pandas: powerful Python data analysis toolkit

Release 0.16.2

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June 13, 2015

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PDF Version

Zipped HTML **Date**: June 13, 2015 **Version**: 0.16.2

Binary Installers: http://pypi.python.org/pypi/pandas

Source Repository: http://github.com/pydata/pandas

Issues & Ideas: https://github.com/pydata/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.

CHAPTER

ONE

WHAT'S NEW

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

1.1 v0.16.2 (June 12, 2015)

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

We recommend that all users upgrade to this version.

Highlights include:

- A new `pipe` method, see *here*
- Documentation on how to use numba with *pandas*, see *here*

What's new in v0.16.2

1.1.1 New features

Pipe

We've introduced a new method `DataFrame.pipe()`. As suggested by the name, `pipe` should be used to pipe data through a chain of function calls. The goal is to avoid confusing nested function calls like

```
# 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

```
(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:

```
In [1]: import statsmodels.formula.api as sm

In [2]: bb = pd.read_csv('data/baseball.csv', index_col='id')

# sm.poisson takes (formula, data)
In [3]: (bb.query('h > 0')
   ...:    .assign(ln_h = lambda df: np.log(df.h))
   ...:    .pipe((sm.poisson, 'data'), 'hr ~ ln_h + year + g + C(lg)')
   ...:    .fit()
   ...:    .summary()
   ...: )
   ...:
Optimization terminated successfully.
         Current function value: 2.116284
         Iterations 24
Out[3]:
<class 'statsmodels.iolib.summary.Summary'>
"""
                          Poisson Regression Results
==============================================================================
Dep. Variable:                     hr   No. Observations:                   68
Model:                        Poisson   Df Residuals:                       63
Method:                           MLE   Df Model:                            4
Date:                Sat, 13 Jun 2015   Pseudo R-squ.:                  0.6878
Time:                        15:15:58   Log-Likelihood:                -143.91
converged:                       True   LL-Null:                       -460.91
                                        LLR p-value:                 6.774e-136
================================================================================
                  coef    std err          z      P>|z|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------
Intercept   -1267.3636    457.867     -2.768      0.006     -2164.767  -369.960
C(lg)[T.NL]    -0.2057      0.101     -2.044      0.041        -0.403    -0.008
ln_h            0.9280      0.191      4.866      0.000         0.554     1.302
year            0.6301      0.228      2.762      0.006         0.183     1.077
g               0.0099      0.004      2.754      0.006         0.003     0.017
================================================================================
"""
```

The pipe method is inspired by unix pipes, which stream text through processes. More recently dplyr and magrittr have introduced the popular `(%>%)` pipe operator for R.

See the *documentation* for more. (GH10129)

Other Enhancements

- Added *rsplit* to Index/Series StringMethods (GH10303)

- Removed the hard-coded size limits on the `DataFrame` HTML representation in the IPython notebook, and leave this to IPython itself (only for IPython v3.0 or greater). This eliminates the duplicate scroll bars that appeared in the notebook with large frames (GH10231).

  Note that the notebook has a `toggle output scrolling` feature to limit the display of very large frames (by clicking left of the output). You can also configure the way DataFrames are displayed using the pandas options, see here *here*.

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

1.1.2 API Changes

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

1.1.3 Performance Improvements

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

1.1.4 Bug Fixes

- Bug in `Series.hist` raises an error when a one row `Series` was given (GH10214)
- Bug where `HDFStore.select` modifies the passed columns list (GH7212)
- Bug in `Categorical` repr with `display.width` of `None` in Python 3 (GH10087)
- Bug in `to_json` with certain orients and a `CategoricalIndex` would segfault (GH10317)
- Bug where some of the nan funcs do not have consistent return dtypes (GH10251)
- Bug in `DataFrame.quantile` on checking that a valid axis was passed (GH9543)
- Bug in `groupby.apply` aggregation for `Categorical` not preserving categories (GH10138)
- Bug in `to_csv` where `date_format` is ignored if the `datetime` is fractional (GH10209)
- Bug in `DataFrame.to_json` with mixed data types (GH10289)
- Bug in cache updating when consolidating (GH10264)
- Bug in `mean()` where integer dtypes can overflow (GH10172)
- Bug where `Panel.from_dict` does not set dtype when specified (GH10058)
- Bug in `Index.union` raises `AttributeError` when passing array-likes. (GH10149)
- Bug in `Timestamp`‘s’ `microsecond`, `quarter`, `dayofyear`, `week` and `daysinmonth` properties return `np.int` type, not built-in `int`. (GH10050)
- Bug in `NaT` raises `AttributeError` when accessing to `daysinmonth`, `dayofweek` properties. (GH10096)
- Bug in Index repr when using the `max_seq_items=None` setting (GH10182).
- Bug in getting timezone data with `dateutil` on various platforms (GH9059, GH8639, GH9663, GH10121)
- Bug in displaying datetimes with mixed frequencies; display ‘ms’ datetimes to the proper precision. (GH10170)
- Bug in `setitem` where type promotion is applied to the entire block (GH10280)

- Bug in `Series` arithmetic methods may incorrectly hold names (GH10068)
- Bug in `GroupBy.get_group` when grouping on multiple keys, one of which is categorical. (GH10132)
- Bug in `DatetimeIndex` and `TimedeltaIndex` names are lost after timedelta arithmetics (GH9926)
- Bug in `DataFrame` construction from nested `dict` with `datetime64` (GH10160)
- Bug in `Series` construction from `dict` with `datetime64` keys (GH9456)
- Bug in `Series.plot(label="LABEL")` not correctly setting the label (GH10119)
- Bug in `plot` not defaulting to matplotlib `axes.grid` setting (GH9792)
- Bug causing strings containing an exponent, but no decimal to be parsed as `int` instead of `float` in `engine='python'` for the `read_csv` parser (GH9565)
- Bug in `Series.align` resets `name` when `fill_value` is specified (GH10067)
- Bug in `read_csv` causing index name not to be set on an empty DataFrame (GH10184)
- Bug in `SparseSeries.abs` resets `name` (GH10241)
- Bug in `TimedeltaIndex` slicing may reset freq (GH10292)
- Bug in `GroupBy.get_group` raises `ValueError` when group key contains `NaT` (GH6992)
- Bug in `SparseSeries` constructor ignores input data name (GH10258)
- Bug in `Categorical.remove_categories` causing a `ValueError` when removing the `NaN` category if underlying dtype is floating-point (GH10156)
- Bug where infer_freq infers timerule (WOM-5XXX) unsupported by to_offset (GH9425)
- Bug in `DataFrame.to_hdf()` where table format would raise a seemingly unrelated error for invalid (non-string) column names. This is now explicitly forbidden. (GH9057)
- Bug to handle masking empty `DataFrame` (GH10126).
- Bug where MySQL interface could not handle numeric table/column names (GH10255)
- Bug in `read_csv` with a `date_parser` that returned a `datetime64` array of other time resolution than `[ns]` (GH10245)
- Bug in `Panel.apply` when the result has ndim=0 (GH10332)
- Bug in `read_hdf` where `auto_close` could not be passed (GH9327).
- Bug in `read_hdf` where open stores could not be used (GH10330).
- Bug in adding empty `DataFrame``s, now results in a ``DataFrame` that `.equals` an empty `DataFrame` (GH10181).
- Bug in `to_hdf` and `HDFStore` which did not check that complib choices were valid (GH4582, GH8874).

1.2 v0.16.1 (May 11, 2015)

This is a minor bug-fix release from 0.16.0 and includes a 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

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

1.2.1 Enhancements

CategoricalIndex

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame/Series` with a `category` dtype would convert this to regular object-based `Index`.

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

In [2]: df
Out[2]:
   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       int32
```

```
B    category
dtype: object

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

setting the index, will create create a `CategoricalIndex`

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

In [6]: df2.index
Out[6]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'c', u'a', u'b'], ordered
```

indexing with `__getitem__`/`.iloc`/`.loc`/`.ix` works similarly to an Index with duplicates. The indexers MUST be in the category or the operation will raise.

```
In [7]: df2.loc['a']
Out[7]:
   A
B
a  0
a  1
a  5
```

and preserves the `CategoricalIndex`

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

sorting will order by the order of the categories

```
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

```
In [10]: df2.groupby(level=0).sum()
Out[10]:
   A
B
c  4
a  6
b  5

In [11]: df2.groupby(level=0).sum().index
Out[11]: CategoricalIndex([u'c', u'a', u'b'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B
```

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 arbitrarly index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```
In [12]: df2.reindex(['a','e'])
Out[12]:
    A
B
a   0
a   1
a   5
e NaN

In [13]: df2.reindex(['a','e']).index
Out[13]: Index([u'a', u'a', u'a', u'e'], dtype='object', name=u'B')

In [14]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde')))
Out[14]:
    A
B
a   0
a   1
a   5
e NaN

In [15]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde'))).index
Out[15]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'b', u'c', u'd', u'e'], ordere
```

See the *documentation* for more. (GH7629, GH10038, GH10039)

Sample

Series, DataFrames, and Panels now have a new method: `sample()`. The method accepts a specific number of rows or columns to return, or a fraction of the total number or rows or columns. It also has options for sampling with or without replacement, for passing in a column for weights for non-uniform sampling, and for setting seed values to facilitate replication. (GH2419)

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

# When no arguments are passed, returns 1
In [17]: example_series.sample()
Out[17]:
0    0
dtype: int64

# One may specify either a number of rows:
In [18]: example_series.sample(n=3)
Out[18]:
4    4
3    3
5    5
dtype: int64

# Or a fraction of the rows:
In [19]: example_series.sample(frac=0.5)
Out[19]:
2    2
3    3
1    1
dtype: int64
```

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

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

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

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

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

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

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

String Methods Enhancements

Continuing from v0.16.0, the following enhancements make string operations easier and more consistent with standard python string operations.

- Added `StringMethods` (`.str` accessor) to `Index` (GH9068)

  The `.str` accessor is now available for both `Series` and `Index`.

  ```
  In [26]: idx = Index([' jack', 'jill ', ' jesse ', 'frank'])

  In [27]: idx.str.strip()
  Out[27]: Index([u'jack', u'jill', u'jesse', u'frank'], dtype='object')
  ```

  One special case for the *.str* accessor on `Index` is that if a string method returns `bool`, the `.str` accessor will return a `np.array` instead of a boolean `Index` (GH8875). This enables the following expression to work naturally:

  ```
  In [28]: idx = Index(['a1', 'a2', 'b1', 'b2'])

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

  In [30]: s
  Out[30]:
  a1    0
  a2    1
  b1    2
  ```

```
b2    3
dtype: int64

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

In [32]: s[s.index.str.startswith('a')]
Out[32]:
a1    0
a2    1
dtype: int64
```

- The following new methods are accesible via `.str` accessor to apply the function to each values. (GH9766, GH9773, GH10031, GH10045, GH10052)

		Methods		
`capitalize()`	`swapcase()`	`normalize()`	`partition()`	`rpartition()`
`index()`	`rindex()`	`translate()`		

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

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

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

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

In [36]: idx = Index(['a,b', 'a,c', 'b,c'])

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

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

- Improved `extract` and `get_dummies` methods for `Index.str` (GH9980)

Other Enhancements

- `BusinessHour` offset is now supported, which represents business hours starting from 09:00 - 17:00 on `BusinessDay` by default. See *Here* for details. (GH7905)

```
In [39]: from pandas.tseries.offsets import BusinessHour

In [40]: Timestamp('2014-08-01 09:00') + BusinessHour()
Out[40]: Timestamp('2014-08-01 10:00:00')

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

In [42]: Timestamp('2014-08-01 16:30') + BusinessHour()
Out[42]: Timestamp('2014-08-04 09:30:00')
```

- `DataFrame.diff` now takes an `axis` parameter that determines the direction of differencing (GH9727)
- Allow `clip`, `clip_lower`, and `clip_upper` to accept array-like arguments as thresholds (This is a regression from 0.11.0). These methods now have an `axis` parameter which determines how the Series or DataFrame will be aligned with the threshold(s). (GH6966)
- `DataFrame.mask()` and `Series.mask()` now support same keywords as `where` (GH8801)
- `drop` function can now accept `errors` keyword to suppress `ValueError` raised when any of label does not exist in the target data. (GH6736)

```
In [43]: df = DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])

In [44]: df.drop(['A', 'X'], axis=1, errors='ignore')
Out[44]: 
          B         C
0 -0.064034 -1.282782
1 -1.071357  0.441153
2  0.583787  0.221471
```

- 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)

1.2.2 API changes

- When passing in an ax to `df.plot( ..., ax=ax)`, the *sharex* kwarg will now default to *False*. The result is that the visibility of xlabels and xticklabels will not anymore be changed. You have to do that by yourself for the right axes in your figure or set `sharex=True` explicitly (but this changes the visible for all axes in the figure, not only the one which is passed in!). If pandas creates the subplots itself (e.g. no passed in *ax* kwarg), then the default is still `sharex=True` and the visibility changes are applied.
- `assign()` now inserts new columns in alphabetical order. Previously the order was arbitrary. (GH9777)
- By default, `read_csv` and `read_table` will now try to infer the compression type based on the file extension. Set `compression=None` to restore the previous behavior (no decompression). (GH9770)

Deprecations

- `Series.str.split`'s `return_type` keyword was removed in favor of `expand` (GH9847)

1.2.3 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 unchanges (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,

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

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

In [47]: pd.Index(range(30), name='foo')
Out[47]:
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
            17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29],
           dtype='int64', name=u'foo')
```

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

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

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

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

In [52]: pd.date_range('20130101',periods=4, name='foo', tz='US/Eastern')
Out[52]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00'],
              dtype='datetime64[ns]', name=u'foo', freq='D', tz='US/Eastern')

In [53]: pd.date_range('20130101',periods=25, freq='D')
Out[53]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10', '2013-01-11', '2013-01-12',
               '2013-01-13', '2013-01-14', '2013-01-15', '2013-01-16',
               '2013-01-17', '2013-01-18', '2013-01-19', '2013-01-20',
               '2013-01-21', '2013-01-22', '2013-01-23', '2013-01-24',
               '2013-01-25'],
              dtype='datetime64[ns]', freq='D', tz=None)

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

```
        dtype='datetime64[ns]', name=u'foo', length=104, freq='D', tz='US/Eastern')
```

1.2.4 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)

1.2.5 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 `TimdeltaIndex` 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)

1.3 v0.16.0 (March 22, 2015)

This is a major release from 0.15.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `DataFrame.assign` method, see *here*
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see *here*
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see *here*
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see *here*
- Changes to the default for ordering in the `Categorical` constructor, see *here*
- Enhancement to the `.str` accessor to make string operations easier, see *here*
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like seaborn, pandas-qt and rpy2 for similar or equivalent functionality, see *here*

Check the *API Changes* and *deprecations* before updating.

What's new in v0.16.0

1.3.1 New features

DataFrame Assign

Inspired by dplyr's `mutate` verb, DataFrame has a new `assign()` method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. The new values are inserted, and the entire DataFrame (with all original and new columns) is returned.

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

In [2]: iris.head()
Out[2]:
   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()
Out[3]:
   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
```

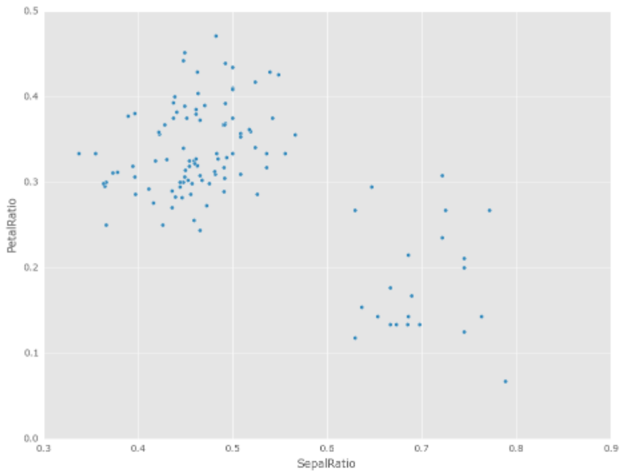
Above was an example of inserting a precomputed value. We can also pass in a function to be evalutated.

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

The power of `assign` comes when used in chains of operations. For example, we can limit the DataFrame to just those with a Sepal Length greater than 5, calculate the ratio, and plot

```
In [5]: (iris.query('SepalLength > 5')
   ...:      .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
   ...:              PetalRatio = lambda x: x.PetalWidth / x.PetalLength)
   ...:      .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
   ...:
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0xa2b4d98c>
```



See the *documentation* for more. (GH9229)

Interaction with scipy.sparse

Added `SparseSeries.to_coo()` and `SparseSeries.from_coo()` methods (GH8048) for converting to and from `scipy.sparse.coo_matrix` instances (see *here*). For example, given a SparseSeries with MultiIndex we can convert to a *scipy.sparse.coo_matrix* by specifying the row and column labels as index levels:

```
In [6]: from numpy import nan

In [7]: s = Series([3.0, nan, 1.0, 3.0, nan, nan])

In [8]: s.index = MultiIndex.from_tuples([(1, 2, 'a', 0),
   ...:                                   (1, 2, 'a', 1),
   ...:                                   (1, 1, 'b', 0),
   ...:                                   (1, 1, 'b', 1),
   ...:                                   (2, 1, 'b', 0),
   ...:                                   (2, 1, 'b', 1)],
   ...:                                   names=['A', 'B', 'C', 'D'])
   ...:

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

```
         1     3
2  1  b  0   NaN
         1   NaN
dtype: float64

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

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

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

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

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

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

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

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

```
In [17]: from scipy import sparse

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

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

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

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

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

String Methods Enhancements

- Following new methods are accesible via `.str` accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. (GH9282, GH9352, GH9386, GH9387, GH9439)

		Methods		
`isalnum()`	`isalpha()`	`isdigit()`	`isdigit()`	`isspace()`
`islower()`	`isupper()`	`istitle()`	`isnumeric()`	`isdecimal()`
`find()`	`rfind()`	`ljust()`	`rjust()`	`zfill()`

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

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

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

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

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

In [27]: s.str.pad(5, fillchar='_')
Out[27]:
0    ___12
1    __300
2    ___25
dtype: object
```

- Added `Series.str.slice_replace()`, which previously raised `NotImplementedError` (GH8888)

```
In [28]: s = Series(['ABCD', 'EFGH', 'IJK'])

In [29]: s.str.slice_replace(1, 3, 'X')
Out[29]:
0    AXD
1    EXH
2     IX
dtype: object

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

Other enhancements

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

```
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)

```
# 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).

1.3.2 Backwards incompatible API changes

Changes in Timedelta

In v0.15.0 a new scalar type `Timedelta` was introduced, that is a sub-class of `datetime.timedelta`. Mentioned *here* was a notice of an API change w.r.t. the `.seconds` accessor. The intent was to provide a user-friendly set of accessors that give the 'natural' value for that unit, e.g. if you had a `Timedelta('1 day, 10:11:12')`, then `.seconds` would return 12. However, this is at odds with the definition of `datetime.timedelta`, which defines `.seconds` as `10 * 3600 + 11 * 60 + 12 == 36672`.

So in v0.16.0, we are restoring the API to match that of `datetime.timedelta`. Further, the component values are still available through the `.components` accessor. This affects the `.seconds` and `.microseconds` accessors, and removes the `.hours`, `.minutes`, `.milliseconds` accessors. These changes affect `TimedeltaIndex` and the Series `.dt` accessor as well. (GH9185, GH9139)

Previous Behavior

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [3]: t.days
Out[3]: 1

In [4]: t.seconds
Out[4]: 12

In [5]: t.microseconds
Out[5]: 123
```

New Behavior

```
In [33]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [34]: t.days
Out[34]: 1L

In [35]: t.seconds
Out[35]: 36672L

In [36]: t.microseconds
Out[36]: 100123L
```

Using `.components` allows the full component access

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

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

Indexing Changes

The behavior of a small sub-set of edge cases for using `.loc` have changed (GH8613). Furthermore we have improved the content of the error messages that are raised:

- Slicing with `.loc` where the start and/or stop bound is not found in the index is now allowed; this previously would raise a `KeyError`. This makes the behavior the same as `.ix` in this case. This change is only for slicing, not when indexing with a single label.

```
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 -0.744471  0.758527  1.729689 -0.964980
2013-01-02 -0.845696 -1.340896  1.846883 -1.328865
2013-01-03  1.682706 -1.717693  0.888782  0.228440
2013-01-04  0.901805  1.171216  0.520260 -1.197071
2013-01-05 -1.066969 -0.303421 -0.858447  0.306996

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 -0.845696 -1.340896  1.846883 -1.328865
2013-01-03  1.682706 -1.717693  0.888782  0.228440
2013-01-04  0.901805  1.171216  0.520260 -1.197071
```

```
2013-01-05 -1.066969 -0.303421 -0.858447  0.306996

In [44]: s.loc[-10:3]
Out[44]:
-2    0
-1    1
 1    2
 2    3
 3    4
dtype: int64
```

- Allow slicing with float-like values on an integer index for `.ix`. Previously this was only enabled for `.loc`:

  Previous Behavior

  ```
  In [8]: s.ix[-1.0:2]
  TypeError: the slice start value [-1.0] is not a proper indexer for this index type (Int64Index)
  ```

  New Behavior

  ```
  In [45]: s.ix[-1.0:2]
  Out[45]:
  -1    1
   1    2
   2    3
  dtype: int64
  ```

- Provide a useful exception for indexing with an invalid type for that index when using `.loc`. For example trying to use `.loc` on an index of type `DatetimeIndex` or `PeriodIndex` or `TimedeltaIndex`, with an integer (or a float).

  Previous Behavior

  ```
  In [4]: df.loc[2:3]
  KeyError: 'start bound [2] is not the [index]'
  ```

  New Behavior

  ```
  In [4]: df.loc[2:3]
  TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with <type '
  ```

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

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

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

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

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

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

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

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

In [54]: s.cat.ordered
```

```
Out[54]: True
```

For ease of creation of series of categorical data, we have added the ability to pass keywords when calling `.astype()`. These are passed directly to the constructor.

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

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

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

In [58]: s
Out[58]:
0    a
1    b
2    c
3    a
dtype: category
Categories (6, object): [a, b, c, d, e, f]
```

Other API Changes

- `Index.duplicated` now returns `np.array(dtype=bool)` rather than `Index(dtype=object)` containing `bool` values. (GH8875)
- `DataFrame.to_json` now returns accurate type serialisation for each column for frames of mixed dtype (GH9037)

  Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

  ```
  In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
  Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1.0,"1":2.0}}'
  ```

  Now each column is serialised using its correct dtype:

  ```
  In [2]:  pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
  Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1,"1":2}}'
  ```

- `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex.summary` now output the same format. (GH9116)
- `TimedeltaIndex.freqstr` now output the same string format as `DatetimeIndex`. (GH9116)
- Bar and horizontal bar plots no longer add a dashed line along the info axis. The prior style can be achieved with matplotlib's `axhline` or `axvline` methods (GH9088).
- `Series` accessors `.dt`, `.cat` and `.str` now raise `AttributeError` instead of `TypeError` if the series does not contain the appropriate type of data (GH9617). This follows Python's built-in exception hierarchy more closely and ensures that tests like `hasattr(s, 'cat')` are consistent on both Python 2 and 3.

