>
<td>The second of the period</td>
</tr>
<tr>
<td>PeriodIndex.start_time</td>
<td>The start time of the period</td>
</tr>
<tr>
<td>PeriodIndex.week</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>PeriodIndex.weekday</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>PeriodIndex.weekofyear</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>PeriodIndex.year</td>
<td>The year of the period</td>
</tr>
</tbody>
</table>

34.13.2.1 pandas.PeriodIndex.end_time

PeriodIndex.end_time

34.13.2.2 pandas.PeriodIndex.qyear

PeriodIndex.qyear

34.13.2.3 pandas.PeriodIndex.start_time

PeriodIndex.start_time

34.13.3 Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PeriodIndex.asfreq(freq, how)</td>
<td>Convert the PeriodIndex to the specified frequency freq.</td>
</tr>
<tr>
<td>PeriodIndex.strftime(date_format)</td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td>PeriodIndex.to_timestamp(freq, how)</td>
<td>Cast to DatetimeIndex</td>
</tr>
<tr>
<td>PeriodIndex.tz_convert(tz)</td>
<td>Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)</td>
</tr>
<tr>
<td>PeriodIndex.tz_localize(tz[, ambiguous])</td>
<td>Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex</td>
</tr>
</tbody>
</table>

34.14 Scalars

34.14.1 Period

<table>
<thead>
<tr>
<th>Period</th>
<th>Represents a period of time</th>
</tr>
</thead>
</table>

34.14.1.1 pandas.Period

class pandas.Period

Represents a period of time

Parameters

value : Period or compat.string_types, default None

The time period represented (e.g., ‘4Q2005’)

freq : str, default None
One of pandas period strings or corresponding objects

- **year**: [int, default None]
- **month**: [int, default 1]
- **quarter**: [int, default None]
- **day**: [int, default 1]
- **hour**: [int, default 0]
- **minute**: [int, default 0]
- **second**: [int, default 0]

### Attributes

- **day**: Get day of the month that a Period falls on.
- **dayofweek**: Return the day of the week.
- **dayofyear**: Return the day of the year.
- **days_in_month**: Get the total number of days in the month that this period falls on.
- **daysinmonth**: Get the total number of days of the month that the Period falls in.
- **hour**: Get the hour of the day component of the Period.
- **minute**: Get minute of the hour component of the Period.
- **second**: Get the second component of the Period.
- **start_time**: Get the Timestamp for the start of the period.
- **week**: Get the week of the year on the given Period.

### pandas.Period.day

**Period.day**

Get day of the month that a Period falls on.

**Returns**

- int

**See also:**

- **Period.dayofweek**: Get the day of the week
- **Period.dayofyear**: Get the day of the year

### Examples

```python
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.day
11
```
pandas.Period.dayofweek

Period.dayofweek
Return the day of the week.

This attribute returns the day of the week on which the particular date for the given period occurs depending on the frequency with Monday=0, Sunday=6.

Returns Int
Range from 0 to 6 (included).

See also:

Period.dayofyear Return the day of the year.
Period.daysinmonth Return the number of days in that month.

Examples

```python
>>> period1 = pd.Period('2012-1-1 19:00', freq='H')
>>> period1
Period('2012-01-01 19:00', 'H')
>>> period1.dayofweek
6

>>> period2 = pd.Period('2013-1-9 11:00', freq='H')
>>> period2
Period('2013-01-09 11:00', 'H')
>>> period2.dayofweek
2
```

pandas.Period.dayofyear

Period.dayofyear
Return the day of the year.

This attribute returns the day of the year on which the particular date occurs. The return value ranges between 1 to 365 for regular years and 1 to 366 for leap years.

Returns int
The day of year.

See also:

Period.day Return the day of the month.
Period.dayofweek Return the day of week.
PeriodIndex.dayofyear Return the day of year of all indexes.

Examples
```python
>>> period = pd.Period("2015-10-23", freq='H')
>>> period.dayofyear
296
>>> period = pd.Period("2012-12-31", freq='D')
>>> period.dayofyear
366
>>> period = pd.Period("2013-01-01", freq='D')
>>> period.dayofyear
1
```

**pandas.Period.days_in_month**

Period.days_in_month

Get the total number of days in the month that this period falls on.

Returns

int

See also:

Period.daysinmonth Gets the number of days in the month.

DatetimeIndex.daysinmonth Gets the number of days in the month.

calendar.monthrange Returns a tuple containing weekday (0-6 ~ Mon-Sun) and number of days (28-31).

**Examples**

```python
>>> p = pd.Period('2018-2-17')
>>> p.days_in_month
28
```

```python
>>> pd.Period('2018-03-01').days_in_month
31
```

Handles the leap year case as well:

```python
>>> p = pd.Period('2016-2-17')
>>> p.days_in_month
29
```

**pandas.Period.daysinmonth**

Period.daysinmonth

Get the total number of days of the month that the Period falls in.

Returns

int

See also:
**Period.days_in_month**  Return the days of the month

**Period.dayofyear**  Return the day of the year

**Examples**

```python
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.daysinmonth
31
```

**pandas.Period.hour**

**Period.hour**  Get the hour of the day component of the Period.

**Returns**  int

The hour as an integer, between 0 and 23.

**See also:**

*Period.second*  Get the second component of the Period.

*Period.minute*  Get the minute component of the Period.

**Examples**

```python
>>> p.hour
13
```

Period longer than a day

```python
>>> p = pd.Period("2018-03-11", freq="M")
>>> p.hour
0
```

**pandas.Period.minute**

**Period.minute**  Get minute of the hour component of the Period.

**Returns**  int

The minute as an integer, between 0 and 59.

**See also:**

*Period.hour*  Get the hour component of the Period.

*Period.second*  Get the second component of the Period.
Examples

```python
>>> p.minute
3
```

**pandas.Period.second**

Period.second
Get the second component of the Period.

**Returns** int
The second of the Period (ranges from 0 to 59).

**See also:**

Period.hour Get the hour component of the Period.
Period.minute Get the minute component of the Period.

Examples

```python
>>> p.second
12
```

**pandas.Period.start_time**

Period.start_time
Get the Timestamp for the start of the period.

**Returns**
Timestamp

**See also:**

Period.end_time Return the end Timestamp.
Period.dayofyear Return the day of year.
Period.daysinmonth Return the days in that month.
Period.dayofweek Return the day of the week.

Examples

```python
>>> period = pd.Period('2012-1-1', freq='D')
>>> period
Period('2012-01-01', 'D')
```
>>> period.start_time
Timestamp('2012-01-01 00:00:00')

>>> period.end_time
Timestamp('2012-01-01 23:59:59.999999999')

**pandas.Period.week**

Period.week
Get the week of the year on the given Period.

**Returns**

int

**See also:**

Period.dayofweek Get the day component of the Period.

Period.weekday Get the day component of the Period.

**Examples**

```python
>>> p = pd.Period("2018-03-11", "H")
>>> p.week
10

>>> p = pd.Period("2018-02-01", "D")
>>> p.week
5

>>> p = pd.Period("2018-01-06", "D")
>>> p.week
1
```

<table>
<thead>
<tr>
<th>end_time</th>
<th>freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>freqstr</td>
<td></td>
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<tr>
<td>is_leap_year</td>
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<tr>
<td>month</td>
<td></td>
</tr>
<tr>
<td>ordinal</td>
<td></td>
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<td>quarter</td>
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<tr>
<td>qyear</td>
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<td>weekday</td>
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</tr>
<tr>
<td>weekofyear</td>
<td></td>
</tr>
<tr>
<td>year</td>
<td></td>
</tr>
</tbody>
</table>

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>asfreq</code></td>
<td>Convert Period to desired frequency, either at the start or end of the interval</td>
</tr>
<tr>
<td><code>strftime</code></td>
<td>Returns the string representation of the Period, depending on the selected fmt.</td>
</tr>
<tr>
<td><code>to_timestamp</code></td>
<td>Return the Timestamp representation of the Period at the target frequency at the specified end (how) of the Period</td>
</tr>
</tbody>
</table>

### pandas.Period.asfreq

**Period.asfreq()**

Convert Period to desired frequency, either at the start or end of the interval

**Parameters**

- **freq** [string]
- **how** : {'E', 'S', 'end', 'start'}, default 'end'
  - Start or end of the timespan

**Returns**

- **resampled** [Period]

### pandas.Period.strftime

**Period.strftime()**

Returns the string representation of the Period, depending on the selected fmt. fmt must be a string containing one or several directives. The method recognizes the same directives as the `time.strftime()` function of the standard Python distribution, as well as the specific additional directives `%f`, `%F`, `%q`. (formatting & docs originally from scikits.timeries)
<table>
<thead>
<tr>
<th>Directive</th>
<th>Meaning</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>%a</td>
<td>Locale’s abbreviated weekday name.</td>
<td></td>
</tr>
<tr>
<td>%A</td>
<td>Locale’s full weekday name.</td>
<td></td>
</tr>
<tr>
<td>%b</td>
<td>Locale’s abbreviated month name.</td>
<td></td>
</tr>
<tr>
<td>%B</td>
<td>Locale’s full month name.</td>
<td></td>
</tr>
<tr>
<td>%c</td>
<td>Locale’s appropriate date and time representation.</td>
<td></td>
</tr>
<tr>
<td>%d</td>
<td>Day of the month as a decimal number [01,31].</td>
<td></td>
</tr>
<tr>
<td>%f</td>
<td>‘Fiscal’ year without a century as a decimal number [00,99]</td>
<td>(1)</td>
</tr>
<tr>
<td>%F</td>
<td>‘Fiscal’ year with a century as a decimal number</td>
<td>(2)</td>
</tr>
<tr>
<td>%h</td>
<td>Hour (24-hour clock) as a decimal number [00,23].</td>
<td></td>
</tr>
<tr>
<td>%H</td>
<td>Hour (12-hour clock) as a decimal number [01,12].</td>
<td></td>
</tr>
<tr>
<td>%j</td>
<td>Day of the year as a decimal number [001,366].</td>
<td></td>
</tr>
<tr>
<td>%m</td>
<td>Month as a decimal number [01,12].</td>
<td></td>
</tr>
<tr>
<td>%M</td>
<td>Minute as a decimal number [00,59].</td>
<td></td>
</tr>
<tr>
<td>%p</td>
<td>Locale’s equivalent of either AM or PM.</td>
<td>(3)</td>
</tr>
<tr>
<td>%q</td>
<td>Quarter as a decimal number [01,04]</td>
<td></td>
</tr>
<tr>
<td>%s</td>
<td>Second as a decimal number [00,61].</td>
<td>(4)</td>
</tr>
<tr>
<td>%U</td>
<td>Week number of the year (Sunday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Sunday are considered to be in week 0.</td>
<td>(5)</td>
</tr>
<tr>
<td>%w</td>
<td>Weekday as a decimal number [0(Sunday),6].</td>
<td></td>
</tr>
<tr>
<td>%W</td>
<td>Week number of the year (Monday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Monday are considered to be in week 0.</td>
<td>(5)</td>
</tr>
<tr>
<td>%x</td>
<td>Locale’s appropriate date representation.</td>
<td></td>
</tr>
<tr>
<td>%X</td>
<td>Locale’s appropriate time representation.</td>
<td></td>
</tr>
<tr>
<td>%y</td>
<td>Year without century as a decimal number [00,99].</td>
<td></td>
</tr>
<tr>
<td>%Y</td>
<td>Year with century as a decimal number.</td>
<td></td>
</tr>
<tr>
<td>%z</td>
<td>Time zone name (no characters if no time zone exists).</td>
<td></td>
</tr>
<tr>
<td>%%</td>
<td>A literal ‘%’ character.</td>
<td></td>
</tr>
</tbody>
</table>

**Notes**

1. The %f directive is the same as %y if the frequency is not quarterly. Otherwise, it corresponds to the ‘fiscal’ year, as defined by the qyear attribute.
2. The %F directive is the same as %Y if the frequency is not quarterly. Otherwise, it corresponds to the ‘fiscal’ year, as defined by the qyear attribute.
3. The %p directive only affects the output hour field if the %I directive is used to parse the hour.
4. The range really is 0 to 61; this accounts for leap seconds and the (very rare) double leap seconds.
5. The %U and %W directives are only used in calculations when the day of the week and the year are specified.

**Examples**
>>> a = Period(freq='Q-JUL', year=2006, quarter=1)
>>> a.strftime('%F-Q%q')
'2006-Q1'
>>> # Output the last month in the quarter of this date
>>> a.strftime('%b-%Y')
'Oct-2005'
>>> a = Period(freq='D', year=2001, month=1, day=1)
>>> a.strftime('%d-%b-%Y')
'01-Jan-2006'
>>> a.strftime('%b. %d, %Y was a %A')
'Jan. 01, 2001 was a Monday'

pandas.Period.to_timestamp

Period.to_timestamp()  
Return the Timestamp representation of the Period at the target frequency at the specified end (how) of the Period

Parameters

dtype: string or DateOffset

Target frequency. Default is ‘D’ if self.freq is week or longer and ‘S’ otherwise

how: str, default ‘S’ (start)


Returns

Timestamp

34.14.2 Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period.day</td>
<td>Get day of the month that a Period falls on.</td>
</tr>
<tr>
<td>Period.dayofweek</td>
<td>Return the day of the week.</td>
</tr>
<tr>
<td>Period.dayofyear</td>
<td>Return the day of the year.</td>
</tr>
<tr>
<td>Period.days_in_month</td>
<td>Get the total number of days in the month that this period falls on.</td>
</tr>
<tr>
<td>Period.daysinmonth</td>
<td>Get the total number of days of the month that the Period falls in.</td>
</tr>
<tr>
<td>Period.end_time</td>
<td>Get the hour of the day component of the Period.</td>
</tr>
<tr>
<td>Period.freq</td>
<td>Get minute of the hour component of the Period.</td>
</tr>
<tr>
<td>Period.freqstr</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.hour</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.is_leap_year</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.minute</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.month</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.ordinal</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.quarter</td>
<td>Get the year component of the Period.</td>
</tr>
<tr>
<td>Period.qyear</td>
<td>Get the year component of the Period.</td>
</tr>
</tbody>
</table>

Continued on next page
34.14.2.1 pandas.Period.end_time

Period.end_time

34.14.2.2 pandas.Period.freq

Period.freq

34.14.2.3 pandas.Period.freqstr

Period.freqstr

34.14.2.4 pandas.Period.is_leap_year

Period.is_leap_year

34.14.2.5 pandas.Period.month

Period.month

34.14.2.6 pandas.Period.ordinal

Period.ordinal

34.14.2.7 pandas.Period.quarter

Period.quarter

34.14.2.8 pandas.Period.qyear

Period.qyear

34.14.2.9 pandas.Period.weekday

Period.weekday

34.14.2.10 pandas.Period.weekofyear

Period.weekofyear
34.14.2.11 pandas.Period.year

Period\texttt{.year}

34.14.3 Methods

<table>
<thead>
<tr>
<th>Period\texttt{.asfreq}</th>
<th>Convert Period to desired frequency, either at the start or end of the interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period\texttt{.now}</td>
<td></td>
</tr>
<tr>
<td>Period\texttt{.strftime}</td>
<td>Returns the string representation of the Period, depending on the selected \texttt{fmt}.</td>
</tr>
<tr>
<td>Period\texttt{.to_timestamp}</td>
<td>Return the Timestamp representation of the Period at the target frequency at the specified end (how) of the Period</td>
</tr>
</tbody>
</table>

34.14.3.1 pandas.Period.now

Period\texttt{.now()}

34.14.4 Timestamp

<table>
<thead>
<tr>
<th>Timestamp</th>
<th>Pandas replacement for datetime.datetime</th>
</tr>
</thead>
</table>

34.14.4.1 pandas.Timestamp

class pandas\texttt{.Timestamp}  
Pandas replacement for datetime.datetime

Timestamp is the pandas equivalent of python’s Datetime and is interchangeable with it in most cases. It’s the type used for the entries that make up a DatetimeIndex, and other timeseries oriented data structures in pandas.

Parameters

\texttt{ts_input} : datetime-like, str, int, float  
Value to be converted to Timestamp

\texttt{freq} : str, Offset
Offset which Timestamp will have

\texttt{tz} : str, pytz.timezone, dateutil.tz.tzfile or None
Time zone for time which Timestamp will have.

\texttt{unit} : str
Unit used for conversion if \texttt{ts_input} is of type int or float. The valid values are ‘D’, ‘h’, ‘m’, ‘s’, ‘ms’, ‘us’, and ‘ns’. For example, ‘s’ means seconds and ‘ms’ means milliseconds.

\texttt{year, month, day} : int
New in version 0.19.0.

\texttt{hour, minute, second, microsecond} : int, optional, default 0
New in version 0.19.0.

\texttt{nanosecond} : int, optional, default 0
New in version 0.23.0.

**tzinfo** : `datetime.tzinfo`, optional, default None

New in version 0.19.0.

**Notes**

There are essentially three calling conventions for the constructor. The primary form accepts four parameters. They can be passed by position or keyword.

The other two forms mimic the parameters from `datetime.datetime`. They can be passed by either position or keyword, but not both mixed together.

**Examples**

Using the primary calling convention:

This converts a datetime-like string >>> `pd.Timestamp('2017-01-01T12')` Timestamp('2017-01-01 12:00:00')

This converts a float representing a Unix epoch in units of seconds >>> `pd.Timestamp(1513393355.5, unit='s')` Timestamp('2017-12-15 03:02:35.500000')

This converts an int representing a Unix-epoch in units of seconds and for a particular timezone >>> `pd.Timestamp(1513393355, unit='s', tz='US/Pacific')` Timestamp('2017-12-15 19:02:35-0800', tz='US/Pacific')

Using the other two forms that mimic the API for `datetime.datetime`:

```python
>>> pd.Timestamp(2017, 1, 1, 12)
Timestamp('2017-01-01 12:00:00')

>>> pd.Timestamp(year=2017, month=1, day=1, hour=12)
Timestamp('2017-01-01 12:00:00')
```

**Attributes**

<table>
<thead>
<tr>
<th>Alias</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>tz</code></td>
<td>Alias for <code>tzinfo</code></td>
</tr>
<tr>
<td><code>weekday_name</code></td>
<td>(DEPRECATED) ..</td>
</tr>
</tbody>
</table>

**pandas.Timestamp.tz**

`Timestamp.tz`

Alias for `tzinfo`

**pandas.Timestamp.weekday_name**

`Timestamp.weekday_name`

Deprecated since version 0.23.0: Use `Timestamp.day_name()` instead
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
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<tr>
<td>astimezone</td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td>ceil</td>
<td>Return a new Timestamp ceiled to this resolution</td>
</tr>
<tr>
<td>combine</td>
<td>(date, time) date, time -&gt; datetime with same date and time fields</td>
</tr>
<tr>
<td>ctime</td>
<td>Return ctime() style string.</td>
</tr>
<tr>
<td>date</td>
<td>Return date object with same year, month and day.</td>
</tr>
<tr>
<td>day_name</td>
<td>Return the day name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>dst</td>
<td>Return self.tzinfo.dst(self).</td>
</tr>
<tr>
<td>floor</td>
<td>Return a new Timestamp floored to this resolution</td>
</tr>
<tr>
<td>fromordinal</td>
<td>(ordinal[, freq, tz]) passed an ordinal, translate and convert to a ts note:</td>
</tr>
<tr>
<td></td>
<td>by definition there cannot be any tz info on the ordinal itself</td>
</tr>
<tr>
<td>fromtimestamp</td>
<td>(ts) timestamp[, tz] -&gt; tz's local time from POSIX timestamp.</td>
</tr>
<tr>
<td>isocalendar</td>
<td>Return a 3-tuple containing ISO year, week number, and weekday.</td>
</tr>
<tr>
<td>isoweekday</td>
<td>Return the day of the week represented by the date.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>month_name</td>
<td>Return the month name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>normalize</td>
<td>Normalize Timestamp to midnight, preserving tz information.</td>
</tr>
<tr>
<td>now([tz])</td>
<td>Returns new Timestamp object representing current time local to tz.</td>
</tr>
<tr>
<td>replace</td>
<td>implements datetime.replace, handles nanoseconds</td>
</tr>
<tr>
<td>round</td>
<td>Round the Timestamp to the specified resolution</td>
</tr>
<tr>
<td>strftime</td>
<td>format -&gt; strftime() style string.</td>
</tr>
<tr>
<td>strptime</td>
<td>string, format -&gt; new datetime parsed from a string (like time.strptime()).</td>
</tr>
<tr>
<td>time</td>
<td>Return time object with same time but with tzinfo=None.</td>
</tr>
<tr>
<td>timestamp</td>
<td>Return POSIX timestamp as float.</td>
</tr>
<tr>
<td>timetz</td>
<td>Return time object with same time and tzinfo.</td>
</tr>
<tr>
<td>to_datetime64</td>
<td>Returns a numpy.datetime64 object with &quot;ns&quot; precision</td>
</tr>
<tr>
<td>to_julian_date</td>
<td>Convert TimeStamp to a Julian Date.</td>
</tr>
<tr>
<td>to_period</td>
<td>Return an period of which this timestamp is an observation.</td>
</tr>
<tr>
<td>to_pydatetime</td>
<td>Convert a Timestamp object to a native Python datetime object.</td>
</tr>
<tr>
<td>today(cls[, tz])</td>
<td>Return the current time in the local timezone.</td>
</tr>
<tr>
<td>toordinal</td>
<td>Return proleptic Gregorian ordinal.</td>
</tr>
<tr>
<td>tz_convert</td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td>tz_localize</td>
<td>Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.</td>
</tr>
<tr>
<td>tzname</td>
<td>Return self.tzinfo.tzname(self).</td>
</tr>
<tr>
<td>utcfromtimestamp(ts)</td>
<td>Construct a naive UTC.datetime from a POSIX timestamp.</td>
</tr>
<tr>
<td>utcnow()</td>
<td>Return a new Timestamp representing UTC day and time.</td>
</tr>
<tr>
<td>utcoffset</td>
<td>Return self.tzinfo.utcoffset(self).</td>
</tr>
<tr>
<td>utctimetuple</td>
<td>Return UTC time tuple, compatible with time.localtime().</td>
</tr>
<tr>
<td>weekday</td>
<td>Return the day of the week represented by the date.</td>
</tr>
</tbody>
</table>

**pandas.Timestamp.astimezone**

Timestamp.astimezone

Convert tz-aware Timestamp to another time zone.

**Parameters**

tz : str, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

**Returns**

converted [Timestamp]

**Raises**

TypeError

If Timestamp is tz-naive.
pandas.Timestamp.ceil

Timestamp.ceil
return a new Timestamp ceiled to this resolution

Parameters
freq [a freq string indicating the ceiling resolution]

pandas.Timestamp.combine

classmethod Timestamp.combine(date, time)
date, time -> datetime with same date and time fields

pandas.Timestamp.ctime

Timestamp.ctime()
Return ctime() style string.

pandas.Timestamp.date

Timestamp.date()
Return date object with same year, month and day.

pandas.Timestamp.day_name

Timestamp.day_name
Return the day name of the Timestamp with specified locale.

Parameters locale : string, default None (English locale)
locale determining the language in which to return the day name

Returns
day_name [string]
.. versionadded:: 0.23.0

pandas.Timestamp.dst

Timestamp.dst()
Return self.tzinfo.dst(self).

pandas.Timestamp.floor

Timestamp.floor
return a new Timestamp floored to this resolution

Parameters
freq [a freq string indicating the flooring resolution]
pandas.Timestamp.fromordinal

classmethod Timestamp.fromordinal(ordinal, freq=None, tz=None)
    passed an ordinal, translate and convert to a ts note: by definition there cannot be any tz info on the ordinal itself

    Parameters ordinal : int
        date corresponding to a proleptic Gregorian ordinal

    freq : str, DateOffset
        Offset which Timestamp will have

    tz : str, pytz.timezone, dateutil.tz.tzfile or None
        Time zone for time which Timestamp will have.

pandas.Timestamp.fromtimestamp

classmethod Timestamp.fromtimestamp(ts)
    timestamp[, tz] -> tz’s local time from POSIX timestamp.

pandas.Timestamp.isocalendar

Timestamp.isocalendar()
    Return a 3-tuple containing ISO year, week number, and weekday.

pandas.Timestamp.isoweekday

Timestamp.isoweekday()
    Return the day of the week represented by the date. Monday == 1 … Sunday == 7

pandas.Timestamp.month_name

Timestamp.month_name
    Return the month name of the Timestamp with specified locale.

    Parameters locale : string, default None (English locale)
        locale determining the language in which to return the month name

    Returns

    month_name [string]
        .. versionadded:: 0.23.0

pandas.Timestamp.normalize

Timestamp.normalize
    Normalize Timestamp to midnight, preserving tz information.
**pandas.Timestamp.now**

**classmethod** `Timestamp.now(tz=None)`  
Returns new Timestamp object representing current time local to tz.  

- **Parameters**  
  - `tz` : str or timezone object, default None  
    Timezone to localize to

**pandas.Timestamp.replace**

`Timestamp.replace` implements datetime.replace, handles nanoseconds  

- **Parameters**  
  - `year` [int, optional]  
  - `month` [int, optional]  
  - `day` [int, optional]  
  - `hour` [int, optional]  
  - `minute` [int, optional]  
  - `second` [int, optional]  
  - `microsecond` [int, optional]  
  - `nanosecond` : int, optional  
  - `tzinfo` [tz-convertible, optional]  
  - `fold` : int, optional, default is 0  
    added in 3.6, Not Implemented  

- **Returns**  
  Timestamp with fields replaced

**pandas.Timestamp.round**

`Timestamp.round`  
Round the Timestamp to the specified resolution  

- **Parameters**  
  - `freq` [a freq string indicating the rounding resolution]  

- **Returns**  
  a new Timestamp rounded to the given resolution of ‘freq’  

- **Raises**  
  ValueError if the freq cannot be converted
pandas.Timestamp.strftime

Timestamp.strftime(format)
    format -> strftime() style string.

pandas.Timestamp.strptime

Timestamp.strptime(string, format)
    string, format -> new datetime parsed from a string (like time.strptime()).

pandas.Timestamp.time

Timestamp.time()
    Return time object with same time but with tzinfo=None.

pandas.Timestamp.timestamp

Timestamp.timestamp()
    Return POSIX timestamp as float.

pandas.Timestamp.timetuple

Timestamp.timetuple()
    Return time tuple, compatible with time.localtime().

pandas.Timestamp.timetz

Timestamp.timetz()
    Return time object with same time and tzinfo.

pandas.Timestamp.to_datetime64

Timestamp.to_datetime64()
    Returns a numpy.datetime64 object with ‘ns’ precision

pandas.Timestamp.to_julian_date

Timestamp.to_julian_date
    Convert TimeStamp to a Julian Date. 0 Julian date is noon January 1, 4713 BC.

pandas.Timestamp.to_period

Timestamp.to_period
    Return an period of which this timestamp is an observation.
pandas.Timestamp.to_pydatetime

Timestamp.to_pydatetime()
Convert a Timestamp object to a native Python datetime object.
If warn=True, issue a warning if nanoseconds is nonzero.

pandas.Timestamp.today

classmethod Timestamp.today(cls, tz=None)
Return the current time in the local timezone. This differs from datetime.today() in that it can be localized to a passed timezone.

Parameters tz : str or timezone object, default None
    Timezone to localize to

pandas.Timestamp.toordinal

Timestamp.toordinal()
Return proleptic Gregorian ordinal. January 1 of year 1 is day 1.

pandas.Timestamp.tz_convert

Timestamp.tz_convert
Convert tz-aware Timestamp to another time zone.

Parameters tz : str, pytz.timezone, dateutil.tz.tzfile or None
    Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

Returns
converted [Timestamp]

Raises TypeError
If Timestamp is tz-naive.

pandas.Timestamp.tz_localize

Timestamp.tz_localize
Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.

Parameters tz : str, pytz.timezone, dateutil.tz.tzfile or None
    Time zone for time which Timestamp will be converted to. None will remove timezone holding local time.

ambiguous : bool, ‘NaT’, default ‘raise’
    • bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates)
    • ‘NaT’ will return NaT for an ambiguous time
• ‘raise’ will raise an AmbiguousTimeError for an ambiguous time
errors: ‘raise’, ‘coerce’, default ‘raise’

• ‘raise’ will raise a NonExistentTimeError if a timestamp is not valid in the specified timezone (e.g. due to a transition from or to DST time)
• ‘coerce’ will return NaT if the timestamp can not be converted into the specified timezone

New in version 0.19.0.

Returns

localized [Timestamp]

Raises TypeError

If the Timestamp is tz-aware and tz is not None.

pandas.Timestamp.tzname

Timestamp.tzname()  
Return self.tzinfo.tzname(self).

pandas.Timestamp.utcfromtimestamp

classmethod Timestamp.utcfromtimestamp(ts)  
Construct a naive UTC datetime from a POSIX timestamp.

pandas.Timestamp.utcnow

classmethod Timestamp.utcnow()  
Return a new Timestamp representing UTC day and time.

pandas.Timestamp.utcoffset

Timestamp.utcoffset()  
Return self.tzinfo.utcoffset(self).

pandas.Timestamp.utctimetuple

Timestamp.utctimetuple()  
Return UTC time tuple, compatible with time.localtime().

pandas.Timestamp.weekday

Timestamp.weekday()  
Return the day of the week represented by the date. Monday == 0 . . . Sunday == 6
34.14.5 Properties

```
Timestamp.asm8
Timestamp.day
Timestamp.dayofweek
Timestamp.dayofyear
Timestamp.days_in_month
Timestamp.daysinmonth
Timestamp.fold
Timestamp.hour
Timestamp.is_leap_year
Timestamp.is_month_end
Timestamp.is_month_start
Timestamp.is_quarter_end
Timestamp.is_quarter_start
Timestamp.is_year_end
Timestamp.is_year_start
Timestamp.max
Timestamp.microsecond
Timestamp.min
Timestamp.month
Timestamp.nanosecond
Timestamp.quarter
Timestamp.resolution
Timestamp.second
Timestamp.tz
    Alias for tzinfo
Timestamp.tzinfo
Timestamp.value
Timestamp.week
Timestamp.weekofyear
Timestamp.year
```

34.14.5.1 pandas.Timestamp.asm8

```
Timestamp.asm8
```

34.14.5.2 pandas.Timestamp.day

```
Timestamp.day
```

34.14.5.3 pandas.Timestamp.dayofweek

```
Timestamp.dayofweek
```

34.14.5.4 pandas.Timestamp.dayofyear

```
Timestamp.dayofyear
```
34.14.5.5 pandas.Timestamp.days_in_month
Timestamp.days_in_month

34.14.5.6 pandas.Timestamp.daysinmonth
Timestamp.daysinmonth

34.14.5.7 pandas.Timestamp.fold
Timestamp.fold

34.14.5.8 pandas.Timestamp.hour
Timestamp.hour

34.14.5.9 pandas.Timestamp.is_leap_year
Timestamp.is_leap_year

34.14.5.10 pandas.Timestamp.is_month_end
Timestamp.is_month_end

34.14.5.11 pandas.Timestamp.is_month_start
Timestamp.is_month_start

34.14.5.12 pandas.Timestamp.is_quarter_end
Timestamp.is_quarter_end

34.14.5.13 pandas.Timestamp.is_quarter_start
Timestamp.is_quarter_start

34.14.5.14 pandas.Timestamp.is_year_end
Timestamp.is_year_end

34.14.5.15 pandas.Timestamp.is_year_start
Timestamp.is_year_start
34.14.5.16 pandas.Timestamp.max

```
Timestamp.max = Timestamp('2262-04-11 23:47:16.854775807')
```

34.14.5.17 pandas.Timestamp.microsecond

```
Timestamp.microsecond
```

34.14.5.18 pandas.Timestamp.min

```
Timestamp.min = Timestamp('1677-09-21 00:12:43.145225')
```

34.14.5.19 pandas.Timestamp.minute

```
Timestamp.minute
```

34.14.5.20 pandas.Timestamp.month

```
Timestamp.month
```

34.14.5.21 pandas.Timestamp.nanosecond

```
Timestamp.nanosecond
```

34.14.5.22 pandas.Timestamp.quarter

```
Timestamp.quarter
```

34.14.5.23 pandas.Timestamp.resolution

```
Timestamp.resolution = datetime.timedelta(0, 0, 1)
```

34.14.5.24 pandas.Timestamp.second

```
Timestamp.second
```

34.14.5.25 pandas.Timestamp.tzinfo

```
Timestamp.tzinfo
```

34.14.5.26 pandas.Timestamp.value

```
Timestamp.value
```
34.14.5.27 pandas.Timestamp.week

Timestamp.week

34.14.5.28 pandas.Timestamp.weekofyear

Timestamp.weekofyear

34.14.5.29 pandas.Timestamp.year

Timestamp.year

### 34.14.6 Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestamp.astimezone</td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td>Timestamp.ceil</td>
<td>return a new Timestamp ceiled to this resolution</td>
</tr>
<tr>
<td>Timestamp.combine(date, time)</td>
<td>date, time -&gt; datetime with same date and time fields</td>
</tr>
<tr>
<td>Timestamp.ceiling</td>
<td>Return ctime() style string.</td>
</tr>
<tr>
<td>Timestamp.date</td>
<td>Return date object with same year, month and day.</td>
</tr>
<tr>
<td>Timestamp.day_name</td>
<td>Return the day name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>Timestamp.dst</td>
<td>Return self.tzinfo.dst(self).</td>
</tr>
<tr>
<td>Timestamp.floor</td>
<td>return a new Timestamp floored to this resolution</td>
</tr>
<tr>
<td>Timestamp.freq</td>
<td></td>
</tr>
<tr>
<td>Timestamp.freqstr</td>
<td></td>
</tr>
<tr>
<td>Timestamp.fromordinal(ordinal[, freq, tz])</td>
<td>passed an ordinal, translate and convert to a ts note: by definition there cannot be any tz info on the ordinal itself</td>
</tr>
<tr>
<td>Timestamp.fromtimestamp(ts)</td>
<td>timestamp[, tz] -&gt; tz’s local time from POSIX timestamp.</td>
</tr>
<tr>
<td>Timestamp.isoformat</td>
<td>Return a 3-tuple containing ISO year, week number, and weekday.</td>
</tr>
<tr>
<td>Timestamp.isocalendar</td>
<td></td>
</tr>
<tr>
<td>Timestamp.isoweekday</td>
<td>Return the day of the week represented by the date.</td>
</tr>
<tr>
<td>Timestamp.month_name</td>
<td>Return the month name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>Timestamp.normalize</td>
<td>Normalize Timestamp to midnight, preserving tz information.</td>
</tr>
<tr>
<td>Timestamp.now([tz])</td>
<td>Returns new Timestamp object representing current time local to tz.</td>
</tr>
<tr>
<td>Timestamp.replace</td>
<td>implements datetime.replace, handles nanoseconds</td>
</tr>
<tr>
<td>Timestamp.round</td>
<td>Round the Timestamp to the specified resolution</td>
</tr>
<tr>
<td>Timestamp.strftime</td>
<td>format -&gt; strftime() style string.</td>
</tr>
<tr>
<td>Timestamp.strptime</td>
<td>string, format -&gt; new datetime parsed from a string (like time.strptime()).</td>
</tr>
<tr>
<td>Timestamp.time</td>
<td>Return time object with same time but with tz-info=None.</td>
</tr>
<tr>
<td>Timestamp.timestamp</td>
<td>Return POSIX timestamp as float.</td>
</tr>
<tr>
<td>Timestamp.timetuple</td>
<td>Return time tuple, compatible with time.localtime().</td>
</tr>
<tr>
<td>Timestamp.timetz</td>
<td>Return time object with same time and tzinfo.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Timestamp.to_datetime64</code></td>
<td>Returns a numpy.datetime64 object with ‘ns’ precision</td>
</tr>
<tr>
<td><code>Timestamp.to_julian_date</code></td>
<td>Convert TimeStamp to a Julian Date.</td>
</tr>
<tr>
<td><code>Timestamp.to_period</code></td>
<td>Return an period of which this timestamp is an observation.</td>
</tr>
<tr>
<td><code>Timestamp.to_pydatetime</code></td>
<td>Convert a Timestamp object to a native Python datetime object.</td>
</tr>
<tr>
<td><code>Timestamp.today</code></td>
<td>Return the current time in the local timezone.</td>
</tr>
<tr>
<td><code>Timestamp.toordinal</code></td>
<td>Return proleptic Gregorian ordinal.</td>
</tr>
<tr>
<td><code>Timestamp.tz_convert</code></td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td><code>Timestamp.tz_localize</code></td>
<td>Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.</td>
</tr>
<tr>
<td><code>Timestamp.tzname</code></td>
<td>Return self.tzinfo.tzname(self).</td>
</tr>
<tr>
<td><code>Timestamp.utcfromtimestamp</code></td>
<td>Construct a naive UTC datetime from a POSIX timestamp.</td>
</tr>
<tr>
<td><code>Timestamp.utcnow()</code></td>
<td>Return a new Timestamp representing UTC day and time.</td>
</tr>
<tr>
<td><code>Timestamp.utcoffset</code></td>
<td>Return self.tzinfo.utcoffset(self).</td>
</tr>
<tr>
<td><code>Timestamp.utctimetuple</code></td>
<td>Return UTC time tuple, compatible with time.localtime().</td>
</tr>
<tr>
<td><code>Timestamp.weekday</code></td>
<td>Return the day of the week represented by the date.</td>
</tr>
</tbody>
</table>

34.14.6.1 pandas.Timestamp.freq

`Timestamp.freq`

34.14.6.2 pandas.Timestamp.freqstr

`Timestamp.freqstr`

34.14.6.3 pandas.Timestamp.isoformat

`Timestamp.isoformat`

34.14.7 Interval

`Interval`

Immutable object implementing an Interval, a bounded slice-like interval.