- `Series` now supports bitwise operation for integral types (GH9016). Previously even if the input dtypes were integral, the output dtype was coerced to `bool`.

  Previous Behavior

```
In [2]: pd.Series([0,1,2,3], list('abcd')) | pd.Series([4,4,4,4], list('abcd'))
Out[2]:
a    True
b    True
c    True
d    True
dtype: bool
```

  New Behavior. If the input dtypes are integral, the output dtype is also integral and the output values are the result of the bitwise operation.

```
In [2]: pd.Series([0,1,2,3], list('abcd')) | pd.Series([4,4,4,4], list('abcd'))
Out[2]:
a    4
b    5
c    6
d    7
dtype: int64
```

- During division involving a `Series` or `DataFrame`, `0/0` and `0//0` now give `np.nan` instead of `np.inf`. (GH9144, GH8445)

  Previous Behavior

```
In [2]: p = pd.Series([0, 1])

In [3]: p / 0
Out[3]:
0    inf
1    inf
dtype: float64

In [4]: p // 0
Out[4]:
0    inf
1    inf
dtype: float64
```

  New Behavior

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

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

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

- `Series.values_counts` and `Series.describe` for categorical data will now put `NaN` entries at the 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 [62]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[62]: Timestamp('2000-02-28 00:00:00')
```

  To reproduce the old behavior, simply add more precision to the label (e.g., use `2000-02-01` instead of `2000-02`).

Deprecations

- The `rplot` trellis plotting interface is deprecated and will be removed in a future version. We refer to external packages like seaborn for similar but more refined functionality (GH3445). The documentation includes some examples how to convert your existing code using `rplot` to seaborn: *rplot docs*.
- The `pandas.sandbox.qtpandas` interface is deprecated and will be removed in a future version. We refer users to the external package pandas-qt. (GH9615)
- The `pandas.rpy` interface is deprecated and will be removed in a future version. Similar functionaility 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)

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)

1.3.3 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)

1.3.4 Bug Fixes

- Changed `.to_html` to remove leading/trailing spaces in table body (GH4987)
- Fixed issue using `read_csv` on s3 with Python 3 (GH9452)
- Fixed compatibility issue in `DatetimeIndex` affecting architectures where `numpy.int_` defaults to `numpy.int32` (GH8943)
- Bug in Panel indexing with an object-like (GH9140)
- Bug in the returned `Series.dt.components` index was reset to the default index (GH9247)
- Bug in `Categorical.__getitem__/__setitem__` with listlike input getting incorrect results from indexer coercion (GH9469)
- Bug in partial setting with a DatetimeIndex (GH9478)
- Bug in groupby for integer and datetime64 columns when applying an aggregator that caused the value to be changed when the number was sufficiently large (GH9311, GH6620)
- Fixed bug in `to_sql` when mapping a `Timestamp` object column (datetime column with timezone info) to the appropriate sqlalchemy type (GH9085).
- Fixed bug in `to_sql dtype` argument not accepting an instantiated SQLAlchemy type (GH9083).
- Bug in `.loc` partial setting with a `np.datetime64` (GH9516)
- Incorrect dtypes inferred on datetimelike looking `Series` & on `.xs` slices (GH9477)
- Items in `Categorical.unique()` (and `s.unique()` if `s` is of dtype `category`) now appear in the order in which they are originally found, not in sorted order (GH9331). This is now consistent with the behavior for other dtypes in pandas.
- Fixed bug on big endian platforms which produced incorrect results in `StataReader` (GH8688).
- Bug in `MultiIndex.has_duplicates` when having many levels causes an indexer overflow (GH9075, GH5873)
- Bug in `pivot` and `unstack` where `nan` values would break index alignment (GH4862, GH7401, GH7403, GH7405, GH7466, GH9497)
- Bug in left `join` on multi-index with `sort=True` or null values (GH9210).

- Bug in MultiIndex where inserting new keys would fail (GH9250).
- Bug in groupby when key space exceeds int64 bounds (GH9096).
- Bug in unstack with TimedeltaIndex or DatetimeIndex and nulls (GH9491).
- Bug in rank where comparing floats with tolerance will cause inconsistent behaviour (GH8365).
- Fixed character encoding bug in read_stata and StataReader when loading data from a URL (GH9231).
- Bug in adding offsets.Nano to other offets raises TypeError (GH9284)
- Bug in DatetimeIndex iteration, related to (GH8890), fixed in (GH9100)
- Bugs in resample around DST transitions. This required fixing offset classes so they behave correctly on DST transitions. (GH5172, GH8744, GH8653, GH9173, GH9468).
- Bug in binary operator method (eg .mul()) alignment with integer levels (GH9463).
- Bug in boxplot, scatter and hexbin plot may show an unnecessary warning (GH8877)
- Bug in subplot with layout kw may show unnecessary warning (GH9464)
- Bug in using grouper functions that need passed thru arguments (e.g. axis), when using wrapped function (e.g. fillna), (GH9221)
- DataFrame now properly supports simultaneous copy and dtype arguments in constructor (GH9099)
- Bug in read_csv when using skiprows on a file with CR line endings with the c engine. (GH9079)
- isnull now detects NaT in PeriodIndex (GH9129)
- Bug in groupby .nth() with a multiple column groupby (GH8979)
- Bug in DataFrame.where and Series.where coerce numerics to string incorrectly (GH9280)
- Bug in DataFrame.where and Series.where raise ValueError when string list-like is passed. (GH9280)
- Accessing Series.str methods on with non-string values now raises TypeError instead of producing incorrect results (GH9184)
- Bug in DatetimeIndex.__contains__ when index has duplicates and is not monotonic increasing (GH9512)
- Fixed division by zero error for Series.kurt() when all values are equal (GH9197)
- Fixed issue in the xlsxwriter engine where it added a default 'General' format to cells if no other format wass 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 mising numeric_only option for `DataFrame.std/var/sem` (GH9201)
- Support constructing `Panel` or `Panel4D` with scalar data (GH8285)
- `Series` text representation disconnected from *max_rows/max_columns* (GH7508).
- `Series` number formatting inconsistent when truncated (GH8532).

  Previous Behavior

```
In [2]: pd.options.display.max_rows = 10
In [3]: s = pd.Series([1,1,1,1,1,1,1,1,1,1,0.9999,1,1]*10)
In [4]: s
Out[4]:
0     1
1     1
2     1
...
127    0.9999
128    1.0000
129    1.0000
Length: 130, dtype: float64
```

  New Behavior

```
0       1.0000
1       1.0000
2       1.0000
3       1.0000
4       1.0000
...
125     1.0000
126     1.0000
127     0.9999
128     1.0000
129     1.0000
dtype: float64
```

- A Spurious `SettingWithCopy` Warning was generated when setting a new item in a frame in some cases (GH8730)

  The following would previously report a `SettingWithCopy` Warning.

```
In [1]: df1 = DataFrame({'x': Series(['a','b','c']), 'y': Series(['d','e','f'])})

In [2]: df2 = df1[['x']]

In [3]: df2['y'] = ['g', 'h', 'i']
```

1.4 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*

1.4.1 API changes

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

```
In [1]: df = pd.DataFrame({'jim':[0, 0, 1, 1],
   ...:                    'joe':['x', 'x', 'z', 'y'],
   ...:                    'jolie':np.random.rand(4)}).set_index(['jim', 'joe'])
   ...:

In [2]: df
Out[2]:
            jolie
jim joe
0   x    0.751953
    x    0.561512
1   z    0.572214
    y    0.740693

In [3]: df.index.lexsort_depth
Out[3]: 1

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning
In [4]: df.loc[(1, 'z')]
Out[4]:
            jolie
jim joe
1   z    0.572214

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

In [6]: df2
Out[6]:
            jolie
jim joe
0   x    0.751953
    x    0.561512
1   y    0.740693
    z    0.572214

In [7]: df2.index.lexsort_depth
Out[7]: 2
```

```
In [8]: df2.loc[(1,'z')]
Out[8]:
             jolie
jim joe
1   z     0.572214
```

- 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]: array(['a', 'b'], dtype=object)
  ```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters. `Series.all`, `Series.any`, `Index.all`, and `Index.any` no longer support the `out` and `keepdims` parameters, which existed for compatibility with ndarray. Various index types no longer support the `all` and `any` aggregation functions and will now raise `TypeError`. (GH8302).
- Allow equality comparisons of Series with a categorical dtype and object dtype; previously these would raise `TypeError` (GH8938)
- Bug in `NDFrame`: conflicting attribute/column names now behave consistently between getting and setting. Previously, when both a column and attribute named `y` existed, `data.y` would return the attribute, while `data.y = z` would update the column (GH8994)

  ```
  In [11]: data = pd.DataFrame({'x':[1, 2, 3]})

  In [12]: data.y = 2

  In [13]: data['y'] = [2, 4, 6]

  In [14]: data
  Out[14]:
     x  y
  0  1  2
  1  2  4
  2  3  6

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

  Old behavior:

  ```
  In [6]: data.y
  Out[6]: 2
  ```

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

New behavior:

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

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

- `Timestamp('now')` is now equivalent to `Timestamp.now()` in that it returns the local time rather than UTC. Also, `Timestamp('today')` is now equivalent to `Timestamp.today()` and both have `tz` as a possible argument. (GH9000)
- Fix negative step support for label-based slices (GH8753)

  Old behavior:

```
In [1]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
Out[1]:
a    0
b    1
c    2
dtype: int64

In [2]: s.loc['c':'a':-1]
Out[2]:
c    2
dtype: int64
```

  New behavior:

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

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

1.4.2 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):

```
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):

```
In [22]: p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)

In [23]: p.all()
Out[23]:
       0      1
0   True  False
1   True  False
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 arithemtic 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).

1.4.3 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)

1.4.4 Bug Fixes

- Bug in concat of Series with `category` dtype which were coercing to `object`. (GH8641)
- Bug in Timestamp-Timestamp not returning a Timedelta type and datelike-datelike ops with timezones (GH8865)
- Made consistent a timezone mismatch exception (either tz operated with None or incompatible timezone), will now return `TypeError` rather than `ValueError` (a couple of edge cases only), (GH8865)
- Bug in using a `pd.Grouper(key=...)` with no level/axis or level only (GH8795, GH8866)
- Report a `TypeError` when invalid/no paramaters are passed in a groupby (GH8015)
- Bug in packaging pandas with `py2app/cx_Freeze` (GH8602, GH8831)
- Bug in `groupby` signatures that didn't include *args or **kwargs (GH8733).
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Unclear error message in csv parsing when passing dtype and names and the parsed data is a different data type (GH8833)
- Bug in slicing a multi-index with an empty list and at least one boolean indexer (GH8781)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo (GH8761).
- `Timedelta` kwargs may now be numpy ints and floats (GH8757).
- Fixed several outstanding bugs for `Timedelta` arithmetic and comparisons (GH8813, GH5963, GH5436).
- `sql_schema` now generates dialect appropriate `CREATE TABLE` statements (GH8697)
- `slice` string method now takes step into account (GH8754)
- Bug in `BlockManager` where setting values with different type would break block integrity (GH8850)
- Bug in `DatetimeIndex` when using `time` object as key (GH8667)
- Bug in `merge` where `how='left'` and `sort=False` would not preserve left frame order (GH7331)
- Bug in `MultiIndex.reindex` where reindexing at level would not reorder labels (GH4088)
- Bug in certain operations with dateutil timezones, manifesting with dateutil 2.3 (GH8639)
- Regression in DatetimeIndex iteration with a Fixed/Local offset timezone (GH8890)
- Bug in `to_datetime` when parsing a nanoseconds using the `%f` format (GH8989)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Fix: The font size was only set on x axis if vertical or the y axis if horizontal. (GH8765)
- Fixed division by 0 when reading big csv files in python 3 (GH8621)
- Bug in outputing a 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)

1.5 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*

1.5.1 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          NaT
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
1      0
2    NaN
3      0
4      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 conflics 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 undeprecated and can be used to get all options data for a given month.

If an expiry date that is not valid is given, data for the next expiry after the given date is returned.

Option data frames are now saved on the instance as `callsYYMMDD` or `putsYYMMDD`. Previously they were saved as `callsMMYY` and `putsMMYY`. The next expiry is saved as `calls` and `puts`.

New features:

- The expiry parameter can now be a single date or a list-like object containing dates.
- A new property `expiry_dates` was added, which returns all available expiry dates.

Current behavior:

```
In [17]: from pandas.io.data import Options

In [18]: aapl = Options('aapl','yahoo')

In [19]: aapl.get_call_data().iloc[0:5,0:1]
Out[19]:
                                             Last
Strike Expiry     Type Symbol
65     2015-06-19 call AAPL150619C00065000  64.25
70     2015-06-19 call AAPL150619C00070000  60.72
75     2015-06-19 call AAPL150619C00075000  57.21
80     2015-06-19 call AAPL150619C00080000  47.50
85     2015-06-19 call AAPL150619C00085000  42.50

In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2015, 6, 19),
 datetime.date(2015, 6, 26),
 datetime.date(2015, 7, 2),
 datetime.date(2015, 7, 10),
 datetime.date(2015, 7, 17),
 datetime.date(2015, 7, 24),
 datetime.date(2015, 7, 31),
 datetime.date(2015, 8, 21),
 datetime.date(2015, 10, 16),
 datetime.date(2015, 12, 18),
 datetime.date(2016, 1, 15),
```

```
 datetime.date(2016, 6, 17),
 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]:
                                              Last
Strike Expiry     Type Symbol
127    2015-06-26 call AAPL150626C00127000  2.00
       2015-07-02 call AAPL150702C00127000  2.36
128    2015-06-19 call AAPL150619C00128000  0.88
       2015-06-26 call AAPL150626C00128000  1.48
       2015-07-02 call AAPL150702C00128000  1.88
```

See the Options documentation in *Remote Data*

- 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).

1.5.2 Enhancements

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

```
In [22]: from collections import deque

In [23]: df1 = pd.DataFrame([1, 2, 3])

In [24]: df2 = pd.DataFrame([4, 5, 6])
```

previous behavior:

```
In [7]: pd.concat(deque((df1, df2)))
TypeError: first argument must be a list-like of pandas objects, you passed an object of type "d
```

current behavior:

```
In [25]: pd.concat(deque((df1, df2)))
Out[25]:
   0
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 underling data array. (GH8456)

```
In [26]: dfi = DataFrame(1,index=pd.MultiIndex.from_product([['a'],range(1000)]),columns=['A'])
```

previous behavior:

```
# this was underreported in prior versions
In [1]: dfi.memory_usage(index=True)
```

```
Out[1]:
Index    8000 # took about 24008 bytes in < 0.15.1
A        8000
dtype: int64
```

current behavior:

```
In [27]: dfi.memory_usage(index=True)
Out[27]:
Index    11020
A         8000
dtype: int64
```

- Added Index properties *is_monotonic_increasing* and *is_monotonic_decreasing* (GH8680).
- Added option to select columns when importing Stata files (GH7935)
- Qualify memory usage in `DataFrame.info()` by adding + if it is a lower bound (GH8578)
- Raise errors in certain aggregation cases where an argument such as `numeric_only` is not handled (GH8592).
- Added support for 3-character ISO and non-standard country codes in `io.wb.download()` (GH8482)
- *World Bank data requests* now will warn/raise based on an `errors` argument, as well as a list of hard-coded country codes and the World Bank's JSON response. In prior versions, the error messages didn't look at the World Bank's JSON response. Problem-inducing input were simply dropped prior to the request. The issue was that many good countries were cropped in the hard-coded approach. All countries will work now, but some bad countries will raise exceptions because some edge cases break the entire response. (GH8482)
- Added option to `Series.str.split()` to return a `DataFrame` rather than a `Series` (GH8428)
- Added option to `df.info(null_counts=None|True|False)` to override the default display options and force showing of the null-counts (GH8701)

1.5.3 Bug Fixes

- Bug in unpickling of a `CustomBusinessDay` object (GH8591)
- Bug in coercing `Categorical` to a records array, e.g. `df.to_records()` (GH8626)
- Bug in `Categorical` not created properly with `Series.to_frame()` (GH8626)
- Bug in coercing in astype of a `Categorical` of a passed `pd.Categorical` (this now raises `TypeError` correctly), (GH8626)
- Bug in `cut`/`qcut` when using `Series` and `retbins=True` (GH8589)
- Bug in writing Categorical columns to an SQL database with `to_sql` (GH8624).
- Bug in comparing `Categorical` of datetime raising when being compared to a scalar datetime (GH8687)
- Bug in selecting from a `Categorical` with `.iloc` (GH8623)
- Bug in groupby-transform with a Categorical (GH8623)
- Bug in duplicated/drop_duplicates with a Categorical (GH8623)
- Bug in `Categorical` reflected comparison operator raising if the first argument was a numpy array scalar (e.g. np.int64) (GH8658)
- Bug in Panel indexing with a list-like (GH8710)
- Compat issue is `DataFrame.dtypes` when `options.mode.use_inf_as_null` is True (GH8722)

- Bug in `read_csv`, `dialect` parameter would not take a string (:issue: *8703*)
- Bug in slicing a multi-index level with an empty-list (GH8737)
- Bug in numeric index operations of add/sub with Float/Index Index with numpy arrays (GH8608)
- Bug in setitem with empty indexer and unwanted coercion of dtypes (GH8669)
- Bug in ix/loc block splitting on setitem (manifests with integer-like dtypes, e.g. datetime64) (GH8607)
- Bug when doing label based indexing with integers not found in the index for non-unique but monotonic indexes (GH8680).
- Bug when indexing a Float64Index with `np.nan` on numpy 1.7 (GH8980).
- Fix `shape` attribute for `MultiIndex` (GH8609)
- Bug in `GroupBy` where a name conflict between the grouper and columns would break `groupby` operations (GH7115, GH8112)
- Fixed a bug where plotting a column `y` and specifying a label would mutate the index name of the original DataFrame (GH8494)
- Fix regression in plotting of a DatetimeIndex directly with matplotlib (GH8614).
- Bug in `date_range` where partially-specified dates would incorporate current date (GH6961)
- Bug in Setting by indexer to a scalar value with a mixed-dtype *Panel4d* was failing (GH8702)
- Bug where `DataReader`'s would fail if one of the symbols passed was invalid. Now returns data for valid symbols and np.nan for invalid (GH8494)
- Bug in `get_quote_yahoo` that wouldn't allow non-float return values (GH5229).

1.6 v0.15.0 (October 18, 2014)

This is a major release from 0.14.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

> **Warning:** pandas >= 0.15.0 will no longer support compatibility with NumPy versions < 1.7.0. If you want to use the latest versions of pandas, please upgrade to NumPy >= 1.7.0 (GH7711)

- Highlights include:
  - The `Categorical` type was integrated as a first-class pandas type, see *here*
  - New scalar type `Timedelta`, and a new index type `TimedeltaIndex`, see *here*
  - New datetimelike properties accessor `.dt` for Series, see *Datetimelike Properties*
  - New DataFrame default display for `df.info()` to include memory usage, see *Memory Usage*
  - `read_csv` will now by default ignore blank lines when parsing, see *here*
  - API change in using Indexes in set operations, see *here*
  - Enhancements in the handling of timezones, see *here*
  - A lot of improvements to the rolling and expanding moment funtions, see *here*
  - Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see *Internal Refactoring*
  - dropping support for `PyTables` less than version 3.0.0, and `numexpr` less than version 2.1 (GH7990)

  - Split indexing documentation into *Indexing and Selecting Data* and *MultiIndex / Advanced Indexing*
  - Split out string methods documentation into *Working with Text Data*
- Check the *API Changes* and *deprecations* before updating
- *Other Enhancements*
- *Performance Improvements*
- *Bug Fixes*

> **Warning:** In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

> **Warning:** The 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*

1.6.1 New features

Categoricals in Series/DataFrame

`Categorical` can now be included in *Series* and *DataFrames* and gained new methods to manipulate. Thanks to Jan Schulz for much of this API/implementation. (GH3943, GH5313, GH5314, GH7444, GH7839, GH7848, GH7864, GH7914, GH7768, GH8006, GH3678, GH8075, GH8076, GH8143, GH8453, GH8518).

For full docs, see the *categorical introduction* and the *API documentation*.

```
In [1]: df = DataFrame({"id":[1,2,3,4,5,6], "raw_grade":['a', 'b', 'b', 'a', 'a', 'e']})

In [2]: df["grade"] = df["raw_grade"].astype("category")

In [3]: df["grade"]
Out[3]: 
0    a
1    b
2    b
3    a
4    a
5    e
Name: grade, dtype: category
Categories (3, object): [a, b, e]

# Rename the categories
In [4]: df["grade"].cat.categories = ["very good", "good", "very bad"]

# Reorder the categories and simultaneously add the missing categories
In [5]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very goo

In [6]: df["grade"]
Out[6]: 
0    very good
1         good
```

```
2          good
3     very good
4     very good
5      very bad
Name: grade, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]

In [7]: df.sort("grade")
Out[7]:
   id raw_grade      grade
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         NaN
medium      NaN
good          2
very good     3
dtype: float64
```

- `pandas.core.group_agg` and `pandas.core.factor_agg` were removed. As an alternative, construct a dataframe and use `df.groupby(<group>).agg(<func>)`.
- Supplying "codes/labels and levels" to the `Categorical` constructor is not supported anymore. Supplying two arguments to the constructor is now interpreted as "values and levels (now called 'categories')". Please change your code to use the `from_codes()` constructor.
- The `Categorical.labels` attribute was renamed to `Categorical.codes` and is read only. If you want to manipulate codes, please use one of the *API methods on Categoricals*.
- The `Categorical.levels` attribute is renamed to `Categorical.categories`.

TimedeltaIndex/Scalar

We introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes. This type is very similar to how `Timestamp` works for `datetimes`. It is a nice-API box for the type. See the *docs*. (GH3009, GH4533, GH8209, GH8187, GH8190, GH7869, GH7661, GH8345, GH8471)

Warning: `Timedelta` scalars (and `TimedeltaIndex`) component fields are *not the same* as the component fields on a `datetime.timedelta` object. For example, `.seconds` on a `datetime.timedelta` object returns the total number of seconds combined between `hours`, `minutes` and `seconds`. In contrast, the pandas `Timedelta` breaks out hours, minutes, microseconds and nanoseconds separately.

```
# 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.

Consruct a scalar

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

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

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

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

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

Access fields for a `Timedelta`

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

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

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

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

Construct a `TimedeltaIndex`

```
In [18]: TimedeltaIndex(['1 days','1 days, 00:00:05',
   ....:                 np.timedelta64(2,'D'),timedelta(days=2,seconds=2)])
   ....:
Out[18]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

Constructing a `TimedeltaIndex` with a regular range

```
In [19]: timedelta_range('1 days',periods=5,freq='D')
Out[19]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]',

In [20]: timedelta_range(start='1 days',end='2 days',freq='30T')
Out[20]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')
```

You can now use a `TimedeltaIndex` as the index of a pandas object

```
In [21]: s = Series(np.arange(5),
   ....:            index=timedelta_range('1 days',periods=5,freq='s'))
   ....:

In [22]: s
Out[22]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
1 days 00:00:03    3
1 days 00:00:04    4
Freq: S, dtype: int32
```

You can select with partial string selections

```
In [23]: s['1 day 00:00:02']
Out[23]: 2
```

```
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: int32
```

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are `NaT` preserving:

```
In [25]: tdi = TimedeltaIndex(['1 days',pd.NaT,'2 days'])

In [26]: tdi.tolist()
Out[26]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [27]: dti = date_range('20130101',periods=3)

In [28]: dti.tolist()
Out[28]:
[Timestamp('2013-01-01 00:00:00', offset='D'),
 Timestamp('2013-01-02 00:00:00', offset='D'),
 Timestamp('2013-01-03 00:00:00', offset='D')]

In [29]: (dti + tdi).tolist()
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()
Out[30]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

- iteration of a `Series` e.g. `list(Series(...))` of `timedelta64[ns]` would prior to v0.15.0 return `np.timedelta64` for each element. These will now be wrapped in `Timedelta`.

Memory Usage

Implemented methods to find memory usage of a DataFrame. See the *FAQ* for more. (GH6852).

A new display option `display.memory_usage` (see *Options and Settings*) sets the default behavior of the `memory_usage` argument in the `df.info()` method. By default `display.memory_usage` is `True`.

```
In [31]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
   ....:           'complex128', 'object', 'bool']
   ....:

In [32]: n = 5000

In [33]: data = dict([ (t, np.random.randint(100, size=n).astype(t))
   ....:                 for t in dtypes])
   ....:

In [34]: df = DataFrame(data)

In [35]: df['categorical'] = df['object'].astype('category')

In [36]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool               5000 non-null bool
```

```
complex128          5000 non-null complex128
datetime64[ns]      5000 non-null datetime64[ns]
float64             5000 non-null float64
int64               5000 non-null int64
object              5000 non-null object
timedelta64[ns]     5000 non-null timedelta64[ns]
categorical         5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), object(1), time
memory usage: 303.5+ KB
```

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

```
In [37]: df.memory_usage(index=True)
Out[37]:
Index               40000
bool                 5000
complex128          80000
datetime64[ns]      40000
float64             40000
int64               40000
object              20000
timedelta64[ns]     40000
categorical          5800
dtype: int64
```

.dt accessor

`Series` has gained an accessor to succinctly return datetime like properties for the *values* of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the *docs*

```
# datetime
In [38]: s = Series(date_range('20130101 09:10:12',periods=4))

In [39]: s
Out[39]:
0   2013-01-01 09:10:12
1   2013-01-02 09:10:12
2   2013-01-03 09:10:12
3   2013-01-04 09:10:12
dtype: datetime64[ns]

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

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

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

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

This enables nice expressions like this:

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

You can easily produce tz aware transformations:

```
In [45]: stz = s.dt.tz_localize('US/Eastern')

In [46]: stz
Out[46]:
0    2013-01-01 09:10:12-05:00
1    2013-01-02 09:10:12-05:00
2    2013-01-03 09:10:12-05:00
3    2013-01-04 09:10:12-05:00
dtype: object

In [47]: stz.dt.tz
Out[47]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [48]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[48]:
0    2013-01-01 04:10:12-05:00
1    2013-01-02 04:10:12-05:00
2    2013-01-03 04:10:12-05:00
3    2013-01-04 04:10:12-05:00
dtype: object
```

The `.dt` accessor works for period and timedelta dtypes.

```
# period
In [49]: s = Series(period_range('20130101',periods=4,freq='D'))

In [50]: s
Out[50]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: object

In [51]: s.dt.year
Out[51]:
0    2013
```

```
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

# timedelta
In [53]: s = Series(timedelta_range('1 day 00:00:05',periods=4,freq='s'))

In [54]: s
Out[54]:
0   1 days 00:00:05
1   1 days 00:00:06
2   1 days 00:00:07
3   1 days 00:00:08
dtype: timedelta64[ns]

In [55]: s.dt.days
Out[55]:
0    1
1    1
2    1
3    1
dtype: int64

In [56]: s.dt.seconds
Out[56]:
0    5
1    6
2    7
3    8
dtype: int64

In [57]: s.dt.components
Out[57]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     1      0        0        5             0             0            0
1     1      0        0        6             0             0            0
2     1      0        0        7             0             0            0
3     1      0        0        8             0             0            0
```

Timezone handling improvements

- `tz_localize(None)` for tz-aware `Timestamp` and `DatetimeIndex` now removes timezone holding local time, previously this resulted in `Exception` or `TypeError` (GH7812)

```
In [58]: ts = Timestamp('2014-08-01 09:00', tz='US/Eastern')

In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-0400', tz='US/Eastern')
```

```
In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [62]: didx
Out[62]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
               '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
               '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
               '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
              dtype='datetime64[ns]', freq='H', tz='US/Eastern')

In [63]: didx.tz_localize(None)
Out[63]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00', '2014-08-01 12:00:00',
               '2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

- `tz_localize` now accepts the `ambiguous` keyword which allows for passing an array of bools indicating whether the date belongs in DST or not, 'NaT' for setting transition times to NaT, 'infer' for inferring DST/non-DST, and 'raise' (default) for an `AmbiguousTimeError` to be raised. See *the docs* for more details (GH7943)
- `DataFrame.tz_localize` and `DataFrame.tz_convert` now accepts an optional `level` argument for localizing a specific level of a MultiIndex (GH7846)
- `Timestamp.tz_localize` and `Timestamp.tz_convert` now raise `TypeError` in error cases, rather than `Exception` (GH8025)
- a timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone (rather than being a naive `datetime64[ns]`) as `object` dtype (GH8411)
- `Timestamp.__repr__` displays `dateutil.tz.tzoffset` info (GH7907)

Rolling/Expanding Moments improvements

- `rolling_min()`, `rolling_max()`, `rolling_cov()`, and `rolling_corr()` now return objects with all `NaN` when `len(arg) < min_periods <= window` rather than raising. (This makes all rolling functions consistent in this behavior). (GH7766)

  Prior to 0.15.0

```
In [64]: s = Series([10, 11, 12, 13])

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

  New behavior

```
In [65]: rolling_min(s, window=10, min_periods=5)
Out[65]:
0   NaN
1   NaN
2   NaN
```

```
3   NaN
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
dtype: float64
```

  New behavior (note final value is `5 = sum([2, 3, NaN])`):

```
In [66]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[66]:
0    1
1    3
2    6
3    5
dtype: float64
```

- `rolling_window()` now normalizes the weights properly in rolling mean mode (*mean=True*) so that the calculated weighted means (e.g. 'triang', 'gaussian') are distributed about the same means as those calculated without weighting (i.e. 'boxcar'). See *the note on normalization* for further details. (GH7618)

```
In [67]: 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
dtype: float64
```

  New behavior

```
In [68]: rolling_window(s, window=3, win_type='triang', center=True)
Out[68]:
0       NaN
1     9.875
2    10.325
3    10.025
4       NaN
dtype: float64
```

- Removed center argument from all expanding_ functions (see *list*), as the results produced when center=True did not make much sense. (GH7925)
- Added optional ddof argument to expanding_cov() and rolling_cov(). The default value of 1 is backwards-compatible. (GH8279)
- Documented the ddof argument to expanding_var(), expanding_std(), rolling_var(), and rolling_std(). These functions' support of a ddof argument (with a default value of 1) was previously undocumented. (GH8064)
- ewma(), ewmstd(), ewmvol(), ewmvar(), ewmcov(), and ewmcorr() now interpret min_periods in the same manner that the rolling_*() and expanding_*() functions do: a given result entry will be NaN if the (expanding, in this case) window does not contain at least min_periods values. The previous behavior was to set to NaN the min_periods entries starting with the first non- NaN value. (GH7977)

  Prior behavior (note values start at index 2, which is min_periods after index 0 (the index of the first non-empty value)):

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

In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0         NaN
1         NaN
2    1.000000
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 [70]: ewma(s, com=3., min_periods=2)
Out[70]:
0         NaN
1         NaN
2         NaN
3         NaN
4    1.759644
5    2.383784
dtype: float64
```

- ewmstd(), ewmvol(), ewmvar(), ewmcov(), and ewmcorr() now have an optional adjust argument, just like ewma() does, affecting how the weights are calculated. The default value of adjust is True, which is backwards-compatible. See *Exponentially weighted moment functions* for details. (GH7911)
- ewma(), ewmstd(), ewmvol(), ewmvar(), ewmcov(), and ewmcorr() now have an optional ignore_na argument. When ignore_na=False (the default), missing values are taken into account in the weights calculation. When ignore_na=True (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. (GH7543)

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

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

```
0    1.0
1    1.0
2    5.2
dtype: float64

In [73]: ewma(Series([1., None, 8.]), com=2., ignore_na=False)  # new default
Out[73]:
0    1.000000
1    1.000000
2    5.846154
dtype: float64
```

> **Warning:** By default (`ignore_na=False`) the `ewm*()` functions' weights calculation in the presence of missing values is different than in pre-0.15.0 versions. To reproduce the pre-0.15.0 calculation of weights in the presence of missing values one must specify explicitly `ignore_na=True`.

- Bug in `expanding_cov()`, `expanding_corr()`, `rolling_cov()`, `rolling_cor()`, `ewmcov()`, and `ewmcorr()` returning results with columns sorted by name and producing an error for non-unique columns; now handles non-unique columns and returns columns in original order (except for the case of two DataFrames with `pairwise=False`, where behavior is unchanged) (GH7542)
- Bug in `rolling_count()` and `expanding_*()` functions unnecessarily producing error message for zero-length data (GH8056)
- Bug in `rolling_apply()` and `expanding_apply()` interpreting `min_periods=0` as `min_periods=1` (GH8080)
- Bug in `expanding_std()` and `expanding_var()` for a single value producing a confusing error message (GH7900)
- Bug in `rolling_std()` and `rolling_var()` for a single value producing `0` rather than `NaN` (GH7900)
- Bug in `ewmstd()`, `ewmvol()`, `ewmvar()`, and `ewmcov()` calculation of de-biasing factors when `bias=False` (the default). Previously an incorrect constant factor was used, based on `adjust=True`, `ignore_na=True`, and an infinite number of observations. Now a different factor is used for each entry, based on the actual weights (analogous to the usual `N/(N-1)` factor). In particular, for a single point a value of `NaN` is returned when `bias=False`, whereas previously a value of (approximately) `0` was returned.

  For example, consider the following pre-0.15.0 results for `ewmvar(..., bias=False)`, and the corresponding debiasing factors:

```
In [74]: s = Series([1., 2., 0., 4.])

In [89]: ewmvar(s, com=2., bias=False)
Out[89]:
0   -2.775558e-16
1    3.000000e-01
2    9.556787e-01
3    3.585799e+00
dtype: float64

In [90]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[90]:
0    1.25
1    1.25
2    1.25
3    1.25
dtype: float64
```

Note that entry `0` is approximately 0, and the debiasing factors are a constant 1.25. By comparison, the following 0.15.0 results have a `NaN` for entry `0`, and the debiasing factors are decreasing (towards 1.25):

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

In [76]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[76]:
0         NaN
1    2.083333
2    1.583333
3    1.425439
dtype: float64
```

See *Exponentially weighted moment functions* for details. (GH7912)

Improvements in the sql io module

- Added support for a `chunksize` parameter to `to_sql` function. This allows DataFrame to be written in chunks and avoid packet-size overflow errors (GH8062).
- Added support for a `chunksize` parameter to `read_sql` function. Specifying this argument will return an iterator through chunks of the query result (GH2908).
- Added support for writing `datetime.date` and `datetime.time` object columns with `to_sql` (GH6932).
- Added support for specifying a `schema` to read from/write to with `read_sql_table` and `to_sql` (GH7441, GH7952). For example:

  ```
  df.to_sql('table', engine, schema='other_schema')
  pd.read_sql_table('table', engine, schema='other_schema')
  ```

- Added support for writing `NaN` values with `to_sql` (GH2754).
- Added support for writing datetime64 columns with `to_sql` for all database flavors (GH7103).

1.6.2 Backwards incompatible API changes

Breaking changes

API changes related to `Categorical` (see *here* for more details):

- The `Categorical` constructor with two arguments changed from "codes/labels and levels" to "values and levels (now called 'categories')". This can lead to subtle bugs. If you use `Categorical` directly, please audit your code by changing it to use the `from_codes()` constructor.

  An old function call like (prior to 0.15.0):

  ```
  pd.Categorical([0,1,0,2,1], levels=['a', 'b', 'c'])
  ```

  will have to adapted to the following to keep the same behaviour:

```
In [2]: pd.Categorical.from_codes([0,1,0,2,1], categories=['a', 'b', 'c'])
Out[2]:
[a, b, a, c, b]
Categories (3, object): [a, b, c]
```

API changes related to the introduction of the `Timedelta` scalar (see *above* for more details):

- Prior to 0.15.0 `to_timedelta()` would return a `Series` for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for Series input, and `Timedelta` for scalar input.

For API changes related to the rolling and expanding functions, see detailed overview *above*.

Other notable API changes:

- Consistency when indexing with `.loc` and a list-like indexer when no values are found.

```
In [77]: df = DataFrame([['a'],['b']],index=[1,2])

In [78]: df
Out[78]:
   0
1  a
2  b
```

  In prior versions there was a difference in these two constructs:

  - `df.loc[[3]]` would return a frame reindexed by 3 (with all `np.nan` values)
  - `df.loc[[3],:]` would raise `KeyError`.

  Both will now raise a `KeyError`. The rule is that *at least 1* indexer must be found when using a list-like and `.loc` (GH7999)

  Furthermore in prior versions these were also different:

  - `df.loc[[1,3]]` would return a frame reindexed by [1,3]
  - `df.loc[[1,3],:]` would raise `KeyError`.

  Both will now return a frame reindex by [1,3]. E.g.

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

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

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

```
In [81]: p = Panel(np.arange(2*3*4).reshape(2,3,4),
   ....:           items=['ItemA','ItemB'],
   ....:           major_axis=[1,2,3],
   ....:           minor_axis=['A','B','C','D'])
   ....:

In [82]: p
```

```
Out[82]:
<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 [83]: p.loc[['ItemA','ItemD'],:,'D']
Out[83]:
   ItemA  ItemD
1      3    NaN
2      7    NaN
3     11    NaN
```

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

```
In [84]: s = Series(np.arange(3,dtype='int64'),
   ....:            index=MultiIndex.from_product([['A'],['foo','bar','baz']],
   ....:                                          names=['one','two'])
   ....:           ).sortlevel()
   ....:

In [85]: s
Out[85]:
one  two
A    bar    1
     baz    2
     foo    0
dtype: int64

In [86]: try:
   ....:    s.loc[['D']]
   ....: except KeyError as e:
   ....:    print("KeyError: " + str(e))
   ....:
KeyError: 'cannot index a multi-index axis with these keys'
```

- Assigning values to `None` now considers the dtype when choosing an 'empty' value (GH7941).

  Previously, assigning to `None` in numeric containers changed the dtype to object (or errored, depending on the call). It now uses `NaN`:

```
In [87]: s = Series([1, 2, 3])

In [88]: s.loc[0] = None

In [89]: s
Out[89]:
0   NaN
1     2
2     3
dtype: float64
```

  `NaT` is now used similarly for datetime containers.

  For object containers, we now preserve `None` values (previously these were converted to `NaN` values).

```
In [90]: s = Series(["a", "b", "c"])

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

In [92]: s
Out[92]:
0    None
1       b
2       c
dtype: object
```

To insert a NaN, you must explicitly use `np.nan`. See the *docs*.

- In prior versions, updating a pandas object inplace would not reflect in other python references to this object. (GH8511, GH5104)

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

In [94]: s2 = s

In [95]: s += 1.5
```

Behavior prior to v0.15.0

```
# the original object
In [5]: s
Out[5]:
0    2.5
1    3.5
2    4.5
dtype: float64


# a reference to the original object
In [7]: s2
Out[7]:
0    1
1    2
2    3
dtype: int64
```

This is now the correct behavior

```
# the original object
In [96]: s
Out[96]:
0    2.5
1    3.5
2    4.5
dtype: float64

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

- Made both the C-based and Python engines for *read_csv* and *read_table* ignore empty lines in input as well as whitespace-filled lines, as long as `sep` is not whitespace. This is an API change that can be controlled by the keyword parameter `skip_blank_lines`. See *the docs* (GH4466)

- A timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone and inserted as `object` dtype rather than being converted to a naive `datetime64[ns]` (GH8411).
- Bug in passing a `DatetimeIndex` with a timezone that was not being retained in DataFrame construction from a dict (GH7822)

  In prior versions this would drop the timezone, now it retains the timezone, but gives a column of `object` dtype:

```
In [98]: i = date_range('1/1/2011', periods=3, freq='10s', tz = 'US/Eastern')

In [99]: i
Out[99]:
DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00',
               '2011-01-01 00:00:20-05:00'],
              dtype='datetime64[ns]', freq='10S', tz='US/Eastern')

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

In [101]: df
Out[101]:
                           a
0  2011-01-01 00:00:00-05:00
1  2011-01-01 00:00:10-05:00
2  2011-01-01 00:00:20-05:00

In [102]: df.dtypes
Out[102]:
a    object
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 dataframe as *df['a'] = i* remains unchanged (this already returned an `object` column with a timezone).

- When passing multiple levels to `stack()`, it will now raise a `ValueError` when the levels aren't all level names or all level numbers (GH7660). See *Reshaping by stacking and unstacking*.
- Raise a `ValueError` in `df.to_hdf` with 'fixed' format, if `df` has non-unique columns as the resulting file will be broken (GH7761)
- `SettingWithCopy` raise/warnings (according to the option `mode.chained_assignment`) will now be issued when setting a value on a sliced mixed-dtype DataFrame using chained-assignment. (GH7845, GH7950)

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

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

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 the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.h
```

- `merge`, `DataFrame.merge`, and `ordered_merge` now return the same type as the `left` argument (GH7737).