34.14.7.1 pandas.Interval

**class** `pandas.Interval`

Immutable object implementing an Interval, a bounded slice-like interval.

New in version 0.20.0.

**Parameters**

- `left` : orderable scalar
  
  Left bound for the interval.

- `right` : orderable scalar

34.14. Scalars
Right bound for the interval.

**closed** : ‘left’, ‘right’, ‘both’, ‘neither’, default ‘right’

Whether the interval is closed on the left-side, right-side, both or neither.

**closed** : ‘right’, ‘left’, ‘both’, ‘neither’, default ‘right’

Whether the interval is closed on the left-side, right-side, both or neither. See the Notes for more detailed explanation.

**See also:**

- **IntervalIndex** An Index of Interval objects that are all closed on the same side.
- **cut** Convert continuous data into discrete bins (Categorical of Interval objects).
- **qcut** Convert continuous data into bins (Categorical of Interval objects) based on quantiles.
- **Period** Represents a period of time.

**Notes**

The parameters *left* and *right* must be from the same type, you must be able to compare them and they must satisfy *left* <= *right*.

A closed interval (in mathematics denoted by square brackets) contains its endpoints, i.e. the closed interval [0, 5] is characterized by the conditions 0 <= x <= 5. This is what closed='both' stands for. An open interval (in mathematics denoted by parentheses) does not contain its endpoints, i.e. the open interval (0, 5) is characterized by the conditions 0 < x < 5. This is what closed='neither' stands for. Intervals can also be half-open or half-closed, i.e. [0, 5) is described by 0 <= x < 5 (closed='left') and (0, 5] is described by 0 < x <= 5 (closed='right').

**Examples**

It is possible to build Intervals of different types, like numeric ones:

```python
>>> iv = pd.Interval(left=0, right=5)
>>> iv
Interval(0, 5, closed='right')
```

You can check if an element belongs to it

```python
>>> 2.5 in iv
True
```

You can test the bounds (closed='right', so 0 < x <= 5):

```python
>>> 0 in iv
False
>>> 5 in iv
True
>>> 0.0001 in iv
True
```

Calculate its length
>>> iv.length
5

You can operate with + and * over an Interval and the operation is applied to each of its bounds, so the result depends on the type of the bound elements

>>> shifted_iv = iv + 3
>>> shifted_iv
Interval(3, 8, closed='right')
>>> extended_iv = iv * 10.0
>>> extended_iv
Interval(0.0, 50.0, closed='right')

To create a time interval you can use Timestamps as the bounds

>>> year_2017 = pd.Interval(pd.Timestamp('2017-01-01 00:00:00'),
... pd.Timestamp('2018-01-01 00:00:00'),
... closed='left')
>>> pd.Timestamp('2017-01-01 00:00') in year_2017
True
>>> year_2017.length
Timedelta('365 days 00:00:00')

And also you can create string intervals

>>> volume_1 = pd.Interval('Ant', 'Dog', closed='both')
>>> 'Bee' in volume_1
True

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>closed</td>
<td>Whether the interval is closed on the left-side, right-side, both or neither</td>
</tr>
<tr>
<td>closed_left</td>
<td>Check if the interval is closed on the left side.</td>
</tr>
<tr>
<td>closed_right</td>
<td>Check if the interval is closed on the right side.</td>
</tr>
<tr>
<td>left</td>
<td>Left bound for the interval</td>
</tr>
<tr>
<td>length</td>
<td>Return the length of the Interval</td>
</tr>
<tr>
<td>mid</td>
<td>Return the midpoint of the Interval</td>
</tr>
<tr>
<td>open_left</td>
<td>Check if the interval is open on the left side.</td>
</tr>
<tr>
<td>open_right</td>
<td>Check if the interval is open on the right side.</td>
</tr>
<tr>
<td>right</td>
<td>Right bound for the interval</td>
</tr>
</tbody>
</table>

pandas.Interval.closed

Interval.closed

Whether the interval is closed on the left-side, right-side, both or neither

pandas.Interval.closed_left

Interval.closed_left

Check if the interval is closed on the left side.
For the meaning of `closed` and `open` see `Interval`.

**Returns** bool

True if the Interval is closed on the left-side, else False.

### pandas.Interval.closed_right

`Interval.closed_right`

Check if the interval is closed on the right side.

For the meaning of `closed` and `open` see `Interval`.

**Returns** bool

True if the Interval is closed on the left-side, else False.

### pandas.Interval.left

`Interval.left`

Left bound for the interval

### pandas.Interval.length

`Interval.length`

Return the length of the Interval

### pandas.Interval.mid

`Interval.mid`

Return the midpoint of the Interval

### pandas.Interval.open_left

`Interval.open_left`

Check if the interval is open on the left side.

For the meaning of `closed` and `open` see `Interval`.

**Returns** bool

True if the Interval is closed on the left-side, else False.

### pandas.Interval.open_right

`Interval.open_right`

Check if the interval is open on the right side.

For the meaning of `closed` and `open` see `Interval`.

**Returns** bool

True if the Interval is closed on the left-side, else False.
pandas.Interval.right

Interval.right
Right bound for the interval

34.14.8 Properties

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval.closed</td>
<td>Whether the interval is closed on the left-side, right-side, both or neither</td>
</tr>
<tr>
<td>Interval.closed_left</td>
<td>Check if the interval is closed on the left side.</td>
</tr>
<tr>
<td>Interval.closed_right</td>
<td>Check if the interval is closed on the right side.</td>
</tr>
<tr>
<td>Interval.left</td>
<td>Left bound for the interval</td>
</tr>
<tr>
<td>Interval.length</td>
<td>Return the length of the Interval</td>
</tr>
<tr>
<td>Interval.mid</td>
<td>Return the midpoint of the Interval</td>
</tr>
<tr>
<td>Interval.open_left</td>
<td>Check if the interval is open on the left side.</td>
</tr>
<tr>
<td>Interval.open_right</td>
<td>Check if the interval is open on the right side.</td>
</tr>
<tr>
<td>Interval.right</td>
<td>Right bound for the interval</td>
</tr>
</tbody>
</table>

34.14.9 Timedelta

Timedelta
Represents a duration, the difference between two dates or times.

34.14.9.1 pandas.Timedelta

class pandas.Timedelta
Represents a duration, the difference between two dates or times.

Timedelta is the pandas equivalent of python's datetime.timedelta and is interchangeable with it in most cases.

Parameters

- **value** [Timedelta, timedelta, np.timedelta64, string, or integer]
  Denote the unit of the input, if input is an integer. Default ‘ns’.

- **days, seconds, microseconds**, 
- **milliseconds, minutes, hours, weeks** : numeric, optional
  Values for construction in compat with datetime.timedelta. np ints and floats will be coerced to python ints and floats.

Notes

The .value attribute is always in ns.
Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>asm8</code></td>
<td>return a numpy timedelta64 array view of myself</td>
</tr>
<tr>
<td><code>components</code></td>
<td>Return a Components NamedTuple-like</td>
</tr>
<tr>
<td><code>days</code></td>
<td>Number of days.</td>
</tr>
<tr>
<td><code>delta</code></td>
<td>Return the timedelta in nanoseconds (ns), for internal compatibility.</td>
</tr>
<tr>
<td><code>microseconds</code></td>
<td>Number of microseconds (&gt;= 0 and less than 1 second).</td>
</tr>
<tr>
<td><code>nanoseconds</code></td>
<td>Return the number of nanoseconds (n), where 0 &lt;= n &lt; 1 microsecond.</td>
</tr>
<tr>
<td><code>resolution</code></td>
<td>return a string representing the lowest resolution that we have</td>
</tr>
<tr>
<td><code>seconds</code></td>
<td>Number of seconds (&gt;= 0 and less than 1 day).</td>
</tr>
</tbody>
</table>

```python
def pandas.Timedelta.asm8
Timedelta.asm8
    return a numpy timedelta64 array view of myself

def pandas.Timedelta.components
Timedelta.components
    Return a Components NamedTuple-like

def pandas.Timedelta.days
Timedelta.days
    Number of days.

def pandas.Timedelta.delta
Timedelta.delta
    Return the timedelta in nanoseconds (ns), for internal compatibility.

    Returns
    int

    Timedelta in nanoseconds.
```

Examples

```python
>>> td = pd.Timedelta('1 days 42 ns')
>>> td.delta
864000000000042

>>> td = pd.Timedelta('3 s')
>>> td.delta
3000000000
```
```python
>>> td = pd.Timedelta('3 ms 5 us')
>>> td.delta
3005000

>>> td = pd.Timedelta(42, unit='ns')
>>> td.delta
42
```

**pandas.Timedelta.microseconds**

Timedelta.microseconds

Number of microseconds (>= 0 and less than 1 second).

**pandas.Timedelta.nanoseconds**

Timedelta.nanoseconds

Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.

Returns int

Number of nanoseconds.

See also:

Timedelta.components Return all attributes with assigned values (i.e. days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds).

**Examples**

Using string input

```python
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.nanoseconds
42
```

Using integer input

```python
>>> td = pd.Timedelta(42, unit='ns')
>>> td.nanoseconds
42
```

**pandas.Timedelta.resolution**

Timedelta.resolution

return a string representing the lowest resolution that we have

**pandas.Timedelta.seconds**

Timedelta.seconds

Number of seconds (>= 0 and less than 1 day).
Methods

- **ceil**
  return a new Timedelta ceiled to this resolution

- **floor**
  return a new Timedelta floored to this resolution

- **isoformat**

- **round**
  Round the Timedelta to the specified resolution

- **to_pydatetime**
  return an actual datetime.timedelta object note: we lose nanosecond resolution if any

- **to_timedelta64**
  Returns a numpy.timedelta64 object with ‘ns’ precision

- **total_seconds**
  Total duration of timedelta in seconds (to ns precision)

- **view**
  array view compat

---

**pandas.Timedelta.ceil**

Timedelta.ceil

return a new Timedelta ceiled to this resolution

**Parameters**

freq [a freq string indicating the ceiling resolution]

---

**pandas.Timedelta.floor**

Timedelta.floor

return a new Timedelta floored to this resolution

**Parameters**

freq [a freq string indicating the flooring resolution]

---

**pandas.Timedelta.isoformat**

Timedelta.isoformat()


New in version 0.20.0.

**Returns**

formatted [str]

**See also:**

Timestamp.isoformat
Notes

The longest component is days, whose value may be larger than 365. Every component is always included, even if its value is 0. Pandas uses nanosecond precision, so up to 9 decimal places may be included in the seconds component. Trailing 0’s are removed from the seconds component after the decimal. We do not 0 pad components, so it’s ...TSH..., not ...T0SH...

Examples

```python
>>> td = pd.Timedelta(days=6, minutes=50, seconds=3,
...                   milliseconds=10, microseconds=10, nanoseconds=12)
>>> td.isoformat()
'P6DT0H50M3.010010012S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(days=500.5).isoformat()
'P500DT12H0MS'
```

pandas.Timedelta.round

Timedelta.round

Round the Timedelta to the specified resolution

Parameters

- freq [a freq string indicating the rounding resolution]

Returns

- a new Timedelta rounded to the given resolution of ‘freq’

Raises

- ValueError if the freq cannot be converted

pandas.Timedelta.to_pytimedelta

Timedelta.to_pytimedelta()

return an actual datetime.timedelta object note: we lose nanosecond resolution if any

pandas.Timedelta.to_timedelta64

Timedelta.to_timedelta64()

Returns a numpy.timedelta64 object with ‘ns’ precision

pandas.Timedelta.total_seconds

Timedelta.total_seconds()

Total duration of timedelta in seconds (to ns precision)
pandas: powerful Python data analysis toolkit, Release 0.23.1

pandas.Timedelta.view

Timedelta.view() array view compat

34.14.10 Properties

<table>
<thead>
<tr>
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<th>Description</th>
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<td>Timedelta.asm8</td>
<td>return a numpy timedelta64 array view of myself</td>
</tr>
<tr>
<td>Timedelta.components</td>
<td>Return a Components NamedTuple-like</td>
</tr>
<tr>
<td>Timedelta.days</td>
<td>Number of days.</td>
</tr>
<tr>
<td>Timedelta.delta</td>
<td>Return the timedelta in nanoseconds (ns), for internal compatibility.</td>
</tr>
<tr>
<td>Timedelta.freq</td>
<td></td>
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<tr>
<td>Timedelta.is_populated</td>
<td></td>
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<tr>
<td>Timedelta.max</td>
<td></td>
</tr>
<tr>
<td>Timedelta.microseconds</td>
<td>Number of micro seconds (&gt;= 0 and less than 1 second).</td>
</tr>
<tr>
<td>Timedelta.min</td>
<td></td>
</tr>
<tr>
<td>Timedelta.nanoseconds</td>
<td>Return the number of nanoseconds (n), where 0 &lt;= n &lt; 1 microsecond.</td>
</tr>
<tr>
<td>Timedelta.resolution</td>
<td>return a string representing the lowest resolution that we have</td>
</tr>
<tr>
<td>Timedelta.seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day).</td>
</tr>
<tr>
<td>Timedelta.value</td>
<td></td>
</tr>
<tr>
<td>Timedelta.view</td>
<td>array view compat</td>
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</tbody>
</table>

34.14.10.1 pandas.Timedelta.freq

Timedelta.freq

34.14.10.2 pandas.Timedelta.is_populated

Timedelta.is_populated

34.14.10.3 pandas.Timedelta.max

Timedelta.max = Timedelta('106751 days 23:47:16.854775')

34.14.10.4 pandas.Timedelta.min

Timedelta.min = Timedelta('-106752 days +00:12:43.145224')

34.14.10.5 pandas.Timedelta.value

Timedelta.value

34.14.11 Methods
Timedelta.ceil
return a new Timedelta ceiled to this resolution

Timedelta.floor
return a new Timedelta floored to this resolution

Timedelta.isoformat
Format Timedelta as ISO 8601 Duration like
[n] s are replaced by the values.

Timedelta.round
Round the Timedelta to the specified resolution

Timedelta.to_pytimedelta
return an actual datetime.timedelta object note: we lose
nanosecond resolution if any

Timedelta.to_timedelta64
Returns a numpy.timedelta64 object with 'ns' precision

Timedelta.total_seconds
Total duration of timedelta in seconds (to ns precision)

34.15 Frequencies

to_offset(freq)
Return DateOffset object from string or tuple representation or datetime.timedelta object

34.15.1 pandas.tseries.frequencies.to_offset

pandas.tseries.frequencies.to_offset (freq)
Return DateOffset object from string or tuple representation or datetime.timedelta object

Parameters

freq [str, tuple, datetime.timedelta, DateOffset or None]

Returns delta : DateOffset

None if freq is None

Raises ValueError

If freq is an invalid frequency

See also:
pandas.DateOffset

Examples

>>> to_offset('5min')
<5 * Minutes>

>>> to_offset('1D1H')
<25 * Hours>

>>> to_offset(('W', 2))
<2 * Weeks: weekday=6>

>>> to_offset((2, 'B'))
<2 * BusinessDays>

>>> to_offset(datetime.timedelta(days=1))
<Day>
34.16 Window

Rolling objects are returned by \texttt{rolling} calls: \texttt{pandas.DataFrame.rolling()}, \texttt{pandas.Series.rolling()}, etc. Expanding objects are returned by \texttt{expanding} calls: \texttt{pandas.DataFrame.expanding()}, \texttt{pandas.Series.expanding()}, etc. EWM objects are returned by \texttt{ewm} calls: \texttt{pandas.DataFrame.ewm()}, \texttt{pandas.Series.ewm()}, etc.

### 34.16.1 Standard moving window functions

<table>
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<tr>
<th>Method</th>
<th>Description</th>
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<td>\texttt{Rolling.count()}</td>
<td>The rolling count of any non-NaN observations inside the window.</td>
</tr>
<tr>
<td>\texttt{Rolling.sum(*args, **kwargs)}</td>
<td>Calculate rolling sum of given DataFrame or Series.</td>
</tr>
<tr>
<td>\texttt{Rolling.mean(*args, **kwargs)}</td>
<td>Calculate the rolling mean of the values.</td>
</tr>
<tr>
<td>\texttt{Rolling.median(**kwargs)}</td>
<td>Calculate the rolling median.</td>
</tr>
<tr>
<td>\texttt{Rolling.var([ddof])}</td>
<td>Calculate unbiased rolling variance.</td>
</tr>
<tr>
<td>\texttt{Rolling.std([ddof])}</td>
<td>Calculate rolling standard deviation.</td>
</tr>
<tr>
<td>\texttt{Rolling.min(*args, **kwargs)}</td>
<td>Calculate the rolling minimum.</td>
</tr>
<tr>
<td>\texttt{Rolling.max(*args, **kwargs)}</td>
<td>rolling maximum</td>
</tr>
<tr>
<td>\texttt{Rolling.corr([other, pairwise])}</td>
<td>rolling sample correlation</td>
</tr>
<tr>
<td>\texttt{Rolling.cov([other, pairwise, ddof])}</td>
<td>rolling sample covariance</td>
</tr>
<tr>
<td>\texttt{Rolling.skew(**kwargs)}</td>
<td>Unbiased rolling skewness</td>
</tr>
<tr>
<td>\texttt{Rolling.kurt(**kwargs)}</td>
<td>Calculate unbiased rolling kurtosis.</td>
</tr>
<tr>
<td>\texttt{Rolling.apply(func[, raw, args, kwargs])}</td>
<td>rolling function apply</td>
</tr>
<tr>
<td>\texttt{Rolling.aggregate(arg, *args, **kwargs)}</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>\texttt{Window.mean(*args, **kwargs)}</td>
<td>Calculate the window mean of the values.</td>
</tr>
<tr>
<td>\texttt{Window.sum(*args, **kwargs)}</td>
<td>Calculate window sum of given DataFrame or Series.</td>
</tr>
</tbody>
</table>

#### 34.16.1.1 pandas.core.window.Rolling.count

\texttt{Rolling.count()}  
The rolling count of any non-NaN observations inside the window.  

**Returns**  
\begin{itemize}
\item Series or DataFrame
\end{itemize}

Returned object type is determined by the caller of the rolling calculation.

**See also:**

- \texttt{pandas.Series.rolling} Calling object with Series data
- \texttt{pandas.DataFrame.rolling} Calling object with DataFrames
- \texttt{pandas.DataFrame.count} Count of the full DataFrame
Examples

```python
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0 1.0
1 2.0
2 1.0
3 1.0
dtype: float64
>>> s.rolling(3).count()
0 1.0
1 2.0
2 2.0
3 2.0
dtype: float64
>>> s.rolling(4).count()
0 1.0
1 2.0
2 2.0
3 3.0
dtype: float64
```

### 34.16.1.2 pandas.core.window.Rolling.sum

Rolling.sum(*args, **kwargs)

Calculate rolling sum of given DataFrame or Series.

**Parameters** *args, **kwargs

For compatibility with other rolling methods. Has no effect on the computed value.

**Returns** Series or DataFrame

Same type as the input, with the same index, containing the rolling sum.

**See also:**

Series.sum Reducing sum for Series.

DataFrame.sum Reducing sum for DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0 1
1 2
2 3
3 4
4 5
dtype: int64

>>> s.rolling(3).sum()
0 NaN
1 NaN
```

(continues on next page)
>>> s.expanding(3).sum()
0   NaN
1   NaN
2    6.0
3   10.0
4   15.0
dtype: float64

>>> s.rolling(3, center=True).sum()
0   NaN
1    6.0
2    9.0
3   12.0
4   NaN
dtype: float64

For DataFrame, each rolling sum is computed column-wise.

```python
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A  B
0  1  1
1  2  4
2  3  9
3  4 16
4  5 25
```

```python
>>> df.rolling(3).sum()
   A  B
0  NaN NaN
1  NaN NaN
2   6.0  14.0
3   9.0  29.0
4  12.0  50.0
```

### 34.16.1.3 pandas.core.window.Rolling.mean

Rolling.mean(*args, **kwargs)

Calculate the rolling mean of the values.

**Parameters**

*args

Under Review.

**kwargs

Under Review.

**Returns**

Series or DataFrame

Returned object type is determined by the caller of the rolling calculation.
See also:

Series.rolling Calling object with Series data

Dataframe.rolling Calling object with DataFrames

Series.mean Equivalent method for Series

Dataframe.mean Equivalent method for DataFrame

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0   NaN
1   1.5
2   2.5
3   3.5
dtype: float64
```

```python
>>> s.rolling(3).mean()
0   NaN
1   NaN
2   2.0
3   3.0
dtype: float64
```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
dtype: float64

34.16.1.5 pandas.core.window.Rolling.var

Rolling.var (ddof=1, *args, **kwargs)
Calculate unbiased rolling variance.

Normalized by N-1 by default. This can be changed using the ddof argument.

   Parameters ddof : int, default 1

   Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \)
   represents the number of elements.

   *args, **kwargs

   For NumPy compatibility. No additional arguments are used.

   Returns Series or DataFrame

   Returns the same object type as the caller of the rolling calculation.

See also:

Series.rolling Calling object with Series data
Dataframe.rolling Calling object with DataFrames
Series.var Equivalent method for Series
Dataframe.var Equivalent method for DataFrame
numpy.var Equivalent method for Numpy array

Notes

The default ddof of 1 used in Series.var() is different than the default ddof of 0 in numpy.var().
A minimum of 1 period is required for the rolling calculation.

Examples

>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0    NaN
1    NaN
2  0.333333
3  1.000000
4  1.000000
5  1.333333

(continues on next page)
6  0.000000  
dtype: float64

```python
>>> s.expanding(3).var()
0    NaN
1    NaN
2  0.333333
3  0.916667
4  0.800000
5  0.700000
6  0.619048
dtype: float64
```

### 34.16.1.6 pandas.core.window.Rolling.std

Rolling.

```
std(ddof=1, *args, **kwargs)
```

Calculate rolling standard deviation.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**

- `ddof` : int, default 1
  
  Delta Degrees of Freedom. The divisor used in calculations is \(N - ddof\), where \(N\) represents the number of elements.

- `*args, **kwargs`
  
  For NumPy compatibility. No additional arguments are used.

**Returns**

- `Series or DataFrame`
  
  Returns the same object type as the caller of the rolling calculation.

See also:

- `Series.rolling` Calling object with Series data
- `DataFrame.rolling` Calling object with DataFrames
- `Series.std` Equivalent method for Series
- `DataFrame.std` Equivalent method for DataFrame
- `numpy.std` Equivalent method for Numpy array

**Notes**

The default `ddof` of 1 used in Series.std is different than the default `ddof` of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

**Examples**
```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0    NaN
1    NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64

>>> s.expanding(3).std()
0    NaN
1    NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

### 34.16.1.7 pandas.core.window.Rolling.min

Rolling.min(*args, **kwargs)

Calculate the rolling minimum.

#### Parameters **kwargs

Under Review.

#### Returns Series or DataFrame

Returned object type is determined by the caller of the rolling calculation.

See also:

- Series.rolling Calling object with a Series
- DataFrame.rolling Calling object with a DataFrame
- Series.min Similar method for Series
- DataFrame.min Similar method for DataFrame

#### Examples

Performing a rolling minimum with a window size of 3.

```python
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0    NaN
1    NaN
2     3.0
3     2.0
4     2.0
dtype: float64
```
34.16.8 pandas.core.window.Rolling.max

Rolling.max(*args, **kwargs)

- **rolling maximum**

  **Returns**

  - same type as input

  **See also:**

  pandas.Series.rolling, pandas.DataFrame.rolling

34.16.1.9 pandas.core.window.Rolling.corr

Rolling.corr(other=None, pairwise=None, **kwargs)

- **rolling sample correlation**

  **Parameters**

  - **other**: Series, DataFrame, or ndarray, optional
    - if not supplied then will default to self and produce pairwise output
  - **pairwise**: bool, default None
    - If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

  **Returns**

  - same type as input

  **See also:**

  pandas.Series.rolling, pandas.DataFrame.rolling

34.16.1.10 pandas.core.window.Rolling.cov

Rolling.cov(other=None, pairwise=None, ddof=1, **kwargs)

- **rolling sample covariance**

  **Parameters**

  - **other**: Series, DataFrame, or ndarray, optional
    - if not supplied then will default to self and produce pairwise output
  - **pairwise**: bool, default None
    - If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.
  - **ddof**: int, default 1
    - Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

  **Returns**

  - same type as input
34.16.1.11 pandas.core.window.Rolling.skew

Rolling.skew(**kwargs)
Unbiased rolling skewness

Returns
same type as input

See also:
pandas.Series.rolling, pandas.DataFrame.rolling

34.16.1.12 pandas.core.window.Rolling.kurt

Rolling.kurt(**kwargs)
Calculate unbiased rolling kurtosis.
This function uses Fisher’s definition of kurtosis without bias.

Parameters
**kwargs

Returns
Series or DataFrame
Returned object type is determined by the caller of the rolling calculation

See also:
Series.rolling Calling object with Series data
DataFrame.rolling Calling object with DataFrames
Series.kurt Equivalent method for Series
DataFrame.kurt Equivalent method for DataFrame
scipy.stats.skew Third moment of a probability density
scipy.stats.kurtosis Reference SciPy method

Notes
A minimum of 4 periods is required for the rolling calculation.

Examples
The example below will show a rolling calculation with a window size of four matching the equivalent function call using scipy.stats.
```python
>>> arr = [1, 2, 3, 4, 999]
>>> fmt = "{0:.6f}"  # limit the printed precision to 6 digits
>>> import scipy.stats
>>> print(fmt.format(scipy.stats.kurtosis(arr[:-1], bias=False)))
-1.200000
>>> print(fmt.format(scipy.stats.kurtosis(arr[1:], bias=False)))
3.999946
>>> s = pd.Series(arr)
>>> s.rolling(4).kurt()
0    NaN
1    NaN
2    NaN
3   -1.20000
4   3.99994
dtype: float64
```

### 34.16.1.13 pandas.core.window.Rolling.apply

**Rolling.apply** *(func, raw=None, args=(), kwags=())*

rolling function apply

**Parameters**

- **func** : function
  
  Must produce a single value from an ndarray input if raw=True or a Series if raw=False

- **raw** : bool, default None
  
  - **False** : passes each row or column as a Series to the function.
  
  - **True or None** : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance. The raw parameter is required and will show a FutureWarning if not passed. In the future raw will default to False.
  
  New in version 0.23.0.

  ***args and **kwargs are passed to the function**

**Returns**

same type as input

**See also:**

pandas.Series.rolling, pandas.DataFrame.rolling

### 34.16.1.14 pandas.core.window.Rolling.aggregate

**Rolling.aggregate** *(arg, *args, **kwargs)*

Aggregate using one or more operations over the specified axis.

**Parameters**

- **func** : function, string, dictionary, or list of string/functions
  
  Function to use for aggregating the data. If a function, must either work when passed a Series/DataFrame or when passed to Series/DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
Accepted combinations are:

- string function name.
- function.
- list of functions.
- dict of column names -> functions (or list of functions).

*args

Positional arguments to pass to func.

**kwargs

Keyword arguments to pass to func.

Returns

aggregated [Series/DataFrame]

See also:

pandas.Series.rolling, pandas.DataFrame.rolling

Notes

agg is an alias for aggregate. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'])
>>> df
    A         B         C
0  2.385977  -0.102758  0.438822
1  1.004295   0.905829  -0.954544
2  0.735167  -0.165272  -1.619346
3  0.702657  -1.340923  -0.706334
4  0.246845   0.211596  -0.901819
5  2.463718   3.157577  -1.380906
6  1.142255   2.340594  -0.039875
7  1.396598  -1.647453   1.677227
8  0.543425   1.761277  -0.220481
9  0.640505   0.289374  -1.550670

>>> df.rolling(3).sum()
    A         B         C
0     NaN        NaN        NaN
1     NaN        NaN        NaN
2 -2.655105   0.637799  -2.135068
3 -0.971785  -0.600366  -3.280224
4 -0.214334  -1.294599  -3.227500
5  1.514216   2.028250  -2.989060
6  1.074618   5.709767  -2.322600
7  2.718061   3.850718   0.256446
8 -0.289082   2.454418   1.416871
9  0.212668   0.403198  -0.093924
```
```python
>>> df.rolling(3).agg({'A':'sum', 'B':'min'})
   A     B
0 NaN   NaN
1 NaN   NaN
2 -2.655105 -0.165272
3 -0.971785 -1.340923
4 -0.214334 -1.340923
5 1.514216 -1.340923
6 1.074618 0.211596
7 2.718061 -1.647453
8 -0.289082 -1.647453
9 0.212668 -1.647453
```

### 34.16.1.15 pandas.core.window.Rolling.quantile

Rolling.quantile(quantile, interpolation='linear', **kwargs)

rolling quantile.

**Parameters**

quantile : float

Quantile to compute. 0 <= quantile <= 1.

interpolation : {'linear', 'lower', 'higher', 'midpoint', 'nearest'}

New in version 0.23.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points $i$ and $j$:

- linear: $i + (j - i) \times fraction$, where fraction is the fractional part of the index surrounded by $i$ and $j$.
- lower: $i$.
- higher: $j$.
- nearest: $i$ or $j$ whichever is nearest.
- midpoint: $(i + j) / 2$.

**kwargs:

For compatibility with other rolling methods. Has no effect on the result.

**Returns**

Series or DataFrame

Returned object type is determined by the caller of the rolling calculation.

See also:

- pandas.Series.quantile Computes value at the given quantile over all data in Series.
- pandas.DataFrame.quantile Computes values at the given quantile over requested axis in DataFrame.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0   NaN
```
(continues on next page)
s.rolling(2).quantile(.4, interpolation='midpoint')

34.16.1.16 pandas.core.window.Window.mean

Window.mean(*args, **kwargs)

Calculate the window mean of the values.

Parameters

*args
Under Review.

**kwargs
Under Review.

Returns Series or DataFrame

Returned object type is determined by the caller of the window calculation.

See also:

Series.window Calling object with Series data
DataFrame.window Calling object with DataFrames
Series.mean Equivalent method for Series
DataFrame.mean Equivalent method for DataFrame

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

```python
>>> s.rolling(3).mean()
0    NaN
1    NaN
2    2.0
3    3.0
dtype: float64
```
34.16.1.17 pandas.core.window.Window.sum

Window.sum(*args, **kwargs)
Calculate window sum of given DataFrame or Series.

Parameters *

For compatibility with other window methods. Has no effect on the computed value.

Returns Series or DataFrame
Same type as the input, with the same index, containing the window sum.

See also:

Series.sum Reducing sum for Series.
DataFrame.sum Reducing sum for DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64

>>> s.rolling(3).sum()
0   NaN
1   NaN
2    6
3    9
4   12
dtype: float64

>>> s.expanding(3).sum()
0   NaN
1   NaN
2    6
3    9
4   15
dtype: float64

>>> s.rolling(3, center=True).sum()
0   NaN
1    6
2    9
3   12
4   NaN
dtype: float64
```

For DataFrame, each window sum is computed column-wise.
>>> df = pd.DataFrame({"A": s, "B": s ** 2})

```python
>>> df
   A  B
0   1  1
1   2  4
2   3  9
3   4 16
4   5 25
```

```python
>>> df.rolling(3).sum()
   A   B
0  NaN  NaN
1  NaN  NaN
2  6.0 14.0
3  9.0 29.0
4 12.0 50.0
```

### 34.16.2 Standard expanding window functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expanding.count(**kwargs)</td>
<td>The expanding count of any non-NaN observations inside the window.</td>
</tr>
<tr>
<td>Expanding.sum(*args, **kwargs)</td>
<td>Calculate expanding sum of given DataFrame or Series.</td>
</tr>
<tr>
<td>Expanding.mean(*args, **kwargs)</td>
<td>Calculate the expanding mean of the values.</td>
</tr>
<tr>
<td>Expanding.median(**kwargs)</td>
<td>Calculate the expanding median.</td>
</tr>
<tr>
<td>Expanding.var([ddof])</td>
<td>Calculate unbiased expanding variance.</td>
</tr>
<tr>
<td>Expanding.std([ddof])</td>
<td>Calculate expanding standard deviation.</td>
</tr>
<tr>
<td>Expanding.min(*args, **kwargs)</td>
<td>Calculate the expanding minimum.</td>
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<tr>
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<td>Unbiased expanding skewness</td>
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<td>Expanding.kurt(**kwargs)</td>
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</tr>
<tr>
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<td>Expanding quantile.</td>
</tr>
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</table>

#### 34.16.2.1 pandas.core.window.Expanding.count

Expanding.count (**kwargs)

The expanding count of any non-NaN observations inside the window.

**Returns** Series or DataFrame

Returned object type is determined by the caller of the expanding calculation.

See also:

- `pandas.Series.expanding` Calling object with Series data
- `pandas.DataFrame.expanding` Calling object with DataFrames
- `pandas.DataFrame.count` Count of the full DataFrame
Examples

```python
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0 1.0
1 2.0
2 1.0
3 1.0
dtype: float64
```  
```python
>>> s.rolling(3).count()
0 1.0
1 2.0
2 2.0
3 2.0
dtype: float64
```  
```python
>>> s.rolling(4).count()
0 1.0
1 2.0
2 2.0
3 3.0
dtype: float64
```

### 34.16.2.2 pandas.core.window.Expanding.sum

Expanding `sum(*args, **kwargs)`  
Calculate expanding sum of given DataFrame or Series.