- Previously an enlargement with a mixed-dtype frame would act unlike `.append` which will preserve dtypes (related GH2578, GH8176):

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

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

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

# dtypes are now preserved
In [106]: df.loc[2] = df.loc[1]

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

In [108]: df.dtypes
Out[108]:
female      bool
fitness    int64
dtype: object
```

- `Series.to_csv()` now returns a string when `path=None`, matching the behaviour of `DataFrame.to_csv()` (GH8215).
- `read_hdf` now raises `IOError` when a file that doesn't exist is passed in. Previously, a new, empty file was created, and a `KeyError` raised (GH7715).
- `DataFrame.info()` now ends its output with a newline character (GH8114)
- Concatenating no objects will now raise a `ValueError` rather than a bare `Exception`.
- Merge errors will now be sub-classes of `ValueError` rather than raw `Exception` (GH8501)
- `DataFrame.plot` and `Series.plot` keywords are now have consistent orders (GH8037)

Internal Refactoring

In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (GH5080, GH7439, GH7796, GH8024, GH8367, GH7997, GH8522):

- you may need to unpickle pandas version < 0.15.0 pickles using `pd.read_pickle` rather than `pickle.load`. See *pickle docs*

- when plotting with a PeriodIndex, the matplotlib internal axes will now be arrays of Period rather than a PeriodIndex (this is similar to how a DatetimeIndex passes arrays of datetimes now)
- MultiIndexes will now raise similary to other pandas objects w.r.t. truth testing, see *here* (GH7897).
- When plotting a DatetimeIndex directly with matplotlib's *plot* function, the axis labels will no longer be formatted as dates but as integers (the internal representation of a datetime64). **UPDATE** This is fixed in 0.15.1, see *here*.

Deprecations

- The attributes Categorical labels and levels attributes are deprecated and renamed to codes and categories.
- The outtype argument to pd.DataFrame.to_dict has been deprecated in favor of orient. (GH7840)
- The convert_dummies method has been deprecated in favor of get_dummies (GH8140)
- The infer_dst argument in tz_localize will be deprecated in favor of ambiguous to allow for more flexibility in dealing with DST transitions. Replace infer_dst=True with ambiguous='infer' for the same behavior (GH7943). See *the docs* for more details.
- The top-level pd.value_range has been deprecated and can be replaced by .describe() (GH8481)
- The Index set operations + and - were deprecated in order to provide these for numeric type operations on certain index types. + can be replaced by .union() or |, and - by .difference(). Further the method name Index.diff() is deprecated and can be replaced by Index.difference() (GH8226)

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

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

# -
Index(['a','b','c']) - Index(['b','c','d'])

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

- The infer_types argument to read_html() now has no effect and is deprecated (GH7762, GH7032).

Removal of prior version deprecations/changes

- Remove DataFrame.delevel method in favor of DataFrame.reset_index

1.6.3 Enhancements

Enhancements in the importing/exporting of Stata files:

- Added support for bool, uint8, uint16 and uint32 datatypes in to_stata (GH7097, GH7365)
- Added conversion option when importing Stata files (GH8527)
- DataFrame.to_stata and StataWriter check string length for compatibility with limitations imposed in dta files where fixed-width strings must contain 244 or fewer characters. Attempting to write Stata dta files with strings longer than 244 characters raises a ValueError. (GH7858)

- read_stata and StataReader can import missing data information into a DataFrame by setting the argument convert_missing to True. When using this options, missing values are returned as StataMissingValue objects and columns containing missing values have object data type. (GH8045)

Enhancements in the plotting functions:

- Added layout keyword to DataFrame.plot. You can pass a tuple of (rows, columns), one of which can be -1 to automatically infer (GH6667, GH8071).
- Allow to pass multiple axes to DataFrame.plot, hist and boxplot (GH5353, GH6970, GH7069)
- Added support for c, colormap and colorbar arguments for DataFrame.plot with kind='scatter' (GH7780)
- Histogram from DataFrame.plot with kind='hist' (GH7809), See *the docs*.
- Boxplot from DataFrame.plot with kind='box' (GH7998), See *the docs*.

Other:

- read_csv now has a keyword parameter float_precision which specifies which floating-point converter the C engine should use during parsing, see *here* (GH8002, GH8044)
- Added searchsorted method to Series objects (GH7447)
- describe() on mixed-types DataFrames is more flexible. Type-based column filtering is now possible via the include/exclude arguments. See the *docs* (GH8164).

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

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

In [111]: df.describe(include=["number", "object"], exclude=["float"])
Out[111]:
       catA catB       numC
count    24   24  24.000000
unique    2    4        NaN
top     foo    d        NaN
freq     16    6        NaN
mean    NaN  NaN  11.500000
std     NaN  NaN   7.071068
min     NaN  NaN   0.000000
25%     NaN  NaN   5.750000
50%     NaN  NaN  11.500000
75%     NaN  NaN  17.250000
max     NaN  NaN  23.000000
```

Requesting all columns is possible with the shorthand 'all'

```
In [112]: df.describe(include='all')
Out[112]:
       catA catB       numC       numD
```

```
count     24   24  24.000000  24.000000
unique     2    4        NaN        NaN
top      foo    d        NaN        NaN
freq      16    6        NaN        NaN
mean     NaN  NaN  11.500000  12.000000
std      NaN  NaN   7.071068   7.071068
min      NaN  NaN   0.000000   0.500000
25%      NaN  NaN   5.750000   6.250000
50%      NaN  NaN  11.500000  12.000000
75%      NaN  NaN  17.250000  17.750000
max      NaN  NaN  23.000000  23.500000
```

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 catagorical columns are encoded as 0's and 1's, while other columns are left untouched.

```
In [113]: df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
   .....:                 'C': [1, 2, 3]})
   .....:

In [114]: pd.get_dummies(df)
Out[114]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0
```

- `PeriodIndex` supports `resolution` as the same as `DatetimeIndex` (GH7708)
- `pandas.tseries.holiday` has added support for additional holidays and ways to observe holidays (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a list of offsets in Python3 (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a days_of_week parameter (GH7070)
- `GroupBy.nth()` now supports selecting multiple nth values (GH7910)

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

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

# get the first, 4th, and last date index for each month
In [117]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
Out[117]:
            a  b
2014-04-01  1  1
2014-04-04  1  1
2014-04-30  1  1
2014-05-01  1  1
2014-05-06  1  1
2014-05-30  1  1
2014-06-02  1  1
2014-06-05  1  1
2014-06-30  1  1
```

- `Period` and `PeriodIndex` supports addition/subtraction with `timedelta`-likes (GH7966)

If `Period` freq is `D`, `H`, `T`, `S`, `L`, `U`, `N`, `Timedelta`-like can be added if the result can have same freq. Otherwise, only the same `offsets` can be added.

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

In [119]: idx
Out[119]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='int64', freq='H')

In [120]: idx + pd.offsets.Hour(2)
Out[120]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')

In [121]: idx + Timedelta('120m')
Out[121]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')

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

In [123]: idx
Out[123]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'], dtype='int64', fr

In [124]: idx + pd.offsets.MonthEnd(3)
Out[124]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype='int64', fr
```

- Added experimental compatibility with `openpyxl` for versions >= 2.0. The `DataFrame.to_excel` method `engine` keyword now recognizes `openpyxl1` and `openpyxl2` which will explicitly require openpyxl v1 and v2 respectively, failing if the requested version is not available. The `openpyxl` engine is a now a meta-engine that automatically uses whichever version of openpyxl is installed. (GH7177)
- `DataFrame.fillna` can now accept a `DataFrame` as a fill value (GH8377)
- Passing multiple levels to `stack()` will now work when multiple level numbers are passed (GH7660). See *Reshaping by stacking and unstacking*.
- `set_names()`, `set_labels()`, and `set_levels()` methods now take an optional `level` keyword argument to all modification of specific level(s) of a MultiIndex. Additionally `set_names()` now accepts a scalar string value when operating on an `Index` or on a specific level of a `MultiIndex` (GH7792)

```
In [125]: idx = MultiIndex.from_product([['a'], range(3), list("pqr")], names=['foo', 'bar', 'ba

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

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

In [128]: idx.set_levels(['a','b','c'], level='bar')
```

```
Out[128]:
MultiIndex(levels=[[u'a'], [u'a', u'b', u'c'], [u'p', u'q', u'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,
           names=[u'foo', u'bar', u'baz'])

In [129]: idx.set_levels([['a','b','c'],[1,2,3]], level=[1,2])
Out[129]:
MultiIndex(levels=[[u'a'], [u'a', u'b', u'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,
           names=[u'foo', u'bar', u'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 [130]: idx = Index([1, 2, 3, 4, 1, 2])

In [131]: idx
Out[131]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')

In [132]: idx.duplicated()
Out[132]: array([False, False, False, False,  True,  True], dtype=bool)

In [133]: idx.drop_duplicates()
Out[133]: 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)

1.6.4 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)

1.6.5 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 reffered internally (GH7748)
- Bug in `Panel` when using `major_xs` and `copy=False` is passed (deprecation warning fails because of missing `warnings`) (GH8152).
- Bug in pickle deserialization that failed for pre-0.14.1 containers with dup items trying to avoid ambiguity when matching block and manager items, when there's only one block there's no ambiguity (GH7794)
- Bug in putting a `PeriodIndex` into a `Series` would convert to `int64` dtype, rather than `object` of `Periods` (GH7932)
- Bug in `HDFStore` iteration when passing a where (GH8014)
- Bug in `DataFrameGroupby.transform` when transforming with a passed non-sorted key (GH8046, GH8430)
- Bug in repeated timeseries line and area plot may result in `ValueError` or incorrect kind (GH7733)
- Bug in inference in a `MultiIndex` with `datetime.date` inputs (GH7888)

- Bug in get where an IndexError would not cause the default value to be returned (GH7725)
- Bug in offsets.apply, rollforward and rollback may reset nanosecond (GH7697)
- Bug in offsets.apply, rollforward and rollback may raise AttributeError if Timestamp has dateutil tzinfo (GH7697)
- Bug in sorting a multi-index frame with a Float64Index (GH8017)
- Bug in inconsistent panel setitem with a rhs of a DataFrame for alignment (GH7763)
- Bug in is_superperiod and is_subperiod cannot handle higher frequencies than S (GH7760, GH7772, GH7803)
- Bug in 32-bit platforms with Series.shift (GH8129)
- Bug in PeriodIndex.unique returns int64 np.ndarray (GH7540)
- Bug in groupby.apply with a non-affecting mutation in the function (GH8467)
- Bug in DataFrame.reset_index which has MultiIndex contains PeriodIndex or DatetimeIndex with tz raises ValueError (GH7746, GH7793)
- Bug in DataFrame.plot with subplots=True may draw unnecessary minor xticks and yticks (GH7801)
- Bug in StataReader which did not read variable labels in 117 files due to difference between Stata documentation and implementation (GH7816)
- Bug in StataReader where strings were always converted to 244 characters-fixed width irrespective of underlying string size (GH7858)
- Bug in DataFrame.plot and Series.plot may ignore rot and fontsize keywords (GH7844)
- Bug in DatetimeIndex.value_counts doesn't preserve tz (GH7735)
- Bug in PeriodIndex.value_counts results in Int64Index (GH7735)
- Bug in DataFrame.join when doing left join on index and there are multiple matches (GH5391)
- Bug in GroupBy.transform() where int groups with a transform that didn't preserve the index were incorrectly truncated (GH7972).
- Bug in groupby where callable objects without name attributes would take the wrong path, and produce a DataFrame instead of a Series (GH7929)
- Bug in groupby error message when a DataFrame grouping column is duplicated (GH7511)
- Bug in read_html where the infer_types argument forced coercion of date-likes incorrectly (GH7762, GH7032).
- Bug in Series.str.cat with an index which was filtered as to not include the first item (GH7857)
- Bug in Timestamp cannot parse nanosecond from string (GH7878)
- Bug in Timestamp with string offset and tz results incorrect (GH7833)
- Bug in tslib.tz_convert and tslib.tz_convert_single may return different results (GH7798)
- Bug in DatetimeIndex.intersection of non-overlapping timestamps with tz raises IndexError (GH7880)
- Bug in alignment with TimeOps and non-unique indexes (GH8363)
- Bug in GroupBy.filter() where fast path vs. slow path made the filter return a non scalar value that appeared valid but wasn't (GH7870).
- Bug in date_range()/DatetimeIndex() when the timezone was inferred from input dates yet incorrect times were returned when crossing DST boundaries (GH7835, GH7901).

- Bug in `to_excel()` where a negative sign was being prepended to positive infinity and was absent for negative infinity (GH7949)
- Bug in area plot draws legend with incorrect `alpha` when `stacked=True` (GH8027)
- `Period` and `PeriodIndex` addition/subtraction with `np.timedelta64` results in incorrect internal representations (GH7740)
- Bug in `Holiday` with no offset or observance (GH7987)
- Bug in `DataFrame.to_latex` formatting when columns or index is a `MultiIndex` (GH7982).
- Bug in `DateOffset` around Daylight Savings Time produces unexpected results (GH5175).
- Bug in `DataFrame.shift` where empty columns would throw `ZeroDivisionError` on numpy 1.7 (GH8019)
- Bug in installation where `html_encoding/*.html` wasn't installed and therefore some tests were not running correctly (GH7927).
- Bug in `read_html` where `bytes` objects were not tested for in `_read` (GH7927).
- Bug in `DataFrame.stack()` when one of the column levels was a datelike (GH8039)
- Bug in broadcasting numpy scalars with `DataFrame` (GH8116)
- Bug in `pivot_table` performed with nameless `index` and `columns` raises `KeyError` (GH8103)
- Bug in `DataFrame.plot(kind='scatter')` draws points and errorbars with different colors when the color is specified by `c` keyword (GH8081)
- Bug in `Float64Index` where `iat` and `at` were not testing and were failing (GH8092).
- Bug in `DataFrame.boxplot()` where y-limits were not set correctly when producing multiple axes (GH7528, GH5517).
- Bug in `read_csv` where line comments were not handled correctly given a custom line terminator or `delim_whitespace=True` (GH8122).
- Bug in `read_html` where empty tables caused a `StopIteration` (GH7575)
- Bug in casting when setting a column in a same-dtype block (GH7704)
- Bug in accessing groups from a `GroupBy` when the original grouper was a tuple (GH8121).
- Bug in `.at` that would accept integer indexers on a non-integer index and do fallback (GH7814)
- Bug with kde plot and NaNs (GH8182)
- Bug in `GroupBy.count` with float32 data type were nan values were not excluded (GH8169).
- Bug with stacked barplots and NaNs (GH8175).
- Bug in resample with non evenly divisible offsets (e.g. '7s') (GH8371)
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).
- Bug with `DatetimeIndex.asof` incorrectly matching partial strings and returning the wrong date (GH8245).
- Bug in plotting methods modifying the global matplotlib rcParams (GH8242).
- Bug in `DataFrame.__setitem__` that caused errors when setting a dataframe column to a sparse array (GH8131)
- Bug where `Dataframe.boxplot()` failed when entire column was empty (GH8181).

- Bug with messed variables in `radviz` visualization (GH8199).
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).
- Bug in `to_clipboard` that would clip long column data (GH8305)
- Bug in `DataFrame` terminal display: Setting max_column/max_rows to zero did not trigger auto-resizing of dfs to fit terminal width/height (GH7180).
- Bug in OLS where running with "cluster" and "nw_lags" parameters did not work correctly, but also did not throw an error (GH5884).
- Bug in `DataFrame.dropna` that interpreted non-existent columns in the subset argument as the 'last column' (GH8303)
- Bug in `Index.intersection` on non-monotonic non-unique indexes (GH8362).
- Bug in masked series assignment where mismatching types would break alignment (GH8387)
- Bug in `NDFrame.equals` gives false negatives with dtype=object (GH8437)
- Bug in assignment with indexer where type diversity would break alignment (GH8258)
- Bug in `NDFrame.loc` indexing when row/column names were lost when target was a list/ndarray (GH6552)
- Regression in `NDFrame.loc` indexing when rows/columns were converted to Float64Index if target was an empty list/ndarray (GH7774)
- Bug in `Series` that allows it to be indexed by a `DataFrame` which has unexpected results. Such indexing is no longer permitted (GH8444)
- Bug in item assignment of a `DataFrame` with multi-index columns where right-hand-side columns were not aligned (GH7655)
- Suppress FutureWarning generated by NumPy when comparing object arrays containing NaN for equality (GH7065)
- Bug in `DataFrame.eval()` where the dtype of the `not` operator (~) was not correctly inferred as `bool`.

1.7 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*

1.7.1 API changes

- Openpyxl now raises a ValueError on construction of the openpyxl writer instead of warning on pandas import (GH7284).
- For `StringMethods.extract`, when no match is found, the result - only containing `NaN` values - now also has `dtype=object` instead of `float` (GH7242)
- `Period` objects no longer raise a `TypeError` when compared using `==` with another object that *isn't* a `Period`. Instead when comparing a `Period` with another object using `==` if the other object isn't a `Period` `False` is returned. (GH7376)
- Previously, the behaviour on resetting the time or not in `offsets.apply`, `rollforward` and `rollback` operations differed between offsets. With the support of the `normalize` keyword for all offsets(see below) with a default value of False (preserve time), the behaviour changed for certain offsets (BusinessMonthBegin, MonthEnd, BusinessMonthEnd, CustomBusinessMonthEnd, BusinessYearBegin, LastWeekOfMonth, FY5253Quarter, LastWeekOfMonth, Easter):

  ```
  In [6]: from pandas.tseries import offsets

  In [7]: d = pd.Timestamp('2014-01-01 09:00')

  # old behaviour < 0.14.1
  In [8]: d + offsets.MonthEnd()
  Out[8]: Timestamp('2014-01-31 00:00:00')
  ```

  Starting from 0.14.1 all offsets preserve time by default. The old behaviour can be obtained with `normalize=True`

  ```
  # new behaviour
  In [1]: d + offsets.MonthEnd()
  Out[1]: Timestamp('2014-01-31 09:00:00')

  In [2]: d + offsets.MonthEnd(normalize=True)
  Out[2]: Timestamp('2014-01-31 00:00:00')
  ```

  Note that for the other offsets the default behaviour did not change.

- Add back `#N/A N/A` as a default NA value in text parsing, (regresion from 0.12) (GH5521)
- Raise a `TypeError` on inplace-setting with a `.where` and a non `np.nan` value as this is inconsistent with a set-item expression like `df[mask] = None` (GH7656)

1.7.2 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` suppports the `normalize` keyword to specify whether `offsets.apply`, `rollforward` and `rollback` resets the time (hour, minute, etc) or not (default `False`, preserves time) (GH7156):

  ```
  In [3]: import pandas.tseries.offsets as offsets

  In [4]: day = offsets.Day()
  ```

```
In [5]: day.apply(Timestamp('2014-01-01 09:00'))
Out[5]: Timestamp('2014-01-02 09:00:00')

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

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

- `PeriodIndex` is represented as the same format as `DatetimeIndex` (GH7601)
- `StringMethods` now work on empty Series (GH7242)
- The file parsers `read_csv` and `read_table` now ignore line comments provided by the parameter *comment*, which accepts only a single character for the C reader. In particular, they allow for comments before file data begins (GH2685)
- Add `NotImplementedError` for simultaneous use of `chunksize` and `nrows` for read_csv() (GH6774).
- Tests for basic reading of public S3 buckets now exist (GH7281).
- `read_html` now sports an `encoding` argument that is passed to the underlying parser library. You can use this to read non-ascii encoded web pages (GH7323).
- `read_excel` now supports reading from URLs in the same way that `read_csv` does. (GH6809)
- Support for dateutil timezones, which can now be used in the same way as pytz timezones across pandas. (GH4688)

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

In [9]: rng.tz
Out[9]: tzfile('/usr/share/zoneinfo/Europe/London')
```

  See *the docs*.

- Implemented `sem` (standard error of the mean) operation for `Series`, `DataFrame`, `Panel`, and `Groupby` (GH6897)
- Add `nlargest` and `nsmallest` to the `Series` `groupby` whitelist, which means you can now use these methods on a `SeriesGroupBy` object (GH7053).
- All offsets `apply`, `rollforward` and `rollback` can now handle `np.datetime64`, previously results in `ApplyTypeError` (GH7452)
- `Period` and `PeriodIndex` can contain `NaT` in its values (GH7485)
- Support pickling `Series`, `DataFrame` and `Panel` objects with non-unique labels along *item* axis (`index`, `columns` and `items` respectively) (GH7370).
- Improved inference of datetime/timedelta with mixed null objects. Regression from 0.13.1 in interpretation of an object Index with all null elements (GH7431)

1.7.3 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 signifcant performance gains (GH7383)
- Regression in groupby aggregation of datetime64 dtypes (GH7555)
- Improvements in *MultiIndex.from_product* for large iterables (GH7627)

1.7.4 Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a multi-indexed `DataFrame`, see *the docs*. (GH5602)
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google `bq.py` command line client. This submodule now uses `httplib2` and the Google `apiclient` and `oauth2client` API client libraries which should be more stable and, therefore, reliable than `bq.py`. See *the docs*. (GH6937).

1.7.5 Bug Fixes

- Bug in `DataFrame.where` with a symmetric shaped frame and a passed other of a DataFrame (GH7506)
- Bug in Panel indexing with a multi-index axis (GH7516)
- Regression in datetimelike slice indexing with a duplicated index and non-exact end-points (GH7523)
- Bug in setitem with list-of-lists and single vs mixed types (GH7551:)
- Bug in timeops with non-aligned Series (GH7500)
- Bug in timedelta inference when assigning an incomplete Series (GH7592)
- Bug in groupby `.nth` with a Series and integer-like column name (GH7559)
- Bug in `Series.get` with a boolean accessor (GH7407)
- Bug in `value_counts` where `NaT` did not qualify as missing (`NaN`) (GH7423)
- Bug in `to_timedelta` that accepted invalid units and misinterpreted 'm/h' (GH7611, GH6423)
- Bug in line plot doesn't set correct `xlim` if `secondary_y=True` (GH7459)
- Bug in grouped `hist` and `scatter` plots use old `figsize` default (GH7394)
- Bug in plotting subplots with `DataFrame.plot`, `hist` clears passed `ax` even if the number of subplots is one (GH7391).
- Bug in plotting subplots with `DataFrame.boxplot` with `by` kw raises `ValueError` if the number of subplots exceeds 1 (GH7391).
- Bug in subplots displays `ticklabels` and `labels` in different rule (GH5897)
- Bug in `Panel.apply` with a multi-index as an axis (GH7469)
- Bug in `DatetimeIndex.insert` doesn't preserve `name` and `tz` (GH7299)
- Bug in `DatetimeIndex.asobject` doesn't preserve `name` (GH7299)
- Bug in multi-index slicing with datetimelike ranges (strings and Timestamps), (GH7429)
- Bug in `Index.min` and `max` doesn't handle `nan` and `NaT` properly (GH7261)
- Bug in `PeriodIndex.min/max` results in `int` (GH7609)
- Bug in `resample` where `fill_method` was ignored if you passed `how` (GH2073)

- Bug in TimeGrouper doesn't exclude column specified by key (GH7227)
- Bug in DataFrame and Series bar and barh plot raises TypeError when bottom and left keyword is specified (GH7226)
- Bug in DataFrame.hist raises TypeError when it contains non numeric column (GH7277)
- Bug in Index.delete does not preserve name and freq attributes (GH7302)
- Bug in DataFrame.query()/eval where local string variables with the @ sign were being treated as temporaries attempting to be deleted (GH7300).
- Bug in Float64Index which didn't allow duplicates (GH7149).
- Bug in DataFrame.replace() where truthy values were being replaced (GH7140).
- Bug in StringMethods.extract() where a single match group Series would use the matcher's name instead of the group name (GH7313).
- Bug in isnull() when mode.use_inf_as_null == True where isnull wouldn't test True when it encountered an inf/-inf (GH7315).
- Bug in inferred_freq results in None for eastern hemisphere timezones (GH7310)
- Bug in Easter returns incorrect date when offset is negative (GH7195)
- Bug in broadcasting with .div, integer dtypes and divide-by-zero (GH7325)
- Bug in CustomBusinessDay.apply raiases NameError when np.datetime64 object is passed (GH7196)
- Bug in MultiIndex.append, concat and pivot_table don't preserve timezone (GH6606)
- Bug in .loc with a list of indexers on a single-multi index level (that is not nested) (GH7349)
- Bug in Series.map when mapping a dict with tuple keys of different lengths (GH7333)
- Bug all StringMethods now work on empty Series (GH7242)
- Fix delegation of *read_sql* to *read_sql_query* when query does not contain 'select' (GH7324).
- Bug where a string column name assignment to a DataFrame with a Float64Index raised a TypeError during a call to np.isnan (GH7366).
- Bug where NDFrame.replace() didn't correctly replace objects with Period values (GH7379).
- Bug in .ix getitem should always return a Series (GH7150)
- Bug in multi-index slicing with incomplete indexers (GH7399)
- Bug in multi-index slicing with a step in a sliced level (GH7400)
- Bug where negative indexers in DatetimeIndex were not correctly sliced (GH7408)
- Bug where NaT wasn't repr'd correctly in a MultiIndex (GH7406, GH7409).
- Bug where bool objects were converted to nan in convert_objects (GH7416).
- Bug in quantile ignoring the axis keyword argument (:issue'7306')
- Bug where nanops._maybe_null_out doesn't work with complex numbers (GH7353)
- Bug in several nanops functions when axis==0 for 1-dimensional nan arrays (GH7354)
- Bug where nanops.nanmedian doesn't work when axis==None (GH7352)
- Bug where nanops._has_infs doesn't work with many dtypes (GH7357)
- Bug in StataReader.data where reading a 0-observation dta failed (GH7369)

- Bug in StataReader when reading Stata 13 (117) files containing fixed width strings (GH7360)
- Bug in StataWriter where encoding was ignored (GH7286)
- Bug in DatetimeIndex comparison doesn't handle NaT properly (GH7529)
- Bug in passing input with tzinfo to some offsets apply, rollforward or rollback resets tzinfo or raises ValueError (GH7465)
- Bug in DatetimeIndex.to_period, PeriodIndex.asobject, PeriodIndex.to_timestamp doesn't preserve name (GH7485)
- Bug in DatetimeIndex.to_period and PeriodIndex.to_timestanp 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).

1.8 v0.14.0 (May 31 , 2014)

This is a major release from 0.13.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - Officially support Python 3.4
  - SQL interfaces updated to use `sqlalchemy`, See *Here*.
  - Display interface changes, See *Here*
  - MultiIndexing Using Slicers, See *Here*.
  - Ability to join a singly-indexed DataFrame with a multi-indexed DataFrame, see *Here*
  - More consistency in groupby results and more flexible groupby specifications, See *Here*
  - Holiday calendars are now supported in `CustomBusinessDay`, see *Here*
  - Several improvements in plotting functions, including: hexbin, area and pie plots, see *Here*.
  - Performance doc section on I/O operations, See *Here*
- *Other Enhancements*
- *API Changes*
- *Text Parsing API Changes*
- *Groupby API Changes*
- *Performance Improvements*
- *Prior Deprecations*
- *Deprecations*
- *Known Issues*
- *Bug Fixes*

> **Warning:** In 0.14.0 all `NDFrame` based containers have undergone significant internal refactoring. Before that each block of homogeneous data had its own labels and extra care was necessary to keep those in sync with the parent container's labels. This should not have any visible user/API behavior changes (GH6745)

1.8.1 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]
Out[3]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

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

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

These are out-of-bounds selections

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

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 preseve 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]: Int64Index([1, 2, 3], dtype='int64')
```

  Previously, the above operation would return `Int64Index`. If you'd like to do this manually, use `Index.astype()`

```
In [9]: i[[0,1,2]].astype(np.int_)
Out[9]: Int64Index([1, 2, 3], dtype='int32')
```

- `set_index` no longer converts MultiIndexes to an Index of tuples. For example, the old behavior returned an Index in this case (GH6459):

```
# Old behavior, casted MultiIndex to an Index
In [10]: tuple_ind
Out[10]: Index([(u'a', u'c'), (u'a', u'd'), (u'b', u'c'), (u'b', u'd')], dtype='object')

In [11]: df_multi.set_index(tuple_ind)
Out[11]:
               0         1
(a, c)  0.471435 -1.190976
(a, d)  1.432707 -0.312652
(b, c) -0.720589  0.887163
(b, d)  0.859588 -0.636524

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

In [13]: df_multi.set_index(mi)
Out[13]:
            0         1
a c  0.471435 -1.190976
  d  1.432707 -0.312652
```

```
b c -0.720589  0.887163
  d  0.859588 -0.636524
```

This also applies when passing multiple indices to `set_index`:

```
# Old output, 2-level MultiIndex of tuples
In [14]: df_multi.set_index([df_multi.index, df_multi.index])
Out[14]:
                      0         1
(a, c) (a, c)  0.471435 -1.190976
(a, d) (a, d)  1.432707 -0.312652
(b, c) (b, c) -0.720589  0.887163
(b, d) (b, d)  0.859588 -0.636524

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

- `pairwise` keyword was added to the statistical moment functions `rolling_cov`, `rolling_corr`, `ewmcov`, `ewmcorr`, `expanding_cov`, `expanding_corr` to allow the calculation of moving window covariance and correlation matrices (GH4950). See *Computing rolling pairwise covariances and correlations* in the docs.

```
In [16]: df = DataFrame(np.random.randn(10,4),columns=list('ABCD'))

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

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

- `Series.iteritems()` is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added `nunique` and `value_counts` functions to `Index` for counting unique elements. (GH6734)
- `stack` and `unstack` now raise a `ValueError` when the `level` keyword refers to a non-unique item in the `Index` (previously raised a `KeyError`). (GH6738)
- drop unused order argument from `Series.sort`; args now are in the same order as `Series.order`; add `na_position` arg to conform to `Series.order` (GH6847)
- default sorting algorithm for `Series.order` is now `quicksort`, to conform with `Series.sort` (and numpy defaults)
- add `inplace` keyword to `Series.order/sort` to make them inverses (GH6859)
- `DataFrame.sort` now places NaNs at the beginning or end of the sort according to the `na_position` parameter. (GH3917)
- accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1

- Added `factorize` functions to `Index` and `Series` to get indexer and unique values (GH7090)
- `describe` on a DataFrame with a mix of Timestamp and string like objects returns a different Index (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with **only** `bool` dtypes now give a warning indicating that they are evaluated in Python space for `+`, `-`, and `*` operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

```
x = pd.Series(np.random.rand(10) > 0.5)
y = True
x + y  # warning generated: should do x | y instead
x / y  # this raises because it doesn't make sense

NotImplementedError: operator '/' not implemented for bool dtypes
```

- In `HDFStore`, `select_as_multiple` will always raise a `KeyError`, when a key or the selector is not found (GH6177)
- `df['col'] = value` and `df.loc[:,'col'] = value` are now completely equivalent; previously the `.loc` would not necessarily coerce the dtype of the resultant series (GH6149)
- `dtypes` and `ftypes` now return a series with `dtype=object` on empty containers (GH5740)
- `df.to_csv` will now return a string of the CSV data if neither a target path nor a buffer is provided (GH6061)
- `pd.infer_freq()` will now raise a `TypeError` if given an invalid `Series/Index` type (GH6407, GH6463)
- A tuple passed to `DataFame.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)

1.8.2 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='20010101',freq='D',periods=10)

In [6]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[6]:
             0   1   2   3   4   5
2001-01-01   0   1   2   3   4   5 ...
2001-01-02  10  11  12  13  14  15 ...
2001-01-03  20  21  22  23  24  25 ...
2001-01-04  30  31  32  33  34  35 ...
2001-01-05  40  41  42  43  44  45 ...
2001-01-06  50  51  52  53  54  55 ...
           ... ... ... ... ... ...

[10 rows x 10 columns]
```

In the current version, large DataFrames are centrally truncated, showing a preview of head and tail in both dimensions.

```
In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[24]:
             0   1   2 ...   7   8   9
2001-01-01   0   1   2 ...   7   8   9
2001-01-02  10  11  12 ...  17  18  19
2001-01-03  20  21  22 ...  27  28  29
...         ..  ..  .. ...  ..  ..  ..
2001-01-08  70  71  72 ...  77  78  79
2001-01-09  80  81  82 ...  87  88  89
2001-01-10  90  91  92 ...  97  98  99

[10 rows x 10 columns]
```

- allow option 'truncate' for display.show_dimensions to only show the dimensions if the frame is truncated (GH6547).

  The default for display.show_dimensions will now be truncate. This is consistent with how Series display length.

```
In [19]: dfd = pd.DataFrame(np.arange(25).reshape(-1,5), index=[0,1,2,3,4], columns=[0,1,2,3,4])

# show dimensions since this is truncated
In [20]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
   ....:                        'display.show_dimensions', 'truncate'):
   ....:     print(dfd)
   ....:
     0 ...   4
0    0 ...   4
```

```
..   .. ...  ..
4   20 ...  24

[5 rows x 5 columns]

# will not show dimensions since it is not truncated
In [21]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40,
   ....:                        'display.show_dimensions', 'truncate'):
   ....:     print(dfd)
   ....:
    0   1   2   3   4
0   0   1   2   3   4
1   5   6   7   8   9
2  10  11  12  13  14
3  15  16  17  18  19
4  20  21  22  23  24
```

- Regression in the display of a MultiIndexed Series with `display.max_rows` is less than the length of the series (GH7101)
- Fixed a bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the *large_repr* set to 'info' (GH7105)
- The *verbose* keyword in `DataFrame.info()`, which controls whether to shorten the `info` representation, is now `None` by default. This will follow the global setting in `display.max_info_columns`. The global setting can be overriden 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)

1.8.3 Text Parsing API Changes

`read_csv()`/`read_table()` will now be noiser 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)

1.8.4 Groupby API Changes

More consistent behaviour for some groupby methods:

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

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

In [23]: g = df.groupby('A')
```

```
In [24]: g.head(1)  # filters DataFrame
Out[24]:
   A  B
0  1  2
2  5  6

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

- groupby head and tail respect column selection:

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

- groupby nth now reduces by default; filtering can be achieved by passing as_index=False. With an optional dropna argument to ignore NaN. See *the docs*.

  Reducing

```
In [27]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [28]: g = df.groupby('A')

In [29]: g.nth(0)
Out[29]:
    B
A
1 NaN
5   6

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

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

  Filtering

```
In [32]: gf = df.groupby('A',as_index=False)

In [33]: gf.nth(0)
Out[33]:
   A   B
```

```
0  1 NaN
2  5   6

In [34]: gf.nth(0, dropna='any')
Out[34]:
   B
A
1  4
5  6
```

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

```
In [35]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])

In [36]: g = df.groupby('A')

In [37]: g.count()
Out[37]:
   B
A
1  1
5  2

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

[16 rows x 1 columns]
```

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

```
In [39]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])

In [40]: g = df.groupby('A',as_index=False)

In [41]: g.count()
Out[41]:
   A  B
0  1  1
1  5  2

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

```
Out[42]:
           A         B
0 count    2  1.000000
  mean     1  4.000000
  std      0       NaN
  min      1  4.000000
  25%      1  4.000000
  50%      1  4.000000
  75%      1  4.000000
...       ..       ...
1 mean     5  7.000000
  std      0  1.414214
  min      5  6.000000
  25%      5  6.500000
  50%      5  7.000000
  75%      5  7.500000
  max      5  8.000000

[16 rows x 2 columns]
```

- Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See *the docs*. (GH3794)
- Better propagation/preservation of Series names when performing groupby operations:
  - `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result (GH6265).
  - If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` (GH6124). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

1.8.5 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:

```
In [43]: from sqlalchemy import create_engine

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

This `engine` can then be used to write or read data to/from this database:

```
In [45]: df = pd.DataFrame({'A': [1,2,3], 'B': ['a', 'b', 'c']})

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

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

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

or by specifying a sql query:

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

Some other enhancements to the sql functions include:

- support for writing the index. This can be controlled with the `index` keyword (default is True).
- specify the column label to use when writing the index with `index_label`.
- specify string columns to parse as datetimes withh 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).

1.8.6 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 MuliIndex for the rows.

You should do this:

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

rather than this:

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

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

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

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

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

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

In [53]: df
Out[53]:
lvl0           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 [54]: df.loc[(slice('A1','A3'),slice(None), ['C1','C3']),:]
Out[54]:
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 a `pd.IndexSlice` to shortcut the creation of these slices

```
In [55]: idx = pd.IndexSlice

In [56]: df.loc[idx[:,:,['C1','C3']],idx[:,'foo']]
Out[56]:
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]
```

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

```
In [57]: df.loc['A1',(slice(None),'foo')]
Out[57]:
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

[16 rows x 2 columns]
```

```
In [58]: df.loc[idx[:,:,['C1','C3']],idx[:,'foo']]
Out[58]:
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 [59]: mask = df[('a','foo')]>200

In [60]: df.loc[idx[mask,:,['C1','C3']],idx[:,'foo']]
Out[60]:
lvl0           a    b
lvl1         foo  foo
A3 B0 C1 D1  204  206
      C3 D0  216  218
         D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254
```

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

```
In [61]: df.loc(axis=0)[:,:,['C1','C3']]
Out[61]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C1 D0    9    8   11   10
         D1   13   12   15   14
```

```
      C3 D0   25   24   27   26
         D1   29   28   31   30
   B1 C1 D0   41   40   43   42
         D1   45   44   47   46
      C3 D0   57   56   59   58
...          ...  ...  ...  ...
A3 B0 C1 D1  205  204  207  206
      C3 D0  217  216  219  218
         D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
      C3 D0  249  248  251  250
         D1  253  252  255  254

[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

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

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

In [64]: df2
Out[64]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
         D1    5    4    7    6
      C1 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10
      C2 D0   17   16   19   18
         D1   21   20   23   22
      C3 D0  -10  -10  -10  -10
...          ...  ...  ...  ...
A3 B1 C0 D1  229  228  231  230
      C1 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10
      C2 D0  241  240  243  242
         D1  245  244  247  246
      C3 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10

[64 rows x 4 columns]
```

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

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

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

In [67]: df2
Out[67]:
lvl0              a               b
lvl1            bar    foo      bah    foo
A0 B0 C0 D0       1      0        3      2
         D1       5      4        7      6
      C1 D0    9000   8000    11000  10000
         D1   13000  12000    15000  14000
      C2 D0      17     16       19     18
```

```
          D1      21      20      23      22
       C3 D0   25000   24000   27000   26000
...              ...     ...     ...     ...
A3 B1  C0 D1     229     228     231     230
       C1 D0  233000  232000  235000  234000
          D1  237000  236000  239000  238000
       C2 D0     241     240     243     242
          D1     245     244     247     246
       C3 D0  249000  248000  251000  250000
          D1  253000  252000  255000  254000

[64 rows x 4 columns]
```

1.8.7 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 coodinates as line plot. However, bar plot may differs unexpectedly when you manually adjust the bar location or drawing area, such as using *set_xlim*, *set_ylim*, etc. In this cases, please modify your script to meet with new coordinates.

- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A `FutureWarning` is raised to alert that the old `colors` argument will not be supported in a future release. (GH6956)
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- `DataFrame.boxplot()` now supports `layout` keyword (GH6769)
- `DataFrame.boxplot()` has a new keyword argument, *return_type*. It accepts `'dict'`, `'axes'`, or `'both'`, in which case a namedtuple with the matplotlib axes and a dict of matplotlib Lines is returned.

1.8.8 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)

1.8.9 Deprecations

- The `pivot_table()`/`DataFrame.pivot_table()` and `crosstab()` functions now take arguments `index` and `columns` instead of `rows` and `cols`. A `FutureWarning` is raised to alert that the old `rows` and `cols` arguments will not be supported in a future release (GH5505)
- The `DataFrame.drop_duplicates()` and `DataFrame.duplicated()` methods now take argument `subset` instead of `cols` to better align with `DataFrame.dropna()`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6680)
- The `DataFrame.to_csv()` and `DataFrame.to_excel()` functions now takes argument `columns` instead of `cols`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6645)
- Indexers will warn `FutureWarning` when used with a scalar indexer and a non-floating point Index (GH4892, GH6960)

```
# non-floating point indexes can only be indexed by integers / labels
In [1]: Series(1,np.arange(5))[3.0]
        pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index shoul
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 shoul
Out[2]: 1

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

1.8.10 Known Issues

- OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

1.8.11 Enhancements

- DataFrame and Series will create a MultiIndex object if passed a tuples dict, See *the docs* (GH3323)

```
In [68]: Series({('a', 'b'): 1, ('a', 'a'): 0,
   ....:         ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
   ....:
Out[68]:
a  a    0
   b    1
   c    2
b  a    3
   b    4
dtype: int64

In [69]: DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
   ....:            ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
   ....:            ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
   ....:            ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
   ....:            ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
   ....:
Out[69]:
      a           b
      a   b   c   a   b
A B   4   1   5   8  10
  C   3   2   6   7 NaN
  D NaN NaN NaN NaN   9
```

- Added the `sym_diff` method to `Index` (GH5543)
- `DataFrame.to_latex` now takes a longtable keyword, which if True will return a table in a longtable environment. (GH6617)
- Add option to turn off escaping in `DataFrame.to_latex` (GH6472)
- `pd.read_clipboard` will, if the keyword `sep` is unspecified, try to detect data copied from a spreadsheet and parse accordingly. (GH6223)
- Joining a singly-indexed DataFrame with a multi-indexed DataFrame (GH3662)

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

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

In [71]: household
Out[71]:
              male    wealth
household_id
1                0  196087.3
2                1  316478.7
3                0  294750.0

In [72]: portfolio = DataFrame(dict(household_id = [1,2,2,3,3,3,4],
   ....:                            asset_id = ["nl0000301109","nl0000289783","gb00b03mlx29",
   ....:                                        "gb00b03mlx29","lu0197800237","nl0000289965",np.
   ....:                            name = ["ABN Amro","Robeco","Royal Dutch Shell","Royal Dutch
   ....:                                    "AAB Eastern Europe Equity Fund","Postbank BioTech F
   ....:                            share = [1.0,0.4,0.6,0.15,0.6,0.25,1.0]),
   ....:                       columns = ['household_id','asset_id','name','share']
```

```
   ....:                         ).set_index(['household_id','asset_id'])
   ....:

In [73]: portfolio
Out[73]:
                                                   name  share
household_id asset_id
1            nl0000301109                     ABN Amro   1.00
2            nl0000289783                       Robeco   0.40
             gb00b03mlx29            Royal Dutch Shell   0.60
3            gb00b03mlx29            Royal Dutch Shell   0.15
             lu0197800237  AAB Eastern Europe Equity Fund   0.60
             nl0000289965         Postbank BioTech Fonds   0.25
4            NaN                                   NaN   1.00

In [74]: household.join(portfolio, how='inner')
Out[74]:
                           male    wealth                            name  \
household_id asset_id
1            nl0000301109     0  196087.3                        ABN Amro
2            nl0000289783     1  316478.7                          Robeco
             gb00b03mlx29     1  316478.7               Royal Dutch Shell
3            gb00b03mlx29     0  294750.0               Royal Dutch Shell
             lu0197800237     0  294750.0  AAB Eastern Europe Equity Fund
             nl0000289965     0  294750.0          Postbank BioTech Fonds

                           share
household_id asset_id
1            nl0000301109   1.00
2            nl0000289783   0.40
             gb00b03mlx29   0.60
3            gb00b03mlx29   0.15
             lu0197800237   0.60
             nl0000289965   0.25
```

- `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)

- `CustomBuisnessMonthBegin` and `CustomBusinessMonthEnd` are now available (GH6866)
- `Series.quantile()` and `DataFrame.quantile()` now accept an array of quantiles.
- `describe()` now accepts an array of percentiles to include in the summary statistics (GH4196)
- `pivot_table` can now accept `Grouper` by `index` and `columns` keywords (GH6913)

```
In [75]: import datetime

In [76]: df = DataFrame({
   ....:   'Branch' : 'A A A A A B'.split(),
   ....:   'Buyer': 'Carl Mark Carl Carl Joe Joe'.split(),
   ....:   'Quantity': [1, 3, 5, 1, 8, 1],
   ....:   'Date' : [datetime.datetime(2013,11,1,13,0), datetime.datetime(2013,9,1,13,5),
   ....:             datetime.datetime(2013,10,1,20,0), datetime.datetime(2013,10,2,10,0),
   ....:             datetime.datetime(2013,11,1,20,0), datetime.datetime(2013,10,2,10,0)],
   ....:   'PayDay' : [datetime.datetime(2013,10,4,0,0), datetime.datetime(2013,10,15,13,5),
   ....:               datetime.datetime(2013,9,5,20,0), datetime.datetime(2013,11,2,10,0),
   ....:               datetime.datetime(2013,10,7,20,0), datetime.datetime(2013,9,5,10,0)]})
   ....:

In [77]: df
Out[77]:
  Branch Buyer                Date              PayDay  Quantity
0      A  Carl 2013-11-01 13:00:00 2013-10-04 00:00:00         1
1      A  Mark 2013-09-01 13:05:00 2013-10-15 13:05:00         3
2      A  Carl 2013-10-01 20:00:00 2013-09-05 20:00:00         5
3      A  Carl 2013-10-02 10:00:00 2013-11-02 10:00:00         1
4      A   Joe 2013-11-01 20:00:00 2013-10-07 20:00:00         8
5      B   Joe 2013-10-02 10:00:00 2013-09-05 10:00:00         1

In [78]: pivot_table(df, index=Grouper(freq='M', key='Date'),
   ....:             columns=Grouper(freq='M', key='PayDay'),
   ....:             values='Quantity', aggfunc=np.sum)
   ....:
Out[78]:
PayDay      2013-09-30  2013-10-31  2013-11-30
Date
2013-09-30         NaN           3         NaN
2013-10-31           6         NaN           1
2013-11-30         NaN           9         NaN
```

- Arrays of strings can be wrapped to a specified width (`str.wrap`) (GH6999)
- Add `nsmallest()` and `Series.nlargest()` methods to Series, See *the docs* (GH3960)
- *PeriodIndex* fully supports partial string indexing like *DatetimeIndex* (GH7043)

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

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

In [81]: ps
Out[81]:
2013-01-01 09:00    0.755414
2013-01-01 10:00    0.215269
2013-01-01 11:00    0.841009
2013-01-01 12:00   -1.445810
2013-01-01 13:00   -1.401973
2013-01-01 14:00   -0.100918
```

```
2013-01-01 15:00   -0.548242
                      ...
2013-01-05 06:00   -0.379811
2013-01-05 07:00    0.702562
2013-01-05 08:00   -0.850346
2013-01-05 09:00    1.176812
2013-01-05 10:00   -0.524336
2013-01-05 11:00    0.700908
2013-01-05 12:00    0.984188
Freq: H, dtype: float64