**Parameters**  
*args, **kwargs  
For compatibility with other expanding methods. Has no effect on the computed value.

**Returns**  
Series or DataFrame  
Same type as the input, with the same index, containing the expanding sum.

**See also:**  
Series `sum` Reducing sum for Series.
DataFrame `sum` Reducing sum for DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0 1
1 2
2 3
3 4
4 5
dtype: int64
```  
```python
>>> s.rolling(3).sum()
0  NaN
(continues on next page)
```
1 NaN
2 6.0
3 9.0
4 12.0
dtype: float64

>>> s.expanding(3).sum()
0 NaN
1 NaN
2 6.0
3 10.0
4 15.0
dtype: float64

>>> s.rolling(3, center=True).sum()
0 NaN
1 6.0
2 9.0
3 12.0
4 NaN
dtype: float64

For DataFrame, each expanding sum is computed column-wise.

>>> df = pd.DataFrame({'A': s, 'B': s ** 2})
>>> df
A   B
0   1   1
1   2   4
2   3   9
3   4  16
4   5  25

>>> df.rolling(3).sum()
   A  B
0  NaN NaN
1  NaN NaN
2   6.0  14.0
3   9.0  29.0
4  12.0  50.0

34.16.2.3 pandas.core.window.Expanding.mean

Expanding.mean(*args, **kwargs)
Calculate the expanding mean of the values.

Parameters
*args

Under Review.

**kwargs

Under Review.

Returns
Series or DataFrame

Returned object type is determined by the caller of the expanding calculation.
See also:

- **Series.expanding** Calling object with Series data
- **DataFrame.expanding** Calling object with DataFrames
- **Series.mean** Equivalent method for Series
- **DataFrame.mean** Equivalent method for DataFrame

**Examples**

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64

>>> s.rolling(3).mean()
0    NaN
1    NaN
2    2.0
3    3.0
dtype: float64
```

### 34.16.2.4 pandas.core.window.Expanding.median

**`Expanding.median(**kwargs)`**

Calculate the expanding median.

**Parameters** **kwargs

For compatibility with other expanding methods. Has no effect on the computed median.

**Returns** Series or DataFrame

Returned type is the same as the original object.

See also:

- **Series.expanding** Calling object with Series data
- **DataFrame.expanding** Calling object with DataFrames
- **Series.median** Equivalent method for Series
- **DataFrame.median** Equivalent method for DataFrame

**Examples**

Compute the rolling median of a series with a window size of 3.
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
dtype: float64

34.16.2.5 pandas.core.window.Expanding.var

Expanding.var(ddof=1, *args, **kwargs)
Calculate unbiased expanding variance.
Normalized by N-1 by default. This can be changed using the ddof argument.

Parameters ddof : int, default 1
Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

*args, **kwargs
For NumPy compatibility. No additional arguments are used.

Returns Series or DataFrame
Returns the same object type as the caller of the expanding calculation.

See also:

Series.expanding Calling object with Series data
DataFrame.expanding Calling object with DataFrames
Series.var Equivalent method for Series
DataFrame.var Equivalent method for DataFrame
numpy.var Equivalent method for Numpy array

Notes
The default ddof of 1 used in Series.var() is different than the default ddof of 0 in numpy.var().
A minimum of 1 period is required for the rolling calculation.

Examples

>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0    NaN
1    NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333

(continues on next page)
6 0.000000
dtype: float64

```python
>>> s.expanding(3).var()
0   NaN
1   NaN
2  0.333333
3  0.916667
4  0.800000
5  0.700000
6  0.619048
dtype: float64
```

### 34.16.2.6 pandas.core.window.Expanding.std

`Expanding.std(ddof=1, *args, **kwargs)`

Calculate expanding standard deviation.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**

- `ddof`: int, default 1
  
  Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

- `*args`, `**kwargs`
  
  For NumPy compatibility. No additional arguments are used.

**Returns**

- `Series` or `DataFrame`
  
  Returns the same object type as the caller of the expanding calculation.

**See also:**

- `Series.expanding` Calling object with Series data
- `DataFrame.expanding` Calling object with DataFrames
- `Series.std` Equivalent method for Series
- `DataFrame.std` Equivalent method for DataFrame
- `numpy.std` Equivalent method for Numpy array

**Notes**

The default `ddof` of 1 used in `Series.std` is different than the default `ddof` of 0 in `numpy.std`.

A minimum of one period is required for the rolling calculation.

**Examples**
34.16.2.7 pandas.core.window.Expanding.min

Expanding.min(*args, **kwargs)

Calculate the expanding minimum.

Parameters

**kwargs

Under Review.

Returns

Series or DataFrame

Returned object type is determined by the caller of the expanding calculation.

See also:

Series.expanding Calling object with a Series

Dataframe.expanding Calling object with a DataFrame

Series.min Similar method for Series

Dataframe.min Similar method for DataFrame

Examples

Performing a rolling minimum with a window size of 3.

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0   NaN
1   NaN
2  0.577350
3  1.000000
4  1.000000
5  1.154701
6   0.000000
dtype: float64

>>> s.expanding(3).std()
0   NaN
1   NaN
2  0.577350
3  0.957427
4  0.894427
5  0.836660
6  0.786796
dtype: float64
```
34.16.2.8 pandas.core.window.Expanding.max

Expanding.max(*args, **kwargs)
expanding maximum

Returns

same type as input

See also:

pandas.Series.expanding, pandas.DataFrame.expanding

34.16.2.9 pandas.core.window.Expanding.corr

Expanding.corr(other=None, pairwise=None, **kwargs)
expanding sample correlation

Parameters other : Series, DataFrame, or ndarray, optional
if not supplied then will default to self and produce pairwise output

pairwise : bool, default None
If False then only matching columns between self and other will be used and the
output will be a DataFrame. If True then all pairwise combinations will be calculated
and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In
the case of missing elements, only complete pairwise observations will be used.

Returns

same type as input

See also:

pandas.Series.expanding, pandas.DataFrame.expanding

34.16.2.10 pandas.core.window.Expanding.cov

Expanding.cov(other=None, pairwise=None, ddof=1, **kwargs)
expanding sample covariance

Parameters other : Series, DataFrame, or ndarray, optional
if not supplied then will default to self and produce pairwise output

pairwise : bool, default None
If False then only matching columns between self and other will be used and the
output will be a DataFrame. If True then all pairwise combinations will be calculated
and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In
the case of missing elements, only complete pairwise observations will be used.

ddof : int, default 1
Delta Degrees of Freedom. The divisor used in calculations is \(N - ddof\), where \(N\)
represents the number of elements.

Returns

same type as input
34.16.2.11 pandas.core.window.Expanding.skew

Expanding.skew(**kwargs)
Unbiased expanding skewness

Returns
same type as input

See also:

pandas.Series.expanding, pandas.DataFrame.expanding

34.16.2.12 pandas.core.window.Expanding.kurt

Expanding.kurt(**kwargs)
Calculate unbiased expanding kurtosis.
This function uses Fisher’s definition of kurtosis without bias.

Parameters
**kwargs
Under Review.

Returns
Series or DataFrame
Returned object type is determined by the caller of the expanding calculation

See also:

Series.expanding Calling object with Series data
DataFrame.expanding Calling object with DataFrames
Series.kurt Equivalent method for Series
DataFrame.kurt Equivalent method for DataFrame
scipy.stats.skew Third moment of a probability density
scipy.stats.kurtosis Reference SciPy method

Notes
A minimum of 4 periods is required for the expanding calculation.

Examples
The example below will show an expanding calculation with a window size of four matching the equivalent function call using scipy.stats.
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> fmt = "{0:.6f}" # limit the printed precision to 6 digits
>>> print(fmt.format(scipy.stats.kurtosis(arr[:-1], bias=False)))
-1.200000
>>> print(fmt.format(scipy.stats.kurtosis(arr, bias=False)))
4.999874
>>> s = pd.Series(arr)
>>> s.expanding(4).kurt()
0    NaN
1    NaN
2    NaN
3   -1.200000
4   4.999874
dtype: float64

34.16.2.13 pandas.core.window.Expanding.apply

Expanding.apply(func, raw=None, args=(), kwargs=())
expanding function apply

Parameters

func : function

Must produce a single value from an ndarray input if raw=True or a Series if raw=False

raw : bool, default None

• False : passes each row or column as a Series to the function.

• True or None : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

The raw parameter is required and will show a FutureWarning if not passed. In the future raw will default to False.

New in version 0.23.0.

*args and **kwargs are passed to the function

Returns

same type as input

See also:

pandas.Series.expanding, pandas.DataFrame.expanding

34.16.2.14 pandas.core.window.Expanding.aggregate

Expanding.aggregate(arg, *args, **kwargs)
Aggregate using one or more operations over the specified axis.

Parameters

func : function, string, dictionary, or list of string/functions

Function to use for aggregating the data. If a function, must either work when passed a Series/DataFrame or when passed to Series/DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
Accepted combinations are:

- string function name.
- function.
- list of functions.
- dict of column names -> functions (or list of functions).

**args**

Positional arguments to pass to `func`.

**kwargs**

Keyword arguments to pass to `func`.

Returns

`aggregated` [Series/DataFrame]

See also:

- pandas.DataFrame.expanding.aggregate
- pandas.DataFrame.rolling.aggregate
- pandas.DataFrame.aggregate

Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'])
>>> df
   A         B         C
0 -2.385977 -0.102758  0.438822
1 -1.004295  0.905829 -0.954544
2  0.735167 -0.165272 -1.619346
3 -0.702657 -1.340923 -0.706334
4  2.463718  3.157577 -1.380906
5 -1.142255  2.340594 -0.039875
6  1.396598 -1.647453  1.677227
7 -0.543425  1.761277 -0.220481
8 -0.640505  0.289374 -1.550670
9  0.680292  0.132049  0.548693
```

```python
>>> df.ewm(alpha=0.5).mean()
   A         B         C
0 -2.385977 -0.102758  0.438822
1 -1.464856  0.569633 -0.954544
2 -0.207700  0.149687 -1.619346
3 -0.471677 -0.645305 -0.706334
4 -0.355635 -0.203033 -0.904111
5  1.076417  1.503943 -1.142255
6 -0.041654  1.925562 -0.220481
7  0.680292  0.132049  0.548693
```

(continues on next page)
34.16.2.15 pandas.core.window.Expanding.quantile

Expanding. `quantile(quantile, interpolation='linear', **kwargs)` expanding quantile.

**Parameters quantile : float**
Quantile to compute. 0 <= quantile <= 1.

New in version 0.23.0.
This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points i and j:

- linear: i + (j - i) * fraction, where fraction is the fractional part of the index surrounded by i and j.
- lower: i.
- higher: j.
- nearest: i or j whichever is nearest.
- midpoint: (i + j) / 2.

**kwargs:
For compatibility with other expanding methods. Has no effect on the result.

**Returns Series or DataFrame**
Returned object type is determined by the caller of the expanding calculation.

See also:

`pandas.Series.quantile` Computes value at the given quantile over all data in Series.

`pandas.DataFrame.quantile` Computes values at the given quantile over requested axis in DataFrame.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0   NaN
1   1.0
2   2.0
3   3.0
dtype: float64

>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0   NaN
1   1.5
2   2.5
```
34.16.3 Exponentially-weighted moving window functions

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<th>Description</th>
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<td>exponential weighted moving average</td>
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<tr>
<td>EWM.std([bias])</td>
<td>exponential weighted moving stddev</td>
</tr>
<tr>
<td>EWM.var([bias])</td>
<td>exponential weighted moving variance</td>
</tr>
<tr>
<td>EWM.corr([other, pairwise])</td>
<td>exponential weighted sample correlation</td>
</tr>
<tr>
<td>EWM.cov([other, pairwise, bias])</td>
<td>exponential weighted sample covariance</td>
</tr>
</tbody>
</table>

### 34.16.3.1 pandas.core.window.EWM.mean

EWM.mean(*args, **kwargs)

exponential weighted moving average

Returns

same type as input

See also:

pandas.Series.ewm, pandas.DataFrame.ewm

### 34.16.3.2 pandas.core.window.EWM.std

EWM.std(bias=False, *args, **kwargs)

exponential weighted moving stddev

Parameters  bias : boolean, default False

Use a standard estimation bias correction

Returns

same type as input

See also:

pandas.Series.ewm, pandas.DataFrame.ewm

### 34.16.3.3 pandas.core.window.EWM.var

EWM.var(bias=False, *args, **kwargs)

exponential weighted moving variance

Parameters  bias : boolean, default False

Use a standard estimation bias correction

Returns

same type as input

See also:

pandas.Series.ewm, pandas.DataFrame.ewm
34.16.3.4 pandas.core.window.EWM.corr

EWM.corr(other=None, pairwise=None, **kwargs)

exponential weighted sample correlation

Parameters

other : Series, DataFrame, or ndarray, optional
    if not supplied then will default to self and produce pairwise output

pairwise : bool, default None
    If False then only matching columns between self and other will be used and the
    output will be a DataFrame. If True then all pairwise combinations will be calculated
    and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In
    the case of missing elements, only complete pairwise observations will be used.

bias : boolean, default False
    Use a standard estimation bias correction

Returns

same type as input

See also:

pandas.Series.ewm, pandas.DataFrame.ewm

34.16.3.5 pandas.core.window.EWM.cov

EWM.cov(other=None, pairwise=None, bias=False, **kwargs)

exponential weighted sample covariance

Parameters

other : Series, DataFrame, or ndarray, optional
    if not supplied then will default to self and produce pairwise output

pairwise : bool, default None
    If False then only matching columns between self and other will be used and the
    output will be a DataFrame. If True then all pairwise combinations will be calculated
    and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In
    the case of missing elements, only complete pairwise observations will be used.

bias : boolean, default False
    Use a standard estimation bias correction

Returns

same type as input

See also:

pandas.Series.ewm, pandas.DataFrame.ewm

34.17 GroupBy

GroupBy objects are returned by groupby calls: pandas.DataFrame.groupby(), pandas.Series.
    groupby(), etc.
34.17.1 Indexing, iteration

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<tr>
<th>Method</th>
<th>Description</th>
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<tbody>
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<td>GroupBy.<strong>iter</strong>()</td>
<td>Groupby iterator&lt;br&gt; Returns Generator yielding sequence of (name, subsetted object) for each group</td>
</tr>
<tr>
<td>GroupBy.groups</td>
<td>dict {group name -&gt; group labels}</td>
</tr>
<tr>
<td>GroupBy.indices</td>
<td>dict {group name -&gt; group indices}</td>
</tr>
<tr>
<td>GroupBy.get_group(name[, obj])</td>
<td>Constructs NDFrame from group with provided name</td>
</tr>
</tbody>
</table>

34.17.1.1 pandas.core.groupby.GroupBy.__iter__

GroupBy.__iter__()<br> Groupby iterator<br> Returns Generator yielding sequence of (name, subsetted object) for each group

34.17.1.2 pandas.core.groupby.GroupBy.groups

GroupBy.groups<br> dict {group name -> group labels}

34.17.1.3 pandas.core.groupby.GroupBy.indices

GroupBy.indices<br> dict {group name -> group indices}

34.17.1.4 pandas.core.groupby.GroupBy.get_group

GroupBy.get_group(name, obj=None)<br> Constructs NDFrame from group with provided name<br> Parameters name : object<br> the name of the group to get as a DataFrame<br> obj : NDFrame, default None<br> the NDFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used<br> Returns group [type of obj]  

Grouper([key, level, freq, axis, sort])<br> A Grouper allows the user to specify a groupby instruction for a target object

34.17.1.5 pandas.Grouper

class pandas.Grouper(key=None, level=None, freq=None, axis=0, sort=False)<br> 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

- **base**, **loffset**

**Returns**

A specification for a groupby instruction

**Examples**

Syntactic sugar for `df.groupby('A')`

```python
>>> df.groupby(Grouper(key='A'))
```

Specify a resample operation on the column `date`

```python
>>> df.groupby(Grouper(key='date', freq='60s'))
```

Specify a resample operation on the level `date` on the columns axis with a frequency of 60s

```python
>>> df.groupby(Grouper(level='date', freq='60s', axis=1))
```
Attributes

| ax  | groups |

### 34.17.2 Function application

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<tbody>
<tr>
<td>Apply function func group-wise and combine the results together.</td>
<td></td>
<td></td>
<td>Apply a function func with arguments to this GroupBy object and return the function’s result.</td>
</tr>
</tbody>
</table>

#### 34.17.2.1 pandas.core.groupby.GroupBy.apply

GroupBy.apply(func, *args, **kwargs)

Apply function func group-wise and combine the results together.

The function passed to apply must take a dataframe as its first argument and return a dataframe, a series or a scalar. apply will then take care of combining the results back together into a single dataframe or series. apply is therefore a highly flexible grouping method.

While apply is a very flexible method, its downside is that using it can be quite a bit slower than using more specific methods. Pandas offers a wide range of method that will be much faster than using apply for their specific purposes, so try to use them before reaching for apply.

**Parameters**

- **func**: function
  - A callable that takes a dataframe as its first argument, and returns a dataframe, a series or a scalar. In addition the callable may take positional and keyword arguments
  - **args, kwargs**: tuple and dict
    - Optional positional and keyword arguments to pass to func

**Returns**

- **applied**: [Series or DataFrame]

**See also**

- **pipe**: Apply function to the full GroupBy object instead of to each group.
  - **aggregate, transform**

**Notes**

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.
Examples

```python
>>> df = pd.DataFrame({'A': 'a a b'.split(), 'B': [1,2,3], 'C': [4,6,5]})
>>> g = df.groupby('A')
```

From `df` above we can see that `g` has two groups, `a`, `b`. Calling `apply` in various ways, we can get different grouping results:

Example 1: below the function passed to `apply` takes a dataframe as its argument and returns a dataframe. `apply` combines the result for each group together into a new dataframe:

```python
>>> g.apply(lambda x: x / x.sum())
   B   C
0 0.333333 0.4
1 0.666667 0.6
2 1.000000 1.0
```

Example 2: The function passed to `apply` takes a dataframe as its argument and returns a series. `apply` combines the result for each group together into a new dataframe:

```python
>>> g.apply(lambda x: x.max() - x.min())
     B   C
A a  1  2
b  0  0
```

Example 3: The function passed to `apply` takes a dataframe as its argument and returns a scalar. `apply` combines the result for each group together into a series, including setting the index as appropriate:

```python
>>> g.apply(lambda x: x.C.max() - x.B.min())
    A
a  5
b  2
dtype: int64
```

34.17.2.2 pandas.core.groupby.GroupBy.aggregate

GroupBy.aggregate(func, *args, **kwargs)

34.17.2.3 pandas.core.groupby.GroupBy.transform

GroupBy.transform(func, *args, **kwargs)

34.17.2.4 pandas.core.groupby.GroupBy.pipe

GroupBy.pipe(func, *args, **kwargs)

Apply a function `func` with arguments to this GroupBy object and return the function’s result.

New in version 0.21.0.

Use .pipe when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing
```
>>> h(g(f(df.groupby('group')), arg1=a), arg2=b, arg3=c)
```

You can write
```
>>> (df.groupby('group')
... .pipe(f)
... .pipe(g, arg1=a)
... .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

**Parameters**

**func**: callable or tuple of (callable, string)

Function to apply to this GroupBy object or, alternatively, a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the GroupBy object.

**args**: iterable, optional

Positional arguments passed into `func`.

**kwargs**: dict, optional

A dictionary of keyword arguments passed into `func`.

**Returns**

**object**: [the return type of `func`.]

**See also:**

- `pandas.Series.pipe` Apply a function with arguments to a series
- `pandas.DataFrame.pipe` Apply a function with arguments to a dataframe
- `apply` Apply function to each group instead of to the full GroupBy object.

**Notes**

See more [here](#).

**Examples**

```
>>> df = pd.DataFrame({'A': 'a b a b'.split(), 'B': [1, 2, 3, 4]})
```

```
>>> df
   A   B
0  a  1
1  b  2
2  a  3
3  b  4
```

To get the difference between each groups maximum and minimum value in one pass, you can do
```
>>> df.groupby('A').pipe(lambda x: x.max() - x.min())
```

```
   B
A
a  2
b  2
```
34.17.3 Computations / Descriptive Stats

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### 34.17.3.1 pandas.core.groupby.GroupBy.all

**GroupBy.all** *(skipna=True)*

Returns True if all values in the group are truthful, else False

**Parameters** skipna : bool, default True

Flag to ignore nan values during truth testing

**See also:**

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

### 34.17.3.2 pandas.core.groupby.GroupBy.any

**GroupBy.any** *(skipna=True)*

Returns True if any value in the group is truthful, else False
pandas: powerful Python data analysis toolkit, Release 0.23.1

Parameters skipna: bool, default True
Flag to ignore nan values during truth testing
See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.3 pandas.core.groupby.GroupBy.bfill

GroupBy.bfill(limit=None)
Backward fill the values
Parameters limit: integer, optional
limit of how many values to fill
See also:
Series.backfill, DataFrame.backfill, Series.fillna, DataFrame.fillna

34.17.3.4 pandas.core.groupby.GroupBy.count

GroupBy.count()
Compute count of group, excluding missing values
See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.5 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.
See also:
ngroup Number the groups themselves.

Examples

```python
>>> df = pd.DataFrame([('a'), ['a'], ['a'], ['b'], ['b'], ['a'])
>>> df
   0  A
   1  a
   2  a
```
(continues on next page)
3  b
4  b
5  a

```python
>>> df.groupby('A').cumcount()
0  0
1  1
2  2
3  0
4  1
5  3
dtype: int64
```

```python
>>> df.groupby('A').cumcount(ascending=False)
0  3
1  2
2  1
3  1
4  0
5  0
dtype: int64
```

---

**34.17.3.6 pandas.core.groupby.GroupBy.ffill**

`GroupBy.ffill(limit=None)`

Forward fill the values

**Parameters**

- `limit` : integer, optional
  - limit of how many values to fill

**See also:**

- `Series.pad`, `DataFrame.pad`, `Series.fillna`, `DataFrame.fillna`

---

**34.17.3.7 pandas.core.groupby.GroupBy.first**

`GroupBy.first(**kwargs)`

Compute first of group values

**See also:**


---

**34.17.3.8 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.

**See also:**

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
```

34.17.3.9 pandas.core.groupby.GroupBy.last

GroupBy.last(**kwargs)
Compute last of group values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.10 pandas.core.groupby.GroupBy.max

GroupBy.max(**kwargs)
Compute max of group values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.11 pandas.core.groupby.GroupBy.mean

GroupBy.mean(*args, **kwargs)
Compute mean of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.12 pandas.core.groupby.GroupBy.median

GroupBy.median(**kwargs)
Compute median of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.17.3.13 pandas.core.groupby.GroupBy.min

**min**(**kwargs)**

Compute min of group values

**See also:**

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.14 pandas.core.groupby.GroupBy.ngroup

**ngroup**(**ascending=True**)

Number each group from 0 to the number of groups - 1.

This is the enumerative complement of cumcount. Note that the numbers given to the groups match the order in
which the groups would be seen when iterating over the groupby object, not the order they are first observed.

New in version 0.20.2.

**Parameters ascending** : bool, default True

If False, number in reverse, from number of group - 1 to 0.

**See also:**

cumcount Number the rows in each group.

**Examples**

```python
>>> df = pd.DataFrame({'A': list('aaabba')})
>>> df
       A
0     a
1     a
2     a
3     b
4     b
5     a
>>> df.groupby('A').ngroup()
0  0
1  0
2  0
3  1
4  1
5  0
dtype: int64
>>> df.groupby('A').ngroup(ascending=False)
0  1
1  1
2  1
3  0
4  0
5  1
dtype: int64
```

(continues on next page)
34.17.3.15 pandas.core.groupby.GroupBy.nth

GroupBy.\(\text{nth}(n, \text{dropna}=\text{None})\)

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  

\(\text{dropna}\) : None or str, optional  
  apply the specified dropna operation before counting which row is the nth row. Needs to be None, ‘any’ or ‘all’

**See also:**

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

**Examples**

```python
>>> df = pd.DataFrame({
    'A': [1, 1, 2, 1, 2],
    'B': [np.nan, 2, 3, 4, 5]
}, columns=['A', 'B'])

>>> g = df.groupby('A')
>>> g.nth(0)
      B
A
1  NaN
2  3.0

>>> g.nth(1)
      B
A
1  2.0
2  5.0

>>> g.nth(-1)
      B
A
1  4.0
2  5.0

>>> g.nth([0, 1])
      B
A
1  NaN
1  2.0
2  3.0
2  5.0
```

Specifying dropna allows count ignoring NaN
>>> g.nth(0, dropna='any')
   B
A  
  1 2.0
  2 3.0

NaNs denote group exhausted when using dropna

>>> g.nth(3, dropna='any')
   B
A  
  1 NaN
  2 NaN

Specifying as_index=False in groupby keeps the original index.

>>> df.groupby('A', as_index=False).nth(1)
   A  B
  1  1 2.0
  4  2 5.0

34.17.3.16 pandas.core.groupby.GroupBy.ohlc

GroupBy.ohlc()
Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.17 pandas.core.groupby.GroupBy.prod

GroupBy.prod(**kwargs)
Compute prod of group values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.18 pandas.core.groupby.GroupBy.rank

GroupBy.rank(method='average', ascending=True, na_option='keep', pct=False, axis=0)
Provides the rank of values within each group.

Parameters method : {'average', 'min', 'max', 'first', 'dense'}, default 'average'
  • average: average rank of group
  • min: lowest rank in group
  • max: highest rank in group
  • first: ranks assigned in order they appear in the array
  • dense: like 'min', but rank always increases by 1 between groups

ascending : boolean, default True
False for ranks by high (1) to low (N)

**na_option** : \{'keep’, ‘top’, ‘bottom’}, default ‘keep’
- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

**pct** : boolean, default False
- Compute percentage rank of data within each group

**axis** : int, default 0
- The axis of the object over which to compute the rank.

**Returns**

- DataFrame with ranking of values within each group

See also:


### 34.17.3.19 pandas.core.groupby.GroupBy.pct_change

**GroupBy.pct_change**(periods=1, fill_method='pad', limit=None, freq=None, axis=0)
- Calculate pct_change of each value to previous entry in group

See also:


### 34.17.3.20 pandas.core.groupby.GroupBy.size

**GroupBy.size()
- Compute group sizes

See also:


### 34.17.3.21 pandas.core.groupby.GroupBy.sem

**GroupBy.sem**(ddof=1)
- Compute standard error of the mean of groups, excluding missing values
- For multiple groupings, the result index will be a MultiIndex

**Parameters**

- **ddof** : integer, default 1
  - degrees of freedom

See also:

34.17.3.22 pandas.core.groupby.GroupBy.std

GroupBy.std(ddof=1, *args, **kwargs)
Compute standard deviation of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

Parameters
ddf : integer, default 1
degrees of freedom

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.23 pandas.core.groupby.GroupBy.sum

GroupBy.sum(**kwargs)
Compute sum of group values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.24 pandas.core.groupby.GroupBy.var

GroupBy.var(ddof=1, *args, **kwargs)
Compute variance of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

Parameters
ddf : integer, default 1
degrees of freedom

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.25 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.

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

Examples

```python
>>> df = DataFrame([["a", 1], ["a", 2], ["b", 1], ["b", 2]],
columns=["A", "B")
>>> df.groupby("A").tail(1)
   A  B
1  a  2
3  b  2
(continues on next page)
```
```
>>> df.groupby('A').head(1)
     A  B
 0  a  1
 2  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.

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<td>Returns True if any value in the group is truthful, else False.</td>
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<td>Compute pairwise correlation of columns, excluding NA/null values.</td>
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<td>Compute count of group, excluding missing values</td>
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<td>Cumulative max for each group</td>
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<td>Return the mean absolute deviation of the values for the requested axis.</td>
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<td><code>DataFrameGroupBy.plot</code></td>
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<td>Provides the rank of values within each group.</td>
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<td><code>DataFrameGroupBy.take</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
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<td>Shift the time index, using the index’s frequency if available.</td>
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34.17.3.26 pandas.core.groupby.DataFrameGroupBy.agg

DataFrameGroupBy. **agg** *(arg, *args, **kwargs)*

Aggregate using one or more operations over the specified axis.

**Parameters**

- **func** : function, string, dictionary, or list of string/functions
  - Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
  - Accepted combinations are:
    - string function name.
    - function.
    - list of functions.
    - dict of column names -> functions (or list of functions).

- **args**
  - Positional arguments to pass to *func*.

- **kwargs**
  - Keyword arguments to pass to *func*.

**Returns**

- **aggregated** [DataFrame]

**See also:**

pandas.DataFrame.groupby.apply, pandas.DataFrame.groupby.transform, pandas.DataFrame.aggregate

**Notes**

- **agg** is an alias for **aggregate**. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

**Examples**
```python
>>> df = pd.DataFrame({'A': [1, 1, 2, 2],
...                    'B': [1, 2, 3, 4],
...                    'C': np.random.randn(4)})

>>> df
            A  B    C
0      1.0  1  0.362838
1      1.0  2  0.227877
2      2.0  3  1.267767
3      2.0  4 -0.562860

The aggregation is for each column.

>>> df.groupby('A').agg('min')
   B    C
A  
1  1  0.227877
2  3 -0.562860

Multiple aggregations

>>> df.groupby('A').agg(['min', 'max'])
                        B    C
min max   min max
A  
1  1  2  0.227877  0.362838
2  3  4 -0.562860  1.267767

Select a column for aggregation

>>> df.groupby('A').B.agg(['min', 'max'])
                        min max
A  
1  1  2
2  3  4

Different aggregations per column

>>> df.groupby('A').agg({'B': ['min', 'max'], 'C': 'sum'})
                        B    C
min max     sum
A  
1  1  2  0.590716
2  3  4  0.704907
```

34.17.3.27 pandas.core.groupby.DataFrameGroupBy.all

DataFrameGroupBy.all(skipna=True)
Returns True if all values in the group are truthful, else False

Parameters skipna: bool, default True
Flag to ignore nan values during truth testing

See also:

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.17.3.28  pandas.core.groupby.DataFrameGroupBy.any

DataFrameGroupBy.\texttt{any}(\texttt{skipna=True})

Returns True if any value in the group is truthful, else False

Parameters skipna : bool, default True

Flag to ignore nan values during truth testing

See also:
  pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.29  pandas.core.groupby.DataFrameGroupBy.bfill

DataFrameGroupBy.\texttt{bfill}(\texttt{limit=None})

Backward fill the values

Parameters limit : integer, optional

limit of how many values to fill

See also:
  Series.backfill, DataFrame.backfill, Seriesfillna, DataFrame.fillna

34.17.3.30  pandas.core.groupby.DataFrameGroupBy.corr

DataFrameGroupBy.\texttt{corr}

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]

34.17.3.31  pandas.core.groupby.DataFrameGroupBy.count

DataFrameGroupBy.\texttt{count}()

Compute count of group, excluding missing values

34.17.3.32  pandas.core.groupby.DataFrameGroupBy.cov

DataFrameGroupBy.\texttt{cov}

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.
Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

**Parameters**  
*min_periods*: int, optional
Minimum number of observations required per pair of columns to have a valid result.

**Returns**  
DataFrame
The covariance matrix of the series of the DataFrame.

**See also:**
- `pandas.Series.cov` compute covariance with another Series
- `pandas.core.window.EWM.cov` exponential weighted sample covariance
- `pandas.core.window.Expanding.cov` expanding sample covariance
- `pandas.core.window.Rolling.cov` rolling sample covariance

**Notes**

Returns the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-1.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

**Examples**

```python
df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
                   columns=['dogs', 'cats'])
df.cov()
dogs   cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667

np.random.seed(42)
df = pd.DataFrame(np.random.randn(1000, 5),
                   columns=['a', 'b', 'c', 'd', 'e'])
df.cov()
a   b   c   d   e
a  0.998438 -0.020161 0.059277 -0.008943 0.014144
b -0.020161  1.059352 -0.008543 -0.024738 0.009826
c  0.059277 -0.008543  1.010670 -0.001486 -0.000271
d -0.008943 -0.024738 -0.001486  0.921297 -0.013692
e  0.014144  0.009826 -0.000271 -0.013692  0.977795
```
Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```python
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...                   columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
   a         b         c
a  0.316741   NaN   -0.150812
b   NaN  1.248003   0.191417
c -0.150812  0.191417   0.895202
```

34.17.33 pandas.core.groupby.DataFrameGroupBy.cummax

```python
DataFrameGroupBy.cummax(axis=0, **kwargs)
```
Cumulative max for each group

See also:
```
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
```

34.17.34 pandas.core.groupby.DataFrameGroupBy.cummin

```python
DataFrameGroupBy.cummin(axis=0, **kwargs)
```
Cumulative min for each group

See also:
```
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
```

34.17.35 pandas.core.groupby.DataFrameGroupBy.cumprod

```python
DataFrameGroupBy.cumprod(axis=0, *args, **kwargs)
```
Cumulative product for each group

See also:
```
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
```

34.17.36 pandas.core.groupby.DataFrameGroupBy.cumsum

```python
DataFrameGroupBy.cumsum(axis=0, *args, **kwargs)
```
Cumulative sum for each group

See also:
```
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
```
pandas: powerful Python data analysis toolkit, Release 0.23.1

34.17.3.37 pandas.core.groupby.DataFrameGroupBy.describe

DataFrameGroupBy.describe(**kwargs)

Generates descriptive statistics that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters percentiles : list-like of numbers, optional

The percentiles to include in the output. All should fall between 0 and 1. The default is [.25,.5,.75], which returns the 25th, 50th, and 75th percentiles.

include : ‘all’, list-like of dtypes or None (default), optional

A white list of data types to include in the result. Ignored for Series. Here are the options:

• ‘all’ : All columns of the input will be included in the output.

• A list-like of dtypes: Limits the results to the provided data types. To limit the result to numeric types submit numpy.number. To limit it instead to object columns submit the numpy.object data type. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To select pandas categorical columns, use 'category'

• None (default) : The result will include all numeric columns.

exclude : list-like of dtypes or None (default), optional,

A black list of data types to omit from the result. Ignored for Series. Here are the options:

• A list-like of dtypes: Excludes the provided data types from the result. To exclude numeric types submit numpy.number. To exclude object columns submit the data type numpy.object. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To exclude pandas categorical columns, use 'category'

• None (default) : The result will exclude nothing.

Returns

summary: Series/DataFrame of summary statistics

See also:

DataFrame.count, DataFrame.max, DataFrame.min, DataFrame.mean, DataFrame.std, DataFrame.select_dtypes

Notes

For numeric data, the result’s index will include count, mean, std, min, max as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include count, unique, top, and freq. The top is the most common value. The freq is the most common value’s frequency. Timestamps also include the first and last items.
If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a DataFrame, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a DataFrame are analyzed for the output. The parameters are ignored when analyzing a Series.

**Examples**

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
   count        mean       std      min      25%      50%      75%       max
0   3.0         2.0       1.0       1.0       1.5       2.0       2.5       3.0
```

Describing a categorical Series.

```python
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count   4
unique   3
top      a
top freq 2
dtype: object
```

Describing a timestamp Series.

```python
>>> s = pd.Series([
...    np.datetime64("2000-01-01"),
...    np.datetime64("2010-01-01"),
...    np.datetime64("2010-01-01")
...])
>>> s.describe()
count   3
unique   2
top 2010-01-01 00:00:00
top freq 2
first 2000-01-01 00:00:00
last 2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({
...    'object': ['a', 'b', 'c'],
...    'numeric': [1, 2, 3],
...    'categorical': pd.Categorical(['d', 'e', 'f'])
...})
```

(continues on next page)
Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
```

<table>
<thead>
<tr>
<th></th>
<th>categorical</th>
<th>numeric</th>
<th>object</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>3</td>
<td>3.0</td>
<td>3</td>
</tr>
<tr>
<td>unique</td>
<td>3</td>
<td>NaN</td>
<td>3</td>
</tr>
<tr>
<td>top</td>
<td>f</td>
<td>NaN</td>
<td>c</td>
</tr>
<tr>
<td>freq</td>
<td>1</td>
<td>NaN</td>
<td>1</td>
</tr>
<tr>
<td>mean</td>
<td>NaN</td>
<td>2.0</td>
<td>NaN</td>
</tr>
<tr>
<td>std</td>
<td>NaN</td>
<td>1.0</td>
<td>NaN</td>
</tr>
<tr>
<td>min</td>
<td>NaN</td>
<td>1.0</td>
<td>NaN</td>
</tr>
<tr>
<td>25%</td>
<td>NaN</td>
<td>1.5</td>
<td>NaN</td>
</tr>
<tr>
<td>50%</td>
<td>NaN</td>
<td>2.0</td>
<td>NaN</td>
</tr>
<tr>
<td>75%</td>
<td>NaN</td>
<td>2.5</td>
<td>NaN</td>
</tr>
<tr>
<td>max</td>
<td>NaN</td>
<td>3.0</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()
count: 3.0
mean: 2.0
std: 1.0
min: 1.0
25%: 1.5
50%: 2.0
75%: 2.5
max: 3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
```