In [82]: ps['2013-01-02']
Out[82]:
2013-01-02 00:00   -0.208499
2013-01-02 01:00    1.033801
2013-01-02 02:00   -2.400454
2013-01-02 03:00    2.030604
2013-01-02 04:00   -1.142631
2013-01-02 05:00    0.211883
2013-01-02 06:00    0.704721
                      ...
2013-01-02 17:00    0.464392
2013-01-02 18:00   -3.563517
2013-01-02 19:00    1.321106
2013-01-02 20:00    0.152631
2013-01-02 21:00    0.164530
2013-01-02 22:00   -0.430096
2013-01-02 23:00    0.767369
Freq: H, dtype: float64
```

- `read_excel` can now read milliseconds in Excel dates and times with xlrd >= 0.9.3. (GH5945)
- `pd.stats.moments.rolling_var` now uses Welford's method for increased numerical stability (GH6817)
- pd.expanding_apply and pd.rolling_apply now take args and kwargs that are passed on to the func (GH6289)
- `DataFrame.rank()` now has a percentage rank option (GH5971)
- `Series.rank()` now has a percentage rank option (GH5971)
- `Series.rank()` and `DataFrame.rank()` now accept `method='dense'` for ranks without gaps (GH6514)
- Support passing `encoding` with xlwt (GH3710)
- Refactor Block classes removing *Block.items* attributes to avoid duplication in item handling (GH6745, GH6988).
- Testing statements updated to use specialized asserts (GH6175)

1.8.12 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).

1.8.13 Experimental

There are no experimental changes in 0.14.0

1.8.14 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 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 propogation 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 reordering 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 regexs 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 coverted 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 `nan` s would make indices claim that they contained all the things (GH7066).
- Bug in `DataFrame.boxplot` where it failed to use the axis passed as the `ax` argument (GH3578)
- Bug in the `XlsxWriter` and `XlwtWriter` implementations that resulted in datetime columns being formatted without the time (GH7075) were being passed to plotting method
- `read_fwf()` treats `None` in `colspec` like regular python slices. It now reads from the beginning or until the end of the line when `colspec` contains a `None` (previously raised a `TypeError`)
- Bug in cache coherence with chained indexing and slicing; add `_is_view` property to `NDFrame` to correctly predict views; mark `is_copy` on `xs` only if its an actual copy (and not a view) (GH7084)
- Bug in DatetimeIndex creation from string ndarray with `dayfirst=True` (GH5917)
- Bug in `MultiIndex.from_arrays` created from `DatetimeIndex` doesn't preserve `freq` and `tz` (GH7090)
- Bug in `unstack` raises `ValueError` when `MultiIndex` contains `PeriodIndex` (GH4342)
- Bug in `boxplot` and `hist` draws unnecessary axes (GH6769)
- Regression in `groupby.nth()` for out-of-bounds indexers (GH6621)
- Bug in `quantile` with datetime values (GH6965)
- Bug in `Dataframe.set_index`, `reindex` and `pivot` don't preserve `DatetimeIndex` and `PeriodIndex` attributes (GH3950, GH5878, GH6631)
- Bug in `MultiIndex.get_level_values` doesn't preserve `DatetimeIndex` and `PeriodIndex` attributes (GH7092)
- Bug in `Groupby` doesn't preserve `tz` (GH3950)
- Bug in `PeriodIndex` partial string slicing (GH6716)
- Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the *large_repr* set to 'info' (GH7105)
- Bug in `DatetimeIndex` specifying `freq` raises `ValueError` when passed value is too short (GH7098)
- Fixed a bug with the *info* repr not honoring the *display.max_info_columns* setting (GH6939)
- Bug `PeriodIndex` string slicing with out of bounds values (GH5407)
- Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables (GH7157)
- Bug in `isnull` when applied to 0-dimensional object arrays (GH7176)
- Bug in `query`/`eval` where global constants were not looked up correctly (GH7178)
- Bug in recognizing out-of-bounds positional list indexers with `iloc` and a multi-axis tuple indexer (GH7189)
- Bug in setitem with a single value, multi-index and integer indices (GH7190, GH7218)
- Bug in expressions evaluation with reversed ops, showing in series-dataframe ops (GH7198, GH7192)
- Bug in multi-axis indexing with > 2 ndim and a multi-index (GH7199)

- Fix a bug where invalid eval/query operations would blow the stack (GH5198)

1.9 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:

```
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:

```
In [4]: df = DataFrame(dict(A = np.array(['foo','bar','bah','foo','bar'])))

In [5]: df.ix[0,'A'] = np.nan

In [6]: df
Out[6]:
     A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

1.9.1 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'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
A    float64
B    float64
C    datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 bytes

# this is the default (same as in 0.13.0)
In [12]: pd.set_option('max_info_rows',max_info_rows)

In [13]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
A    7 non-null float64
B    10 non-null float64
C    7 non-null datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 bytes
```

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

```
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:

```
  age                 today               diff
0 2001-01-01 00:00:00 2013-04-19 00:00:00 4491 days, 00:00:00
1 2004-06-01 00:00:00 2013-04-19 00:00:00 3244 days, 00:00:00
```

  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]:
         age      today      diff
0 2001-01-01 2013-04-19 4491 days
1 2004-06-01 2013-04-19 3244 days

[2 rows x 3 columns]
```

1.9.2 API changes

- Add -NaN and -nan to the default set of NA values (GH5952). See *NA Values*.
- Added Series.str.get_dummies vectorized string method (GH6021), to extract dummy/indicator variables for separated string columns:

```
In [23]: s = Series(['a', 'a|b', np.nan, 'a|c'])

In [24]: s.str.get_dummies(sep='|')
Out[24]:
   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())
Out[28]: True

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

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

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

- `DataFrame.apply` will use the `reduce` argument to determine whether a `Series` or a `DataFrame` should be returned when the `DataFrame` is empty (GH6007).

  Previously, calling `DataFrame.apply` an empty `DataFrame` would return either a `DataFrame` if there were no columns, or the function being applied would be called with an empty `Series` to guess whether a `Series` or `DataFrame` should be returned:

```
In [32]: def applied_func(col):
   ....:     print("Apply function being called with: ", col)
   ....:     return col.sum()
   ....:

In [33]: empty = DataFrame(columns=['a', 'b'])

In [34]: empty.apply(applied_func)
('Apply function being called with: ', Series([], dtype: float64))
Out[34]:
a   NaN
b   NaN
dtype: float64
```

  Now, when `apply` is called on an empty `DataFrame`: if the `reduce` argument is `True` a `Series` will returned, if it is `False` a `DataFrame` will be returned, and if it is `None` (the default) the function being applied will be called with an empty series to try and guess the return type.

```
In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a   NaN
b   NaN
dtype: float64

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

[0 rows x 2 columns]
```

1.9.3 Prior Version Deprecations/Changes

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

1.9.4 Deprecations

There are no deprecations of prior behavior in 0.13.1

1.9.5 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 [37]: shades = ['light', 'dark']

In [38]: colors = ['red', 'green', 'blue']

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

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

```
In [40]: import pandas.util.testing as tm

In [41]: panel = tm.makePanel(5)

In [42]: panel
Out[42]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [43]: panel['ItemA']
Out[43]:
                   A         B         C         D
2000-01-03  0.952478 -1.239072 -1.409432 -0.014752
2000-01-04  0.988138  0.139683  1.422986  1.272395
2000-01-05 -0.072608 -0.223019 -2.147855 -1.449567
2000-01-06 -0.550603  2.123692 -1.347533 -1.195524
2000-01-07 -0.938153  0.122273  0.363565 -0.591863

[5 rows x 4 columns]
```

Specifying an `apply` that operates on a Series (to return a single element)

```
In [44]: panel.apply(lambda x: x.dtype, axis='items')
Out[44]:
                  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 [45]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[45]:
      ItemA     ItemB     ItemC
A  0.379252 -3.696907  3.709335
B  0.923558  0.504242  4.656781
C -3.118269 -1.545718  3.188329
D -1.979310 -0.758060 -1.436483

[4 rows x 3 columns]
```

This is equivalent to

```
In [46]: panel.sum('major_axis')
Out[46]:
      ItemA     ItemB     ItemC
A  0.379252 -3.696907  3.709335
B  0.923558  0.504242  4.656781
C -3.118269 -1.545718  3.188329
D -1.979310 -0.758060 -1.436483

[4 rows x 3 columns]
```

A transformation operation that returns a Panel, but is computing the z-score across the major_axis

```
In [47]: result = panel.apply(
   ....:            lambda x: (x-x.mean())/x.std(),
   ....:            axis='major_axis')
   ....:

In [48]: result
Out[48]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [49]: result['ItemA']
Out[49]:
                   A         B         C         D
2000-01-03  1.004994 -1.166509 -0.535027  0.350970
2000-01-04  1.045875 -0.036892  1.393532  1.536326
2000-01-05 -0.170198 -0.334055 -1.037810 -0.970374
2000-01-06 -0.718186  1.588611 -0.492880 -0.736422
2000-01-07 -1.162486 -0.051156  0.672185 -0.180500
```

```
[5 rows x 4 columns]
```

- Panel `apply()` operating on cross-sectional slabs. (GH1148)

```
In [50]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T

In [51]: result = panel.apply(f, axis = ['items','major_axis'])

In [52]: result
Out[52]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [53]: result.loc[:,:,'ItemA']
Out[53]:
                   A         B         C         D
2000-01-03  0.116579 -0.667845 -1.151538 -0.157547
2000-01-04  0.650448 -1.114910  0.841527  0.760706
2000-01-05 -0.987433 -0.438897 -1.154468 -0.015033
2000-01-06  0.494000  1.060450 -0.775993 -1.140165
2000-01-07 -0.363770  0.013169  0.392036 -1.123913

[5 rows x 4 columns]
```

This is equivalent to the following

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

In [55]: result
Out[55]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [56]: result.loc[:,:,'ItemA']
Out[56]:
                   A         B         C         D
2000-01-03  0.116579 -0.667845 -1.151538 -0.157547
2000-01-04  0.650448 -1.114910  0.841527  0.760706
2000-01-05 -0.987433 -0.438897 -1.154468 -0.015033
2000-01-06  0.494000  1.060450 -0.775993 -1.140165
2000-01-07 -0.363770  0.013169  0.392036 -1.123913

[5 rows x 4 columns]
```

1.9.6 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)

1.9.7 Experimental

There are no experimental changes in 0.13.1

1.9.8 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.

1.10 v0.13.0 (January 3, 2014)

This is a major release from 0.12.0 and includes a number of API changes, several new features and enhancements along with a large number of bug fixes.

Highlights include:

- support for a new index type `Float64Index`, and other Indexing enhancements
- `HDFStore` has a new string based syntax for query specification
- support for new methods of interpolation
- updated `timedelta` operations
- a new string manipulation method `extract`
- Nanosecond support for Offsets
- `isin` for DataFrames

Several experimental features are added, including:

- new `eval/query` methods for expression evaluation
- support for `msgpack` serialization
- an i/o interface to Google's `BigQuery`

Their are several new or updated docs sections including:

- *Comparison with SQL*, which should be useful for those familiar with SQL but still learning pandas.
- *Comparison with R*, idiom translations from R to pandas.

- *Enhancing Performance*, ways to enhance pandas performance with `eval/query`.

> **Warning:** In 0.13.0 `Series` has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similar to the rest of the pandas containers. This should be a transparent change with only very limited API implications. See *Internal Refactoring*

1.10.1 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):

```
# 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

```
In [3]: arr = np.array([1, 2, 3, 4])

In [4]: arr2 = np.array([5, 3, 2, 1])

In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])

In [6]: Series(arr) // Series(arr2)
Out[6]:
0    0
1    0
```

```
2    1
3    4
dtype: int64
```

True Division

```
In [7]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[7]:
0    0.200000
1    0.666667
2    1.500000
3    4.000000
dtype: float64
```

- Infer and downcast dtype if `downcast='infer'` is passed to `fillna/ffill/bfill` (GH4604)
- `__nonzero__` for all NDFrame objects, will now raise a `ValueError`, this reverts back to (GH1073, GH4633) behavior. See *gotchas* for a more detailed discussion.

  This prevents doing boolean comparison on *entire* pandas objects, which is inherently ambiguous. These all will raise a `ValueError`.

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

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

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

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

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

In [4]: DataFrame([[False]]).bool()
Out[4]: False
```

- All non-Index NDFrames (`Series`, `DataFrame`, `Panel`, `Panel4D`, `SparsePanel`, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). `SparsePanel` does not support `pow` or `mod` with non-scalars. (GH3765)
- `Series` and `DataFrame` now have a `mode()` method to calculate the statistical mode(s) by axis/Series. (GH5367)
- Chained assignment will now by default warn if the user is assigning to a copy. This can be changed with the option `mode.chained_assignment`, allowed options are `raise/warn/None`. See *the docs*.

```
In [5]: dfc = DataFrame({'A':['aaa','bbb','ccc'],'B':[1,2,3]})

In [6]: pd.set_option('chained_assignment','warn')
```

  The following warning / exception will show if this is attempted.

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

```
Traceback (most recent call last)
   ...
SettingWithCopyWarning:
   A value is trying to be set on a copy of a slice from a DataFrame.
   Try using .loc[row_index,col_indexer] = value instead
```

Here is the correct method of assignment.

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

In [9]: dfc
Out[9]:
     A  B
0   11  1
1  bbb  2
2  ccc  3

[3 rows x 2 columns]
```

- **`Panel.reindex` has the following call signature `Panel.reindex(items=None, major_axis=None, minor_ax`** 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 *i*** min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element. (GH6214)

1.10.2 Prior Version Deprecations/Changes

These were announced changes in 0.12 or prior that are taking effect as of 0.13.0

- Remove deprecated `Factor` (GH3650)
- Remove deprecated `set_printoptions/reset_printoptions` (GH3046)
- Remove deprecated `_verbose_info` (GH3215)
- Remove deprecated `read_clipboard/to_clipboard/ExcelFile/ExcelWriter` from `pandas.io.parsers` (GH3717) These are available as functions in the main pandas namespace (e.g. `pd.read_clipboard`)
- default for `tupleize_cols` is now `False` for both `to_csv` and `read_csv`. Fair warning in 0.12 (GH3604)
- default for *display.max_seq_len* is now 100 rather then *None*. This activates truncated display (”...”) of long sequences in various places. (GH3391)

1.10.3 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`.

1.10.4 Indexing API Changes

Prior to 0.13, it was impossible to use a label indexer (`.loc/.ix`) to set a value that was not contained in the index of a particular axis. (GH2578). See *the docs*

In the `Series` case this is effectively an appending operation

```
In [10]: s = Series([1,2,3])

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

In [12]: s[5] = 5.

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

In [14]: dfi = DataFrame(np.arange(6).reshape(3,2),
   ....:                 columns=['A','B'])
   ....:

In [15]: dfi
Out[15]:
   A  B
0  0  1
1  2  3
2  4  5

[3 rows x 2 columns]
```

This would previously `KeyError`

```
In [16]: dfi.loc[:,'C'] = dfi.loc[:,'A']

In [17]: dfi
Out[17]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4

[3 rows x 3 columns]
```

This is like an `append` operation.

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

In [19]: dfi
Out[19]:
   A  B  C
0  0  1  0
```

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

[4 rows x 3 columns]
```

A Panel setting operation on an arbitrary axis aligns the input to the Panel

```
In [20]: p = pd.Panel(np.arange(16).reshape(2,4,2),
   ....:               items=['Item1','Item2'],
   ....:               major_axis=pd.date_range('2001/1/12',periods=4),
   ....:               minor_axis=['A','B'],dtype='float64')
   ....:

In [21]: p
Out[21]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to B

In [22]: p.loc[:,:,'C'] = Series([30,32],index=p.items)

In [23]: p
Out[23]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to C

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

[4 rows x 2 columns]
```

1.10.5 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
Out[28]:
1.5    0
2.0    1
3.0    2
4.5    3
5.0    4
dtype: int64
```

Scalar selection for `[]`, `.ix`, `.loc` will always be label based. An integer will match an equal float index (e.g. `3` is equivalent to `3.0`)

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

In [30]: s.ix[3]
Out[30]: 2

In [31]: s.loc[3]
Out[31]: 2
```

The only positional indexing is via `iloc`

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

A scalar index that is not found will raise `KeyError`

Slicing is ALWAYS on the values of the index, for `[]`, `ix`, `loc` and ALWAYS positional with `iloc`

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

In [34]: s.ix[2:4]
Out[34]:
2    1
3    2
dtype: int64

In [35]: s.loc[2:4]
Out[35]:
2    1
3    2
dtype: int64

In [36]: s.iloc[2:4]
Out[36]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [37]: s[2.1:4.6]
Out[37]:
3.0    2
4.5    3
```

```
dtype: int64

In [38]: s.loc[2.1:4.6]
Out[38]:
3.0    2
4.5    3
dtype: int64
```

- Indexing on other index types are preserved (and positional fallback for `[],ix`), with the exception, that floating point slicing on indexes on non `Float64Index` will now raise a `TypeError`.

```
In [1]: 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
```

1.10.6 HDFStore API Changes

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

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

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

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

Use boolean expressions, with in-line function evaluation.

```
In [42]: read_hdf(path,'dfq',
   ....:     where="index>Timestamp('20130104') & columns=['A', 'B']")
   ....:
Out[42]:
                   A         B
2013-01-05 -1.392054  1.153922
2013-01-06 -0.881047  0.295080
2013-01-07 -1.407085  0.126781
2013-01-08 -0.838843  0.553921
2013-01-09  1.529401  0.205455
2013-01-10  0.299071  1.076541

[6 rows x 2 columns]
```

Use an inline column reference

```
In [43]: read_hdf(path,'dfq',
   ....:     where="A>0 or C>0")
   ....:
Out[43]:
                   A         B         C         D
```

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

[8 rows x 4 columns]
```

- the `format` keyword now replaces the `table` keyword; allowed values are `fixed(f)` or `table(t)` the same defaults as prior < 0.13.0 remain, e.g. `put` implies `fixed` format and `append` implies `table` format. This default format can be set as an option by setting `io.hdf.default_format`.

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

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

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

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

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

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

- Significant table writing performance improvements
- handle a passed `Series` in table format (GH4330)
- can now serialize a `timedelta64[ns]` dtype in a table (GH3577), See *the docs*.
- added an `is_open` property to indicate if the underlying file handle is_open; a closed store will now report 'CLOSED' when viewing the store (rather than raising an error) (GH4409)
- a close of a `HDFStore` now will close that instance of the `HDFStore` but will only close the actual file if the ref count (by `PyTables`) w.r.t. all of the open handles are 0. Essentially you have a local instance of `HDFStore` referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise `ClosedFileError`

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

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

In [52]: store1 = HDFStore(path)

In [53]: store2 = HDFStore(path)

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

In [55]: store2.append('df2',df)
```

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

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

In [58]: store1.close()

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

In [60]: store2.close()

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

- removed the `_quiet` attribute, replace by a `DuplicateWarning` if retrieving duplicate rows from a table (GH4367)
- removed the `warn` argument from `open`. Instead a `PossibleDataLossError` exception will be raised if you try to use `mode='w'` with an OPEN file handle (GH4367)
- allow a passed locations array or mask as a `where` condition (GH4467). See *the docs* for an example.
- add the keyword `dropna=True` to `append` to change whether ALL nan rows are not written to the store (default is `True`, ALL nan rows are NOT written), also settable via the option `io.hdf.dropna_table` (GH4625)
- pass thru store creation arguments; can be used to support in-memory stores

1.10.7 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.

2010-03-29	13.70	13.88	13.39	13.57	158225000	12.98
2010-03-30	13.55	13.64	13.18	13.28	142055200	12.70
	...	...	...	...	...	...

771 rows × 6 columns

To get the info view, call `DataFrame.info()`. If you prefer the info view as the repr for large DataFrames, you can set this by running `set_option('display.large_repr', 'info')`.

1.10.8 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*

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

[3 rows x 2 columns]

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

[3 rows x 3 columns]
```

- `timedelta64[ns]` operations. See *the docs*.

  Warning: Most of these operations require `numpy >= 1.7`

Using the new top-level `to_timedelta`, you can convert a scalar or array from the standard timedelta format (produced by `to_csv`) into a timedelta type (`np.timedelta64` in `nanoseconds`).

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

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

In [66]: to_timedelta(['1 days 06:05:01.00003','15.5us','nan'])
Out[66]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timede

In [67]: to_timedelta(np.arange(5),unit='s')
Out[67]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='tim

In [68]: to_timedelta(np.arange(5),unit='d')
Out[68]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[n
```

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.

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

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

In [71]: td[2] += np.timedelta64(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')
Out[74]: 
0    31.000000
1    31.000000
2    31.003507
3          NaN
dtype: float64

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

# to seconds
In [76]: td / np.timedelta64(1,'s')
Out[76]: 
0    2678400
1    2678400
```

```
2    2678703
3        NaN
dtype: float64

In [77]: td.astype('timedelta64[s]')
Out[77]:
0    2678400
1    2678400
2    2678703
3        NaN
dtype: float64
```

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

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

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

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

```
In [80]: from pandas import offsets

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

Fillna is now supported for timedeltas

```
In [82]: td.fillna(0)
Out[82]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    0 days 00:00:00
dtype: timedelta64[ns]

In [83]: td.fillna(timedelta(days=1,seconds=5))
Out[83]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    1 days 00:00:05
dtype: timedelta64[ns]
```

You can do numeric reduction operations on timedeltas.

```
In [84]: td.mean()
Out[84]: Timedelta('31 days 00:01:41')

In [85]: td.quantile(.1)
Out[85]: Timedelta('31 days 00:00:00')
```

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to scipy.stats.gaussian_kde() (for scipy >= 0.11.0) to set the bandwidth, and to gkde.evaluate() to specify the indices at which it is evaluated, respectively. See scipy docs. (GH4298)
- DataFrame constructor now accepts a numpy masked record array (GH3478)
- The new vectorized string method `extract` return regular expression matches more conveniently.

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

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

```
In [87]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
Out[87]:
     0    1
0    a    1
1    b    2
2  NaN  NaN

[3 rows x 2 columns]
```

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

[3 rows x 2 columns]
```

and optional groups can also be used.

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

```
2    NaN     3

[3 rows x 2 columns]
```

- `read_stata` now accepts Stata 13 format (GH4291)
- `read_fwf` now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function (GH4488).
- support for nanosecond times as an offset

  Warning: These operations require `numpy >= 1.7`

  Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [90]: date_range('2013-01-01', periods=5, freq='5N')
Out[90]:
DatetimeIndex(['2013-01-01', '2013-01-01', '2013-01-01', '2013-01-01',
               '2013-01-01'],
              dtype='datetime64[ns]', freq='5N', tz=None)
```

  or with frequency as offset

```
In [91]: date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[91]:
DatetimeIndex(['2013-01-01', '2013-01-01', '2013-01-01', '2013-01-01',
               '2013-01-01'],
              dtype='datetime64[ns]', freq='5N', tz=None)
```

  Timestamps can be modified in the nanosecond range

```
In [92]: t = Timestamp('20130101 09:01:02')

In [93]: t + pd.datetools.Nano(123)
Out[93]: Timestamp('2013-01-01 09:01:02.000000123')
```

- A new method, `isin` for DataFrames, which plays nicely with boolean indexing. The argument to `isin`, what we're comparing the DataFrame to, can be a DataFrame, Series, dict, or array of values. See *the docs* for more.