<table>
<thead>
<tr>
<th></th>
<th>numeric</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>3.0</td>
</tr>
<tr>
<td>mean</td>
<td>2.0</td>
</tr>
<tr>
<td>std</td>
<td>1.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
</tr>
<tr>
<td>25%</td>
<td>1.5</td>
</tr>
<tr>
<td>50%</td>
<td>2.0</td>
</tr>
<tr>
<td>75%</td>
<td>2.5</td>
</tr>
<tr>
<td>max</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Including only string columns in a DataFrame description.
```python
>>> df.describe(include=[np.object])
    object
   count   3
   unique   3
top      c
freq     1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
    categorical
   count   3
   unique   3
top      f
freq     1
```

Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
    categorical     object
   count   3      3
   unique   3      3
top      f      c
freq     1      1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.object])
    categorical     numeric
   count   3      3.0
   unique   3     NaN
top      f     NaN
freq     1     NaN
mean     NaN     2.0
std      NaN     1.0
min      NaN     1.0
25%      NaN     1.5
50%      NaN     2.0
75%      NaN     2.5
max      NaN     3.0
```

34.17.3.38 pandas.core.groupby.DataFrameGroupBy.diff

DataFrameGroupBy.**diff**

First discrete difference of element.

Calculates the difference of a DataFrame element compared with another element in the DataFrame (default is the element in the same column of the previous row).

**Parameters**

- **periods**: int, default 1
  
  Periods to shift for calculating difference, accepts negative values.

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  
  Take difference over rows (0) or columns (1).

New in version 0.16.1..
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Returns

diffed  [DataFrame]

See also:

**Series.diff**  First discrete difference for a Series.

**DataFrame.pct_change**  Percent change over given number of periods.

**DataFrame.shift**  Shift index by desired number of periods with an optional time freq.

Examples

Difference with previous row

```python
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                     'b': [1, 1, 2, 3, 5, 8],
...                     'c': [1, 4, 9, 16, 25, 36]})
>>> df
   a  b  c
0  1  1  1
1  2  1  4
2  3  2  9
3  4  3 16
4  5  5 25
5  6  8 36
```

```python
>>> df.diff()
   a     b     c
0  NaN  NaN  NaN
1  1.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

Difference with previous column

```python
>>> df.diff(axis=1)
   a     b     c
0  NaN  0.0  0.0
1  NaN -1.0  3.0
2  NaN -1.0  7.0
3  NaN -1.0 13.0
4  NaN  0.0 20.0
5  NaN  2.0 28.0
```

Difference with 3rd previous row

```python
>>> df.diff(periods=3)
   a     b     c
0  NaN  NaN  NaN
1  NaN  NaN  NaN
2  NaN  NaN  NaN
3  3.0  2.0 15.0
4  3.0  4.0 21.0
5  3.0  6.0 27.0
```
Difference with following row

```python
>>> df.diff(periods=-1)
a   b   c
0  -1  0  -3
1  -1 -1  -5
2  -1 -1  -7
3  -1 -2  -9
4  -1 -3 -11
5   NaN NaN  NaN
```

### 34.17.3.39 pandas.core.groupby.DataFrameGroupBy.ffill

`DataFrameGroupBy.ffill(limit=None)`

Forward fill the values

**Parameters**

- `limit`: integer, optional
  - limit of how many values to fill

**See also:**

- `Series.pad`, `DataFrame.pad`, `Series.fillna`, `DataFrame.fillna`

### 34.17.3.40 pandas.core.groupby.DataFrameGroupBy.fillna

`DataFrameGroupBy.fillna(value=None, method=None, axis=0, inplace=False, limit=None)`

Fill NA/Nan values using the specified method

**Parameters**

- `value`: scalar, dict, Series, or DataFrame
  - Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.
- `method`: {'backfill', 'bfill', 'pad', 'ffill', None}, default None
  - Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap
- `axis`: [0 or 'index', 1 or 'columns']
- `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. Must be greater than 0 if not None.
- `downcast`: dict, default is None

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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:

interpolate Fill NaN values using interpolation.

reindex, asfreq

Examples

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                    columns=list('ABCD'))
>>> df
   A   B   C   D
0 NaN 2.0  NaN 0.0
1 3.0 4.0  NaN 1.0
2 NaN NaN  NaN 5.0
3 NaN 3.0  NaN 4.0

Replace all NaN elements with 0s.

```python
>>> df.fillna(0)
   A   B   C   D
0  0.0 2.0  0.0 0.0
1  3.0 4.0  0.0 1.0
2  0.0 0.0  0.0 5.0
3  0.0 3.0  0.0 4.0

We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
   A   B   C   D
0 NaN 2.0  NaN 0.0
1 3.0 4.0  NaN 1.0
2 3.0 4.0  NaN 5.0
3 3.0 3.0  NaN 4.0

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
   A   B   C   D
0  0.0 2.0  2.0 0.0
1  3.0 4.0  2.0 1.0
2  0.0 1.0  2.0 5.0
3  0.0 3.0  2.0 4.0

Only replace the first NaN element.
>>> df.fillna(value=values, limit=1)
   A  B  C  D
0  0.0  2.0  2.0  0.0
1  3.0  4.0  NaN  1.0
2  NaN  1.0  NaN  5.0
3  NaN  3.0  NaN  4.0

34.17.3.41 pandas.core.groupby.DataFrameGroupBy.filter

DataFrameGroupBy.filter(func, dropna=True, *args, **kwargs)

Return a copy of a DataFrame excluding elements from groups that do not satisfy the boolean criterion specified by func.

Parameters

- **f**: function
  - Function to apply to each subframe. Should return True or False.
- **dropna**: Drop groups that do not pass the filter. True by default; if False, groups that evaluate False are filled with NaNs.

Returns

filtered [DataFrame]

Notes

Each subframe is endowed the attribute ‘name’ in case you need to know which group you are working on.

Examples

```python
>>> import pandas as pd
>>> df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
...                         'foo', 'bar'],
...                    'B': [1, 2, 3, 4, 5, 6],
...                    'C': [2.0, 5.0, 8.0, 1.0, 2.0, 9.0]})
>>> grouped = df.groupby('A')
>>> grouped.filter(lambda x: x['B'].mean() > 3.)
   A  B  C
0  bar 2.0  5.0
1  bar 4.0  1.0
2  bar 6.0  9.0
```

34.17.3.42 pandas.core.groupby.DataFrameGroupBy.hist

DataFrameGroupBy.hist

Make a histogram of the DataFrame’s.

A histogram is a representation of the distribution of data. This function calls matplotlib.pyplot.hist(), on each series in the DataFrame, resulting in one histogram per column.

Parameters

- **data**: DataFrame
  - The pandas object holding the data.
column : 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. For example, a value of 90 displays the x labels rotated 90
degrees clockwise.

ylabelsize : int, default None
If specified changes the y-axis label size.

yrot : float, default None
Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90
degrees clockwise.

ax : Matplotlib axes object, default None
The axes to plot the histogram on.

sharex : 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. Note 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 in inches of the figure to create. Uses the value in matplotlib.rcParams by
default.

layout : tuple, optional
Tuple of (rows, columns) for the layout of the histograms.

bins : integer or sequence, default 10
Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are
calculated and returned. If bins is a sequence, gives bin edges, including left edge of
first bin and right edge of last bin. In this case, bins is returned unmodified.

**kwds
All other plotting keyword arguments to be passed to matplotlib.pyplot.

hist().

Returns
axes [matplotlib.AxesSubplot or numpy.ndarray of them]

See also:
**matplotlib.pyplot.hist** Plot a histogram using matplotlib.

**Examples**

This example draws a histogram based on the length and width of some animals, displayed in three bins:

```python
>>> df = pd.DataFrame({
...     'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1],
... }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```

### 34.17.3.43 pandas.core.groupby.DataFrameGroupBy.idxmax

DataFrameGroupBy.**idxmax**

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

**Parameters**

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  - 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**

- **idxmax** [Series]

**Raises**

- `ValueError`
  - If the row/column is empty

**See also**

- `Series.idxmax`

**Notes**

This method is the DataFrame version of `ndarray.argmax`.

### 34.17.3.44 pandas.core.groupby.DataFrameGroupBy.idxmin

DataFrameGroupBy.**idxmin**

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

**Parameters**

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  - 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]

**Raises**

- `ValueError`
• If the row/column is empty

See also:
Series.idxmin

Notes

This method is the DataFrame version of ndarray.argmin.

34.17.3.45 pandas.core.groupby.DataFrameGroupBy.mad

DataFrameGroupBy.mad
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 when computing the result.

level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing
into a Series

numeric_only : boolean, default None
Include only float, int, boolean columns. If None, will attempt to use everything,
then use only numeric data. Not implemented for Series.

Returns

mad [Series or DataFrame (if level specified)]

34.17.3.46 pandas.core.groupby.DataFrameGroupBy.pct_change

DataFrameGroupBy.pct_change(periods=1, fill_method='pad', limit=None, freq=None, axis=0)
Calculate pct_change of each value to previous entry in group

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.47 pandas.core.groupby.DataFrameGroupBy.plot

DataFrameGroupBy.plot
Class implementing the .plot attribute for groupby objects

34.17.3.48 pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.quantile
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

**numeric_only**: boolean, default True

If False, the quantile of datetime and timedelta data will be computed as well

**interpolation**: {'linear', 'lower', 'higher', 'midpoint', 'nearest'}

New in version 0.18.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points $i$ and $j$:

- **linear**: $i + (j - i) * fraction$, where *fraction* is the fractional part of the index surrounded by $i$ and $j$.
- **lower**: $i$.
- **higher**: $j$.
- **nearest**: $i$ or $j$ whichever is nearest.
- **midpoint**: $(i + j) / 2$.

**Returns** 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.

See also:

`pandas.core.window.Rolling.quantile`

**Examples**

```python
>>> df = pd.DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                   columns=['a', 'b'])
>>> df.quantile(.1)
a 1.3
b 3.7
dtype: float64
>>> df.quantile([.1, .5])
   a  b
0.1 1.3 3.7
0.5 2.5 55.0
```

Specifying **numeric_only=False** will also compute the quantile of datetime and timedelta data.

```python
>>> df = pd.DataFrame({'A': [1, 2],
                     'B': [pd.Timestamp('2010'),
                          pd.Timestamp('2011')],
                     'C': [pd.Timedelta('1 days'),
                          pd.Timedelta('2 days')])
>>> df.quantile(0.5, numeric_only=False)
A  1.5
```

(continues on next page)
34.17.3.49 pandas.core.groupby.DataFrameGroupBy.rank

DataFrameGroupBy.rank (method='average', ascending=True, na_option='keep', pct=False, axis=0)
Provides the rank of values within each group.

Parameters

- **method**: {'average', 'min', 'max', 'first', 'dense'}, default 'average'
  - average: average rank of group
  - min: lowest rank in group
  - max: highest rank in group
  - first: ranks assigned in order they appear in the array
  - dense: like 'min', but rank always increases by 1 between groups

- **ascending**: boolean, default True
  False for ranks by high (1) to low (N)

- **na_option**: {'keep', 'top', 'bottom'}, default 'keep'
  - keep: leave NA values where they are
  - top: smallest rank if ascending
  - bottom: smallest rank if descending

- **pct**: boolean, default False
  Compute percentage rank of data within each group

- **axis**: int, default 0
  The axis of the object over which to compute the rank.

Returns

DataFrame with ranking of values within each group

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.17.3.50 pandas.core.groupby.DataFrameGroupBy.resample

DataFrameGroupBy.resample (rule, *args, **kwargs)
Provide resampling when using a TimeGrouper Return a new grouper with our resampler appended

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.17.3.51 pandas.core.groupby.DataFrameGroupBy.shift

DataFrameGroupBy.shift(periods=1, freq=None, axis=0)
Shift each group by periods observations

Parameters

- **periods**: integer, default 1
  number of periods to shift

- **freq**: [frequency string]

- **axis**: [axis to shift, default 0]

See also:


34.17.3.52 pandas.core.groupby.DataFrameGroupBy.size

DataFrameGroupBy.size()
Compute group sizes

See also:


34.17.3.53 pandas.core.groupby.DataFrameGroupBy.skew

DataFrameGroupBy.skew
Return unbiased skew over requested axis Normalized by N-1

Parameters

- **axis**: [index (0), columns (1)]

- **skipna**: boolean, default True
  Exclude NA/null values when computing the result.

- **level**: int or level name, default None
  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

- **numeric_only**: boolean, default None
  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

- **skew**: [Series or DataFrame (if level specified)]

34.17.3.54 pandas.core.groupby.DataFrameGroupBy.take

DataFrameGroupBy.take
Return the elements in the given positional indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.
Parameters

**indices**: array-like

An array of ints indicating which positions to take.

**axis**: {0 or ‘index’, 1 or ‘columns’, None}, default 0

The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.

**convert**: bool, default True

Whether to convert negative indices into positive ones. For example, −1 would map to the \( \text{len(axis)} - 1 \). The conversions are similar to the behavior of indexing a regular Python list.

Deprecated since version 0.21.0: In the future, negative indices will always be converted.

**is_copy**: bool, default True

Whether to return a copy of the original object or not.

**kwargs

For compatibility with `numpy.take()`. Has no effect on the output.

Returns

**taken**: type of caller

An array-like containing the elements taken from the object.

See also:

- `DataFrame.loc` Select a subset of a DataFrame by labels.
- `DataFrame.iloc` Select a subset of a DataFrame by positions.
- `numpy.take` Take elements from an array along an axis.

Examples

```python
>>> df = pd.DataFrame({
    'falcon': ('bird', 389.0),
    'parrot': ('bird', 24.0),
    'lion': ('mammal', 80.5),
    'monkey': ('mammal', np.nan),
},
   columns=['name', 'class', 'max_speed'],
   index=[0, 2, 3, 1])
>>> df
   name  class  max_speed
0  falcon  bird     389.0
2  parrot  bird     24.0
3   lion  mammal     80.5
1  monkey  mammal    NaN

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That’s because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
Take elements at indices 1 and 2 along the axis 1 (column selection).

```python
>>> df.take([1, 2], axis=1)
   class     max_speed
0   bird     389.0
2   bird      24.0
3  mammal      80.5
1  mammal       NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```python
>>> df.take([-1, -2])
   name       class     max_speed
1  monkey   mammal      NaN
3    lion   mammal      80.5
```

### 34.17.3.55 pandas.core.groupby.DataFrameGroupBy.tshift

**DataFrameGroupBy.tshift**

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 the tseries 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.

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<thead>
<tr>
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<td>Return the largest ( n ) elements.</td>
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<tr>
<td>SeriesGroupBy.nsmallest</td>
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<td>SeriesGroupBy.nunique([dropna])</td>
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<tr>
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<td>Return unique values of Series object.</td>
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<td>SeriesGroupBy.value_counts([normalize, ...])</td>
<td>Return boolean if values in the object are monotonic_increasing</td>
</tr>
<tr>
<td>SeriesGroupBy.is_monotonic_increasing</td>
<td>Return boolean if values in the object are monotonic_decreasing</td>
</tr>
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<td>SeriesGroupBy.is_monotonic_decreasing</td>
<td></td>
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</tbody>
</table>
SeriesGroupBy.nlargest

Return the largest \( n \) elements.

**Parameters**

- **n**: int
  
  Return this many descending sorted values

- **keep**: {'first', 'last'}, default 'first'
  
  Where there are duplicate values: - *first*: take the first occurrence. - *last*: take the last occurrence.

**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(10**6))
>>> s.nlargest(10)  # only sorts up to the N requested
219921  4.644710
82124   4.608745
421689   4.564644
425277   4.447014
718691   4.414137
43154    4.403520
283187   4.313922
595519   4.273635
503969   4.250236
121637   4.240952
dtype: float64
```

SeriesGroupBy.nsmallest

Return the smallest \( n \) elements.

**Parameters**

- **n**: int
  
  Return this many ascending sorted values

- **keep**: {'first', 'last'}, default 'first'
  
  Where there are duplicate values: - *first*: take the first occurrence. - *last*: take the last occurrence.
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(10**6))
>>> s.nsmallest(10)  # only sorts up to the N requested
288532 -4.954580
732345 -4.835960
64803  -4.812550
446457 -4.609998
501225 -4.483945
669476 -4.472935
973615 -4.401699
621279 -4.355126
773916 -4.347355
359919 -4.331927

dtype: float64
```

34.17.3.58 pandas.core.groupby.SeriesGroupBy.nunique

`SeriesGroupBy.nunique(dropna=True)`

Returns number of unique elements in the group

34.17.3.59 pandas.core.groupby.SeriesGroupBy.unique

`SeriesGroupBy.unique`

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

Returns `ndarray` or `Categorical`

The unique values returned as a NumPy array. In case of categorical data type, returned as a Categorical.

See also:

`pandas.unique` top-level unique method for any 1-d array-like object.

`Index.unique` return Index with unique values from an Index object.
Examples

```python
>>> pd.Series([2, 1, 3, 3], name='A').unique()
dtype='int64'
array([2, 1, 3])

>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
dtype='datetime64[ns]'
array(['2016-01-01T00:00:00.000000000'],
      dtype='datetime64[ns]')

>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern') for _ in range(3)]).unique()
dtype='datetime64[ns]'
array([Timestamp('2016-01-01 00:00:00-0500'),
      Timestamp('2016-01-01 00:00:00-0500')])
```

An unordered Categorical will return categories in the order of appearance.

```python
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```python
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'), ordered=True)).unique()
Categories (3, object): [a < b < c]
```

34.17.3.60 pandas.core.groupby.SeriesGroupBy.value_counts

SeriesGroupBy.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)

34.17.3.61 pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing

SeriesGroupBy.is_monotonic_increasing
Return boolean if values in the object are monotonic_increasing
New in version 0.19.0.

Returns

- is_monotonic [boolean]

34.17.3.62 pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing

SeriesGroupBy.is_monotonic_decreasing
Return boolean if values in the object are monotonic_decreasing
New in version 0.19.0.

Returns

- is_monotonic_decreasing [boolean]

The following methods are available only for DataFrameGroupBy objects.
### DataFrameGroupBy.corrwith

**DataFrameGroupBy.corrwith**

Compute pairwise correlation between rows or columns of two DataFrame objects.

**Parameters**

- **other** [DataFrame, Series]
- **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]

### DataFrameGroupBy.boxplot

**DataFrameGroupBy.boxplot(\[subplots, column, \ldots\])**

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** : Keyword Arguments

---

**34.17.3.63 pandas.core.groupby.DataFrameGroupBy.corrwith**

**DataFrameGroupBy.corrwith**

Compute pairwise correlation between rows or columns of two DataFrame objects.

**Parameters**

- **other** [DataFrame, Series]
- **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]

**34.17.3.64 pandas.core.groupby.DataFrameGroupBy.boxplot**

**DataFrameGroupBy.boxplot(\[subplots=True, column=None, fontsize=None, rot=0, grid=True, ax=None, figsize=None, layout=None, **kwds\])**

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** : Keyword Arguments
All other plotting keyword arguments to be passed to matplotlib’s boxplot function

Returns

dict of key/value = group key/DataFrame.boxplot return value
or DataFrame.boxplot return value in case subplots=figures=False

Examples

```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)
```

### 34.18 Resampling

Resampler objects are returned by resample calls: `pandas.DataFrame.resample()` , `pandas.Series.resample()`.

#### 34.18.1 Indexing, iteration

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<td>dict {group name -&gt; group indices}</td>
</tr>
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<td>Resampler.get_group(name[, obj])</td>
<td>Constructs NDFrame from group with provided name</td>
</tr>
</tbody>
</table>

#### 34.18.1.1 pandas.core.resample.Resampler.__iter__

`Resampler.__iter__()`

Groupby iterator

Returns

Generator yielding sequence of (name, subsetted object)
for each group

#### 34.18.1.2 pandas.core.resample.Resampler.groups

`Resampler.groups`

dict {group name -> group labels}
34.18.1.3 pandas.core.resample.Resampler.indices

Resampler.indices
dict {group name -> group indices}

34.18.1.4 pandas.core.resample.Resampler.get_group

Resampler.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]

34.18.2 Function application

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<th>Resampler.apply</th>
<th>Aggregate using one or more operations over the specified axis.</th>
</tr>
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<tr>
<td>Resampler.aggregate</td>
<td>Aggregate using one or more operations over the specified axis.</td>
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</table>
| Resampler.transform | Call function producing a like-indexed Series on each
group and return a Series with the transformed values |
| Resampler.pipe | Apply a function func with arguments to this Resampler
object and return the function’s result. |

34.18.2.1 pandas.core.resample.Resampler.apply

Resampler.apply(arg, *args, **kwargs)
Aggregate using one or more operations over the specified axis.

Parameters
func : function, string, dictionary, or list of string/functions
Function to use for aggregating the data. If a function, must either work when passed
a DataFrame or when passed to DataFrame.apply. For a DataFrame, can pass a dict,
if the keys are DataFrame column names.

Accepted combinations are:
• string function name.
• function.
• list of functions.
• dict of column names -> functions (or list of functions).

*args
Positional arguments to pass to func.
**kwargs

Keyword arguments to pass to `func`.

Returns

- **aggregated** [DataFrame]

See also:

- pandas.DataFrame.groupby.aggregate,
- pandas.DataFrame.resample.transform,
- pandas.DataFrame.aggregate

Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = Series([1,2,3,4,5],
              index=pd.date_range('20130101',
                                periods=5,freq='s'))
2013-01-01 00:00:00    1
2013-01-01 00:00:01    2
2013-01-01 00:00:02    3
2013-01-01 00:00:03    4
2013-01-01 00:00:04    5
Freq: S, dtype: int64

>>> r = s.resample('2s')
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left,
label=left, convention=start, base=0]

>>> r.agg(np.sum)
2013-01-01 00:00:00    3
2013-01-01 00:00:02    7
2013-01-01 00:00:04    5
Freq: 2S, dtype: int64

>>> r.agg(['sum','mean','max'])
       sum  mean  max
2013-01-01 00:00:00  3.0  1.5  2.0
2013-01-01 00:00:02  7.0  3.5  4.0
2013-01-01 00:00:04  5.0  5.0  5.0

>>> r.agg({'result' : lambda x: x.mean() / x.std(),
         'total' : np.sum})
        total  result
2013-01-01 00:00:00  3.00  2.121320
2013-01-01 00:00:02  7.00  4.949747
2013-01-01 00:00:04  5.00  NaN
```
34.18.2.2 pandas.core.resample.Resampler.aggregate

Resampler.aggregate(arg, *args, **kwargs)
Aggregate using one or more operations over the specified axis.

Parameters

func : function, string, dictionary, or list of string/functions
Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. For a DataFrame, can pass a dict, if the keys are DataFrame column names.
Accepted combinations are:
• string function name.
• function.
• list of functions.
• dict of column names -> functions (or list of functions).

*args
Positional arguments to pass to func.

**kwargs
Keyword arguments to pass to func.

Returns

aggregated [DataFrame]

See also:
pandas.DataFrame.groupby.aggregate, pandas.DataFrame.resample.transform, pandas.DataFrame.aggregate

Notes

agg is an alias for aggregate. Use the alias.
A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = Series([1,2,3,4,5],
             index=pd.date_range('20130101',
                                 periods=5,freq='s'))
2013-01-01 00:00:00  1
2013-01-01 00:00:01  2
2013-01-01 00:00:02  3
2013-01-01 00:00:03  4
2013-01-01 00:00:04  5
Freq: S, dtype: int64

>>> r = s.resample('2s')
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left, label=left, convention=start, base=0]
```
34.18.2.3 pandas.core.resample.Resampler.transform

Resampler.transform(arg, *args, **kwargs)

Call function producing a like-indexed Series on each group and return a Series with the transformed values

Parameters func : function
To apply to each group. Should return a Series with the same index

Returns
transformed [Series]

Examples

```python
>>> resampled.transform(lambda x: (x - x.mean()) / x.std())
```

34.18.2.4 pandas.core.resample.Resampler.pipe

Resampler.pipe(func, *args, **kwargs)

Apply a function func with arguments to this Resampler object and return the function’s result.

New in version 0.23.0.

Use .pipe when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```python
>>> h(g(f(df.groupby('group'))), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.groupby('group')
... .pipe(f)
... .pipe(g, arg1=a)
... .pipe(h, arg2=b, arg3=c))
```
which is much more readable.

**Parameters**

- **func** : callable or tuple of (callable, string)

  Function to apply to this Resampler object or, alternatively, a (callable, data_keyword) tuple where data_keyword is a string indicating the keyword of callable that expects the Resampler object.

- **args** : iterable, optional

  Positional arguments passed into func.

- **kwargs** : dict, optional

  A dictionary of keyword arguments passed into func.

**Returns**

- **object** [the return type of func.]

**See also:**

- **pandas.Series.pipe** Apply a function with arguments to a series
- **pandas.DataFrame.pipe** Apply a function with arguments to a dataframe
- **apply** Apply function to each group instead of to the full Resampler object.

**Notes**

See more here

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4]},
                    index=pd.date_range('2012-08-02', periods=4))
>>> df
   A
2012-08-02  1
2012-08-03  2
2012-08-04  3
2012-08-05  4
To get the difference between each 2-day period’s maximum and minimum value in one pass, you can do
```
```python
>>> df.resample('2D').pipe(lambda x: x.max() - x.min())
   A
2012-08-02  1
2012-08-04  1
```

**34.18.3 Upsampling**

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<th>Resampler.ffill([limit])</th>
<th>Forward fill the values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resampler.backfill([limit])</td>
<td>Backward fill the new missing values in the resampled data.</td>
</tr>
</tbody>
</table>
In statistics, imputation is the process of replacing missing data with substituted values. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

<table>
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<tr>
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<td><strong>backfill</strong></td>
<td>Backward fill the new missing values in the resampled data.</td>
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<tr>
<td><strong>ffill</strong></td>
<td>Forward fill the values</td>
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<td><strong>pad</strong></td>
<td>Forward fill NaN values.</td>
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<td><strong>nearest</strong></td>
<td>Fill NaN values with nearest neighbor starting from center.</td>
</tr>
<tr>
<td><strong>fillna</strong></td>
<td>Fill missing values introduced by upsampling.</td>
</tr>
<tr>
<td><strong>interpolate</strong></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><strong>asfreq</strong></td>
<td>Return the values at the new freq, essentially a reindex.</td>
</tr>
</tbody>
</table>

### 34.18.3.1 pandas.core.resample.Resampler.ffill

**Resampler.ffill(limit=None)**

Forward fill the values.

- **Parameters**
  - `limit`: integer, optional
    - Limit of how many values to fill.

- **Returns**
  - An upsampled Series.

### 34.18.3.2 pandas.core.resample.Resampler.backfill

**Resampler.backfill(limit=None)**

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

- **Parameters**
  - `limit`: integer, optional
    - Limit of how many values to fill.

- **Returns**
  - Series, DataFrame
    - An upsampled Series or DataFrame with backward filled NaN values.

See also:
- `bfill` Alias of backfill.
- `fillna` Fill NaN values using the specified method, which can be ‘backfill’.
- `nearest` Fill NaN values with nearest neighbor starting from center.
- `pad` Forward fill NaN values.
- `pandas.Series.fillna` Fill NaN values in the Series using the specified method, which can be ‘backfill’.
- `pandas.DataFrame.fillna` Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.
Examples

Resampling a Series:

```python
>>> s = pd.Series([1, 2, 3],
                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64

>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64

>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1
2018-01-01 00:15:00   NaN
2018-01-01 00:30:00    2
2018-01-01 00:45:00    2
2018-01-01 01:00:00    2
2018-01-01 01:15:00   NaN
2018-01-01 01:30:00    3
2018-01-01 01:45:00    3
2018-01-01 02:00:00    3
Freq: 15T, dtype: float64
```

Resampling a DataFrame that has missing values:

```python
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
                    index=pd.date_range('20180101', periods=3,
                    freq='h'))
>>> df
     a   b
2018-01-01 2.0 1
2018-01-01  NaN 3
2018-01-01 6.0 5

>>> df.resample('30min').backfill()
     a   b
2018-01-01 2.0 1
2018-01-01  NaN 3
2018-01-01  NaN 3
2018-01-01 6.0 5
2018-01-01 6.0 5
```
34.18.3.3 pandas.core.resample.Resampler.bfill

Resampler.bfill(limit=None)

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values \([R31]\). When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

Parameters

- **limit**: integer, optional
  - Limit of how many values to fill.

Returns

- **Series, DataFrame**
  - An upsampled Series or DataFrame with backward filled NaN values.

See also:

- **bfill** Alias of backfill.
- **fillna** Fill NaN values using the specified method, which can be ‘backfill’.
- **nearest** Fill NaN values with nearest neighbor starting from center.
- **pad** Forward fill NaN values.
- **pandas.Series.fillna** Fill NaN values in the Series using the specified method, which can be ‘backfill’.
- **pandas.DataFrame.fillna** Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.

References

\([R31]\)

Examples

Resampling a Series:

```python
>>> s = pd.Series([1, 2, 3],
...                index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
```

(continues on next page)
Resampling a DataFrame that has missing values:

```python
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
                     index=pd.date_range('20180101', periods=3,
                     freq='h'))
>>> df
     a   b
2018-01-01 00:00:00 2.0 1
2018-01-01 01:00:00 NaN 3
2018-01-01 02:00:00 6.0 5
```

```python
>>> df.resample('30min').backfill()
          a   b
2018-01-01 00:00:00 2.0 1
2018-01-01 00:30:00 NaN NaN
2018-01-01 01:00:00 NaN NaN
2018-01-01 01:30:00 6.0 5
2018-01-01 02:00:00 6.0 5
```

```python
>>> df.resample('15min').backfill(limit=2)
          a   b
2018-01-01 00:00:00 2.0 1
2018-01-01 00:15:00 NaN NaN
2018-01-01 00:30:00 NaN 3
2018-01-01 00:45:00 NaN 3
2018-01-01 01:00:00 NaN 3
2018-01-01 01:15:00 NaN NaN
2018-01-01 01:30:00 6.0 5
2018-01-01 01:45:00 6.0 5
2018-01-01 02:00:00 6.0 5
```
34.18.3.4 pandas.core.resample.Resampler.pad

Resampler.pad(limit=None)
Forward fill the values

Parameters
limit : integer, optional
        limit of how many values to fill

Returns
an upsampled Series

See also:
Series.fillna, DataFrame.fillna

34.18.3.5 pandas.core.resample.Resampler.nearest

Resampler.nearest(limit=None)
Fill values with nearest neighbor starting from center

Parameters
limit : integer, optional
        limit of how many values to fill
New in version 0.21.0.

Returns
an upsampled Series

See also:
Series.fillna, DataFrame.fillna

34.18.3.6 pandas.core.resample.Resampler.fillna

Resampler.fillna(method, limit=None)
Fill missing values introduced by upsampling.

In statistics, imputation is the process of replacing missing data with substituted values [R32]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). Missing values that existed in the original data will not be modified.

Parameters
method : {'pad', 'backfill', 'ffill', 'bfill', 'nearest'}
        Method to use for filling holes in resampled data
        • ‘pad’ or ‘ffill’: use previous valid observation to fill gap (forward fill).
        • ‘backfill’ or ‘bfill’: use next valid observation to fill gap.
        • ‘nearest’: use nearest valid observation to fill gap.
limit : integer, optional
        Limit of how many consecutive missing values to fill.

Returns
Series or DataFrame
        An upsampled Series or DataFrame with missing values filled.

See also:
**backfill** Backward fill NaN values in the resampled data.

**pad** Forward fill NaN values in the resampled data.

**nearest** Fill NaN values in the resampled data with nearest neighbor starting from center.

**interpolate** Fill NaN values using interpolation.

**pandas.Series.fillna** Fill NaN values in the Series using the specified method, which can be ‘bfill’ and ‘ffill’.

**pandas.DataFrame.fillna** Fill NaN values in the DataFrame using the specified method, which can be ‘bfill’ and ‘ffill’.

**References**

[R32]

**Examples**

Resampling a Series:

```python
>>> s = pd.Series([1, 2, 3],
                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00 1
2018-01-01 01:00:00 2
2018-01-01 02:00:00 3
Freq: H, dtype: int64
```

Without filling the missing values you get:

```python
>>> s.resample("30min").asfreq()
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 NaN
2018-01-01 01:00:00 2.0
2018-01-01 01:30:00 NaN
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

```python
>>> s.resample('30min').fillna("backfill")
2018-01-01 00:00:00 1
2018-01-01 00:30:00 2
2018-01-01 01:00:00 2
2018-01-01 01:30:00 3
2018-01-01 02:00:00 3
Freq: 30T, dtype: int64
```

```python
>>> s.resample('15min').fillna("backfill", limit=2)
2018-01-01 00:00:00 1.0
2018-01-01 00:15:00 NaN
2018-01-01 00:30:00 2.0
2018-01-01 00:45:00 2.0
2018-01-01 01:00:00 2.0
2018-01-01 01:15:00 NaN
2018-01-01 01:30:00 3.0
```

(continues on next page)
<table>
<thead>
<tr>
<th>Time</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018-01-01 01:45:00</td>
<td>3.0</td>
</tr>
<tr>
<td>2018-01-01 02:00:00</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Freq: 15T, dtype: float64

```python
>>> s.resample('30min').fillna("pad")
2018-01-01 00:00:00 1
2018-01-01 00:30:00 1
2018-01-01 01:00:00 2
2018-01-01 01:30:00 2
2018-01-01 02:00:00 3
Freq: 30T, dtype: int64
```

```python
>>> s.resample('30min').fillna("nearest")
2018-01-01 00:00:00 1
2018-01-01 00:30:00 2
2018-01-01 01:00:00 2
2018-01-01 01:30:00 3
2018-01-01 02:00:00 3
Freq: 30T, dtype: int64
```

Missing values present before the upsampling are not affected.

```python
>>> sm = pd.Series([1, None, 3],
                  index=pd.date_range('20180101', periods=3, freq='h'))
>>> sm
2018-01-01 00:00:00     1.0
2018-01-01 01:00:00   NaN
2018-01-01 02:00:00     3.0
Freq: H, dtype: float64
```

```python
>>> sm.resample('30min').fillna('backfill')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 NaN
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 3.0
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

```python
>>> sm.resample('30min').fillna('pad')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 1.0
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 NaN
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

```python
>>> sm.resample('30min').fillna('nearest')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 NaN
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 3.0
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

Dataframe resampling is done column-wise. All the same options are available.
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...       index=pd.date_range('20180101', periods=3,
...       freq='h'))
>>> df
   a     b
2018-01-01 00:00:00 2.0 1
2018-01-01 01:00:00 NaN 3
2018-01-01 02:00:00 6.0 5

>>> df.resample('30min').fillna("bfill")
   a     b
2018-01-01 00:00:00 2.0 1
2018-01-01 00:30:00 NaN 3
2018-01-01 01:00:00 NaN 3
2018-01-01 01:30:00 6.0 5
2018-01-01 02:00:00 6.0 5

34.18.3.7 pandas.core.resample.Resampler.asfreq

Resampler.asfreq(fill_value=None)

return the values at the new freq, essentially a reindex

Parameters fill_value: scalar, optional

Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

New in version 0.20.0.

See also:
Series.asfreq, DataFrame.asfreq

34.18.3.8 pandas.core.resample.Resampler.interpolate

Resampler.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)

Interpolate values according to different methods.

New in version 0.18.1.

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', 'from_derivatives', 'pchip', 'akima'}

  • ‘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’, ‘pchip’ and ‘akima’ are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. For more information on their behavior, see the scipy documentation and tutorial documentation

- ‘from_derivatives’ refers to BPoly.from_derivatives which replaces ‘piecewise_polynomial’ interpolation method in scipy 0.18

New in version 0.18.1: Added support for the ‘akima’ method Added interpolate method ‘from_derivatives’ which replaces ‘piecewise_polynomial’ in scipy 0.18; backwards-compatible with scipy < 0.18

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. Must be greater than 0.

limit_direction : [{‘forward’, ‘backward’, ‘both’}, default ‘forward’]

limit_area : {‘inside’, ‘outside’}, default None

- None: (default) no fill restriction
- ‘inside’ Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’ Only fill NaNs outside valid values (extrapolate).

If limit is specified, consecutive NaNs will be filled in this direction.

New in version 0.21.0.

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

34.18.4 Computations / Descriptive Stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resampler.count</td>
<td>Compute count of group, excluding missing values</td>
</tr>
<tr>
<td>Resampler.nunique</td>
<td>Returns number of unique elements in the group</td>
</tr>
<tr>
<td>Resampler.first</td>
<td>Compute first of group values</td>
</tr>
<tr>
<td>Resampler.last</td>
<td>Compute last of group values</td>
</tr>
<tr>
<td>Resampler.max</td>
<td>Compute max of group values</td>
</tr>
<tr>
<td>Resampler.mean</td>
<td>Compute mean of groups, excluding missing values</td>
</tr>
<tr>
<td>Resampler.median</td>
<td>Compute median of groups, excluding missing values</td>
</tr>
<tr>
<td>Resampler.min</td>
<td>Compute min of group values</td>
</tr>
<tr>
<td>Resampler.ohlc</td>
<td>Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex</td>
</tr>
<tr>
<td>Resampler.prod</td>
<td>Compute prod of group values</td>
</tr>
<tr>
<td>Resampler.size</td>
<td>Compute group sizes</td>
</tr>
<tr>
<td>Resampler.sem</td>
<td>Compute standard error of the mean of groups, excluding missing values</td>
</tr>
<tr>
<td>Resampler.std</td>
<td>Compute standard deviation of groups, excluding missing values</td>
</tr>
<tr>
<td>Resampler.sum</td>
<td>Compute sum of group values</td>
</tr>
<tr>
<td>Resampler.var</td>
<td>Compute variance of groups, excluding missing values</td>
</tr>
</tbody>
</table>

34.18.4.1 pandas.core.resample.Resampler.count

Resampler.count(_method='count')
Compute count of group, excluding missing values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.2 pandas.core.resample.Resampler.nunique

Resampler.nunique(_method='nunique')
Returns number of unique elements in the group

34.18.4.3 pandas.core.resample.Resampler.first

Resampler.first(_method='first', *args, **kwargs)
Compute first of group values

See also:
pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.18.4.4 pandas.core.resample.Resampler.last

Resampler.last(_method='last', *args, **kwargs)
    Compute last of group values

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.5 pandas.core.resample.Resampler.max

Resampler.max(_method='max', *args, **kwargs)
    Compute max of group values

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.6 pandas.core.resample.Resampler.mean

Resampler.mean(_method='mean', *args, **kwargs)
    Compute mean of groups, excluding missing values
    For multiple groupings, the result index will be a MultiIndex

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.7 pandas.core.resample.Resampler.median

Resampler.median(_method='median', *args, **kwargs)
    Compute median of groups, excluding missing values
    For multiple groupings, the result index will be a MultiIndex

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.8 pandas.core.resample.Resampler.min

Resampler.min(_method='min', *args, **kwargs)
    Compute min of group values

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.9 pandas.core.resample.Resampler.ohlc

Resampler.ohlc(_method='ohlc', *args, **kwargs)
    Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex

See also:
    pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.18.4.10 pandas.core.resample.Resampler.prod

Resampler.prod(_method='prod', min_count=0, *args, **kwargs)
Compute prod of group values

See also:

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.11 pandas.core.resample.Resampler.size

Resampler.size()
Compute group sizes

See also:

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.12 pandas.core.resample.Resampler.sem

Resampler.sem(_method='sem', *args, **kwargs)
Compute standard error of the mean of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

Parameters
ddof : integer, default 1
  degrees of freedom

See also:

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby

34.18.4.13 pandas.core.resample.Resampler.std

Resampler.std(ddof=1, *args, **kwargs)
Compute standard deviation of groups, excluding missing values

Parameters
ddof [integer, default 1]
  degrees of freedom

34.18.4.14 pandas.core.resample.Resampler.sum

Resampler.sum(_method='sum', min_count=0, *args, **kwargs)
Compute sum of group values

See also:

pandas.Series.groupby, pandas.DataFrame.groupby, pandas.Panel.groupby
34.18.4.15 pandas.core.resample.Resampler.var

Resampler.var(ddof=1, *args, **kwargs)
Compute variance of groups, excluding missing values

Parameters

ddof [integer, default 1]
degrees of freedom

34.19 Style

Styler objects are returned by pandas.DataFrame.style.

34.19.1 Styler Constructor

Styler(data[, precision, table_styles, ...])
Helps style a DataFrame or Series according to the data with HTML and CSS.

Styler.from_custom_template(searchpath, name)
Factory function for creating a subclass of Styler with a custom template and Jinja environment.

34.19.1.1 pandas.io.formats.style.Styler

class pandas.io.formats.style.Styler(data, precision=None, table_styles=None, uuid=None, caption=None, table_attributes=None)
Helps style a DataFrame or Series according to the data with HTML and CSS.

Parameters

data: Series or DataFrame
precision: int
precision to round floats to, defaults to pd.options.display.precision

table_styles: list-like, default None
list of {selector: (attr, value)} dicts; see Notes

uuid: str, default None
a unique identifier to avoid CSS collisions; generated automatically

caption: str, default None
caption to attach to the table

See also:
pandas.DataFrame.style

Notes

Most styling will be done by passing style functions into Styler.apply or Styler.applymap. Style functions should return values with strings containing CSS 'attr: value' that will be applied to the indicated cells.
If using in the Jupyter notebook, Styler has defined a _repr_html_ to automatically render itself. Otherwise call Styler.render to get the generated HTML.

CSS classes are attached to the generated HTML:

- Index and Column names include index_name and level<k> where k is its level in a MultiIndex
- Index label cells include
  - row_heading
  - row<n> where n is the numeric position of the row
  - level<k> where k is the level in a MultiIndex
- Column label cells include *col_heading* *col<n>* where n is the numeric position of the column
  *level<k>* where k is the level in a MultiIndex
- Blank cells include blank
- Data cells include data

## Attributes

<table>
<thead>
<tr>
<th>env</th>
<th>(Jinja2 Environment)</th>
</tr>
</thead>
<tbody>
<tr>
<td>template</td>
<td>(Jinja2 Template)</td>
</tr>
<tr>
<td>loader</td>
<td>(Jinja2 Loader)</td>
</tr>
</tbody>
</table>

## Methods

- **apply**(func[, axis, subset]) Apply a function column-wise, row-wise, or table-wise, updating the HTML representation with the result.
- **applymap**(func[, subset]) Apply a function elementwise, updating the HTML representation with the result.
- **background_gradient**([, cmap, low, high, axis, ...]) Color the background in a gradient according to the data in each column (optionally row).
- **bar**([, subset, axis, color, width, align]) Color the background color proportional to the values in each column.
- **clear**() “Reset” the styler, removing any previously applied styles.
- **export**() Export the styles to applied to the current Styler.
- **format**(formatter[, subset]) Format the text display value of cells.
- **from_custom_template**(searchpath, name) Factory function for creating a subclass of Styler with a custom template and Jinja environment.
- **hide_columns**(subset) Hide columns from rendering.
- **hide_index**() Hide any indices from rendering.
- **highlight_max**([, subset, color, axis]) Highlight the maximum by shading the background
- **highlight_min**([, subset, color, axis]) Highlight the minimum by shading the background
- **highlight_null**([, null_color]) Shade the background null_color for missing values.
- **render**(**kwargs) Render the built up styles to HTML
- **set_caption**(caption) Set the caption on a Styler

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#### Table 175 – continued from previous page

<table>
<thead>
<tr>
<th>Method/Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>set_precision(precision)</code></td>
<td>Set the precision used to render.</td>
</tr>
<tr>
<td><code>set_properties([subset])</code></td>
<td>Convenience method for setting one or more non-data dependent properties or each cell.</td>
</tr>
<tr>
<td><code>set_table_attributes(attributes)</code></td>
<td>Set the table attributes.</td>
</tr>
<tr>
<td><code>set_table_styles(table_styles)</code></td>
<td>Set the table styles on a Styler.</td>
</tr>
<tr>
<td><code>set_uuid(uuid)</code></td>
<td>Set the uuid for a Styler.</td>
</tr>
<tr>
<td><code>to_excel(excel_writer[, sheet_name, na_rep, ...])</code></td>
<td>Write Styler to an excel sheet</td>
</tr>
<tr>
<td><code>use(styles)</code></td>
<td>Set the styles on the current Styler, possibly using styles from Styler.export.</td>
</tr>
<tr>
<td><code>where(cond, value[, other, subset])</code></td>
<td>Apply a function elementwise, updating the HTML representation with a style which is selected in accordance with the return value of a function.</td>
</tr>
</tbody>
</table>

---

#### pandas.io.formats.style.Styler.apply

**Styler.apply** *(func, axis=0, subset=None, **kwargs)*

Apply a function column-wise, row-wise, or table-wise, updating the HTML representation with the result.

**Parameters**

- **func**: function
  
  `func` should take a Series or DataFrame (depending on `axis`), and return an object with the same shape. Must return a DataFrame with identical index and column labels when `axis=None`
  
  - **axis**: int, str or None
    
    apply to each column (`axis=0` or `'index'`) or to each row (`axis=1` or `'columns'`) or to the entire DataFrame at once with `axis=None`
  
  - **subset**: IndexSlice
    
    a valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice
  
  - **kwargs**: dict
    
    pass along to `func`

**Returns**

- **self** [Styler]

**Notes**

The output shape of `func` should match the input, i.e. if `x` is the input row, column, or table (depending on `axis`), then `func(x.shape) == x.shape` should be true.

This is similar to `DataFrame.apply`, except that `axis=None` applies the function to the entire DataFrame at once, rather than column-wise or row-wise.
Examples

```python
>>> def highlight_max(x):
...     return ['background-color: yellow' if v == x.max() else ''
...             for v in x]
...     
>>> df = pd.DataFrame(np.random.randn(5, 2))
>>> df.style.apply(highlight_max)
```

**pandas.io.formats.style.Styler.applymap**

Styler.applymap (func, subset=None, **kwargs)

Apply a function elementwise, updating the HTML representation with the result.

- **Parameters**
  - **func**: function
    - func should take a scalar and return a scalar
  - **subset**: IndexSlice
    - a valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice
  - **kwargs**: dict
    - pass along to func

- **Returns**
  - self [Styler]

See also:

Styler.where

**pandas.io.formats.style.Styler.background_gradient**

Styler.background_gradient (cmap='PuBu', low=0, high=0, axis=0, subset=None)

Color the background in a gradient according to the data in each column (optionally row). Requires matplotlib.

- **Parameters**
  - **cmap**: str or colormap
    - matplotlib colormap
  - **low, high**: float
    - compress the range by these values.
  - **axis**: int or str
    - 1 or ‘columns’ for columnwise, 0 or ‘index’ for rowwise
  - **subset**: IndexSlice
    - a valid slice for data to limit the style application to

- **Returns**
  - self [Styler]
Notes

Tune low and high to keep the text legible by not using the entire range of the color map. These extend the range of the data by \( \text{low} \times (x_{\text{max}} - x_{\text{min}}) \) and \( \text{high} \times (x_{\text{max}} - x_{\text{min}}) \) before normalizing.

**pandas.io.formats.style.Styler.bar**

Styler.bar(subset=None, axis=0, color='#d65f5f', width=100, align='left')

Color the background color proportional to the values in each column. Excludes non-numeric data by default.

**Parameters**

- **subset**: IndexSlice, default None
  
a valid slice for data to limit the style application to

- **axis**: int

- **color**: str or 2-tuple/list
  
  If a str is passed, the color is the same for both negative and positive numbers. If 2-tuple/list is used, the first element is the color_negative and the second is the color_positive (eg: ['#d65f5f', '#5fba7d'])

- **width**: float
  
  A number between 0 or 100. The largest value will cover width percent of the cell’s width

- **align**: {'left', 'zero', 'mid'}, default ‘left’
  
  • ‘left’: the min value starts at the left of the cell
  • ‘zero’: a value of zero is located at the center of the cell
  • ‘mid’: the center of the cell is at (max-min)/2, or if values are all negative (positive) the zero is aligned at the right (left) of the cell

New in version 0.20.0.

**Returns**

self [Styler]

**pandas.io.formats.style.Styler.clear**

Styler.clear()

“Reset” the styler, removing any previously applied styles. Returns None.

**pandas.io.formats.style.Styler.export**

Styler.export()

Export the styles to applied to the current Styler. Can be applied to a second style with Styler.use.

**Returns**

styles: list
See also:

Styler.use

pandas.io.formats.style.Styler.format

Styler.format (formatter, subset=None)

Format the text display value of cells.

New in version 0.18.0.

Parameters

- formatter: str, callable, or dict
- subset: IndexSlice

  An argument to DataFrame.loc that restricts which elements formatter is applied to.

Returns

- self [Styler]

Notes

- formatter is either an a or a dict {column name: a} where a is one of
  - str: this will be wrapped in: a.format(x)
  - callable: called with the value of an individual cell

The default display value for numeric values is the “general” (g) format with pd.options.display.precision precision.

Examples

```python
>>> df = pd.DataFrame(np.random.randn(4, 2), columns=['a', 'b'])
>>> df.style.format('0:.2%')
>>> df['c'] = ['a', 'b', 'c', 'd']
>>> df.style.format({'c': str.upper})
```

pandas.io.formats.style.Styler.from_custom_template

classmethod Styler.from_custom_template(searchpath, name)

Factory function for creating a subclass of Styler with a custom template and Jinja environment.

Parameters

- searchpath: str or list
  Path or paths of directories containing the templates
- name: str
  Name of your custom template to use for rendering

Returns

- MyStyler: subclass of Styler
  has the correct env and template class attributes set.
pandas.io.formats.style.Styler.hide_columns

Styler.hide_columns(subset)
Hide columns from rendering.
New in version 0.23.0.

Parameters subset: IndexSlice
An argument to DataFrame.loc that identifies which columns are hidden.

Returns
self [Styler]

pandas.io.formats.style.Styler.hide_index

Styler.hide_index()
Hide any indices from rendering.
New in version 0.23.0.

Returns
self [Styler]

pandas.io.formats.style.Styler.highlight_max

Styler.highlight_max(subset=None, color='yellow', axis=0)
Highlight the maximum by shading the background

Parameters subset: IndexSlice, default None
a valid slice for data to limit the style application to

color: str, default ‘yellow’

axis: int, str, or None; default 0
0 or ‘index’ for columnwise (default), 1 or ‘columns’ for rowwise, or None for tablewise

Returns
self [Styler]

pandas.io.formats.style.Styler.highlight_min

Styler.highlight_min(subset=None, color='yellow', axis=0)
Highlight the minimum by shading the background

Parameters subset: IndexSlice, default None
a valid slice for data to limit the style application to

color: str, default ‘yellow’

axis: int, str, or None; default 0
0 or ‘index’ for columnwise (default), 1 or ‘columns’ for rowwise, or None for
tablewise

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_null

Styler.highlight_null(null_color='red')

Shade the background null_color for missing values.

Parameters

null_color: str

Returns

self [Styler]

pandas.io.formats.style.Styler.render

Styler.render(**kwargs)

Render the built up styles to HTML

Parameters **kwargs:

Any additional keyword arguments are passed through to self.template.
render. This is useful when you need to provide additional variables for a
custom template.

New in version 0.20.

Returns rendered: str

the rendered HTML

Notes

Styler objects have defined the _repr_html_ method which automatically calls self.render() when it's the last item in a Notebook cell. When calling Styler.render() directly, wrap the result in IPython.display.HTML to view the rendered HTML in the notebook.

Pandas uses the following keys in render. Arguments passed in **kwargs take precedence, so think carefully if you want to override them:

• head
• cellstyle
• body
• uuid
• precision
• table_styles
• caption
• table_attributes
pandas.io.formats.style.Styler.set_caption

Styler.set_caption(caption)
Set the caption on a Styler

Parameters
  caption: str

Returns
  self [Styler]

pandas.io.formats.style.Styler.set_precision

Styler.set_precision(precision)
Set the precision used to render.

Parameters
  precision: int

Returns
  self [Styler]

pandas.io.formats.style.Styler.set_properties

Styler.set_properties(subset=None, **kwargs)
Convenience method for setting one or more non-data dependent properties or each cell.

Parameters
  subset: IndexSlice
    a valid slice for data to limit the style application to
  kwargs: dict
    property: value pairs to be set for each cell

Returns
  self [Styler]

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_properties(color="white", align="right")
>>> df.style.set_properties(**{'background-color': 'yellow'})
```

pandas.io.formats.style.Styler.set_table_attributes

Styler.set_table_attributes(attributes)
Set the table attributes. These are the items that show up in the opening <table> tag in addition to automatic (by default) id.

Parameters
attributes [string]

Returns

self [Styler]

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_attributes('class="pure-table"')
# ... <table class="pure-table"> ...
```

pandas.io.formats.style.Styler.set_table_styles

Styler.set_table_styles(table_styles)

Set the table styles on a Styler. These are placed in a <style> tag before the generated HTML table.

Parameters

- table_styles: list
  
  Each individual table_style should be a dictionary with selector and props keys. selector should be a CSS selector that the style will be applied to (automatically prefixed by the table’s UUID) and props should be a list of tuples with (attribute, value).

Returns

self [Styler]

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_styles([{'selector': 'tr:hover',
...                           'props': [('background-color', 'yellow')]}])
```

pandas.io.formats.style.Styler.set_uuid

Styler.set_uuid(uuid)

Set the uuid for a Styler.

Parameters

- uuid: str

Returns

self [Styler]
pandas.io.formats.style.Styler.to_excel

Styler.to_excel(excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True, freeze_panes=None)

Write Styler to an excel sheet

New in version 0.20.

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 the column names. If a list of strings 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

gine : 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)**

**freeze_panes** : tuple of integer (length 2), default None

Specifies the one-based bottommost row and rightmost column that is to be frozen

New in version 0.20.0.

**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 = pd.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.io.formats.style.Styler.use**

```python
Styler.use(styles)
```

Set the styles on the current Styler, possibly using styles from Styler.export.

**Parameters**
- **styles**: list
  - list of style functions

**Returns**
- **self** [Styler]

**See also:**
- Styler.export

**pandas.io.formats.style.Styler.where**

```python
Styler.where(cond, value=None, other=None, subset=None, **kwargs)
```

Apply a function elementwise, updating the HTML representation with a style which is selected in accordance with the return value of a function.

New in version 0.21.0.

**Parameters**
- **cond** : callable
  - `cond` should take a scalar and return a boolean
- **value** : str
  - applied when `cond` returns true
- **other** : str
  - applied when `cond` returns false
- **subset** : IndexSlice
  - a valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice
kwarg : dict
    pass along to cond

Returns
self [Styler]

See also:
Styler.applymap

34.19.2 Styler Attributes

Styler.env
Styler.template
Styler.loader

34.19.2.1 pandas.io.formats.style.Styler.env

Styler.env = <jinja2.environment.Environment object>

34.19.2.2 pandas.io.formats.style.Styler.template

Styler.template = <Template 'html.tpl'>

34.19.2.3 pandas.io.formats.style.Styler.loader

Styler.loader = <jinja2.loaders.PackageLoader object>

34.19.3 Style Application

Styler.apply(func[, axis, subset])  Apply a function column-wise, row-wise, or table-wise, updating the HTML representation with the result.

Styler.applymap(func[, subset])  Apply a function elementwise, updating the HTML representation with the result.

Styler.where(cond, value[, other, subset])  Apply a function elementwise, updating the HTML representation with a style which is selected in accordance with the return value of a function.

Styler.format(formatter[, subset])  Format the text display value of cells.

Styler.set_precision(precision)  Set the precision used to render.

Styler.set_table_styles(table_styles)  Set the table styles on a Styler.

Styler.set_table_attributes(attributes)  Set the table attributes.

Styler.set_caption(caption)  Set the caption on a Styler

Styler.set_properties([subset])  Convenience method for setting one or more non-data dependent properties or each cell.

Styler.set_uuid(uuid)  Set the uuid for a Styler.

Styler.clear()  “Reset” the styler, removing any previously applied styles.
34.19.4 Built-in Styles

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Styler.highlight_max([subset, color, axis])</code></td>
<td>Highlight the maximum by shading the background</td>
</tr>
<tr>
<td><code>Styler.highlight_min([subset, color, axis])</code></td>
<td>Highlight the minimum by shading the background</td>
</tr>
<tr>
<td><code>Styler.highlight_null([null_color])</code></td>
<td>Shade the background <code>null_color</code> for missing values.</td>
</tr>
<tr>
<td><code>Styler.background_gradient([cmap, low, ...])</code></td>
<td>Color the background in a gradient according to the data in each column (optionally row).</td>
</tr>
<tr>
<td><code>Styler.bar([subset, axis, color, width, align])</code></td>
<td>Color the background <code>color</code> proportional to the values in each column.</td>
</tr>
</tbody>
</table>

34.19.5 Style Export and Import

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Styler.render(**kwargs)</code></td>
<td>Render the built up styles to HTML</td>
</tr>
<tr>
<td><code>Styler.export()</code></td>
<td>Export the styles to applied to the current Styler.</td>
</tr>
<tr>
<td><code>Styler.use(styles)</code></td>
<td>Set the styles on the current Styler, possibly using styles from <code>Styler.export</code>.</td>
</tr>
<tr>
<td><code>Styler.to_excel(excel_writer[, sheet_name, ...])</code></td>
<td>Write Styler to an excel sheet</td>
</tr>
</tbody>
</table>

34.20 Plotting

The following functions are contained in the `pandas.plotting` module.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>andrews_curves(frame, class_column[, ax,...])</code></td>
<td>Generates a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.</td>
</tr>
<tr>
<td><code>bootstrap_plot(series[, fig, size, samples])</code></td>
<td>Bootstrap plot on mean, median and mid-range statistics.</td>
</tr>
<tr>
<td><code>deregister_matplotlib_converters()</code></td>
<td>Remove pandas’ formatters and converters</td>
</tr>
<tr>
<td><code>lag_plot(series[, lag, ax])</code></td>
<td>Lag plot for time series.</td>
</tr>
<tr>
<td><code>parallel_coordinates(frame, class_column[, ...])</code></td>
<td>Parallel coordinates plotting.</td>
</tr>
<tr>
<td><code>radviz(frame, class_column[, ax, color, ...])</code></td>
<td>Plot a multidimensional dataset in 2D.</td>
</tr>
<tr>
<td><code>register_matplotlib_converters([explicit])</code></td>
<td>Register Pandas Formatters and Converters with matplotlib</td>
</tr>
<tr>
<td><code>scatter_matrix(frame[, alpha, figsize, ax,...])</code></td>
<td>Draw a matrix of scatter plots.</td>
</tr>
</tbody>
</table>

34.20.1 pandas.plotting.andrews_curves

`pandas.plotting.andrews_curves(frame, class_column, ax=None, samples=200, color=None, colormap=None, **kwds)`

Generates a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.

Andrews curves have the functional form:

\[ f(t) = \frac{x_1}{\sqrt{2}} + x_2 \sin(t) + x_3 \cos(t) + x_4 \sin(2t) + x_5 \cos(2t) + \ldots \]

Where `x` coefficients correspond to the values of each dimension and `t` is linearly spaced between `-pi` and `+pi`. Each row of `frame` then corresponds to a single curve.

**Parameters**

- `frame` : DataFrame

34.20. Plotting
Data to be plotted, preferably normalized to (0.0, 1.0)

**class_column** [Name of the column containing class names]

**ax** [matplotlib axes object, default None]

**samples** [Number of points to plot in each curve]

**color**: list or tuple, optional

Colors to use for the different classes

**colormap** : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

**kwds**: keywords

Options to pass to matplotlib plotting method

Returns

**ax**: Matplotlib axis object

### 34.20.2 pandas.plotting.bootstrap_plot

**pandas.plotting.bootstrap_plot** *(series, fig=None, size=50, samples=500, **kwds)*

Bootstrap plot on mean, median and mid-range statistics.

The bootstrap plot is used to estimate the uncertainty of a statistic by relaying on random sampling with replacement [R33]. This function will generate bootstrapping plots for mean, median and mid-range statistics for the given number of samples of the given size.

**Parameters**

- **series**: pandas.Series
  
  Pandas Series from where to get the samplings for the bootstrapping.

- **fig**: matplotlib.figure.Figure, default None
  
  If given, it will use the fig reference for plotting instead of creating a new one with default parameters.

- **size**: int, default 50
  
  Number of data points to consider during each sampling. It must be greater or equal than the length of the series.

- **samples**: int, default 500
  
  Number of times the bootstrap procedure is performed.

- **kwds**:

  Options to pass to matplotlib plotting method.

**Returns**

- **fig**: matplotlib.figure.Figure
  
  Matplotlib figure

See also:

- **pandas.DataFrame.plot** Basic plotting for DataFrame objects.
- **pandas.Series.plot** Basic plotting for Series objects.
Examples

```python
>>> import numpy as np
>>> s = pd.Series(np.random.uniform(size=100))
>>> fig = pd.plotting.bootstrap_plot(s)
```

### 34.20.3 pandas.plotting.deregister_matplotlib_converters

`deregister_matplotlib_converters()`

Remove pandas’ formatters and converters

Removes the custom converters added by `register()`. This attempts to set the state of the registry back to the state before pandas registered its own units. Converters for pandas’ own types like Timestamp and Period are removed completely. Converters for types pandas overwrites, like `datetime.datetime`, are restored to their original value.

**See also:**

deregister_matplotlib_converters

### 34.20.4 pandas.plotting.lag_plot

`lag_plot(series, lag=1, ax=None, **kwds)`

Lag plot for time series.

**Parameters**

- `series`: Time series
- `lag`: lag of the scatter plot, default 1
- `ax`: Matplotlib axis object, optional
- `kwds`: Matplotlib scatter method keyword arguments, optional

**Returns**

- `ax`: Matplotlib axis object

### 34.20.5 pandas.plotting.parallel_coordinates

`parallel_coordinates(frame, class_column, cols=None, ax=None, color=None, use_columns=False, xticks=None, colormap=None, axvlines=True, axvlines_kwds=None, sort_labels=False, **kwds)`

Parallel coordinates plotting.

**Parameters**

- `frame`: DataFrame
- `class_column`: str
  
  Column name containing class names
- `cols`: list, optional
  
  A list of column names to use
**pandas: powerful Python data analysis toolkit, Release 0.23.1**

ax: matplotlib.axis, optional
    matplotlib axis object

color: list or tuple, optional
    Colors to use for the different classes

use_columns: bool, optional
    If true, columns will be used as xticks

xticks: list or tuple, optional
    A list of values to use for xticks

colormap: str or matplotlib colormap, default None
    Colormap to use for line colors.

axvlines: bool, optional
    If true, vertical lines will be added at each xtick

axvlines_kwds: keywords, optional
    Options to be passed to axvline method for vertical lines

sort_labels: bool, False
    Sort class_column labels, useful when assigning colors
    New in version 0.20.0.

kwds: keywords
    Options to pass to matplotlib plotting method

Returns
    ax: matplotlib axis object

**Examples**

```python
>>> from pandas import read_csv
>>> from pandas.tools.plotting import parallel_coordinates
>>> from matplotlib import pyplot as plt

>>> df = read_csv('https://raw.github.com/pandas-dev/pandas/master' +
    '/pandas/tests/data/iris.csv')

>>> parallel_coordinates(df, 'Name', color=('#556270',
    '#4ECDC4', '#C7F464'))

>>> plt.show()
```

**34.20.6 pandas.plotting.radviz**

pandas.plotting.radviz(frame, class_column, ax=None, color=None, colormap=None, **kwds)

Plot a multidimensional dataset in 2D.

Each Series in the DataFrame is represented as a evenly distributed slice on a circle. Each data point is rendered in the circle according to the value on each Series. Highly correlated Series in the DataFrame are placed closer on the unit circle.
RadViz allow to project a N-dimensional data set into a 2D space where the influence of each dimension can be interpreted as a balance between the influence of all dimensions.

More info available at the original article describing RadViz.

**Parameters**

- **frame**: `DataFrame`
  - Pandas object holding the data.

- **class_column**: `str`
  - Column name containing the name of the data point category.

- **ax**: `matplotlib.axes.Axes`, optional
  - A plot instance to which to add the information.

- **color**: `list[str]` or `tuple[str]`, optional
  - Assign a color to each category. Example: ['blue', 'green'].

- **colormap**: `str` or `matplotlib.colors.Colormap`, default None
  - Colormap to select colors from. If string, load colormap with that name from matplotlib.

- **kwds**: optional
  - Options to pass to matplotlib scatter plotting method.

**Returns**

- **axes**: `[matplotlib.axes.Axes]`

**See also:**

- `pandas.plotting.andrews_curves` Plot clustering visualization

**Examples**

```python
>>> df = pd.DataFrame({
...    'SepalLength': [6.5, 7.7, 5.1, 5.8, 7.6, 5.0, 5.4, 4.6,
...                     6.7, 4.6],
...    'SepalWidth': [3.0, 3.8, 3.8, 2.7, 3.0, 2.3, 3.0, 3.2,
...                    3.3, 3.6],
...    'PetalLength': [5.5, 6.7, 1.9, 5.1, 6.6, 3.3, 4.5, 1.4,
...                     5.7, 1.0],
...    'PetalWidth': [1.8, 2.2, 0.4, 1.9, 2.1, 1.0, 1.5, 0.2,
...                   2.1, 0.2],
...    'Category': ['virginica', 'virginica', 'setosa',
...                  'virginica', 'virginica', 'versicolor',
...                  'versicolor', 'setosa', 'virginica',
...                  'setosa']
... })
>>> rad_viz = pd.plotting.radviz(df, 'Category')
```

### 34.20.7 pandas.plotting.register_matplotlib_converters

`pandas.plotting.register_matplotlib_converters`(*explicit=True*)

Register Pandas Formatters and Converters with matplotlib
This function modifies the global `matplotlib.units.registry` dictionary. Pandas adds custom converters for:

- `pd.Timestamp`
- `pd.Period`
- `np.datetime64`
- `datetime.datetime`
- `datetime.date`
- `datetime.time`

See also:

deregister_matplotlib_converter

### 34.20.8 `pandas.plotting.scatter_matrix`

**pandas.plotting.scatter_matrix** *(frame, alpha=0.5, figsize=None, ax=None, grid=False, diagonal='hist', marker='.', density_kwds=None, hist_kwds=None, range_padding=0.05, **kwds)*

Draw a matrix of scatter plots.

**Parameters**

- **frame** ([DataFrame])
- **alpha** : float, optional
  amount of transparency applied
- **figsize** : (float,float), optional
  a tuple (width, height) in inches
- **ax** : [Matplotlib axis object, optional]
- **grid** : bool, optional
  setting this to True will show the grid
- **diagonal** : {'hist', 'kde'}
  pick between 'kde' and 'hist' for either Kernel Density Estimation or Histogram plot in the diagonal
- **marker** : str, optional
  Matplotlib marker type, default ‘.’
- **hist_kwds** : other plotting keyword arguments
  To be passed to hist function
- **density_kwds** : other plotting keyword arguments
  To be passed to kernel density estimate plot
- **range_padding** : float, optional
  relative extension of axis range in x and y with respect to `(x_max - x_min) or (y_max - y_min)`, default 0.05
kwds : other plotting keyword arguments

To be passed to scatter function

Examples

```python
>>> df = DataFrame(np.random.randn(1000, 4), columns=['A','B','C','D'])
>>> scatter_matrix(df, alpha=0.2)
```

## 34.21 General utility functions

### 34.21.1 Working with options

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#### 34.21.1.1 pandas.describe_option

```python
pandas.describe_option (pat, _print_desc=False) = <pandas.core.config.CallableDynamicDoc object>
```

Prints the description for one or more registered options.

Call with no arguments to get a listing for all registered options.

Available options:

- `compute.[use_bottleneck, use_numexpr]`
- `display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]`
- `display.html.[border, table_schema, use_mathjax]`
- `display.[large repr]`
- `display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]`
- `display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]`
- `display.unicode.[ambiguous_as_wide, east_asian_width]`
- `display.[width]`
- `html.[border]`
- `io.excel.xls.[writer]`
- `io.excel.xlsm.[writer]`
- `io.excel.xlsx.[writer]`
Parameters

pat : str

Regexp pattern. All matching keys will have their description displayed.

_print_desc : bool, default True

If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

Returns

None by default, the description(s) as a unicode string if _print_desc is False

Notes

The available options with its descriptions:

compute.use_bottleneck [bool] Use the bottleneck library to accelerate if it is installed, the default is True
 Valid values: False,True [default: True] [currently: True]

compute.use_numexpr [bool] Use the numexpr library to accelerate computation if it is installed, the default is True
 Valid values: False,True [default: True] [currently: True]

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple "pages" if its width exceeds display.width. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

display.html.border [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]
display.html.table_schema [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

display.html.use_mathjax [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

display.large_repr [‘truncate’/’info’] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable [bool] This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: True]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: 1] [currently: 1]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int] 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 than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “… ” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]
display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,’deep’ [default: True] [currently: True]

display.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]

html.border [int] A border= \n attribute is inserted in the  tag for the DataFrame HTML repr. [default: 1] [currently: 1] (Deprecated, use display.html.border instead.)


io.hdf.default_format [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]
mode.use_inf_as_null  [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)

plotting.matplotlib.register_converters  [bool] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: True] [currently: True]

34.21.1.2 pandas.reset_option

pandas.reset_option (pat) = <pandas.core.config.CallableDynamicDoc object>
Reset one or more options to their default value.
Pass “all” as argument to reset all options.

Available options:

• compute.[use_bottleneck, use_numexpr]
• display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
• display.html.[border, table_schema, use_mathjax]
• display.large_repr
• display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
• display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
• display.unicode.[ambiguous_as_wide, east_asian_width]
• display.[width]
• html.[border]
• io.excel.xls.[writer]
• io.excel.xlsm.[writer]
• io.excel.xlsx.[writer]
• io.hdf.[default_format, dropna_table]
• io.parquet.[engine]
• mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
• plotting.matplotlib.[register_converters]

Parameters pat  : str/regex

If specified only options matching prefix* will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns None

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Notes

The available options with its descriptions:

**compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True. Valid values: False, True [default: True] [currently: True]

**compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True. Valid values: False, True [default: True] [currently: True]

**display.chop_threshold** [float or None] If set to a float value, all float values smaller than the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

**display.colheader_justify** ['left'/ 'right'] Controls the justification of column headers. Used by DataFrameFormatter. [default: right] [currently: right]

**display.column_space** No description available. [default: 12] [currently: 12]

**display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

**display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

**display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple "pages" if its width exceeds display.width. [default: True] [currently: True]

**display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. [default: False] [currently: False]

**display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. [default: True] [currently: True]

**display.large_repr** ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False, True [default: False] [currently: False]

**display.latex.longtable :bool** This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False, True [default: False] [currently: False]

**display.latex.multicolumn** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False, True [default: False] [currently: False]

**display.latex.multicolumn_format** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False, True [default: False] [currently: False]
**display.latex.multirow** [bool] This specifies if the to_latex method of a DataFrame uses multirows to pretty-print MultiIndex rows. Valid values: False, True [default: False] [currently: False]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max_categories** [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max_columns** [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max_colwidth** [int] 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 than specified. [default: 1690785] [currently: 1690785]

**display.max_rows** [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max_seq_items** [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True, False, ‘deep’ [default: True] [currently: True]

**display.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]

html.border [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1] (Deprecated, use display.html.border instead.)


io.hdf.default_format [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)

plotting.matplotlib.register_converters [bool] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: True] [currently: True]

34.21.1.3 pandas.get_option

pandas.get_option(pat) = <pandas.core.config.CallableDynamicDoc object>
Retrieves the value of the specified option.