  To get the rows where any of the conditions are met:

```
In [94]: dfi = DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})

In [95]: dfi
Out[95]:
   A  B
0  1  a
1  2  b
2  3  f
3  4  n

[4 rows x 2 columns]

In [96]: other = DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})

In [97]: mask = dfi.isin(other)

In [98]: mask
```

```
Out[98]:
       A      B
0   True  False
1  False  False
2   True   True
3  False  False

[4 rows x 2 columns]

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

[2 rows x 2 columns]
```

- Series now supports a to_frame method to convert it to a single-column DataFrame (GH5164)
- All R datasets listed here http://stat.ethz.ch/R-manual/R-devel/library/datasets/html/00Index.html can now be loaded into Pandas objects

```
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- tz_localize can infer a fall daylight savings transition based on the structure of the unlocalized data (GH4230), see *the docs*
- DatetimeIndex is now in the API documentation, see *the docs*
- json_normalize() is a new method to allow you to create a flat table from semi-structured JSON data. See *the docs* (GH1067)
- Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
- Python csv parser now supports usecols (GH4335)
- Frequencies gained several new offsets:
  - LastWeekOfMonth (GH4637)
  - FY5253, and FY5253Quarter (GH4511)
- DataFrame has a new interpolate method, similar to Series (GH4434, GH1892)

```
In [100]: df = DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
   .....:                 'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})
   .....:

In [101]: df.interpolate()
Out[101]:
     A      B
0  1.0   0.25
1  2.1   1.50
2  3.4   2.75
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40

[6 rows x 2 columns]
```

Additionally, the `method` argument to `interpolate` has been expanded to include `'nearest'`, `'zero'`, `'slinear'`, `'quadratic'`, `'cubic'`, `'barycentric'`, `'krogh'`, `'piecewise_polynomial'`, `'pchip'`, `‘polynomial‘`, `'spline'` The new methods require scipy. Consult the Scipy reference guide and documentation for more information about when the various methods are appropriate. See *the docs*.

Interpolate now also accepts a `limit` keyword argument. This works similar to `fillna`'s limit:

```
In [102]: ser = Series([1, 3, np.nan, np.nan, np.nan, 11])

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

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

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

In [105]: df = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
   .....:                    "A1980" : {0 : "d", 1 : "e", 2 : "f"},
   .....:                    "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
   .....:                    "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
   .....:                    "X"     : dict(zip(range(3), np.random.randn(3)))
   .....:                   })
   .....:

In [106]: df["id"] = df.index

In [107]: df
Out[107]:
  A1970 A1980  B1970  B1980         X  id
0     a     d    2.5    3.2 -1.085631   0
1     b     e    1.2    1.3  0.997345   1
2     c     f    0.7    0.1  0.282978   2

[3 rows x 6 columns]

In [108]: wide_to_long(df, ["A", "B"], i="id", j="year")
Out[108]:
                X  A    B
id year
0  1970 -1.085631  a  2.5
1  1970  0.997345  b  1.2
2  1970  0.282978  c  0.7
0  1980 -1.085631  d  3.2
1  1980  0.997345  e  1.3
2  1980  0.282978  f  0.1

[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)

1.10.9 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,

```
In [109]: nrows, ncols = 20000, 100

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

# eval with NumExpr backend
In [111]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 14 ms per loop

# pure Python evaluation
In [112]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 24.1 ms per loop
```

  For more details, see the *the docs*

- Similar to pandas.eval, DataFrame has a new DataFrame.eval method that evaluates an expression in the context of the DataFrame. For example,

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

In [114]: df.eval('a + b')
Out[114]:
0   -0.685204
1    1.589745
2    0.325441
3   -1.784153
4   -0.432893
5    0.171850
6    1.895919
7    3.065587
8   -0.092759
9    1.391365
dtype: float64
```

- query() method has been added that allows you to select elements of a DataFrame using a natural query syntax nearly identical to Python syntax. For example,

```
In [115]: n = 20

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

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

[2 rows x 3 columns]
```

selects all the rows of `df` where `a < b < c` evaluates to `True`. For more details see the *the docs*.

- `pd.read_msgpack()` and `pd.to_msgpack()` are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See *the docs*

> **Warning:** Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```
In [118]: df = DataFrame(np.random.rand(5,2),columns=list('AB'))

In [119]: df.to_msgpack('foo.msg')

In [120]: pd.read_msgpack('foo.msg')
Out[120]:
          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 [121]: s = Series(np.random.rand(5),index=date_range('20130101',periods=5))

In [122]: pd.to_msgpack('foo.msg', df, s)

In [123]: pd.read_msgpack('foo.msg')
Out[123]:
[          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, dtype: float64]
```

You can pass `iterator=True` to iterator over the unpacked results

```
In [124]: 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, 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,
# publicata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA gsod data.

query = """SELECT station_number as STATION,
month as MONTH, AVG(mean_temp) as MEAN_TEMP
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC"""

# Fetch the result set for this query

# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://code.google.com/apis/console/b/0/?noredirect
projectid = xxxxxxxxx;

df = gbq.read_gbq(query, project_id = projectid)

# Use pandas to process and reshape the dataset

df2 = df.pivot(index='STATION', columns='MONTH', values='MEAN_TEMP')
df3 = pandas.concat([df2.min(), df2.mean(), df2.max()],
                    axis=1,keys=["Min Tem", "Mean Temp", "Max Temp"])
```

The resulting DataFrame is:

```
> df3
            Min Tem  Mean Temp    Max Temp
 MONTH
 1     -53.336667  39.827892   89.770968
 2     -49.837500  43.685219   93.437932
 3     -77.926087  48.708355   96.099998
 4     -82.892858  55.070087   97.317240
 5     -92.378261  61.428117  102.042856
 6     -77.703334  65.858888  102.900000
 7     -87.821428  68.169663  106.510714
 8     -89.431999  68.614215  105.500000
 9     -86.611112  63.436935  107.142856
 10    -78.209677  56.880838   92.103333
 11    -50.125000  48.861228   94.996428
 12    -50.332258  42.286879   94.396774
```

> **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.

1.10.10 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 [125]: s = Series([1,2,3,4])
```

Numpy Usage

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

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

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

Pandonic Usage

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

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

In [131]: s.where(s>1)
Out[131]:
0   NaN
1     2
2     3
3     4
dtype: float64
```

- Passing a `Series` directly to a cython function expecting an `ndarray` type will no long work directly, you must pass `Series.values`, See *Enhancing Performance*
- `Series(0.5)` would previously return the scalar `0.5`, instead this will return a 1-element `Series`
- This change breaks `rpy2<=2.3.8`. an Issue has been opened against rpy2 and a workaround is detailed in GH5698. Thanks @JanSchulz.

- Pickle compatibility is preserved for pickles created prior to 0.13. These must be unpickled with `pd.read_pickle`, see *Pickling*.
- Refactor of series.py/frame.py/panel.py to move common code to generic.py
  - added `_setup_axes` to created generic NDFrame structures
  - moved methods
    - `from_axes,_wrap_array,axes,ix,loc,iloc,shape,empty,swapaxes,transpose,pop`

    * `__iter__`,`keys`,`__contains__`,`__len__`,`__neg__`,`__invert__`
    * `convert_objects`,`as_blocks`,`as_matrix`,`values`
    * `__getstate__`,`__setstate__` (compat remains in frame/panel)
    * `__getattr__`,`__setattr__`
    * `_indexed_same`,`reindex_like`,`align`,`where`,`mask`
    * `fillna`,`replace` (`Series` replace is now consistent with `DataFrame`)
    * `filter` (also added axis argument to selectively filter on a different axis)
    * `reindex`,`reindex_axis`,`take`
    * `truncate` (moved to become part of `NDFrame`)

- These are API changes which make `Panel` more consistent with `DataFrame`
  - `swapaxes` on a `Panel` with the same axes specified now return a copy
  - support attribute access for setting
  - filter supports the same API as the original `DataFrame` filter
- Reindex called with no arguments will now return a copy of the input object
- `TimeSeries` is now an alias for `Series`. the property `is_time_series` can be used to distinguish (if desired)
- Refactor of Sparse objects to use BlockManager
  - Created a new block type in internals, `SparseBlock`, which can hold multi-dtypes and is non-consolidatable. `SparseSeries` and `SparseDataFrame` now inherit more methods from there hierarchy (Series/DataFrame), and no longer inherit from `SparseArray` (which instead is the object of the `SparseBlock`)
  - Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
  - Operations on sparse structures within DataFrames should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
  - enable setitem on `SparseSeries` for boolean/integer/slices
  - `SparsePanels` implementation is unchanged (e.g. not using BlockManager, needs work)
- added `ftypes` method to Series/DataFrame, similar to `dtypes`, but indicates if the underlying is sparse/dense (as well as the dtype)
- All `NDFrame` objects can now use `__finalize__()` to specify various values to propagate to new objects from an existing one (e.g. `name` in `Series` will follow more automatically now)
- Internal type checking is now done via a suite of generated classes, allowing `isinstance(value, klass)` without having to directly import the klass, courtesy of @jtratner
- Bug in Series update where the parent frame is not updating its cache based on changes (GH4080) or types (GH3217), fillna (GH3386)
- Indexing with dtype conversions fixed (GH4463, GH4204)
- Refactor `Series.reindex` to core/generic.py (GH4604, GH4618), allow `method=` in reindexing on a Series to work
- `Series.copy` no longer accepts the `order` parameter and is now consistent with `NDFrame` copy

- Refactor `rename` methods to core/generic.py; fixes `Series.rename` for (GH4605), and adds `rename` with the same signature for `Panel`
- Refactor `clip` methods to core/generic.py (GH4798)
- Refactor of `_get_numeric_data/_get_bool_data` to core/generic.py, allowing Series/Panel functionality
- `Series` (for index) / `Panel` (for items) now allow attribute access to its elements (GH1903)

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

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

In [134]: s.a = 5

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

1.10.11 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.

1.11 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.

1.11.1 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 similary to `float` dtypes to return `np.nan` or `np.inf` as appropriate (GH3590). This correct a numpy bug that treats `integer` and `float` dtypes differently.

```
In [1]: p = DataFrame({ 'first' : [4,5,8], 'second' : [0,0,3] })

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

[3 rows x 2 columns]

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

[3 rows x 2 columns]

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

[3 rows x 2 columns]

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

[3 rows x 2 columns]
```

- Add `squeeze` keyword to `groupby` to allow reduction from DataFrame -> Series if groups are unique. This is a Regression from 0.10.1. We are reverting back to the prior behavior. This means groupby will return the same shaped objects whether the groups are unique or not. Revert this issue (GH2893) with (GH3596).

```
In [6]: df2 = DataFrame([{"val1": 1, "val2" : 20}, {"val1":1, "val2": 19},
   ...:                  {"val1":1, "val2": 27}, {"val1":1, "val2": 12}])
   ...:

In [7]: def func(dataf):
   ...:     return dataf["val2"]  - dataf["val2"].mean()
   ...:

# squeezing the result frame to a series (because we have unique groups)
In [8]: df2.groupby("val1", squeeze=True).apply(func)
Out[8]:
0    0.5
1   -0.5
2    7.5
3   -7.5
Name: 1, dtype: float64

# no squeezing (the default, and behavior in 0.10.1)
In [9]: df2.groupby("val1").apply(func)
Out[9]:
val2    0    1    2    3
val1
1     0.5 -0.5  7.5 -7.5

[1 rows x 4 columns]
```

- Raise on `iloc` when boolean indexing with a label based indexer mask e.g. a boolean Series, even with integer labels, will raise. Since `iloc` is purely positional based, the labels on the Series are not alignable (GH3631)

  This case is rarely used, and there are plently of alternatives. This preserves the `iloc` API to be *purely* positional based.

```
In [10]: df = DataFrame(lrange(5), list('ABCDE'), columns=['a'])

In [11]: mask = (df.a%2 == 0)

In [12]: mask
Out[12]:
A     True
B    False
C     True
D    False
E     True
Name: a, dtype: bool

# this is what you should use
In [13]: df.loc[mask]
Out[13]:
   a
A  0
C  2
E  4

[3 rows x 1 columns]
```

```
# this will work as well
In [14]: df.iloc[mask.values]
Out[14]:
   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

    ```
    from pandas.io.parsers import ExcelFile
    xls = ExcelFile('path_to_file.xls')
    xls.parse('Sheet1', index_col=None, na_values=['NA'])
    ```

    With

    ```
    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

    ```
    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 perfomed on a `Series` and return an *empty* `Series` when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of `slice` objects:
  - sum, prod, mean, std, var, skew, kurt, corr, and cov

- `read_html` now defaults to `None` when reading, and falls back on `bs4` + `html5lib` when lxml fails to parse. a list of parsers to try until success is also valid
- The internal `pandas` class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the baseclass for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). (GH4090, GH4092)
- New `StringMixin` that, given a `__unicode__` method, gets python 2 and python 3 compatible string methods (`__str__`, `__bytes__`, and `__repr__`). Plus string safety throughout. Now employed in many places throughout the pandas library. (GH4090, GH4092)

1.11.2 I/O Enhancements

- `pd.read_html()` can now parse HTML strings, files or urls and return DataFrames, courtesy of @cpcloud. (GH3477, GH3605, GH3606, GH3616). It works with a *single* parser backend: BeautifulSoup4 + html5lib *See the docs*

  You can use `pd.read_html()` to read the output from `DataFrame.to_html()` like so

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

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

[3 rows x 2 columns]

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

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

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

[3 rows x 2 columns]
```

  Note that `alist` here is a Python `list` so `pd.read_html()` and `DataFrame.to_html()` are not inverses.

  – `pd.read_html()` no longer performs hard conversion of date strings (GH3656).

  Warning: You may have to install an older version of BeautifulSoup4, *See the installation docs*

- Added module for reading and writing Stata files: `pandas.io.stata` (GH1512) accessable 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` accessable 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 compatiblity for the pre 0.12 behavior of writing and reading `MultIndex` columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a `MultiIndex` column.

  Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default *to* write and read `MultiIndex` columns will be in the new format. (GH3571, GH1651, GH3141)
- If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False`), then any `names` on the columns index will be *lost*.

```
In [20]: from pandas.util.testing import makeCustomDataframe as mkdf

In [21]: df = mkdf(5,3,r_idx_nlevels=2,c_idx_nlevels=4)

In [22]: df.to_csv('mi.csv',tupleize_cols=False)

In [23]: print(open('mi.csv').read())
C0,,C_l0_g0,C_l0_g1,C_l0_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l2_g0,C_l2_g1,C_l2_g2
C3,,C_l3_g0,C_l3_g1,C_l3_g2
R0,R1,,,
R_l0_g0,R_l1_g0,R0C0,R0C1,R0C2
R_l0_g1,R_l1_g1,R1C0,R1C1,R1C2
R_l0_g2,R_l1_g2,R2C0,R2C1,R2C2
R_l0_g3,R_l1_g3,R3C0,R3C1,R3C2
R_l0_g4,R_l1_g4,R4C0,R4C1,R4C2


In [24]: pd.read_csv('mi.csv',header=[0,1,2,3],index_col=[0,1],tupleize_cols=False)
Out[24]:
C0                C_l0_g0 C_l0_g1 C_l0_g2
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

[5 rows x 3 columns]
```

- Support for `HDFStore` (via `PyTables 3.0.0`) on Python3
- Iterator support via `read_hdf` that automatically opens and closes the store when iteration is finished. This is only for *tables*

```
In [25]: path = 'store_iterator.h5'

In [26]: DataFrame(randn(10,2)).to_hdf(path,'df',table=True)

In [27]: for df in read_hdf(path,'df', chunksize=3):
   ....:     print(df)
   ....:
          0         1
0  1.392665 -0.123497
```

```
1 -0.402761 -0.246604
2 -0.288433 -0.763434

[3 rows x 2 columns]
          0         1
3  2.069526 -1.203569
4  0.591830  0.841159
5 -0.501083 -0.816561

[3 rows x 2 columns]
          0         1
6 -0.207082 -0.664112
7  0.580411 -0.965628
8 -0.038605 -0.460478

[3 rows x 2 columns]
          0         1
9 -0.310458  0.866493

[1 rows x 2 columns]
```

- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters

1.11.3 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

```
In [28]: df = DataFrame({'a': list('ab..'), 'b': [1, 2, 3, 4]})

In [29]: df.replace(regex=r'\s*\.\s*', value=np.nan)
Out[29]:
     a  b
0    a  1
1    b  2
2  NaN  3
3  NaN  4

[4 rows x 2 columns]
```

  to replace all occurrences of the string `'.'` with zero or more instances of surrounding whitespace with `NaN`.

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

```
In [30]: df.replace('.', np.nan)
Out[30]:
     a  b
0    a  1
1    b  2
2  NaN  3
3  NaN  4

[4 rows x 2 columns]
```

  to replace all occurrences of the string `'.'` with `NaN`.

- `pd.melt()` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame.
- `pd.set_option()` now allows N option, value pairs (GH3667).

  Let's say that we had an option `'a.b'` and another option `'b.c'`. We can set them at the same time:

```
In [31]: pd.get_option('a.b')
Out[31]: 2

In [32]: pd.get_option('b.c')
Out[32]: 3

In [33]: pd.set_option('a.b', 1, 'b.c', 4)

In [34]: pd.get_option('a.b')
Out[34]: 1

In [35]: pd.get_option('b.c')
Out[35]: 4
```

- The `filter` method for group objects returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [36]: sf = Series([1, 1, 2, 3, 3, 3])

In [37]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[37]:
3    3
4    3
5    3
dtype: int64
```

  The argument of `filter` must a function that, applied to the group as a whole, returns `True` or `False`.

  Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [38]: dff = DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

In [39]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[39]:
   A  B
2  2  b
3  3  b
4  4  b
5  5  b

[4 rows x 2 columns]
```

  Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [40]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[40]:
     A    B
0  NaN  NaN
1  NaN  NaN
2    2    b
3    3    b
4    4    b
```

```
5   5    b
6 NaN  NaN
7 NaN  NaN

[8 rows x 2 columns]
```

- Series and DataFrame hist methods now take a `figsize` argument (GH3834)
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations (GH3877)
- Timestamp.min and Timestamp.max now represent valid Timestamp instances instead of the default datetime.min and datetime.max (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and BeautifulSoup==4.2.0 is detected (GH4214)

1.11.4 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 [41]: from pandas.tseries.offsets import CustomBusinessDay

In [42]: from datetime import datetime

# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [43]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [44]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]

In [45]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [46]: dt = datetime(2013, 4, 30)

In [47]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00

In [48]: dts = date_range(dt, periods=5, freq=bday_egypt)

In [49]: print(Series(dts.weekday, dts).map(Series('Mon Tue Wed Thu Fri Sat Sun'.split())))
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

1.11.5 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 elimnates 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,

```
In [50]: strs = 'go', 'bow', 'joe', 'slow'

In [51]: ds = Series(strs)

In [52]: for s in ds.str:
   ....:     print(s)
   ....:
0    g
1    b
2    j
3    s
dtype: object
0    o
1    o
2    o
3    l
dtype: object
0    NaN
1      w
2      e
3      o
dtype: object
0    NaN
1    NaN
2    NaN
3      w
dtype: object

In [53]: s
Out[53]:
0    NaN
1    NaN
2    NaN
3      w
dtype: object

In [54]: s.dropna().values.item() == 'w'
Out[54]: True
```

The last element yielded by the iterator will be a `Series` containing the last element of the longest string in the `Series` with all other elements being `NaN`. Here since `'slow'` is the longest string and there are no other strings with the same length `'w'` is the only non-null string in the yielded `Series`.

- `HDFStore`
  - will retain index attributes (freq,tz,name) on recreation (GH3499)
  - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as data_columns (GH2852)

- Non-unique index support clarified (GH3468).
  - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
  - Fix construction of a DataFrame with a duplicate index
  - ref_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) (GH2194)
  - applymap on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
  - Fix to_csv to handle non-unique columns (GH3495)
  - Duplicate indexes with getitem will return items in the correct order (GH3455, GH3457) and handle missing elements like unique indices (GH3561)
  - Duplicate indexes with and empty DataFrame.from_records will return a correct frame (GH3562)
  - Concat to produce a non-unique columns when duplicates are across dtypes is fixed (GH3602)
  - Allow insert/delete to non-unique columns (GH3679)
  - Non-unique indexing with a slice via `loc` and friends fixed (GH3659)
  - Allow insert/delete to non-unique columns (GH3679)
  - Extend `reindex` to correctly deal with non-unique indices (GH3679)
  - `DataFrame.itertuples()` now works with frames with duplicate column names (GH3873)
  - Bug in non-unique indexing via `iloc` (GH4017); added `takeable` argument to `reindex` for location-based taking
  - Allow non-unique indexing in series via `.ix/.loc` and `__getitem__` (GH4246)
  - Fixed non-unique indexing memory allocation issue with `.ix/.loc` (GH4280)
- `DataFrame.from_records` did not accept empty recarrays (GH3682)
- `read_html` now correctly skips tests (GH3741)
- Fixed a bug where `DataFrame.replace` with a compiled regular expression in the `to_replace` argument wasn't working (GH3907)
- Improved `network` test decorator to catch `IOError` (and therefore `URLError` as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. (GH3910, GH3914)
- Fixed testing issue where too many sockets where open thus leading to a connection reset issue (GH3982, GH3985, GH4028, GH4054)
- Fixed failing tests in test_yahoo, test_google where symbols were not retrieved but were being accessed (GH3982, GH3985, GH4028, GH4054)
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a 1xN DataFrame would barf on a 1xN mask (GH4071)
- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way (GH4062, GH4063)
- Fixed bug where sharex and sharey were not being passed to grouped_hist (GH4089)
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when regex=False (GH4115)
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` (GH4152)

- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 (GH4215)
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
- Fixed bug where Index slices weren't carrying the name attribute (GH4226)
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
- Fixed bug where html5lib wasn't being properly skipped (GH4265)
- Fixed bug where get_data_famafrench wasn't using the correct file edges (GH4281)

See the *full release notes* or issue tracker on GitHub for a complete list.

1.12 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*

1.12.1 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*.

1.12.2 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.

1.12.3 Dtypes

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

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

In [2]: df1
Out[2]:
          A
0  0.245972
1  0.319442
2  1.378512
3  0.292502
4  0.329791
5  1.392047
6  0.769914
7 -2.472300

[8 rows x 1 columns]

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

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

In [5]: df2
Out[5]:
          A         B    C
0 -0.611328 -0.270630  255
```

```
1  1.044922 -1.685677    0
2  1.503906 -0.440747    0
3 -1.328125 -0.115070    1
4  1.024414 -0.632102    0
5  0.660156 -0.585977    0
6  1.236328 -1.444787    0
7 -2.169922 -0.201135    0

[8 rows x 3 columns]

In [6]: df2.dtypes
Out[6]:
A    float16
B    float64
C      uint8
dtype: object

# here you get some upcasting
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [8]: df3
Out[8]:
          A         B    C
0 -0.365356 -0.270630  255
1  1.364364 -1.685677    0
2  2.882418 -0.440747    0
3 -1.035623 -0.115070    1
4  1.354205 -0.632102    0
5  2.052203 -0.585977    0
6  2.006243 -1.444787    0
7 -4.642221 -0.201135    0

[8 rows x 3 columns]

In [9]: df3.dtypes
Out[9]:
A    float32
B    float64
C    float64
dtype: object
```

1.12.4 Dtype Conversion

This is lower-common-denomicator upcasting, meaning you get the dtype which can accomodate 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
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
dtype: object

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

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

In [17]: df3.dtypes
Out[17]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

Forcing Date coercion (and setting `NaT` when not datelike)

```
In [18]: from datetime import datetime

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

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

1.12.5 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
```

```
dtype: object

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

In [23]: DataFrame({'a' : 1 }, index=range(2)).dtypes
Out[23]:
a    int64
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.