Available options:

• compute.[use_bottleneck, use_numexpr]
• display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
• display.html.[border, table_schema, use_mathjax]
• display.[large_repr]
• display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
• display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows,
  max_seq_items, memory_usage, multi_sparse, notebook_repr_html, pprint_nest_depth, precision,
  show_dimensions]
• display.unicode.[ambiguous_as_wide, east_asian_width]
• display.[width]
• html.[border]
• io.excel.xls.[writer]
• io.excel.xlsm.[writer]
• io.excel.xlsx.[writer]
• io.hdf.[default_format, dropna_table]
• io.parquet.[engine]
• mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
• plotting.matplotlib.[register_converters]

Parameters pat : str

Regexp which should match a single option. Note: partial matches are supported for
convenience, but unless you use the full option name (e.g. x.y.z.option_name), your
code may break in future versions if new options with similar names are introduced.

Returns

result [the value of the option]

Raises

OptionError [if no such option exists]

Notes

The available options with its descriptions:

**compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True
Valid values: False,True [default: True] [currently: True]

**compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default
is True Valid values: False,True [default: True] [currently: True]

**display.chop_threshold** [float or None] if set to a float value, all float values smaller then the given threshold
will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

**display.colheader_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFor-
matter. [default: right] [currently: right]

**display.column_space** No description available. [default: 12] [currently: 12]

**display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default:
False] [currently: False]

**display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default:
False] [currently: False]
**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

**display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple “pages” if its width exceeds display.width. [default: True] [currently: True]

**display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

**display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

**display.large_repr** ['truncate’/’info’] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

**display.latex.longtable :bool** This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

**display.latex.multicolumn** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

**display.latex.multicolumn_format** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

**display.latex.multirow** [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max_categories** [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max_columns** [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max_colwidth** [int] 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 than specified. [default: 1690785] [currently: 1690785]

**display.max_rows** [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max_seq_items** [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of ‘...’ to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True, False,’deep’ [default: True] [currently: True]

**display.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]

**html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1] (Deprecated, use display.html.border instead.)


**io.hdf.default_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]
io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]
mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]
mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]
mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)
plotting.matplotlib.register_converters [bool] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: True] [currently: True]

34.21.1.4 pandas.set_option

pandas.set_option (pat, value) = <pandas.core.config.CallableDynamicDoc object>
Sets the value of the specified option.
Available options:
• compute.[use_bottleneck, use_numexpr]
• display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
• display.html.[border, table_schema, use_mathjax]
• display.[large_repr]
• display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
• display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
• display.unicode.[ambiguous_as_wide, east_asian_width]
• display.[width]
• html.[border]
• io.excel.xls.[writer]
• io.excel.xlsm.[writer]
• io.excel.xlsx.[writer]
• io.hdf.[default_format, dropna_table]
• io.parquet.[engine]
• mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
• plotting.matplotlib.[register_converters]
Parameters `pat`: str

Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. `x.y.z.option_name`), your code may break in future versions if new options with similar names are introduced.

`value`:

new value of option.

Returns

None

Raises

`OptionError` if no such option exists

Notes

The available options with its descriptions:

- **compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True
  Valid values: False,True [default: True] [currently: True]

- **compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True
  Valid values: False,True [default: True] [currently: True]

- **display.chop_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

- **display.colheader_justify** `['left'/'right']` Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

- **display.column_space** No description available. [default: 12] [currently: 12]

- **display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

- **display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

- **display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

- **display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, `max_columns` is still respected, but the output will wrap-around across multiple “pages” if its width exceeds `display.width`. [default: True] [currently: True]

- **display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

- **display.html.border** [int] A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr. [default: 1] [currently: 1]

- **display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

- **display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]
display.large_repr ['truncate'/INFO'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width.

The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int] 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 than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height.

The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,’deep’ [default: True] [currently: True]

display.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]

**html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1] (Deprecated, use display.html.border instead.)


**io.hdf.default_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

**io.hdf.dropna_table** [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


**mode.chained_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

**mode.sim_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

**mode.use_inf_as_na** [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

**mode.use_inf_as_null** [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)

**plotting.matplotlib.register_converters** [bool] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: True] [currently: True]
34.21.1.5 pandas.option_context

class pandas.option_context(*args)
    Context manager to temporarily set options in the with statement context.
    You need to invoke as option_context(pat, val, [(pat, val), ...]).

Examples

```python
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
...     ...
```

34.21.2 Testing functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>testing.assert_frame_equal()</td>
<td>left, right, check_dtype=True, check_index_type='equiv', check_column_type='equiv', check_less_precise=False, by_blocks=False, check_datetimelike_compat=False, check_categorical=True, check_frame_type=True, check_like=True, check_names=True, obj='DataFrame'</td>
</tr>
<tr>
<td>testing.assert_series_equal()</td>
<td>left, right, check_dtype=True, check_index_type='equiv', check_less_precise=False, check_names=True, check_exact=False, check_like=True, check_categorical=True</td>
</tr>
<tr>
<td>testing.assert_index_equal()</td>
<td>left, right, check_dtype=True, check_index_type='equiv', check_less_precise=False, check_names=True, check_exact=False, check_like=True, check_categorical=True</td>
</tr>
</tbody>
</table>

Check that left and right DataFrame are equal.

Parameters

- **left** [DataFrame]  
- **right** [DataFrame]  
- **check_dtype** : bool, default True  
  Whether to check the DataFrame dtype is identical.  
- **check_index_type** : bool / string {‘equiv’}, default False  
  Whether to check the Index class, dtype and inferred_type are identical.  
- **check_column_type** : bool / string {‘equiv’}, default False  
  Whether to check the columns class, dtype and inferred_type are identical.  
- **check_frame_type** : bool, default False  
  Whether to check the DataFrame class is identical.  
- **check_less_precise** : bool or int, default False  
  Whether to check the DataFrame is less precise.
Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

**check_names**: bool, default True
Whether to check the Index names attribute.

**by_blocks**: bool, default False
Specify how to compare internal data. If False, compare by columns. If True, compare by blocks.

**check_exact**: bool, default False
Whether to compare number exactly.

**check_datetimelike_compat**: bool, default False
Compare datetime-like which is comparable ignoring dtype.

**check_categorical**: bool, default True
Whether to compare internal Categorical exactly.

**check_like**: bool, default False
If true, ignore the order of rows & columns

**obj**: str, default ‘DataFrame’
Specify object name being compared, internally used to show appropriate assertion message

### 34.21.2.2 pandas.testing.assert_series_equal

**pandas.testing.assert_series_equal**

```python
def assert_series_equal(left, right, check_dtype=True, check_index_type='equiv', check_series_type=True, check_less_precise=False, check_names=True, check_exact=False, check_datetimelike_compat=False, check_categorical=True, obj='Series'):
```

Check that left and right Series are equal.

**Parameters**

- **left**: [Series]
- **right**: [Series]
- **check_dtype**: bool, default True
  Whether to check the Series dtype is identical.
- **check_index_type**: bool / string {'equiv'}, default 'equiv'
  Whether to check the Index class, dtype and inferred_type are identical.
- **check_series_type**: bool, default True
  Whether to check the Series class is identical.
- **check_less_precise**: bool or int, default False
  Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

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**check_exact** : bool, default False

Whether to compare number exactly.

**check_names** : bool, default True

Whether to check the Series and Index names attribute.

**check_datetimelike_compat** : bool, default False

Compare datetime-like which is comparable ignoring dtype.

**check_categorical** : bool, default True

Whether to compare internal Categorical exactly.

**obj** : str, default ‘Series’

Specify object name being compared, internally used to show appropriate assertion message

### 34.21.2.3 pandas.testing.assert_index_equal

**pandas.testing.assert_index_equal**(left, right, **exact=’equiv’**, **check_names=True**, **check_less_precise=False**, **check_exact=True**, **check_categorical=True**, **obj=’Index’)

Check that left and right Index are equal.

**Parameters**

- **left** [Index]
- **right** [Index]
- **exact** : bool / string {‘equiv’}, default False

Whether to check the Index class, dtype and inferred_type are identical. If ‘equiv’, then RangeIndex can be substituted for Int64Index as well.

- **check_names** : bool, default True

Whether to check the names attribute.

- **check_less_precise** : bool or int, default False

Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare

- **check_exact** : bool, default True

Whether to compare number exactly.

- **check_categorical** : bool, default True

Whether to compare internal Categorical exactly.

- **obj** : str, default ‘Index’

Specify object name being compared, internally used to show appropriate assertion message

### 34.21.3 Exceptions and warnings
**errors.DtypeWarning**
Warning raised when reading different dtypes in a column from a file.

**errors.EmptyDataError**
Exception that is thrown in `pd.read_csv` (by both the C and Python engines) when empty data or header is encountered.

**errors.OutOfBoundsDatetime**

**errors.ParserError**
Exception that is raised by an error encountered in `pd.read_csv`.

**errors.ParserWarning**
Warning raised when reading a file that doesn’t use the default ‘c’ parser.

**errors.PerformanceWarning**
Warning raised when there is a possible performance impact.

**errors.UnsortedIndexError**
Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted.

**errors.UnsupportedFunctionCall**
Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g.

### 34.21.3.1 pandas.errors.DtypeWarning

**exception pandas.errors.DtypeWarning**
Warning raised when reading different dtypes in a column from a file.

Raised for a dtype incompatibility. This can happen whenever `read_csv` or `read_table` encounter non-uniform dtypes in a column(s) of a given CSV file.

**See also:**

- `pandas.read_csv` Read CSV (comma-separated) file into a DataFrame.
- `pandas.read_table` Read general delimited file into a DataFrame.

**Notes**

This warning is issued when dealing with larger files because the dtype checking happens per chunk read.

Despite the warning, the CSV file is read with mixed types in a single column which will be an object type. See the examples below to better understand this issue.

**Examples**

This example creates and reads a large CSV file with a column that contains `int` and `str`.

```python
>>> df = pd.DataFrame({'a': ([1] * 100000 + ['X'] * 100000 +
... ['1'] * 100000),
... 'b': ['b'] * 300000})
>>> df.to_csv('test.csv', index=False)
>>> df2 = pd.read_csv('test.csv')
... # DtypeWarning: Columns (0) have mixed types
```

Important to notice that `df2` will contain both `str` and `int` for the same input, ‘1’.

---

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One way to solve this issue is using the `dtype` parameter in the `read_csv` and `read_table` functions to explicit the conversion:

```python
>>> df2 = pd.read_csv('test.csv', sep=',', dtype={'a': str})
No warning was issued.
```

34.21.3.2 pandas.errors.EmptyDataError

`exception pandas.errors.EmptyDataError`

Exception that is thrown in `pd.read_csv` (by both the C and Python engines) when empty data or header is encountered.

34.21.3.3 pandas.errorsOutOfBoundsDatetime

`exception pandas.errors.OutOfBoundsDatetime`

34.21.3.4 pandas.errors.ParserError

`exception pandas.errors.ParserError`

Exception that is raised by an error encountered in `pd.read_csv`.

34.21.3.5 pandas.errors.ParserWarning

`exception pandas.errors.ParserWarning`

Warning raised when reading a file that doesn’t use the default ‘c’ parser.

Raised by `pd.read_csv` and `pd.read_table` when it is necessary to change parsers, generally from the default ‘c’ parser to ‘python’.

It happens due to a lack of support or functionality for parsing a particular attribute of a CSV file with the requested engine.

Currently, ‘c’ unsupported options include the following parameters:

1. `sep` other than a single character (e.g. regex separators)
2. `skipfooter` higher than 0
3. `sep=None` with `delim_whitespace=False`
The warning can be avoided by adding `engine='python'` as a parameter in `pd.read_csv` and `pd.read_table` methods.

**See also:**

- `pd.read_csv` Read CSV (comma-separated) file into DataFrame.
- `pd.read_table` Read general delimited file into DataFrame.

**Examples**

Using a `sep` in `pd.read_csv` other than a single character:

```python
>>> import io
>>> csv = u'''a;b;c
... 1;1,8
... 1;2,1'''
>>> df = pd.read_csv(io.StringIO(csv), sep='[;]')
... # ParserWarning: Falling back to the 'python' engine...
```

Adding `engine='python'` to `pd.read_csv` removes the Warning:

```python
>>> df = pd.read_csv(io.StringIO(csv), sep='[;]', engine='python')
```

### 34.21.3.6 pandas.errors.PerformanceWarning

**exception pandas.errors.PerformanceWarning**

Warning raised when there is a possible performance impact.

### 34.21.3.7 pandas.errors.UnsortedIndexError

**exception pandas.errors.UnsortedIndexError**

Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted. Subclass of `KeyError`.

New in version 0.20.0.

### 34.21.3.8 pandas.errors.UnsupportedFunctionCall

**exception pandas.errors.UnsupportedFunctionCall**

Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g. `np.cumsum(groupby_object)`.

### 34.21.4 Data types related functionality

```python
api.types.union_categoricals([to_union, ...])
api.types.infer_dtype
```

Combine list-like of Categorical-like, unioning categories.

Efficiently infer the type of a passed val, or list-like array of values.

Continued on next page
34.21.4.1 pandas.api.types.union_categoricals

Combine list-like of Categorical-like, unioning categories. All categories must have the same dtype.

New in version 0.19.0.

**Parameters**
- `to_union`: list-like of Categorical, CategoricalIndex,
  or Series with dtype='category'
- `sort_categories`: boolean, default False
  If true, resulting categories will be lexsorted, otherwise they will be ordered as they appear in the data.
- `ignore_order`: boolean, default False
  If true, the ordered attribute of the Categoricals will be ignored. Results in an unordered categorical.

New in version 0.20.0.

**Returns**
- `result`: [Categorical]

**Raises**
- `TypeError`
  - all inputs do not have the same dtype
  - all inputs do not have the same ordered property
  - all inputs are ordered and their categories are not identical
  - `sort_categories=True` and Categoricals are ordered

**ValueError**
- Empty list of categoricals passed

**Notes**

To learn more about categories, see [link](#)

**Examples**

```python
>>> from pandas.api.types import union_categoricals

If you want to combine categoricals that do not necessarily have the same categories, `union_categoricals` will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```
By default, the resulting categories will be ordered as they appear in the `categories` of the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```python
>>> union_categoricals([a, b], sort_categories=True)
[b, c, a, b]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with the case of combining two categoricals of the same categories and order information (e.g. what you could also `append` for).

```python
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "a"], ordered=True)
>>> union_categoricals([a, b])
[a, b, a, b, a]
Categories (2, object): [a < b]
```

Raies `TypeError` because the categories are ordered and not identical.

```python
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "c"], ordered=True)
>>> union_categoricals([a, b])
Type Error: to union ordered Categoricals, all categories must be the same
```

New in version 0.20.0

Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```python
>>> a = pd.Categorical(["a", "b", "c"], ordered=True)
>>> b = pd.Categorical(["c", "b", "a"], ordered=True)
>>> union_categoricals([a, b], ignore_order=True)
[a, b, c, b, a]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`

```python
>>> a = pd.Series(["b", "c"], dtype='category')
>>> b = pd.Series(["a", "b"], dtype='category')
>>> union_categoricals([a, b])
[b, c, a, b]
Categories (3, object): [b, c, a]
```

### 34.21.4.2 pandas.api.types.infer_dtype

`pandas.api.types.infer_dtype()`

Efficiently infer the type of a passed val, or list-like array of values. Return a string describing the type.

**Parameters**

- `value` [scalar, list, ndarray, or pandas type]
- `skipna` : bool, default False
Ignore NaN values when inferring the type. The default of False will be deprecated in a later version of pandas.

New in version 0.21.0.

Returns

string describing the common type of the input data.

Results can include:

- string
- unicode
- bytes
- floating
- integer
- mixed-integer
- mixed-integer-float
- decimal
- complex
- categorical
- boolean
- datetime64
- datetime
- date
- timedelta64
- timedelta
- time
- period
- mixed

Raises

TypeError if ndarray-like but cannot infer the dtype

Notes

- ‘mixed’ is the catchall for anything that is not otherwise specialized
- ‘mixed-integer-float’ are floats and integers
- ‘mixed-integer’ are integers mixed with non-integers
Examples

```python
>>> infer_dtype(['foo', 'bar'])
'string'

>>> infer_dtype(['a', np.nan, 'b'], skipna=True)
'string'

>>> infer_dtype(['a', np.nan, 'b'], skipna=False)
'mixed'

>>> infer_dtype(['b'foo', 'b'bar'])
'bytes'

>>> infer_dtype([1, 2, 3])
'integer'

>>> infer_dtype([1, 2, 3.5])
'mixed-integer-float'

>>> infer_dtype([1.0, 2.0, 3.5])
'floating'

>>> infer_dtype(['a', 1])
'mixed-integer'

>>> infer_dtype([Decimal(1), Decimal(2.0)])
'decimal'

>>> infer_dtype([True, False])
'boolean'

>>> infer_dtype([True, False, np.nan])
'mixed'

>>> infer_dtype([pd.Timestamp('20130101')])
'datetime'

>>> infer_dtype([datetime.date(2013, 1, 1)])
'date'

>>> infer_dtype([np.datetime64('2013-01-01')])
'datetime64'

>>> infer_dtype([datetime.timedelta(0, 1, 1)])
'timedelta'

>>> infer_dtype(pd.Series(list('aabc')).astype('category'))
'categorical'
```
34.21.4.3 pandas.api.types.pandas_dtype

pandas.api.types.pandas_dtype(dtype)

Converts input into a pandas only dtype object or a numpy dtype object.

Parameters

dtype [object to be converted]

Returns

np.dtype or a pandas dtype

Dtype introspection

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34.21.4.4 pandas.api.types.is_bool_dtype

pandas.api.types.is_bool_dtype(arr_or_dtype)
Check whether the provided array or dtype is of a boolean dtype.

Parameters arr_or_dtype : array-like
The array or dtype to check.

Returns

boolean [Whether or not the array or dtype is of a boolean dtype.]

Examples

```python
>>> is_bool_dtype(str)
False
>>> is_bool_dtype(int)
False
>>> is_bool_dtype(bool)
True
>>> is_bool_dtype(np.bool)
True
>>> is_bool_dtype(np.array(['a', 'b']))
False
>>> is_bool_dtype(pd.Series([1, 2]))
False
>>> is_bool_dtype(np.array([True, False]))
True
```

34.21.4.5 pandas.api.types.is_categorical_dtype

pandas.api.types.is_categorical_dtype(arr_or_dtype)
Check whether an array-like or dtype is of the Categorical dtype.

Parameters arr_or_dtype : array-like
The array-like or dtype to check.

Returns

boolean : Whether or not the array-like or dtype is of the Categorical dtype.

Examples

```python
>>> is_categorical_dtype(object)
False
>>> is_categorical_dtype(CategoricalDtype())
True
```
>>> is_categorical_dtype([1, 2, 3])
False
>>> is_categorical_dtype(pd.Categorical([1, 2, 3]))
True
>>> is_categorical_dtype(pd.CategoricalIndex([1, 2, 3]))
True

34.21.4.6 pandas.api.types.is_complex_dtype

pandas.api.types.is_complex_dtype(arr_or_dtype)
Check whether the provided array or dtype is of a complex dtype.

Parameters

arr_or_dtype : array-like
The array or dtype to check.

Returns

boolean [Whether or not the array or dtype is of a complex dtype.]

Examples

>>> is_complex_dtype(str)
False
>>> is_complex_dtype(int)
False
>>> is_complex_dtype(np.complex)
True
>>> is_complex_dtype(np.array(['a', 'b']))
False
>>> is_complex_dtype(pd.Series([1, 2]))
False
>>> is_complex_dtype(np.array([1 + 1j, 5]))
True

34.21.4.7 pandas.api.types.is_datetime64_any_dtype

pandas.api.types.is_datetime64_any_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the datetime64 dtype.

Parameters

arr_or_dtype : array-like
The array or dtype to check.

Returns

boolean [Whether or not the array or dtype is of the datetime64 dtype.]

Examples
```python
>>> is_datetime64_any_dtype(str)
False
>>> is_datetime64_any_dtype(int)
False
>>> is_datetime64_any_dtype(np.datetime64)  # can be tz-naive
True
>>> is_datetime64_any_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_any_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_any_dtype(np.array([1, 2]))
False
>>> is_datetime64_any_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_any_dtype(pd.DatetimeIndex([1, 2, 3],
                                           dtype=np.datetime64))
True
```

### 34.21.4.8 pandas.api.types.is_datetime64_dtype

`pandas.api.types.is_datetime64_dtype(arr_or_dtype)`

Check whether an array-like or dtype is of the datetime64 dtype.

**Parameters**

- `arr_or_dtype` : array-like
  
The array-like or dtype to check.

**Returns**

- `boolean` : Whether or not the array-like or dtype is of the datetime64 dtype.

#### Examples

```python
>>> is_datetime64_dtype(object)
False
>>> is_datetime64_dtype(np.datetime64)
True
>>> is_datetime64_dtype(np.array([], dtype=int))
False
>>> is_datetime64_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_dtype([1, 2, 3])
False
```

### 34.21.4.9 pandas.api.types.is_datetime64_ns_dtype

`pandas.api.types.is_datetime64_ns_dtype(arr_or_dtype)`

Check whether the provided array or dtype is of the datetime64[ns] dtype.

**Parameters**

- `arr_or_dtype` : array-like
  
The array or dtype to check.

**Returns**

- `boolean` : Whether or not the array or dtype is of the datetime64[ns] dtype.
Examples

```python
>>> is_datetime64_ns_dtype(str)
False
>>> is_datetime64_ns_dtype(int)
False
>>> is_datetime64_ns_dtype(np.datetime64)  # no unit
False
>>> is_datetime64_ns_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_ns_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_ns_dtype(np.array([1, 2]))
False
>>> is_datetime64_ns_dtype(np.array([], dtype=np.datetime64))  # no unit
False
>>> is_datetime64_ns_dtype(np.array([], dtype="datetime64[ps]")  # wrong unit
False
>>> is_datetime64_ns_dtype(pd.DatetimeIndex([1, 2, 3],
                                            dtype=np.datetime64))  # has 'ns' unit
True
```

34.21.4.10 pandas.api.types.is_datetime64tz_dtype

pandas.api.types.is_datetime64tz_dtype(arr_or_dtype)
Check whether an array-like or dtype is of a DatetimeTZDtype dtype.

Parameters

- **arr_or_dtype**: array-like
  
The array-like or dtype to check.

Returns

- **boolean**: Whether or not the array-like or dtype is of a DatetimeTZDType dtype.

Examples

```python
>>> is_datetime64tz_dtype(object)
False
>>> is_datetime64tz_dtype([1, 2, 3])
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3]))  # tz-naive
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
```
34.21.4.11 pandas.api.types.is_extension_type

pandas.api.types.is_extension_type(arr)

Check whether an array-like is of a pandas extension class instance.

Extension classes include categoricals, pandas sparse objects (i.e. classes represented within the pandas library and not ones external to it like scipy sparse matrices), and datetime-like arrays.

Parameters

arr : array-like

The array-like to check.

Returns

boolean : Whether or not the array-like is of a pandas extension class instance.

Examples

```python
>>> is_extension_type([1, 2, 3])
False
>>> is_extension_type(np.array([1, 2, 3]))
False
>>> cat = pd.Categorical([1, 2, 3])
>>> is_extension_type(cat)
True
>>> is_extension_type(pd.Series(cat))
True
>>> is_extension_type(pd.SparseArray([1, 2, 3]))
True
>>> is_extension_type(pd.SparseSeries([1, 2, 3]))
True
>>> from scipy.sparse import bsr_matrix
>>> is_extension_type(bsr_matrix([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_extension_type(s)
True
```

34.21.4.12 pandas.api.types.is_float_dtype

pandas.api.types.is_float_dtype(arr_or_dtype)

Check whether the provided array or dtype is of a float dtype.

Parameters

arr_or_dtype : array-like

The array or dtype to check.

Returns
**Examples**

```python
>>> is_float_dtype(str)
False
>>> is_float_dtype(int)
False
>>> is_float_dtype(float)
True
>>> is_float_dtype(np.array(['a', 'b']))
False
>>> is_float_dtype(pd.Series([1, 2]))
False
>>> is_float_dtype(pd.Index([1, 2.]))
True
```

34.21.4.13 pandas.api.types.is_int64_dtype

pandas.api.types.is_int64_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the int64 dtype.

Parameters

arr_or_dtype : array-like
The array or dtype to check.

Returns

boolean [Whether or not the array or dtype is of the int64 dtype.]

Notes

Depending on system architecture, the return value of is_int64_dtype(int) will be True if the OS uses 64-bit integers and False if the OS uses 32-bit integers.

**Examples**

```python
>>> is_int64_dtype(str)
False
>>> is_int64_dtype(np.int32)
False
>>> is_int64_dtype(np.int64)
True
>>> is_int64_dtype(float)
False
>>> is_int64_dtype(np.uint64)  # unsigned
False
>>> is_int64_dtype(np.array(['a', 'b']))
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.int64))
True
>>> is_int64_dtype(pd.Index([1, 2.]))  # float
False
```
>>> is_int64_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False

### `pandas.api.types.is_integer_dtype`

**pandas.api.types.is_integer_dtype(arr_or_dtype)**

Check whether the provided array or dtype is of an integer dtype.

Unlike in `in_any_int_dtype`, timedelta64 instances will return False.

**Parameters**

`arr_or_dtype` : array-like
    The array or dtype to check.

**Returns**

boolean : Whether or not the array or dtype is of an integer dtype and not an instance of timedelta64.

#### Examples

```python
>>> is_integer_dtype(str)
False

>>> is_integer_dtype(int)
True

>>> is_integer_dtype(float)
False

>>> is_integer_dtype(np.uint64)
True

>>> is_integer_dtype(np.datetime64)
False

>>> is_integer_dtype(np.timedelta64)
False

>>> is_integer_dtype(np.array(['a', 'b']))
False

>>> is_integer_dtype(pd.Series([1, 2]))
True

>>> is_integer_dtype(np.array([], dtype=np.timedelta64))
False

>>> is_integer_dtype(pd.Index([1, 2.]))  # float
False
```

### `pandas.api.types.is_interval_dtype`

**pandas.api.types.is_interval_dtype(arr_or_dtype)**

Check whether an array-like or dtype is of the Interval dtype.

**Parameters**

`arr_or_dtype` : array-like
    The array-like or dtype to check.

**Returns**

boolean : Whether or not the array-like or dtype is of the Interval dtype.
Examples

```python
>>> is_interval_dtype(object)
False
>>> is_interval_dtype(IntervalDtype())
True
>>> is_interval_dtype([1, 2, 3])
False
>>> interval = pd.Interval(1, 2, closed="right")
>>> is_interval_dtype(interval)
False
>>> is_interval_dtype(pd.IntervalIndex([interval]))
True
```

34.21.4.16 pandas.api.types.is_numeric_dtype

pandas.api.types.is_numeric_dtype(arr_or_dtype)
Check whether the provided array or dtype is of a numeric dtype.

Parameters
arr_or_dtype : array-like
The array or dtype to check.

Returns
boolean [Whether or not the array or dtype is of a numeric dtype.]

Examples

```python
>>> is_numeric_dtype(str)
False
>>> is_numeric_dtype(int)
True
>>> is_numeric_dtype(float)
True
>>> is_numeric_dtype(np.uint64)
True
>>> is_numeric_dtype(np.datetime64)
False
>>> is_numeric_dtype(np.timedelta64)
False
>>> is_numeric_dtype(np.array(['a', 'b']))
False
>>> is_numeric_dtype(pd.Series([1, 2]))
True
>>> is_numeric_dtype(pd.Index([1, 2.]))
True
>>> is_numeric_dtype(np.array([], dtype=np.timedelta64))
False
```

34.21.4.17 pandas.api.types.is_object_dtype

pandas.api.types.is_object_dtype(arr_or_dtype)
Check whether an array-like or dtype is of the object dtype.
Parameters **arr_or_dtype** : array-like

The array-like or dtype to check.

Returns

**boolean** [Whether or not the array-like or dtype is of the object dtype.]

Examples

```python
>>> is_object_dtype(object)
True
>>> is_object_dtype(int)
False
>>> is_object_dtype(np.array([], dtype=object))
True
>>> is_object_dtype(np.array([], dtype=int))
False
>>> is_object_dtype([1, 2, 3])
False
```

34.21.4.18 pandas.api.types.is_period_dtype

pandas.api.types.is_period_dtype(*arr_or_dtype*)

Check whether an array-like or dtype is of the Period dtype.

Parameters **arr_or_dtype** : array-like

The array-like or dtype to check.

Returns

**boolean** [Whether or not the array-like or dtype is of the Period dtype.]

Examples

```python
>>> is_period_dtype(object)
False
>>> is_period_dtype(PeriodDtype(freq="D"))
True
>>> is_period_dtype([1, 2, 3])
False
>>> is_period_dtype(pd.Period("2017-01-01"))
False
>>> is_period_dtype(pd.PeriodIndex([], freq="A"))
True
```

34.21.4.19 pandas.api.types.is_signed_integer_dtype

pandas.api.types.is_signed_integer_dtype(*arr_or_dtype*)

Check whether the provided array or dtype is of a signed integer dtype.

Unlike in in any_int_dtype, timedelta64 instances will return False.

Parameters **arr_or_dtype** : array-like
The array or dtype to check.

Returns boolean: Whether or not the array or dtype is of a signed integer dtype and not an instance of timedelta64.

Examples

```python
>>> is_signed_integer_dtype(str)
False
>>> is_signed_integer_dtype(int)
True
>>> is_signed_integer_dtype(float)
False
>>> is_signed_integer_dtype(np.uint64)  # unsigned
False
>>> is_signed_integer_dtype(np.datetime64)
False
>>> is_signed_integer_dtype(np.timedelta64)
False
>>> is_signed_integer_dtype(np.array(['a', 'b']))
False
>>> is_signed_integer_dtype(pd.Series([1, 2]))
True
>>> is_signed_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_signed_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_signed_integer_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False
```

34.21.4.20 pandas.api.types.is_string_dtype

pandas.api.types.is_string_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the string dtype.

Parameters arr_or_dtype : array-like
The array or dtype to check.

Returns

boolean [Whether or not the array or dtype is of the string dtype.]

Examples

```python
>>> is_string_dtype(str)
True
>>> is_string_dtype(object)
True
>>> is_string_dtype(int)
False
>>> is_string_dtype(np.array(['a', 'b']))
True
```
34.21.4.21 pandas.api.types.is_timedelta64_dtype

pandas.api.types.is_timedelta64_dtype(arr_or_dtype)

Check whether an array-like or dtype is of the timedelta64 dtype.

Parameters

arr_or_dtype : array-like
    The array-like or dtype to check.

Returns

boolean : Whether or not the array-like or dtype is
    of the timedelta64 dtype.

Examples

```python
>>> is_timedelta64_dtype(pd.Series([1, 2]))
False
```

34.21.4.22 pandas.api.types.is_timedelta64_ns_dtype

pandas.api.types.is_timedelta64_ns_dtype(arr_or_dtype)

Check whether the provided array or dtype is of the timedelta64[ns] dtype.

This is a very specific dtype, so generic ones like np.timedelta64 will return False if passed into this function.

Parameters

arr_or_dtype : array-like
    The array or dtype to check.

Returns

boolean : Whether or not the array or dtype is of the
timedelta64[ns] dtype.

Examples

```python
>>> is_timedelta64_ns_dtype(np.dtype('m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.dtype('m8[ps]'))  # Wrong frequency
False
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype='m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype=np.timedelta64))
False
```
34.21.4.23 pandas.api.types.is_unsigned_integer_dtype

pandas.api.types.is_unsigned_integer_dtype(arr_or_dtype)
Check whether the provided array or dtype is of an unsigned integer dtype.

Parameters arr_or_dtype : array-like
   The array or dtype to check.

Returns boolean : Whether or not the array or dtype is of an
   unsigned integer dtype.

Examples

```python
>>> is_unsigned_integer_dtype(str)
False
>>> is_unsigned_integer_dtype(int)  # signed
False
>>> is_unsigned_integer_dtype(float)
False
>>> is_unsigned_integer_dtype(np.uint64)
True
>>> is_unsigned_integer_dtype(np.array(['a', 'b']))
False
>>> is_unsigned_integer_dtype(pd.Series([1, 2]))  # signed
False
>>> is_unsigned_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_unsigned_integer_dtype(np.array([1, 2], dtype=np.uint32))
True
```

34.21.4.24 pandas.api.types.is_sparse

pandas.api.types.is_sparse(arr)
Check whether an array-like is a pandas sparse array.

Parameters arr : array-like
   The array-like to check.

Returns
   boolean [Whether or not the array-like is a pandas sparse array.]

Examples

```python
>>> is_sparse(np.array([1, 2, 3]))
False
>>> is_sparse(pd.SparseArray([1, 2, 3]))
True
>>> is_sparse(pd.SparseSeries([1, 2, 3]))
True
```

This function checks only for pandas sparse array instances, so sparse arrays from other libraries will return False.
Iterable introspection

<table>
<thead>
<tr>
<th>API function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_dict_like(obj)</code></td>
<td>Check if the object is dict-like.</td>
</tr>
<tr>
<td><code>is_file_like(obj)</code></td>
<td>Check if the object is file-like.</td>
</tr>
<tr>
<td><code>is_list_like(obj)</code></td>
<td>Check if the object is list-like.</td>
</tr>
<tr>
<td><code>is_named_tuple(obj)</code></td>
<td>Check if the object is a named tuple.</td>
</tr>
<tr>
<td><code>is_iterator(obj)</code></td>
<td>Check if the object is an iterator.</td>
</tr>
</tbody>
</table>

#### 34.21.4.25 pandas.api.types.is_dict_like

pandas.api.types.`is_dict_like` `obj`

Check if the object is dict-like.

**Parameters**

- **obj** [The object to check.]

**Returns** `is_dict_like`: bool

Whether `obj` has dict-like properties.

**Examples**

```python
>>> is_dict_like({1: 2})
True
>>> is_dict_like([1, 2, 3])
False
```

#### 34.21.4.26 pandas.api.types.is_file_like

pandas.api.types.`is_file_like` `obj`

Check if the object is a file-like object.

For objects to be considered file-like, they must be an iterator AND have either a `read` and/or `write` method as an attribute.

Note: file-like objects must be iterable, but iterable objects need not be file-like.

New in version 0.20.0.

**Parameters**

- **obj** [The object to check.]

**Returns** `is_file_like`: bool

Whether `obj` has file-like properties.
Examples

```python
>>> buffer(StringIO("data"))
>>> is_file_like(buffer)
True
>>> is_file_like([1, 2, 3])
False
```

34.21.4.27 pandas.api.types.is_list_like

`pandas.api.types.is_list_like(obj)`

Check if the object is list-like.

Objects that are considered list-like are for example Python lists, tuples, sets, NumPy arrays, and Pandas Series.

Strings and datetime objects, however, are not considered list-like.

Parameters

- `obj` [The object to check.]

Returns

- `is_list_like` : `bool`  
  Whether `obj` has list-like properties.

Examples

```python
>>> is_list_like([1, 2, 3])
True
>>> is_list_like({1, 2, 3})
True
>>> is_list_like(datetime(2017, 1, 1))
False
>>> is_list_like("foo")
False
>>> is_list_like(1)
False
```

34.21.4.28 pandas.api.types.is_named_tuple

`pandas.api.types.is_named_tuple(obj)`

Check if the object is a named tuple.

Parameters

- `obj` [The object to check.]

Returns

- `is_named_tuple` : `bool`  
  Whether `obj` is a named tuple.

Examples
>>> Point = namedtuple("Point", ["x", "y"])  
>>> p = Point(1, 2)  
>>> is_named_tuple(p)  
True  
>>> is_named_tuple((1, 2))  
False

34.21.4.29 pandas.api.types.is_iterator

pandas.api.types.is_iterator(obj)
Check if the object is an iterator.
For example, lists are considered iterators but not strings or datetime objects.

Parameters

- obj [The object to check.]

Returns is_iter: bool
Whether obj is an iterator.

Examples

>>> is_iterator([1, 2, 3])
True
>>> is_iterator(datetime(2017, 1, 1))
False
>>> is_iterator("foo")
False
>>> is_iterator(1)
False

Scalar introspection

api.types.is_bool
api.types.is_categorical(arr) Check whether an array-like is a Categorical instance.
api.types.is_complex
api.types.is_datetimetz(arr) Check whether an array-like is a datetime array-like with a timezone component in its dtype.
api.types.is_float
api.types.is_hashable(obj) Return True if hash(obj) will succeed, False otherwise.
api.types.is_integer
api.types.is_interval
api.types.is_number(obj) Check if the object is a number.
api.types.is_period(arr) Check whether an array-like is a periodical index.
api.types.is_re(obj) Check if the object is a regex pattern instance.
api.types.is_re_compilable(obj) Check if the object can be compiled into a regex pattern instance.
api.types.is_scalar
Return True if given value is scalar.
34.21.30 pandas.api.types.is_bool

pandas.api.types.is_bool()

34.21.31 pandas.api.types.is_categorical

pandas.api.types.is_categorical(arr)

Check whether an array-like is a Categorical instance.

Parameters arr: array-like

The array-like to check.

Returns boolean [Whether or not the array-like is of a Categorical instance.]

Examples

>>> is_categorical([1, 2, 3])
False

Categoricals, Series Categoricals, and CategoricalIndex will return True.

>>> cat = pd.Categorical([1, 2, 3])
>>> is_categorical(cat)
True
>>> is_categorical(pd.Series(cat))
True
>>> is_categorical(pd.CategoricalIndex([1, 2, 3]))
True

34.21.32 pandas.api.types.is_complex

pandas.api.types.is_complex()

34.21.33 pandas.api.types.is_datetimetz

pandas.api.types.is_datetimetz(arr)

Check whether an array-like is a datet ime array-like with a timezone component in its dtype.

Parameters arr: array-like

The array-like to check.

Returns boolean: Whether or not the array-like is a datetime array-like with a timezone component in its dtype.

Examples

>>> is_datetimetz([1, 2, 3])
False
Although the following examples are both DatetimeIndex objects, the first one returns False because it has no timezone component unlike the second one, which returns True.

```python
>>> is_datetimetz(pd.DatetimeIndex([1, 2, 3]))
False
>>> is_datetimetz(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
```

The object need not be a DatetimeIndex object. It just needs to have a dtype which has a timezone component.

```python
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_datetimetz(s)
True
```

### 34.21.4.34 pandas.api.types.is_float

`pandas.api.types.is_float()`

### 34.21.4.35 pandas.api.types.is_hashable

`pandas.api.types.is_hashable(obj)`

Return True if hash(obj) will succeed, False otherwise.

Some types will pass a test against collections.Hashable but fail when they are actually hashed with hash(). Distinguish between these and other types by trying the call to hash() and seeing if they raise TypeError.

**Examples**

```python
>>> a = ([],)
>>> isinstance(a, collections.Hashable)
True
>>> is_hashable(a)
False
```

### 34.21.4.36 pandas.api.types.is_integer

`pandas.api.types.is_integer()`

### 34.21.4.37 pandas.api.types.is_interval

`pandas.api.types.is_interval()`

### 34.21.4.38 pandas.api.types.is_number

`pandas.api.types.is_number(obj)`

Check if the object is a number.

Returns True when the object is a number, and False if is not.

**Parameters**

- `obj`: any type
The object to check if is a number.

**Returns** is_number : bool

Whether *obj* is a number or not.

**See also:**

`pandas.api.types.is_integer` checks a subgroup of numbers

**Examples**

```python
gt> pd.api.types.is_number(1)
True
> gt> pd.api.types.is_number(7.15)
True

Booleans are valid because they are int subclass.

```python
gt> pd.api.types.is_number(False)
True
```

```python
gt> pd.api.types.is_number("foo")
False
> gt> pd.api.types.is_number("5")
False
```

### 34.21.4.39 pandas.api.types.is_period

**pandas.api.types.is_period(arr)**

Check whether an array-like is a periodical index.

**Parameters**

*arr* : array-like

The array-like to check.

**Returns**

* boolean  [Whether or not the array-like is a periodical index.]

**Examples**

```python
>> is_period([1, 2, 3])
False
> is_period(pd.Index([1, 2, 3]))
False
> is_period(pd.PeriodIndex(["2017-01-01"], freq="D"))
True
```

### 34.21.4.40 pandas.api.types.is_re

**pandas.api.types.is_re(obj)**

Check if the object is a regex pattern instance.
Parameters

**obj** [The object to check.]

**Returns**  
**is_regex** : bool  
Whether *obj* is a regex pattern.

**Examples**

```python
>>> is_re(re.compile(".*"))
True
>>> is_re("foo")
False
```

### pandas.api.types.is_re_compilable

**pandas.api.types.is_re_compilable**(obj)

Check if the object can be compiled into a regex pattern instance.

**Parameters**

**obj** [The object to check.]

**Returns**  
**is_regex_compilable** : bool  
Whether *obj* can be compiled as a regex pattern.

**Examples**

```python
>>> is_re_compilable(".*")
True
>>> is_re_compilable(1)
False
```

### pandas.api.types.is_scalar

**pandas.api.types.is_scalar**()

Return True if given value is scalar.

This includes:

- numpy array scalar (e.g. np.int64)
- Python builtin numerics
- Python builtin byte arrays and strings
- None
- instances of datetime.datetime
- instances of datetime.timedelta
- Period
- instances of decimal.Decimal
- Interval
- DateOffset

### Extensions

These are primarily intended for library authors looking to extend pandas objects.

- [Register a custom accessor on DataFrame objects](#).
- [Register a custom accessor on Series objects](#).
- [Register a custom accessor on Index objects](#).

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<th>A custom data type, to be paired with an ExtensionArray.</th>
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</thead>
<tbody>
<tr>
<td>api.extensions.ExtensionArray</td>
<td>Abstract base class for custom 1-D array types.</td>
</tr>
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</table>

### 34.22.1 pandas.api.extensions.register_dataframe_accessor

*pandas.api.extensions.register_dataframe_accessor*(name)

Register a custom accessor on DataFrame objects.

**Parameters** name: str

Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

**See also:**

*register_series_accessor*, *register_index_accessor*

**Notes**

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```python
def __init__(self, pandas_object):
```

For consistency with pandas methods, you should raise an *AttributeError* if the data passed to your accessor has an incorrect dtype.

```python
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...  
AttributeError: Can only use .dt accessor with datetimelike values
```

**Examples**

In your library code:

```python
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor(object):
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

@property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
```

(continues on next page)
# plot this array's data on a map, e.g., using Cartopy
pass

Back in an interactive IPython session:

```python
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                     'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

## 34.22.2 pandas.api.extensions.register_series_accessor

### pandas.api.extensions.register_series_accessor(name)

Register a custom accessor on Series objects.

**Parameters**

- **name** : str
  
  Name under which the accessor should be registered. A warning is issued if this
  name conflicts with a preexisting attribute.

**See also:**

- `register_dataframe_accessor`
- `register_index_accessor`

**Notes**

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the
signature must be

```python
def __init__(self, pandas_object):
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your ac-

```python
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

**Examples**

In your library code:

```python
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor(object):
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

@property
```

(continues on next page)
```python
def center(self):
    # return the geographic center point of this DataFrame
    lat = self._obj.latitude
    lon = self._obj.longitude
    return (float(lon.mean()), float(lat.mean()))

def plot(self):
    # plot this array's data on a map, e.g., using Cartopy
    pass
```

Back in an interactive IPython session:

```python
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                     'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

### 34.22.3 pandas.api.extensions.register_index_accessor

`pandas.api.extensions.register_index_accessor(name)`

Register a custom accessor on Index objects.

**Parameters**

- **name**: str
  
  Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

**See also:**

- `register_dataframe_accessor`
- `register_series_accessor`

**Notes**

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```python
def __init__(self, pandas_object):
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```python
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

**Examples**

In your library code:
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor(object):
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

def plot(self):
    # plot this array's data on a map, e.g., using Cartopy
    pass

Back in an interactive IPython session:

```python
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                    'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

## 34.22.4 pandas.api.extensions.ExtensionDtype

class pandas.api.extensions.ExtensionDtype
A custom data type, to be paired with an ExtensionArray.

New in version 0.23.0.

### Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- type
- name
- construct_from_string

The `na_value` class attribute can be used to set the default NA value for this type. `numpy.nan` is used by default.

This class does not inherit from `abc.ABCMeta` for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

### Attributes
### pandas.api.extensions.ExtensionDtype.kind

`ExtensionDtype.kind`

A character code (one of `biufcmMOSUV`), default ‘O’

This should match the NumPy dtype used when the array is converted to an `ndarray`, which is probably ‘O’ for object if the extension type cannot be represented as a built-in NumPy type.

See also:

`numpy.dtype.kind`

### pandas.api.extensions.ExtensionDtype.name

`ExtensionDtype.name`

A string identifying the data type.

Will be used for display in, e.g. `Series.dtype`

### pandas.api.extensions.ExtensionDtype.names

`ExtensionDtype.names`

Ordered list of field names, or None if there are no fields.

This is for compatibility with NumPy arrays, and may be removed in the future.

### pandas.api.extensions.ExtensionDtype.type

`ExtensionDtype.type`

The scalar type for the array, e.g. `int`

It's expected `ExtensionArray[item]` returns an instance of `ExtensionDtype.type` for scalar item.

#### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>construct_from_string(string)</code></td>
<td>Attempt to construct this type from a string.</td>
</tr>
<tr>
<td><code>is_dtype(dtype)</code></td>
<td>Check if we match 'dtype'.</td>
</tr>
</tbody>
</table>

### pandas.api.extensions.ExtensionDtype.construct_from_string

#### classmethod

`ExtensionDtype.construct_from_string(string)`

Attempt to construct this type from a string.

Parameters
string [str]

Returns

self [instance of ‘cls’]

Raises TypeError

If a class cannot be constructed from this ‘string’.

Examples

If the extension dtype can be constructed without any arguments, the following may be an adequate implementation.

```python
>>> @classmethod
... def construct_from_string(cls, string)
... if string == cls.name:
...     return cls()
... else:
...     raise TypeError("Cannot construct a '{}' from "
...                   "'{}'".format(cls, string))
```

34.22.4.6 pandas.api.extensions.ExtensionDtype.is_dtype

classmethod ExtensionDtype.is_dtype(dtype)
Check if we match ‘dtype’.

Parameters dtype : object
The object to check.

Returns

is_dtype [bool]

Notes

The default implementation is True if
1. cls.construct_from_string(dtype) is an instance of cls.
2. dtype is an object and is an instance of cls
3. dtype has a dtype attribute, and any of the above conditions is true for dtype.dtype.

34.22.5 pandas.api.extensions.ExtensionArray

class pandas.api.extensions.ExtensionArray
Abstract base class for custom 1-D array types.
pandas will recognize instances of this class as proper arrays with a custom type and will not attempt to coerce
them to objects. They may be stored directly inside a DataFrame or Series.
New in version 0.23.0.
Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- \_from\_sequence
- \_from\_factorized
- \__getitem__
- \__len__
- dtype
- nbytes
- isna
- take
- copy
- \_concat\_same\_type

An additional method is available to satisfy pandas’ internal, private block API:

- \_formatting\_values

Some methods require casting the ExtensionArray to an ndarray of Python objects with `self.astype(object)`, which may be expensive. When performance is a concern, we highly recommend overriding the following methods:

- fillna
- unique
- factorize \_values\_for\_factorize
- argsort \_values\_for\_argsort

This class does not inherit from ‘abc.ABCMeta’ for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

ExtensionArrays are limited to 1 dimension.

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 address may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists. Pandas makes no assumptions on how the data are stored, just that it can be converted to a NumPy array. The ExtensionArray interface does not impose any rules on how this data is stored. However, currently, the backing data cannot be stored in attributes called `.values` or `.\_values` to ensure full compatibility with pandas internals. But other names as `.data`, `.\_data`, `.\_items`,... can be freely used.

Attributes

<table>
<thead>
<tr>
<th>dtype</th>
<th>An instance of ‘ExtensionDtype’.</th>
</tr>
</thead>
<tbody>
<tr>
<td>nbytes</td>
<td>The number of bytes needed to store this object in memory.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>ndim</th>
<th>Extension Arrays are only allowed to be 1-dimensional.</th>
</tr>
</thead>
<tbody>
<tr>
<td>shape</td>
<td>Return a tuple of the array dimensions.</td>
</tr>
</tbody>
</table>

### 34.22.5.1 pandas.api.extensions.ExtensionArray.dtype

ExtensionArray.

dtype

An instance of ‘ExtensionDtype’.

### 34.22.5.2 pandas.api.extensions.ExtensionArray.nbytes

ExtensionArray.

nbytes

The number of bytes needed to store this object in memory.

### 34.22.5.3 pandas.api.extensions.ExtensionArray.ndim

ExtensionArray.

ndim

Extension Arrays are only allowed to be 1-dimensional.

### 34.22.5.4 pandas.api.extensions.ExtensionArray.shape

ExtensionArray.

shape

Return a tuple of the array dimensions.

### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>argsort([ascending, kind])</td>
<td>Return the indices that would sort this array.</td>
</tr>
<tr>
<td>astype(dtype, copy)</td>
<td>Cast to a NumPy array with ‘dtype’.</td>
</tr>
<tr>
<td>copy([deep])</td>
<td>Return a copy of the array.</td>
</tr>
<tr>
<td>factorize([na_sentinel])</td>
<td>Encode the extension array as an enumerated type.</td>
</tr>
<tr>
<td>fillna([value, method, limit])</td>
<td>Fill NA/NaN values using the specified method.</td>
</tr>
<tr>
<td>isnan()</td>
<td>Boolean NumPy array indicating if each value is missing.</td>
</tr>
<tr>
<td>take(indices[, allow_fill, fill_value])</td>
<td>Take elements from an array.</td>
</tr>
<tr>
<td>unique()</td>
<td>Compute the ExtensionArray of unique values.</td>
</tr>
</tbody>
</table>

### 34.22.5.5 pandas.api.extensions.ExtensionArray.argsort

ExtensionArray.

argsort(ascending=True, kind='quicksort', *args, **kwargs)

Return the indices that would sort this array.

**Parameters**

- ascending : bool, default True
  
  Whether the indices should result in an ascending or descending sort.

- kind : {'quicksort', 'mergesort', 'heapsort'}, optional
  
  Sorting algorithm.

*args, **kwargs:
passed through to `numpy.argsort()`.

**Returns**

index_array : ndarray

Array of indices that sort `self`.

**See also:**

`numpy.argsort` Sorting implementation used internally.

### 34.22.5.6 pandas.api.extensions.ExtensionArray.astype

ExtensionArray.**astype**(dtype, copy=True)

Cast to a NumPy array with `dtype`.

**Parameters**

dtype : str or dtype

Typecode or data-type to which the array is cast.

copy : bool, default True

Whether to copy the data, even if not necessary. If False, a copy is made only if the old dtype does not match the new dtype.

**Returns**

array : ndarray

NumPy ndarray with `dtype` for its dtype.

### 34.22.5.7 pandas.api.extensions.ExtensionArray.copy

ExtensionArray.**copy**(deep=False)

Return a copy of the array.

**Parameters**

deeper : bool, default False

Also copy the underlying data backing this array.

**Returns**

ExtensionArray

### 34.22.5.8 pandas.api.extensions.ExtensionArray.factorize

ExtensionArray.**factorize**(na_sentinel=-1)

Encode the extension array as an enumerated type.

**Parameters**

na_sentinel : int, default -1

Value to use in the `labels` array to indicate missing values.

**Returns**

labels : ndarray

An integer NumPy array that’s an indexer into the original ExtensionArray.

uniques : ExtensionArray

An ExtensionArray containing the unique values of `self`.

**Note:** uniques will *not* contain an entry for the NA value of the ExtensionArray if there are any missing values present in `self`.  

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See also:

pandas.factorize Top-level factorize method that dispatches here.

Notes

pandas.factorize() offers a sort keyword as well.

34.22.5.9 pandas.api.extensions.ExtensionArray.fillna

ExtensionArray.fillna(value=None, method=None, limit=None)
Fill NA/NaN values using the specified method.

Parameters

value: scalar, array-like
If a scalar value is passed it is used to fill all missing values. Alternatively, an array-like ‘value’ can be given. It’s expected that the array-like have the same length as ‘self’.

method: {'backfill', 'bfill', 'pad', 'ffill', None}, default None
Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

limit: int, default None
If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

Returns

filled [ExtensionArray with NA/NaN filled]

34.22.5.10 pandas.api.extensions.ExtensionArray.isna

ExtensionArray.isna()
Boolean NumPy array indicating if each value is missing.
This should return a 1-D array the same length as ‘self’.

34.22.5.11 pandas.api.extensions.ExtensionArray.take

ExtensionArray.take(indices, allow_fill=False, fill_value=None)
Take elements from an array.

Parameters

indices: sequence of integers
Indices to be taken.

allow_fill: bool, default False
How to handle negative values in indices.
• False: negative values in indices indicate positional indices from the right (the default). This is similar to numpy.take().

• True: negative values in indices indicate missing values. These values are set to fill_value. Any other other negative values raise a ValueError.

fill_value: any, optional

Fill value to use for NA-indices when allow_fill is True. This may be None, in which case the default NA value for the type, self.dtype.na_value, is used.

For many ExtensionArrays, there will be two representations of fill_value: a user-facing “boxed” scalar, and a low-level physical NA value. fill_value should be the user-facing version, and the implementation should handle translating that to the physical version for processing the take if necessary.

Returns

ExtensionArray

Raises

IndexError

When the indices are out of bounds for the array.

ValueError

When indices contains negative values other than -1 and allow_fill is True.

See also:

numpy.take, pandas.api.extensions.take

Notes

ExtensionArray.take is called by Series.__getitem__, .loc, .iloc, when indices is a sequence of values. Additionally, it’s called by Series.reindex(), or any other method that causes realignment, with a fill_value.

Examples

Here’s an example implementation, which relies on casting the extension array to object dtype. This uses the helper method pandas.api.extensions.take().

```python
def take(self, indices, allow_fill=False, fill_value=None):
    from pandas.core.algorithms import take

    # If the ExtensionArray is backed by an ndarray, then
    # just pass that here instead of coercing to object.
    data = self.astype(object)

    if allow_fill and fill_value is None:
        fill_value = self.dtype.na_value

    # fill value should always be translated from the scalar
    # type for the array, to the physical storage type for
    # the data, before passing to take.

    result = take(data, indices, fill_value=fill_value,
```

(continues on next page)
allow_fill=allow_fill)
return self._from_sequence(result)

34.22.5.12 pandas.api.extensions.ExtensionArray.unique

ExtensionArray.unique()
Compute the ExtensionArray of unique values.

Returns
uniques [ExtensionArray]

34.22.6 pandas.Index.asi8

Index.asi8 = None

34.22.7 pandas.Index.holds_integer

Index.holds_integer()

34.22.8 pandas.Index.is_type_compatible

Index.is_type_compatible(kind)

34.22.9 pandas.Index.nlevels

Index.nlevels

34.22.10 pandas.Index.sort

Index.sort(*args, **kwargs)

34.22.11 pandas.Panel.agg

Panel.agg(func, *args, **kwargs)

34.22.12 pandas.Panel.aggregate

Panel.aggregate(func, *args, **kwargs)

34.22.13 pandas.Panel.is_copy

Panel.is_copy
34.22.14 pandas.Series.imag

Series.imag

34.22.15 pandas.Series.real

Series.real
This section will focus on downstream applications of pandas.

35.1 Storing pandas DataFrame objects in Apache Parquet format

The Apache Parquet format provides key-value metadata at the file and column level, stored in the footer of the Parquet file:

```plaintext
3: optional list<KeyValue> key_value_metadata
```

where `KeyValue` is

```plaintext
struct KeyValue {
  1: required string key
  2: optional string value
}
```

So that a `pandas.DataFrame` can be faithfully reconstructed, we store a `pandas` metadata key in the `FileMetaData` with the value stored as:

```plaintext
{"index_columns": ["__index_level_0__", '__index_level_1__', ...],
 'column_indexes': [<ci0>, <ci1>, ..., <ciN>],
 'columns': [<c0>, <c1>, ...],
 'pandas_version': $VERSION}
```

Here, `<c0>`/`<ci0>` and so forth are dictionaries containing the metadata for each column. This has JSON form:

```plaintext
{"name": column_name,
 'pandas_type': pandas_type,
 'numpy_type': numpy_type,
 'metadata': metadata}
```

`pandas_type` is the logical type of the column, and is one of:

- **Boolean**: 'bool'
- **Integers**: 'int8', 'int16', 'int32', 'int64', 'uint8', 'uint16', 'uint32', 'uint64'
- **Floats**: 'float16', 'float32', 'float64'
- **Date and Time Types**: 'datetime', 'datetimetz', 'timedelta'
- **String**: 'unicode', 'bytes'
• Categorical: 'categorical'
• Other Python objects: 'object'

The numpy_type is the physical storage type of the column, which is the result of str(dtype) for the underlying NumPy array that holds the data. So for datetimetz this is datetime64[ns] and for categorical, it may be any of the supported integer categorical types.

The metadata field is None except for:

• datetimetz: {'timezone': zone, 'unit': 'ns'}, e.g. {'timezone': 'America/New_York', 'unit': 'ns'}. The 'unit' is optional, and if omitted it is assumed to be nanoseconds.
• categorical: {'num_categories': K, 'ordered': is_ordered, 'type': $TYPE}
  – Here 'type' is optional, and can be a nested pandas type specification here (but not categorical)
• unicode: {'encoding': encoding}
  – The encoding is optional, and if not present is UTF-8
• object: {'encoding': encoding}. Objects can be serialized and stored in BYTE_ARRAY Parquet columns. The encoding can be one of:
  - 'pickle'
  - 'msgpack'
  - 'bson'
  - 'json'
• timedelta: {'unit': 'ns'}. The 'unit' is optional, and if omitted it is assumed to be nanoseconds. This metadata is optional altogether

For types other than these, the 'metadata' key can be omitted. Implementations can assume None if the key is not present.

As an example of fully-formed metadata:

```json
{"index_columns": ["__index_level_0__"],
 'column_indexes': [
 {"name": None,
 'pandas_type': 'string',
 'numpy_type': 'object',
 'metadata': None}
 ],
 'columns': [
 {"name": 'c0',
 'pandas_type': 'int8',
 'numpy_type': 'int8',
 'metadata': None},
 {"name": 'c1',
 'pandas_type': 'bytes',
 'numpy_type': 'object',
 'metadata': None},
 {"name": 'c2',
 'pandas_type': 'categorical',
 'numpy_type': 'int16',
 'metadata': {'num_categories': 1000, 'ordered': False}},
 {"name": 'c3',
 'pandas_type': 'datetimetz',
 'numpy_type': 'datetime64[ns]'},
```
35.1. Storing pandas DataFrame objects in Apache Parquet format

| 'metadata': {'timezone': 'America/Los_Angeles'}}, |
| {'name': 'c4', |
| 'pandas_type': 'object', |
| 'numpy_type': 'object', |
| 'metadata': {'encoding': 'pickle'}}, |
| {'name': '__index_level_0__', |
| 'pandas_type': 'int64', |
| 'numpy_type': 'int64', |
| 'metadata': None} |
| 'pandas_version': '0.20.0'} |
This section will provide a look into some of pandas internals. It’s primarily intended for developers of pandas itself.

### 36.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- **Index**: the generic “ordered set” object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do $O(1)$ lookups.
- **Int64Index**: a version of Index highly optimized for 64-bit integer data, such as time stamps
- **Float64Index**: a version of Index highly optimized for 64-bit float data
- **MultiIndex**: the standard hierarchical index object
- **DatetimeIndex**: An Index object with Timestamp boxed elements (impl are the int64 values)
- **TimedeltaIndex**: An Index object with Timedelta boxed elements (impl are the int64 values)
- **PeriodIndex**: An Index object with Period elements

There are functions that make the creation of a regular index easy:

- **date_range**: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Python datetime objects
- **period_range**: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Period objects, representing Timespans

The motivation for having an Index class in the first place was to enable different implementations of indexing. This means that it’s possible for you, the user, to implement a custom Index subclass that may be better suited to a particular application than the ones provided in pandas.

From an internal implementation point of view, the relevant methods that an Index must define are one or more of the following (depending on how incompatible the new object internals are with the Index functions):

- **get_loc**: returns an “indexer” (an integer, or in some cases a slice object) for a label
- **slice_locs**: returns the “range” to slice between two labels
- **get_indexer**: Computes the indexing vector for reindexing / data alignment purposes. See the source / docstrings for more on this
- **get_indexer_non_unique**: Computes the indexing vector for reindexing / data alignment purposes when the index is non-unique. See the source / docstrings for more on this
- **reindex**: Does any pre-conversion of the input index then calls get_indexer
• union, intersection: computes the union or intersection of two Index objects
• insert: Inserts a new label into an Index, yielding a new object
• delete: Delete a label, yielding a new object
• drop: Deletes a set of labels
• take: Analogous to ndarray.take

### 36.1.1 MultiIndex

Internally, the MultiIndex consists of a few things: the levels, the integer labels, and the level names:

```python
In [1]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])
In [2]: index
Out[2]:
MultiIndex(levels=[[0, 1, 2], ['one', 'two']],
          labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
          names=['first', '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.

### 36.1.2 Values

Pandas extends NumPy’s type system with custom types, like Categorical or datetimes with a timezone, so we have multiple notions of “values”. For 1-D containers (Index classes and Series) we have the following convention:

- cls._ndarray_values is always a NumPy ndarray. Ideally, _ndarray_values is cheap to compute. For example, for a Categorical, this returns the codes, not the array of objects.
- cls._values refers is the “best possible” array. This could be an ndarray, ExtensionArray, or in Index subclass (note: we’re in the process of removing the index subclasses here so that it’s always an ndarray or ExtensionArray).

So, for example, Series[category]._values is a Categorical, while Series[category]._ndarray_values is the underlying codes.
36.2 Subclassing pandas Data Structures

This section has been moved to Subclassing pandas Data Structures.
While pandas provides a rich set of methods, containers, and data types, your needs may not be fully satisfied. Pandas offers a few options for extending pandas.

### 37.1 Registering Custom Accessors

Libraries can use the decorators `pandas.api.extensions.register_dataframe_accessor()`, `pandas.api.extensions.register_series_accessor()`, and `pandas.api.extensions.register_index_accessor()`, to add additional “namespaces” to pandas objects. All of these follow a similar convention: you decorate a class, providing the name of attribute to add. The class’s `__init__` method gets the object being decorated. For example:

```python
@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor(object):
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Now users can access your methods using the `geo` namespace:

```python
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
... 'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

This can be a convenient way to extend pandas objects without subclassing them. If you write a custom accessor, make a pull request adding it to our `pandas Ecosystem` page.
37.2 Extension Types

New in version 0.23.0.

Warning: The pandas.api.extension.ExtensionDtype and pandas.api.extension.ExtensionArray APIs are new and experimental. They may change between versions without warning.

Pandas defines an interface for implementing data types and arrays that extend NumPy’s type system. Pandas itself uses the extension system for some types that aren’t built into NumPy (categorical, period, interval, datetime with timezone).

Libraries can define a custom array and data type. When pandas encounters these objects, they will be handled properly (i.e. not converted to an ndarray of objects). Many methods like pandas.isna() will dispatch to the extension type’s implementation.

If you’re building a library that implements the interface, please publicize it on Extension Data Types.

The interface consists of two classes.

37.2.1 ExtensionDtype

A pandas.api.extension.ExtensionDtype is similar to a numpy.dtype object. It describes the data type. Implementors are responsible for a few unique items like the name.

One particularly important item is the type property. This should be the class that is the scalar type for your data. For example, if you were writing an extension array for IP Address data, this might be ipaddress.IPv4Address.

See the extension dtype source for interface definition.

37.2.2 ExtensionArray

This class provides all the array-like functionality. ExtensionArrays are limited to 1 dimension. An ExtensionArray is linked to an ExtensionDtype via the dtype attribute.

Pandas makes no restrictions on how an extension array is created via its __new__ or __init__, and puts no restrictions on how you store your data. We do require that your array be convertible to a NumPy array, even if this is relatively expensive (as it is for Categorical).

They may be backed by none, one, or many NumPy arrays. For example, pandas.Categorical is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 addresses may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists.

See the extension array source for the interface definition. The docstrings and comments contain guidance for properly implementing the interface.

We provide a test suite for ensuring that your extension arrays satisfy the expected behavior. To use the test suite, you must provide several pytest fixtures and inherit from the base test class. The required fixtures are found in https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/conftest.py.

To use a test, subclass it:

```python
from pandas.tests.extension import base
```
Warning: There are some easier alternatives before considering subclassing pandas data structures.

1. Extensible method chains with pipe
2. Use composition. See here.
3. Extending by registering an accessor
4. Extending by extension type

This section describes how to subclass pandas data structures to meet more specific needs. There are two points that need attention:

1. Override constructor properties.
2. Define original properties

Note: You can find a nice example in geopandas project.

### 37.3.1 Override Constructor Properties

Each data structure has several constructor properties for returning a new data structure as the result of an operation. By overriding these properties, you can retain subclasses through pandas data manipulations.

There are 3 constructor properties to be defined:

- `_constructor`: Used when a manipulation result has the same dimensions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as DataFrame single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as Series.to_frame() 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>
</tr>
</thead>
<tbody>
<tr>
<td>_constructor</td>
<td>Series</td>
<td>DataFrame</td>
</tr>
<tr>
<td>_constructor_sliced</td>
<td>NotImplementedException</td>
<td>Series</td>
</tr>
<tr>
<td>_constructor_expanddim</td>
<td>DataFrame</td>
<td>Panel</td>
</tr>
</tbody>
</table>

Below example shows how to define SubclassedSeries and SubclassedDataFrame overriding constructor properties.
```python
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

>>> type(df)
<class '__main__.SubclassedDataFrame'>

>>> sliced1 = df[['A', 'B']]  
>>> sliced1
   A  B
0  1  4
1  2  5
2  3  6

>>> type(sliced1)
<class '__main__.SubclassedDataFrame'>

>>> sliced2 = df['A']
>>> sliced2
0 1
1 2
2 3
Name: A, dtype: int64
>>> type(sliced2)
<class '__main__.SubclassedSeries'>
```

Chapter 37. Extending Pandas
37.3.2 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 __getattribute__. Defining original properties can be done in one of 2 ways:

1. Define _internal_names and _internal_names_set for temporary properties which WILL NOT be passed to manipulation results.
2. Define _metadata for normal properties which will be passed to manipulation results.

Below is an example to define two original properties, “internal_cache” as a temporary property and “added_property” as a normal property

```python
class SubclassedDataFrame2(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
```
RELEASE NOTES

This is the list of changes to pandas between each release. For full details, see the commit logs at http://github.com/pandas-dev/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/pandas-dev/pandas
- Binary installers on PyPI: https://pypi.org/project/pandas
- Documentation: http://pandas.pydata.org

38.1 pandas 0.23.1

Release date: June 12, 2018

This is a minor release from 0.23.0 and includes a number of bug fixes and performance improvements.

See the full whatsnew for a list of all the changes.

38.1.1 Thanks

A total of 30 people contributed to this release. People with a “+” by their names contributed a patch for the first time.

- Adam J. Stewart
- Adam Kim +
- Aly Sivji
- Chalmer Lowe +
- Damini Satya +
- Dr. Irv
- Gabe Fernando +
- Giftlin Rajaiah
- Jeff Reback
38.2 pandas 0.23.0

Release date: May 15, 2018

This is a major release from 0.22.0 and includes a number of API changes, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Round-trippable JSON format with ‘table’ orient.
- Instantiation from dicts respects order for Python 3.6+.
- Dependent column arguments for assign.
- Merging / sorting on a combination of columns and index levels.
- Extending Pandas with custom types.
- Excluding unobserved categories from groupby.
- Changes to make output shape of DataFrame.apply consistent.

See the full whatstnew for a list of all the changes.
38.2.1 Thanks

A total of 328 people contributed to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Critchley
- AbdealiJK +
- Adam Hooper +
- Albert Villanova del Moral
- Alejandro Giacometti +
- Alejandro Hohmann +
- Alex Rychyk
- Alexander Buchkovsky
- Alexander Lenail +
- Alexander Michael Schade
- Aly Sivji +
- Andreas Költringer +
- Andrew
- Andrew Bui +
- András Novoszáth +
- Andy Craze +
- Andy R. Terrel
- Anh Le +
- Anil Kumar Pullekondu +
- Antoine Pitrou +
- Antonio Linde +
- Antonio Molina +
- Antonio Quinonez +
- Armin Varshokar +
- Artem Bogachev +
- Avi Sen +
- Azeez Oluwafemi +
- Ben Auffarth +
- Bernhard Thiel +
- Bhavesh Poddar +
- BielStela +
- Blair +
- Bob Haffner
• Brett Naul +
• Brock Mendel
• Bryce Guinta +
• Carlos Eduardo Moreira dos Santos +
• Carlos García Márquez +
• Carol Willing
• Cheuk Ting Ho +
• Chitrunk Dixit +
• Chris
• Chris Burr +
• Chris Catalfo +
• Chris Mazzullo
• Christian Chwala +
• Cihan Ceyhan +
• Clemens Brunner
• Colin +
• Cornelius Riemenschneider
• Crystal Gong +
• DaanVanHauwermeiren
• Dan Dixey +
• Daniel Frank +
• Daniel Garrido +
• Daniel Sakuma +
• DataOmbudsman +
• Dave Hirschfeld
• Dave Lewis +
• David Adrián Cañones Castellano +
• David Arcos +
• David C Hall +
• David Fischer
• David Hoese +
• David Lutz +
• David Polo +
• David Stansby
• Dennis Kamau +
• Dillon Niederhut
• Dimitri +
• Dr. Irv
• Dror Atariah
• Eric Chea +
• Eric Kisslinger
• Eric O. LEBIGOT (EOL) +
• FAN-GOD +
• Fabian Retkowski +
• Fer Sar +
• Gabriel de Maeztu +
• Gianpaolo Macario +
• Giftlin Rajaiah
• Gilberto Olimpio +
• Gina +
• Gjelt +
• Graham Inggs +
• Grant Roch
• Grant Smith +
• Grzegorz Konefał +
• Guilherme Beltramini
• Hagai Hargil +
• Hamish Pitkeathly +
• Hammad Mashkoor +
• Hannah Ferchland +
• Hans
• Haochen Wu +
• Hissashi Rocha +
• Iain Barr +
• Ibrahim Sharaf ElDen +
• Ignasi Fosch +
• Igor Conrado Alves de Lima +
• Igor Shelvinskyi +
• Imanflow +
• Ingolf Becker
• Israel Saeta Pérez
• Iva Koevska +
• Jakub Nowacki +
• Jan F-F +
• Jan Koch +
• Jan Werkmann
• Janelle Zoutkamp +
• Jason Bandlow +
• Jaume Bonet +
• Jay Alammar +
• Jeff Reback
• JennaVergeynst
• Jimmy Woo +
• Jing Qiang Goh +
• Joachim Wagner +
• Joan Martin Miralles +
• Joel Nothman
• Joeun Park +
• John Cant +
• Johnny Metz +
• Jon Mease
• Jonas Schulze +
• Jongwony +
• Jordi Contestí +
• Joris Van den Bossche
• José F. R. Fonseca +
• Jovixe +
• Julio Martinez +
• Jörg Döpfert
• KOBAYASHI Ittoku +
• Kate Surta +
• Kenneth +
• Kevin Kuhl
• Kevin Sheppard
• Krzysztof Chomski
• Ksenia +
• Ksenia Bobrova +
• Kunal Gosar +
• Kurtis Kerstein +
• Kyle Barron +
• Laksh Arora +
• Laurens Geffert +
• Leif Walsh
• Liam Marshall +
• Liam3851 +
• Licht Takeuchi
• Liudmila +
• Ludovico Russo +
• Mabel Villalba +
• Manan Pal Singh +
• Manraj Singh
• Marc +
• Marc Garcia
• Marco Hemken +
• Maria del Mar Bibiloni +
• Mario Corchero +
• Mark Woodbridge +
• Martin Journois +
• Mason Gallo +
• Matias Heikkilä +
• Matt Braymer-Hayes
• Matt Kirk +
• Matt Maybeno +
• Matthew Kirk +
• Matthew Rocklin +
• Matthew Roeschke
• Matthias Bussonnier +
• Max Mikhaylov +
• Maxim Veksler +
• Maximilian Roos
• Maximiliano Greco +
• Michael Penkov
• Michael Röttger +
• Michael Selik +
• Michael Waskom
• Mic~~~
• Mike Kutzma +
• Ming Li +
• Mitar +
• Mitch Negus +
• Montana Low +
• Moritz Münst +
• Mortada Mehyar
• Myles Braithwaite +
• Nate Yoder
• Nicholas Ursa +
• Nick Chmura
• Nikos Karagiannakis +
• Nipun Sadvilkar +
• Nis Martensen +
• Noah +
• Noémi Élvető +
• Olivier Bilodeau +
• Ondrej Kokes +
• Onno Eberhard +
• Paul Ganssle +
• Paul Mannino +
• Paul Reidy
• Paulo Roberto de Oliveira Castro +
• Pepe Flores +
• Peter Hoffmann
• Phil Ngo +
• Pietro Battiston
• Pranav Suri +
• Priyanka Ojha +
• Pulkit Maloo +
• README Bot +
• Ray Bell +
• Riccardo Magliocchetti +
• Ridhwan Luthra +
• Robert Meyer
• Robin
• Robin Kiplang’at +
• Rohan Pandit +
• Rok Mihevc +
• Rouz Azari
• Ryszard T. Kaleta +
• Sam Cohan
• Sam Foo
• Samir Musali +
• Samuel Sinayoko +
• Sangwoong Yoon
• Sarah Jessica +
• Sharad Vijalapuram +
• Shubham Chaudhary +
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• Ted Petrou +
• Thomas A Caswell
• Tim Hoffmann +
• Tim Swast
• Tom Augspurger
• Tommy +
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• Tushar Gupta +
• Tushar Mittal +
• Upkar Lidder +
• Victor Villas +
• Vince W +
• Vinícius Figueiredo +
• Vipin Kumar +
• WBare
• Wenhuan +
• Wes Turner
• William Ayd
• Wilson Lin +
• Xbar
• Yaroslav Halchenko
• Yee Mey
• Yeongseon Choe +
• Yian +
• Yimeng Zhang
• ZhuBaohe +
• Zihao Zhao +
• adatasetaday +
• akielbowicz +
• akosel +
• alinde1 +
• amuta +
• bolkedebruin
• cbertinato
• cgholk
• charlie0389 +
• chris-b1
• csfarkas +
• dajcs +
• deflatSOCO +
• derestle-HTWG
• discort
• dmanikowski-reef +
• donK23 +
• elrubio +
• fivemok +
• fjiod
• fjetter +
• froessler +
• gabrieplow
• gfyoun
• ghasenaddaf
• h-vetinari +
• himanshu awasthi +
• ignamv +
• jayfoad +
• jazzmuesli +
• jbrockmendel
• jen w +
• jjames34 +
• joaovf +
• joders +
• jschendel
• juan huguet +
• 1736x +
• luzpaz +
• mdeboc +
• miguelmorin +
• miker985
• miquelcamprodon +
• orereta +
• ottiP +
• peterpanmj +
• rafarui +
• raph-m +
• readyready15728 +
• rmihael +
• samghelms +
• scriptomation +
• sfoo +
• stefansimik +
• stonebig
38.3 pandas 0.22.0

Release date: December 29, 2017

This is a major release from 0.21.1 and includes a single, API-breaking change. We recommend that all users upgrade to this version after carefully reading the release note.

The only changes are:

- The sum of an empty or all-NA Series is now 0
- The product of an empty or all-NA Series is now 1
- We’ve added a min_count parameter to .sum() and .prod() controlling the minimum number of valid values for the result to be valid. If fewer than min_count non-NA values are present, the result is NA. The default is 0. To return NaN, the 0.21 behavior, use min_count=1.

See the v0.22.0 Whatsnew overview for further explanation of all the places in the library this affects.

38.4 pandas 0.21.1

Release date: December 12, 2017

This is a minor bug-fix release in the 0.21.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Temporarily restore matplotlib datetime plotting functionality. This should resolve issues for users who relied implicitly on pandas to plot datetimes with matplotlib. See here.
- Improvements to the Parquet IO functions introduced in 0.21.0. See here.

See the v0.21.1 Whatsnew overview for an extensive list of all the changes for 0.21.1.

38.4.1 Thanks

A total of 46 people contributed to this release. People with a “+” by their names contributed a patch for the first time.
38.4.1.1 Contributors

• Aaron Critchley +
• Alex Rychyk
• Alexander Buchkovsky +
• Alexander Michael Schade +
• Chris Mazzullo
• Cornelius Riemenschneider +
• Dave Hirschfeld +
• David Fischer +
• David Stansby +
• Dror Atariah +
• Eric Kisslinger +
• Hans +
• Ingolf Becker +
• Jan Werkmann +
• Jeff Reback
• Joris Van den Bossche
• Jörg Döpfert +
• Kevin Kuhl +
• Krzysztof Chomski +
• Leif Walsh
• Licht Takeuchi
• Manraj Singh +
• Matt Braymer-Hayes +
• Michael Waskom +
• Mie-~~~ +
• Peter Hoffmann +
• Robert Meyer +
• Sam Cohan +
• Sietse Brouwer +
• Sven +
• Tim Swast
• Tom Augspurger
• Wes Turner
• William Ayd +
• Yee Mey +
• bolkedebruin +
• cgholke
• derestle-hwlg +
• fjdiod +
• gabrielclow +
• gfyounf
• ghasemnaddaf +
• jbrockmendel
• jschendel
• miker985 +
• toppter-123

38.5 pandas 0.21.0

Release date: October 27, 2017

This is a major release from 0.20.3 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

• Integration with Apache Parquet, including a new top-level read_parquet() function and DataFrame. to_parquet() method, see here.
• New user-facing pandas.api.types.CategoricalDtype for specifying categoricals independent of the data, see here.
• The behavior of sum and prod on all-NaN Series/DataFrames is now consistent and no longer depends on whether bottleneck is installed, and sum and prod on empty Series now return NaN instead of 0, see here.
• Compatibility fixes for pypy, see here.
• Additions to the drop, reindex and rename API to make them more consistent, see here.
• Addition of the new methods DataFrame.infer_objects (see here) and GroupBy.pipe (see here).
• Indexing with a list of labels, where one or more of the labels is missing, is deprecated and will raise a Key Error in a future version, see here.

See the v0.21.0 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.21.0

38.5.1 Thanks

A total of 206 people contributed to this release. People with a “+” by their names contributed a patch for the first time.
38.5.1.1 Contributors

- 3553x +
- Aaron Barber
- Adam Gleave +
- Adam Smith +
- AdamShamlian +
- Adrian Liaw +
- Alan Velasco +
- Alan Yee +
- Alex B +
- Alex Lubbock +
- Alex Marchenko +
- Alex Rychyk +
- Amol K +
- Andreas Winkler
- Andrew +
- Andrew
- André Jonasson +
- Becky Sweger
- Berkay +
- Bob Haffner +
- Bran Yang
- Brian Tu +
- Brock Mendel +
- Carol Willing +
- Carter Green +
- Chankey Pathak +
- Chris
- Chris Billington
- Chris Filo Gorgolewski +
- Chris Kerr
- Chris M +
- Chris Mazzullo +
- Christian Prinoth
- Christian Stade-Schuldt
- Christoph Moehl +
• JimStearns206
• Joel Nothman
• John W. O’Brien
• Jon Crall +
• Jon Mease
• Jonathan J. Helmus +
• Joris Van den Bossche
• Joseph Wagner
• Juarez Bochi
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• Margaret Sy +
• MarsGuy +
• Matt Bark +
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• Matti Picus
• Mehmet Ali “Mali” Akmanalp
• Michael Gasvoda +
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- aviolog +
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- ccclauss +
- chernick
- chris-b1
- dkamm +
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- economy
- faic +
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- gfyounb
- guygoldberg +
- hhuuggoo +
- huashuai +
- ian
- iulia +
- jaredsnyder
- jbrockmendel +
- jdeschenes
- jebob +
- jschendel +
- keitakurita
- kernc +
- kiwirob +
- kjford
38.6 pandas 0.20.0 / 0.20.1

Release date: May 5, 2017

This is a major release from 0.19.2 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- New `.agg()` API for Series/DataFrame similar to the groupby-rolling-resample API’s, see here
• Integration with the feather-format, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see [here](#).

• The `.ix` indexer has been deprecated, see [here](#)

• Panel has been deprecated, see [here](#)

• Addition of an `IntervalIndex` and `Interval` scalar type, see [here](#)

• Improved user API when grouping by index levels in `.groupby()`, see [here](#)

• Improved support for `UInt64` dtypes, see [here](#)

• A new orient for JSON serialization, `orient='table'`, that uses the Table Schema spec and that gives the possibility for a more interactive repr in the Jupyter Notebook, see [here](#)

• Experimental support for exporting styled DataFrames (`DataFrame.style`) to Excel, see [here](#)

• Window binary corr/cov operations now return a MultiIndexed `DataFrame` rather than a `Panel`, as `Panel` is now deprecated, see [here](#)

• Support for S3 handling now uses `s3fs`, see [here](#)

• Google BigQuery support now uses the `pandas-gbq` library, see [here](#)

See the [v0.20.1 Whatsnew](#) overview for an extensive list of all enhancements and bugs that have been fixed in 0.20.1.

**Note:** This is a combined release for 0.20.0 and 0.20.1. Version 0.20.1 contains one additional change for backwards-compatibility with downstream projects using pandas' `utils` routines. (GH16250)

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- Carlos Souza
- chaimdemulder
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- chris-b1
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- Christoph Paulik
- Chris Warth
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- Dave Willmer
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- David Gwynne
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- David Krych
- dickreuter
- Diego Fernandez
- Dimitris Spathis
- discort
- Dmitry L
- Dody Suria Wijaya
- Dominik Stanczak
- Dr-Irv
• Dr. Irv
• dr-leo
• D.S. McNeil
• dubourg
• dwkenefick
• Elliott Sales de Andrade
• Ennemoser Christoph
• Francesc Alted
• Fumito Hamamura
• funnycrab
• gfyounq
• Giacomo Ferroni
• goldenbull
• Graham R. Jeffries
• Greg Williams
• Guilherme Beltrimini
• Guilherme Samora
• Hao Wu
• Harshit Patni
• hesham.shabana@hotmail.com
• Ilya V. Schurov
• Iván Vallés Pérez
• Jackie Leng
• Jaehoon Hwang
• James Draper
• James Goppert
• James McBride
• James Santucci
• Jan Schulz
• Jeff Carey
• Jeff Reback
• JennaVergeynst
• Jim
• Jim Crist
• Joe Jevnik
• Joel Nothman
• John
• John Tucker
• John W. O’Brien
• John Zwinck
• jojomdt
• Jonathan de Bruin
• Jonathan Whitmore
• Jon Mease
• Jon M. Mease
• Joost Kranendonk
• Joris Van den Bossche
• Joshua Bradt
• Julian Santander
• Julien Marrec
• Jun Kim
• Justin Solinsky
• Kacawi
• Kamal Kamalaldin
• Kerby Shedden
• Kernc
• Keshav Ramaswamy
• Kevin Sheppard
• Kyle Kelley
• Larry Ren
• Leon Yin
• linebp
• Line Pedersen
• Lorenzo Cestaro
• Luca Scarabello
• Lukasz
• Mahmoud Lababidi
• manu
• manuels
• Mark Mandel
• Matthew Brett
• Matthew Roeschke
• mattip
• Matti Picus
• Matt Roeschke
• maxalbert
• Maximilian Roos
• mcocdawc
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• Nate Yoder
• Nathalie Rud
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• nuffe
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• paul-mannino
• Pawel Kordek
• pbreach
• Pete Huang
• Peter
• Peter Csizsek
• Petio Petrov
• Phil Ruffwind
• Pietro Battiston
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• Rob Forgione
• Robin
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• Sarma Tangirala
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• Scott Sanderson
• Sebastian Bank
• Sebastian Gsänger
• Sébastien de Menten
• Shawn Heide
• Shyam Saladi
• sinhrks
• Sinhrks
• Stephen Rauch
• stijnvanoey
• Tara Adiseshan
• themrmmax
• the-nose-knows
• Thiago Serafin
• Thoralf Gutierrez
• Thrasibule
• Tobias Gustafsson
• Tom Augspurger
• tomrod
• Tong Shen
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• tzinckgraf
• Uwe
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• watercrossing
• wcwagner
38.7 pandas 0.19.2

Release date: December 24, 2016

This is a minor bug-fix release in the 0.19.x series and includes some small regression fixes, bug fixes and performance improvements.

Highlights include:

- Compatibility with Python 3.6
- Added a Pandas Cheat Sheet. (GH13202).

See the v0.19.2 Whatsnew page for an overview of all bugs that have been fixed in 0.19.2.

38.7.1 Thanks

- Ajay Saxena
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- Jeff Reback
- Joe Jevnik
- Joris Van den Bossche
- Julian Santander
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38.8 pandas 0.19.1

Release date: November 3, 2016

This is a minor bug-fix release from 0.19.0 and includes some small regression fixes, bug fixes and performance improvements.

See the v0.19.1 Whatsnew page for an overview of all bugs that have been fixed in 0.19.1.

38.8.1 Thanks

• Adam Chainz
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• Ben Kandel
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• chris-b1
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• gfyoun
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38.9 pandas 0.19.0

Release date: October 2, 2016

This is a major release from 0.18.1 and includes number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

• `merge_asof()` for asof-style time-series joining, see here
• `.rolling()` is now time-series aware, see here
• `read_csv()` now supports parsing Categorical data, see here
• A function `union_categorical()` has been added for combining categoricals, see here
• `PeriodIndex` now has its own `period` dtype, and changed to be more consistent with other `Index` classes. See here
• Sparse data structures gained enhanced support of `int` and `bool` dtypes, see here
• Comparison operations with `Series` no longer ignores the index, see here for an overview of the API changes.
• Introduction of a pandas development API for utility functions, see here.
• Deprecation of `Panel4D` and `PanelND`. We recommend to represent these types of n-dimensional data with the `xarray` package.
• Removal of the previously deprecated modules `pandas.io.data`, `pandas.io.wb`, `pandas.tools.rplot`.

See the v0.19.0 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.19.0.
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- adneu
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- Alex Alekseyev
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- Andy R. Terrel
- Anthonios Partheniou
- babakkeyvani
- Ben Kandel
- Bob Baxley
- Brett Rosen
- c123w
- Camilo Cota
- Chris
- chris-b1
- Chris Grinolds
- Christian Hudon
- Christopher C. Aycock
- Chris Warth
- cmazzullo
- conquistador1492
- cr3
- Daniel Siladji
- Douglas McNeil
- Drewrey Lupton
- dsm054
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- Gábor Lipták
• Geraint Duck
• gflyoung
• Giacomo Ferroni
• Grant Roch
• Haleemur Ali
• harshul1610
• Hassan Shamim
• iamsimha
• Iulius Curt
• Ivan Nazarov
• jackieleng
• Jeff Reback
• Jeffrey Gerard
• Jenn Olsen
• Jim Crist
• Joe Jevnik
• John Evans
• John Freeman
• John Liekezer
• Johnny Gill
• John W. O’Brien
• John Zwinck
• Jordan Erenrich
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• Mike Graham
• Mortada Mehyar
• mpuels
• Muhammad Haseeb Tariq
• Nate George
• Neil Parley
• Nicolas Bonnotte
• OXPHOS
• Pan Deng / Zora
• Paul
• Pauli Virtanen
• Paul Mestemaker
• Pawel Kordek
• Pietro Battiston
• pijucha
• Piotr Jucha
• priyankjain
• Ravi Kumar Nimmi
• Robert Gieseke
• Robert Kern
• Roger Thomas
• Roy Keyes
• Russell Smith
• Sahil Dua
• Sanjiv Lobo
• Sašo Stanovnik
• Shawn Heide
• sinhrks
• Sinhrks
• Stephen Kappel
• Steve Choi
• Stewart Henderson
• Sudarshan Konge
• Thomas A Caswell
• Tom Augspurger
• Tom Bird
• Uwe Hoffmann
• wcwagner
• WillAyd
• Xiang Zhang
• Yadunandan
• Yaroslav Halchenko
• YG-Riku
• Yuichiro Kaneko
• yui- knk
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• znmean
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38.10 pandas 0.18.1

Release date: (May 3, 2016)

This is a minor release from 0.18.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements.

Highlights include:

• .groupby(...) has been enhanced to provide convenient syntax when working with .rolling(...), .expanding(...) and .resample(...) per group, see here
• pd.to_datetime() has gained the ability to assemble dates from a DataFrame, see here
• Method chaining improvements, see here.
• Custom business hour offset, see here.
• Many bug fixes in the handling of sparse, see here
• Expanded the Tutorials section with a feature on modern pandas, courtesy of @TomAugsburger, (GH13045).

See the v0.18.1 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.18.1.

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• Jeff Reback
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• Joshua Storck
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• Maoyuan Liu
• Mark Roth
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• MaxU
• Maximilian Roos
• Michael Droettboom
• Nick Eubank
• Nicolas Bonnotte
• OXPHOS
• Pauli Virtanen
• Peter Waller
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• Robin Wilson
• Roger Thomas
• Sebastian Bank
• Stephen Hoover
• Tim Hopper
• Tom Augspurger
• WANG Aiyong
• Wes Turner
• Winand
• Xbar
Highlights include:

- Moving and expanding window functions are now methods on Series and DataFrame, similar to .groupby, see here.
- Adding support for a RangeIndex as a specialized form of the Int64Index for memory savings, see here.
- API breaking change to the .resample method to make it more .groupby like, see here.
- Removal of support for positional indexing with floats, which was deprecated since 0.14.0. This will now raise a TypeError, see here.
- The .to_xarray() function has been added for compatibility with the xarray package, see here.
- The read_sas function has been enhanced to read sas7bdat files, see here.
- Addition of the .str.extractall() method, and API changes to the .str.extract() method and .str.cat() method.
- pd.test() top-level nose test runner is available (GH4327).

See the v0.18.0 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.18.0.

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• Christopher Scanlin
• Cody
• Da Wang
• Daniel Grady
• Dorozhko Anton
• Dr-Irv
• Erik M. Bray
• Evan Wright
• Francis T. O’Donovan
• Frank Cleary
• Gianluca Rossi
• Graham Jeffries
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• Henry Hammond
• Isaac Schwabacher
• Jean-Mathieu Deschenes
• Jeff Reback
• Joe Jevnik
• John Freeman
• John Fremlin
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• Joris Van den Bossche
• Joris Vankerschaver
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• Justin Lin
• Ka Wo Chen
• Keming Zhang
• Kerby Shedden
• Kyle
• Marco Farrugia
• MasonGallo
• MattRijk
• Matthew Lurie
• Maximilian Roos
• Mayank Asthana
• Mortada Mehyar
• Moussa Taifi
• Navreet Gill
• Nicolas Bonnotte
• Paul Reiners
• Philip Gura
• Pietro Battistone
• RahulHP
• Randy Carnevale
• Rinoc Johnson
• Rishipuri
• Sangmin Park
• Scott E Lasley
• Sereger13
• Shannon Wang
• Skipper Seabold
• Thierry Moisan
• Thomas A Caswell
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• Will Thompson
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38.12 pandas 0.17.1

**Release date:** (November 21, 2015)

This is a minor release from 0.17.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements.

Highlights include:

- Releasing the GIL on the csv reader & other ops, see [here](https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html#csv-management)
- Regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)
See the v0.17.1 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.17.1.

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- Evan Wright
- Guillaume Gay
- Hamed Saljooghinejad
- Iblis Lin
- Jake VanderPlas
- Jan Schulz
- Jean-Mathieu Deschenes
- Jeff Reback
- Jimmy Callin
- Joris Van den Bossche
- K.-Michael Aye
- Ka Wo Chen
- Loïc Séguin-C
- Luo Yicheng
- Magnus Jöud
- Manuel Leonhardt
- Matthew Gilbert
- Maximilian Roos
- Michael
- Nicholas Stahl
- Nicolas Bonnotte
- Pastafarianist
38.13 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 datetime-likes, and Series.dt.total_seconds to generate each duration of the timedelta in seconds. See here
• Period and PeriodIndex can handle multiplied freq like 3D, which corresponding to 3 days span. See here
• Development installed versions of pandas will now have PEP440 compliant version strings (GH9518)
• Development support for benchmarking with the Air Speed Velocity library (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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38.14 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.

38.14.1 Thanks

- Andrew Rosenfeld
- Artemy Kolchinsky
38.15 pandas 0.16.1

Release date: (May 11, 2015)

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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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.

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38.17 pandas 0.15.2

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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.

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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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38.19 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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38.20 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 `read_csv()` text parser.
- New documentation section on Options and Settings.
- Lots of bug fixes.

See the v0.14.1 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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38.21 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.

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38.22 pandas 0.13.1

Release date: (February 3, 2014)

38.22.1 New Features

- Added date_format and datetime_format attribute to ExcelWriter. (GH4133)

38.22.2 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).

38.22.3 Experimental Features

38.22.4 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 @lexical 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)

38.22.5 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 “NaT” (GH5708)
• Fixed string-representation for Timestamp to show nanoseconds if present (GH5912)
• pd.match not returning passed sentinel
• Panel.to_frame() no longer fails when major_axis is a MultiIndex (GH5402).
• Bug in pd.read_msgpack with inferring a DateTimeIndex frequency incorrectly (GH5947)
• Fixed `to_datetime` for array with both Tz-aware datetimes and NaT’s (GH5961)
• Bug in rolling skew/kurtosis when passed a Series with bad data (GH5749)
• Bug in scipy interpolate methods with a datetime index (GH5975)
• Bug in NaT comparison if a mixed datetime/np.datetime64 with NaT were passed (GH5968)
• Fixed bug with `pd.concat` losing dtype information if all inputs are empty (GH5742)
• Recent changes in IPython cause warnings to be emitted when using previous versions of pandas in QTConsole, now fixed. If you’re using an older version and need to suppress the warnings, see (GH5922).
• Bug in merging timedelta dtypes (GH5695)
• Bug in plotting.scatter_matrix function. Wrong alignment among diagonal and off-diagonal plots, see (GH5497).
• Regression in Series with a 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 propagating `_ref_locs` during construction of a DataFrame with dups index/columns (GH6121)
• Bug in `DataFrame.apply` when using mixed datelike reductions (GH6125)
• Bug in `DataFrame.append` when appending a row with different columns (GH6129)
• Bug in DataFrame construction with recarray and non-ns datetime dtype (GH6140)
• Bug in `.loc` setitem indexing with a dataframe on rhs, multiple item setting, and a datetimelike (GH6152)
• Fixed a bug in `query/eval` during lexicographic string comparisons (GH6155).
• Fixed a bug in `query` where the index of a single-element `Series` was being thrown away (GH6148).
• Bug in HDFStore on appending a dataframe with 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)
38.23 pandas 0.13.0

Release date: January 3, 2014

38.23.1 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)

38.23.2 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)

38.23.3 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` dtyped 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 `PeriodsIndex` 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 xlsx 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 context managers. (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

Better 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 a to_frame method to convert it to a single-column DataFrame (GH5164)

Datet imeIndex (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** to merge cells in MultIndex 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])

### 38.23.4 API Changes

- **DataFrame.reindex()** and forward/backward filling now raises **ValueError** if either index is not monotonic ([GH4843], [GH4844]).
- **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`). ([GH4390])
- **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 `t` 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 @tavistmorph 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 dtype if downcast='infer' is passed tofillna/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.timedelta.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 after dates are given (GH5242)

• Timestamp now supports now/today/utcnow class methods (GH5339)
- default for `display.max_seq_len` is now 100 rather than `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.

```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]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[6]:
   0    0.200000
   1    0.666667
   2    1.500000
   3     4.000000
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)

### 38.23.5 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).
• 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)

38.23.6 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 pyt3 (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 parser 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 datetimes (GH4532)

• Fix arithmetic with `series/datetimeindex` and `np.timedelta64` not working the same (GH4134) and buggy `timedelta` in NumPy 1.6 (GH4135)

• Fix bug in `pd.read_clipboard` on windows with PY3 (GH4561); not decoding properly

• `tslib.get_period_field()` and `tslib.get_period_field_arr()` now raise if code argument out of range (GH4519, GH4520)

• Fix boolean indexing on an empty series loses index names (GH4235), `infer_dtype` works with empty arrays.

• Fix reindexing with multiple axes; if an axes match was not replacing the current axes, leading to a possible lazy frequency inference issue (GH3317)

• Fixed issue where `DataFrame.apply` was reraising exceptions incorrectly (causing the original stack trace to be truncated).

• Fix selection with `ix/loc` and non_unique selectors (GH4619)

• Fix assignment with `iloc/loc` involving a dtype change in an existing column (GH4312, GH5702) have internal `setitem_with_indexer` in core/indexing to use `Block.setitem`

• Fixed bug where thousands operator was not handled correctly for floating point numbers in `csv_import` (GH4322)

• Fix an issue with `CacheableOffset` not properly being used by many `DateOffset`; this prevented the `DateOffset` from being cached (GH4609)

• Fix boolean comparison with a `DataFrame` on the lhs, and a list/tuple on the rhs (GH4576)

• Fix error/dtype conversion with `setitem` of `None` on `Series/DataFrame` (GH4667)

• Fix decoding based on a passed in non-default encoding in `pd.read_stata` (GH4626)

• Fix `DataFrame.from_records` with a plain-vanilla `ndarray`. (GH4727)

• Fix some inconsistencies with `Index.rename` and `MultiIndex.rename`, etc. (GH4718, GH4628)

• Bug in using `iloc/loc` with a cross-sectional and duplicate indices (GH4726)

• Bug with using `QUOTE_NONE` with `to_csv` causing `Exception`. (GH4328)

• Bug with Series indexing not raising an error when the right-hand-side has an incorrect length (GH2702)

• Bug in 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/np.datetime64) (GH4993)
• Fix repr for DateOffset. No longer show duplicate entries in kwds. Removed unused offset fields. (GH4638)
• Fixed wrong index name during read_csv if using usecols. Applies to 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 whereDatetimeIndexjoins 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 @yarkoptic!)
• Fixed html tests on win32. (GH4580)
• Make sure that head/tail are iloc based, (GH5370)
• Fixed bug for PeriodIndex string representation if there are 1 or 2 elements. (GH5372)
• The GroupBy methods transform and filter can be used on Series and DataFrames that have repeated (non-unique) indices. (GH4620)
• Fix empty series not printing name in repr (GH4651)
• Make tests create temp files in temp directory by default. (GH5419)
• pd.to_timedelta of a scalar returns a scalar (GH5410)
• pd.to_timedelta accepts NaN and NaT, returning NaT instead of raising (GH5437)
• performance improvements in isnull on larger size pandas objects
• Fixed various setitem with 1d ndarray that does not have a matching length to the indexer (GH5508)
• Bug in getitem with a 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)

38.24 pandas 0.12.0

Release date: 2013-07-24
38.24.1 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 into_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)

38.24.2 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 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)

### 38.24.3 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=True 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/timedeltalike 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).

• 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)

### 38.24.4 Experimental Features

- Added experimental CustomBusinessDay class to support DateOffsets with custom holiday calendars and custom weekmasks. (GH2301)

### 38.24.5 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 NaN 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 (GH3465, 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 similarly 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)
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- 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 xmlslib wasn’t being properly skipped (GH4265)
• Fixed bug where get_data_famafrench wasn’t using the correct file edges (GH4281)

38.25 pandas 0.11.0

Release date: 2013-04-22

38.25.1 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)

**38.25.2 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.

```
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.reindex(items=['ItemA']).squeeze()
```

(continues on next page)
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]:
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)

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]:
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)
pandas: powerful Python data analysis toolkit, Release 0.23.1

- 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 \texttt{time} method to \texttt{DatetimeIndex} (GH3180)
- Return NA when using \texttt{Series.str[...] for values that are not long enough} (GH3223)
- Display cursor coordinate information in time-series plots (GH1670)
- \texttt{to_html()} now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes & , in addition to < and >. (GH2919)

38.25.3 API Changes

- Do not automatically upcast numeric specified dtypes to \texttt{int64} or \texttt{float64} (GH622 and GH797)
- DataFrame construction of lists and scalars, with no dtype present, will result in casting to \texttt{int64} or \texttt{float64}, regardless of platform. This is not an apparent change in the API, but noting it.
- Guarantee that \texttt{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)
- \texttt{backfill/pad/take/diff/ohlc} will now support \texttt{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)
  - \texttt{timedelta64} are returned in appropriate cases (e.g. Series - Series, when both are \texttt{datetime64})
  - mixed datetimes and objects (GH2751) in a constructor will be cast correctly
  - \texttt{astype} on datetimes to object are now handled (as well as NaT conversions to np.nan)
  - all \texttt{timedelta} like objects will be correctly assigned to \texttt{timedelta64} with mixed NaN and/or NaT allowed
- arguments to \texttt{DataFrame.clip} were inconsistent to NumPy and Series clipping (GH2747)
- \texttt{util.testing.assert_frame_equal} now checks the column and index names (GH2964)
- Constructors will now return a more informative \texttt{ValueError} on failures when invalid shapes are passed
- Don’t suppress \texttt{TypeError} in \texttt{GroupBy.agg} (GH3238)
- Methods return None when inplace=True (GH1893)
  - \texttt{HDFStore}
    - added the method \texttt{select_column} to select a single column from a table as a Series.
    - deprecated the \texttt{unique} method, can be replicated by \texttt{select_column(key, column).unique()}.
    - \texttt{min_itemsize} parameter will now automatically create data_columns for passed keys
- Downcast on pivot if possible (GH3283), adds argument \texttt{downcast} to \texttt{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.

**38.25.4 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(2001,1,0,0))`), 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, timedelta, 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 .iloc, .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 similarly 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)
• fixed pretty printing 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)

38.26 pandas 0.10.1

Release date: 2013-01-22

38.26.1 New Features

• Add data interface to World Bank WDI pandas.io.wb (GH2592)
38.26.2 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

38.26.3 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` to inform 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)
38.26.4 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)
38.27 pandas 0.10.0

Release date: 2012-12-17

38.27.1 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)

### 38.27.2 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

### 38.27.3 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
38.27.4 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)

38.27.5 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 issued 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.icol/irow 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)

38.28 pandas 0.9.1

Release date: 2012-11-14
38.28.1 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)

38.28.2 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)

38.28.3 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)

38.28.4 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 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)

38.29 pandas 0.9.0

Release date: 10/7/2012

38.29.1 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)

38.29.2 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)

38.29.3 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 printoptions 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)
• Enable skipfooter parameter in text parsers as an alias for skip_footer

38.29.4 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 isnull 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 anchored 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. Isnnull 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)

38.30 pandas 0.8.1

Release date: July 22, 2012

38.30.1 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)
• Add multi_sparse option to set_printoptions to modify display of hierarchical indexes (GH1538)
• Add dropna method to Panel (GH171)

38.30.2 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)

38.30.3 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)

38.31 pandas 0.8.0

Release date: 6/29/2012

38.31.1 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

38.31.2 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.rename 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_dtypes 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)

38.31.3 API Changes

• Rename pandas._tseries 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)

38.31.4 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 segfault caused by empty groups passed to groupby (GH1048)
• Fix occasionally misbehaved 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 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)

38.32 pandas 0.7.3

Release date: April 12, 2012

38.32.1 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)

38.32.2 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)

38.32.3 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 dtypes DataFrame construction from data with NaN (GH846)

38.32. pandas 0.7.3
• 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)

38.33 pandas 0.7.2

Release date: March 16, 2012

38.33.1 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

38.33.2 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)

38.33.3 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)

38.33.4 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 NotImplementedError 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)

38.34 pandas 0.7.1

Release date: February 29, 2012

38.34.1 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

38.34.2 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)
38.34.3 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)

38.35 pandas 0.7.0

Release date: 2/9/2012

38.35.1 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.apply` (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
38.35.2 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)

38.35.3 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)

38.35.4 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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38.36 pandas 0.6.1

Release date: 12/13/2011

38.36.1 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)

38.36.2 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 (GH114)
- Add Series.from_csv function (GH482)

38.36.3 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

38.36.4 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)
38.36.5 Thanks

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38.37 pandas 0.6.0

Release date: 11/25/2011

38.37.1 API Changes

- Arithmetic methods like `sum` will attempt to sum `dtype=object` values by default instead of excluding them (GH382)

38.37.2 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 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 cov instance methods to Series and DataFrame (GH194, GH362)
• 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)

38.37.3 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 (GH 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

38.37.4 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)
• setupegg.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 swaplevel (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)

38.37.5 Thanks

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pandas: powerful Python data analysis toolkit, Release 0.23.1

- Ted Square
- Aman Thakral
- Chris Uga
- Dieter Vandenbussche
- carljv
- rsamson

38.38 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.

38.38.1 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`
  - `_firstTimeWithVal` use `first_valid_index`

38.38. pandas 0.5.0 2545
– _lastTimeWithValue 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
  – _firstTimeWithValue use first_valid_index
  – _lastTimeWithValue use last_valid_index
  – toDataMatrix 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

38.38.2 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

38.38.3 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__` (GH253)
• Can use & and | to intersection / union Index objects, respectively (GH261)
• Added `pivot_table` convenience function to pandas namespace (GH234)
• Implemented `Panel.rename_axis` function (GH243)
• DataFrame will show index level names in console output
• 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

38.38.4 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 ppx file dependencies in Cython module build (GH271)
38.38.5 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
38.38.6 Thanks

- Thomas Kluyver
- Daniel Fortunov
- Aman Thakral
- Luca Beltrame
- Wouter Overmeire

38.39 pandas 0.4.3

Release date: 10/9/2011

This is largely a bugfix release from 0.4.2 but also includes a handful of new and enhanced features. Also, pandas can now be installed and used on Python 3 (thanks Thomas Kluyver!).

38.39.1 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)

38.39.2 Improvements to existing features

- Skip xlrd-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 Sparse Series 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

38.39.3 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

38.39.4 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

38.39.5 Thanks

• Thomas Kluyver
• rsamson

38.40 pandas 0.4.2

Release date: 10/3/2011
This is a performance optimization release with several bug fixes. The new Int64Index and new merging / joining Cython code and related Python infrastructure are the main new additions

38.40.1 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 datetime64 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

38.40.2 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)

• Implemented informative Exception when passing dict to `DataFrame` groupby aggregation with axis != 0

38.40.3 API Changes

38.40.4 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

38.40.5 Thanks

• Uri Laserson

• Scott Sinclair

38.41 pandas 0.4.1

Release date: 9/25/2011

This is primarily a bug fix release but includes some new features and improvements

38.41.1 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`
38.41.2 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

38.41.3 API Changes

38.41.4 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 (GH 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

38.41.5 Thanks

- Yaroslav Halchenko
- Jeff Reback
- Skipper Seabold
- Dan Lovell
- Nick Pentreath
38.42 pandas 0.4.0

Release date: 9/12/2011

38.42.1 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[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

### 38.42.2 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* / *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).

### 38.42.3 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

### 38.42.4 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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38.43 pandas 0.3.0

Release date: February 20, 2011
38.43.1 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

38.43.2 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.)

38.43.3 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

38.43.4 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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