```
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  0  0  255  1  1
1  1 -1    0  1  1
2  2  0    0  1  1
3 -1  0    1  1  1
4  1  0    0  1  1
5  2  0    0  1  1
6  2 -1    0  1  1
7 -4  0    0  1  1

[8 rows x 5 columns]

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

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

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

```
[8 rows x 5 columns]

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

While float dtypes are unchanged.

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

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

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

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

In [35]: casted
Out[35]:
          A   B    C  D  E
0       NaN NaN  255  1  1
1  1.364364 NaN  NaN  1  1
2  2.882418 NaN  NaN  1  1
3       NaN NaN    1  1  1
4  1.354205 NaN  NaN  1  1
5  2.052203 NaN  NaN  1  1
6  2.006243 NaN  NaN  1  1
7       NaN NaN  NaN  1  1

[8 rows x 5 columns]

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

1.12.6 Datetimes Conversion

Datetime64[ns] columns in a DataFrame (or a Series) allow the use of `np.nan` to indicate a nan value, in addition to the traditional `NaT`, or not-a-time. This allows convenient nan setting in a generic way. Furthermore `datetime64[ns]` columns are created by default, when passed datetimelike objects (*this change was introduced in*

0.10.1) (GH2809, GH2810)

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

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

In [39]: df
Out[39]:
                   A         B  timestamp
2001-01-02 -1.448835  0.153437 2001-01-03
2001-01-03 -1.123570 -0.791498 2001-01-03
2001-01-04  0.105400  1.262401 2001-01-03
2001-01-05 -0.721844 -0.647645 2001-01-03
2001-01-06 -0.830631  0.761823 2001-01-03
2001-01-07  0.597819  1.045558 2001-01-03

[6 rows x 3 columns]

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

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

In [42]: df
Out[42]:
                   A         B  timestamp
2001-01-02 -1.448835  0.153437 2001-01-03
2001-01-03 -1.123570 -0.791498 2001-01-03
2001-01-04       NaN  1.262401        NaT
2001-01-05       NaN -0.647645        NaT
2001-01-06 -0.830631  0.761823 2001-01-03
2001-01-07  0.597819  1.045558 2001-01-03

[6 rows x 3 columns]
```

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

```
In [43]: import datetime

In [44]: s = Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])

In [45]: s.dtype
Out[45]: dtype('<M8[ns]')

In [46]: s[1] = np.nan

In [47]: s
Out[47]:
0   2001-01-02
1          NaT
2   2001-01-02
dtype: datetime64[ns]

In [48]: s.dtype
```

```
Out[48]: dtype('<M8[ns]')

In [49]: s = s.astype('O')

In [50]: s
Out[50]:
0    2001-01-02 00:00:00
1                    NaN
2    2001-01-02 00:00:00
dtype: object

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

1.12.7 API changes

- Added to_series() method to indicies, 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

1.12.8 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'])
    Out[54]:
       A  B
    3  3  3
    4  4  4

    [2 rows x 2 columns]
    ```

  - provide dotted attribute access to `get` from stores, e.g. `store.df == store['df']`
  - new keywords `iterator=boolean`, and `chunksize=number_in_a_chunk` are provided to 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    0.483450
2001-11-30    0.407530
2001-12-31    0.965096
Freq: M, dtype: float64

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

In [59]: df['2001']
Out[59]:
                   A
2001-10-31  0.483450
2001-11-30  0.407530
2001-12-31  0.965096

[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
Out[61]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D

In [62]: p.reindex(items=['ItemA']).squeeze()
Out[62]:
                   A         B         C         D
2001-01-02  0.396537  0.534880 -0.488797 -1.539385
2001-01-03 -0.829037  0.306681 -0.331032  1.544977
2001-01-04 -0.621754  1.026208 -0.413106 -1.490869
2001-01-05 -1.253235 -0.538879 -1.487449 -1.426475

[4 rows x 4 columns]

In [63]: p.reindex(items=['ItemA'],minor=['B']).squeeze()
Out[63]:
2001-01-02    0.534880
2001-01-03    0.306681
2001-01-04    1.026208
2001-01-05   -0.538879
Freq: D, Name: B, dtype: float64
```

- In pd.io.data.Options,
  - Fix bug when trying to fetch data for the current month when already past expiry.

  - Now using lxml to scrape html instead of BeautifulSoup (lxml was faster).
  - New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply `calls` and `puts`. Also works for future expiry months and save the instance variable as `callsMMYY` or `putsMMYY`, where `MMYY` are, respectively, the month and year of the option's expiry.
  - `Options.get_near_stock_price` now allows the user to specify the month for which to get relevant options data.
  - `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.

1.13 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.

1.13.1 API changes

- Functions taking an `inplace` option return the calling object as before. A deprecation message has been added
- Groupby aggregations Max/Min no longer exclude non-numeric data (GH2700)
- Resampling an empty DataFrame now returns an empty DataFrame instead of raising an exception (GH2640)
- The file reader will now raise an exception when NA values are found in an explicitly specified integer column instead of converting the column to float (GH2631)
- DatetimeIndex.unique now returns a DatetimeIndex with the same name and
- timezone instead of an array (GH2563)

1.13.2 New features

- MySQL support for database (contribution from Dan Allan)

1.13.3 HDFStore

You may need to upgrade your existing data files. Please visit the **compatibility** section in the main docs.

You can designate (and index) certain columns that you want to be able to perform queries on a table, by passing a list to `data_columns`

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

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

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

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

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

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

In [7]: df
Out[7]:
                   A         B         C string string2
2000-01-01 -1.601262 -0.256718  0.239369    foo    cool
2000-01-02  0.174122 -1.131794 -1.948006    foo    cool
2000-01-03  0.980347 -0.674429 -0.361633    foo    cool
2000-01-04 -0.761218  1.768215  0.152288    foo    cool
2000-01-05 -0.862613 -0.210968 -0.859278    NaN    cool
2000-01-06  1.498195  0.462413 -0.647604    NaN    cool
2000-01-07  1.511487 -0.727189 -0.342928    foo    cool
2000-01-08 -0.007364  1.427674  0.104020    bar    cool

[8 rows x 5 columns]

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

In [9]: store.select('df',[ 'B > 0', 'string == foo' ])
Out[9]:
                   A         B         C string string2
2000-01-04 -0.761218  1.768215  0.152288    foo    cool

[1 rows x 5 columns]

# this is in-memory version of this type of selection
In [10]: df[(df.B > 0) & (df.string == 'foo')]
Out[10]:
                   A         B         C string string2
2000-01-04 -0.761218  1.768215  0.152288    foo    cool

[1 rows x 5 columns]
```

Retrieving unique values in an indexable or data column.

```
# note that this is deprecated as of 0.14.0
# can be replicated by: store.select_column('df','index').unique()
store.unique('df','index')
store.unique('df','string')
```

You can now store `datetime64` in data columns

```
In [11]: df_mixed               = df.copy()

In [12]: df_mixed['datetime64'] = Timestamp('20010102')

In [13]: df_mixed.ix[3:4,['A','B']] = np.nan

In [14]: store.append('df_mixed', df_mixed)

In [15]: df_mixed1 = store.select('df_mixed')

In [16]: df_mixed1
Out[16]:
                   A         B         C string string2 datetime64
2000-01-01 -1.601262 -0.256718  0.239369    foo    cool 2001-01-02
2000-01-02  0.174122 -1.131794 -1.948006    foo    cool 2001-01-02
2000-01-03  0.980347 -0.674429 -0.361633    foo    cool 2001-01-02
2000-01-04       NaN       NaN  0.152288    foo    cool 2001-01-02
2000-01-05 -0.862613 -0.210968 -0.859278    NaN    cool 2001-01-02
2000-01-06  1.498195  0.462413 -0.647604    NaN    cool 2001-01-02
2000-01-07  1.511487 -0.727189 -0.342928    foo    cool 2001-01-02
2000-01-08 -0.007364  1.427674  0.104020    bar    cool 2001-01-02

[8 rows x 6 columns]

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

You can pass `columns` keyword to select to filter a list of the return columns, this is equivalent to passing a `Term('columns',list_of_columns_to_filter)`

```
In [18]: store.select('df',columns = ['A','B'])
Out[18]:
                   A         B
2000-01-01 -1.601262 -0.256718
2000-01-02  0.174122 -1.131794
2000-01-03  0.980347 -0.674429
2000-01-04 -0.761218  1.768215
2000-01-05 -0.862613 -0.210968
2000-01-06  1.498195  0.462413
2000-01-07  1.511487 -0.727189
2000-01-08 -0.007364  1.427674

[8 rows x 2 columns]
```

`HDFStore` now serializes multi-index dataframes when appending tables.

```
In [19]: index = MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
   ....:                            ['one', 'two', 'three']],
```

```
   ....:                    labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
   ....:                            [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
   ....:                    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    2.052171 -1.230963 -0.019240
    two   -1.713238  0.838912 -0.637855
    three  0.215109 -1.515362  1.586924
bar one   -0.447974 -1.573998  0.630925
    two   -0.071659 -1.277640 -0.102206
baz two    0.870302  1.275280 -1.199212
    three  1.060780  1.673018  1.249874
qux one    1.458210 -0.710542  0.825392
    two    1.557329  1.993441 -0.616293
    three  0.150468  0.132104  0.580923

[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    2.052171 -1.230963 -0.019240
    two   -1.713238  0.838912 -0.637855
    three  0.215109 -1.515362  1.586924
bar one   -0.447974 -1.573998  0.630925
    two   -0.071659 -1.277640 -0.102206
baz two    0.870302  1.275280 -1.199212
    three  1.060780  1.673018  1.249874
qux one    1.458210 -0.710542  0.825392
    two    1.557329  1.993441 -0.616293
    three  0.150468  0.132104  0.580923

[10 rows x 3 columns]

# the levels are automatically included as data columns
In [24]: store.select('mi', Term('foo=bar'))
Out[24]:
                A         B         C
foo bar
bar one -0.447974 -1.573998  0.630925
    two -0.071659 -1.277640 -0.102206

[2 rows x 3 columns]
```

Multi-table creation via `append_to_multiple` and selection via `select_as_multiple` can create/select from multiple tables and return a combined result, by using `where` on a selector table.

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

In [26]: df_mt['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_m

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

# indiviual tables were created
In [29]: store.select('df1_mt')
Out[29]:
                   A         B
2000-01-01 -0.128750  1.445964
2000-01-02 -0.688741  0.228006
2000-01-03  0.932498 -2.200069
2000-01-04  1.298390  1.662964
2000-01-05 -0.462446 -0.112019
2000-01-06 -1.626124  0.982041
2000-01-07  0.942864  2.502156
2000-01-08  0.268766 -1.225092

[8 rows x 2 columns]

In [30]: store.select('df2_mt')
Out[30]:
                   C         D         E         F  foo
2000-01-01 -0.431163  0.016640  0.904578 -1.645852  bar
2000-01-02  0.800353 -0.451572  0.831767  0.228760  bar
2000-01-03  1.239198  0.185437 -0.540770 -0.370038  bar
2000-01-04 -0.040863  0.290110 -0.096145  1.717830  bar
2000-01-05 -0.134024 -0.205969  1.348944 -1.198246  bar
2000-01-06  0.059493 -0.460111 -1.565401 -0.025706  bar
2000-01-07 -0.302741  0.261551 -0.066342  0.897097  bar
2000-01-08  0.582752 -1.490764 -0.639757 -0.952750  bar

[8 rows x 5 columns]

# as a multiple
In [31]: store.select_as_multiple(['df1_mt','df2_mt'], where = [ 'A>0','B>0' ], selector = 'df1_mt')
Out[31]:
                   A         B         C         D         E         F  foo
2000-01-04  1.298390  1.662964 -0.040863  0.290110 -0.096145  1.717830  bar
2000-01-07  0.942864  2.502156 -0.302741  0.261551 -0.066342  0.897097  bar

[2 rows x 7 columns]
```

Enhancements

- `HDFStore` now can read native PyTables table format tables
- You can pass `nan_rep = 'my_nan_rep'` to append, to change the default nan representation on disk (which converts to/from *np.nan*), this defaults to *nan*.
- You can pass `index` to `append`. This defaults to `True`. This will 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 signficantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expectedrows that `PyTables` will expected. This will optimize read/write performance.
- `Select` now supports passing `start` and `stop` to provide selection space limiting in selection.
- Greatly improved ISO8601 (e.g., yyyy-mm-dd) date parsing for file parsers (GH2698)
- Allow `DataFrame.merge` to handle combinatorial sizes too large for 64-bit integer (GH2690)
- Series now has unary negation (-series) and inversion (~series) operators (GH2686)
- DataFrame.plot now includes a `logx` parameter to change the x-axis to log scale (GH2327)
- Series arithmetic operators can now handle constant and ndarray input (GH2574)
- ExcelFile now takes a `kind` argument to specify the file type (GH2613)
- A faster implementation for Series.str methods (GH2602)

Bug Fixes

- `HDFStore` tables can now store `float32` types correctly (cannot be mixed with `float64` however)
- Fixed Google Analytics prefix when specifying request segment (GH2713).
- Function to reset Google Analytics token store so users can recover from improperly setup client secrets (GH2687).
- Fixed groupby bug resulting in segfault when passing in MultiIndex (GH2706)
- Fixed bug where passing a Series with datetime64 values into *to_datetime* results in bogus output values (GH2699)
- Fixed bug in `pattern in HDFStore` expressions when pattern is not a valid regex (GH2694)
- Fixed performance issues while aggregating boolean data (GH2692)
- When given a boolean mask key and a Series of new values, Series __setitem__ will now align the incoming values with the original Series (GH2686)
- Fixed MemoryError caused by performing counting sort on sorting MultiIndex levels with a very large number of combinatorial values (GH2684)
- Fixed bug that causes plotting to fail when the index is a DatetimeIndex with a fixed-offset timezone (GH2683)
- Corrected businessday subtraction logic when the offset is more than 5 bdays and the starting date is on a weekend (GH2680)
- Fixed C file parser behavior when the file has more columns than data (GH2668)
- Fixed file reader bug that misaligned columns with data in the presence of an implicit column and a specified *usecols* value
- DataFrames with numerical or datetime indices are now sorted prior to plotting (GH2609)
- Fixed DataFrame.from_records error when passed columns, index, but empty records (GH2633)

- Several bug fixed for Series operations when dtype is datetime64 (GH2689, GH2629, GH2626)

See the *full release notes* or issue tracker on GitHub for a complete list.

1.14 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.

1.14.1 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

1.14.2 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 -0.892402  0.505987 -0.681624  0.850162
2000-01-02  0.586586  1.175843 -0.160391  0.481679
2000-01-03  0.408279  1.641246  0.383888 -1.495227
```

```
2000-01-04  1.166096 -0.802272 -0.275253  0.517938
2000-01-05 -0.750872  1.216537 -0.910343 -0.606534
2000-01-06 -0.410659  0.264024 -0.069315 -1.814768

[6 rows x 4 columns]

# deprecated now
In [4]: df - df[0]
Out[4]:
            0         1         2         3
2000-01-01  0  1.398389  0.210778  1.742564
2000-01-02  0  0.589256 -0.746978 -0.104908
2000-01-03  0  1.232968 -0.024391 -1.903505
2000-01-04  0 -1.968368 -1.441350 -0.648158
2000-01-05  0  1.967410 -0.159471  0.144338
2000-01-06  0  0.674682  0.341344 -1.404109

[6 rows x 4 columns]

# Change your code to
In [5]: df.sub(df[0], axis=0) # align on axis 0 (rows)
Out[5]:
            0         1         2         3
2000-01-01  0  1.398389  0.210778  1.742564
2000-01-02  0  0.589256 -0.746978 -0.104908
2000-01-03  0  1.232968 -0.024391 -1.903505
2000-01-04  0 -1.968368 -1.441350 -0.648158
2000-01-05  0  1.967410 -0.159471  0.144338
2000-01-06  0  0.674682  0.341344 -1.404109

[6 rows x 4 columns]
```

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).

Note:

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

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

In [8]: series
Out[8]:
2000-01-01 00:00:00     0
2000-01-01 04:00:00     1
2000-01-01 08:00:00     2
2000-01-01 12:00:00     3
2000-01-01 16:00:00     4
2000-01-01 20:00:00     5
2000-01-02 00:00:00     6
                       ..
2000-01-04 00:00:00    18
```

```
2000-01-04 04:00:00    19
2000-01-04 08:00:00    20
2000-01-04 12:00:00    21
2000-01-04 16:00:00    22
2000-01-04 20:00:00    23
2000-01-05 00:00:00    24
Freq: 4H, dtype: int32

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

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

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

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

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

In [13]: s.fillna(0)
Out[13]:
0    1.500000
1         inf
2    3.400000
3        -inf
dtype: float64

In [14]: pd.set_option('use_inf_as_null', True)

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

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

In [17]: pd.reset_option('use_inf_as_null')
```

- Methods with the `inplace` option now all return `None` instead of the calling object. E.g. code written like `df = df.fillna(0, inplace=True)` may stop working. To fix, simply delete the unnecessary variable assignment.
- `pandas.merge` no longer sorts the group keys (`sort=False`) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnecessary.
- The default column names for a file with no header have been changed to the integers `0` through `N - 1`. This is to create consistency with the DataFrame constructor with no columns specified. The v0.9.0 behavior (names `X0`, `X1`, ...) can be reproduced by specifying `prefix='X'`:

```
In [18]: data= 'a,b,c\n1,Yes,2\n3,No,4'

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

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

[3 rows x 3 columns]

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

[3 rows x 3 columns]
```

- Values like `'Yes'` and `'No'` are not interpreted as boolean by default, though this can be controlled by new `true_values` and `false_values` arguments:

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

In [23]: pd.read_csv(StringIO(data))
Out[23]:
   a    b  c
0  1  Yes  2
```

```
1  3   No  4

[2 rows x 3 columns]

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

[2 rows x 3 columns]
```

- The file parsers will not recognize non-string values arising from a converter function as NA if passed in the `na_values` argument. It's better to do post-processing using the `replace` function instead.
- 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 [25]: s = Series([np.nan, 1., 2., np.nan, 4])

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

In [27]: s.fillna(0)
Out[27]:
0    0
1    1
2    2
3    0
4    4
dtype: float64

In [28]: s.fillna(method='pad')
Out[28]:
0   NaN
1     1
2     2
3     2
4     4
dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [29]: s.ffill()
Out[29]:
0   NaN
1     1
2     2
3     2
4     4
dtype: float64
```

- `Series.apply` will now operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame

```
In [30]: def f(x):
   ....:     return Series([ x, x**2 ], index = ['x', 'x^2'])
   ....:

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

In [32]: s
Out[32]:
0    0.013135
1    0.909855
2    0.098093
3    0.023540
4    0.141354
dtype: float64

In [33]: s.apply(f)
Out[33]:
          x       x^2
0  0.013135  0.000173
1  0.909855  0.827836
2  0.098093  0.009622
3  0.023540  0.000554
4  0.141354  0.019981

[5 rows x 2 columns]
```

- New API functions for working with pandas options (GH2097):
  - `get_option` / `set_option` - get/set the value of an option. Partial names are accepted. - `reset_option` - reset one or more options to their default value. Partial names are accepted. - `describe_option` - print a description of one or more options. When called with no arguments. print all registered options.

  Note: `set_printoptions`/ `reset_printoptions` are now deprecated (but functioning), the print options now live under "display.XYZ". For example:

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

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

1.14.3 New features

1.14.4 Wide DataFrame Printing

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

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

In [36]: wide_frame
Out[36]:
         0         1         2         3         4         5         6   \
0  2.520045  1.570114 -0.360875 -0.880096  0.235532  0.207232 -1.983857
1  0.422194  0.288403 -0.487393 -0.777639  0.055865  1.383381  0.085638
2  0.585174 -0.568825 -0.719412  1.191340 -0.456362  0.089931  0.776079
```

```
3  1.218080 -0.564705 -0.581790  0.286071  0.048725  1.002440  1.276582
4 -0.376280  0.511936 -0.116412 -0.625256 -0.550627  1.261433 -0.552429

         7         8         9         10        11        12        13  \
0 -1.702547 -1.621234 -0.906840  1.014601 -0.475108 -0.358944  1.262942
1  0.246392  0.965887  0.246354 -0.727728 -0.094414 -0.276854  0.158399
2  0.752889 -1.195795 -1.425911 -0.548829  0.774225  0.740501  1.510263
3  0.054399  0.241963 -0.471786  0.314510 -0.059986 -2.069319 -1.115104
4  1.695803 -1.025917 -0.910942  0.426805 -0.131749  0.432600  0.044671

         14        15
0 -0.412451 -0.462580
1 -0.277255  1.331263
2 -1.642511  0.432560
3 -0.369325 -1.502617
4 -0.341265  1.844536

[5 rows x 16 columns]
```

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

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

In [38]: wide_frame
Out[38]:
         0         1         2         3         4         5         6         7         8         9
0  2.520045  1.570114 -0.360875 -0.880096  0.235532  0.207232 -1.983857 -1.702547 -1.621234 -0.90684
1  0.422194  0.288403 -0.487393 -0.777639  0.055865  1.383381  0.085638  0.246392  0.965887  0.24635
2  0.585174 -0.568825 -0.719412  1.191340 -0.456362  0.089931  0.776079  0.752889 -1.195795 -1.42591
3  1.218080 -0.564705 -0.581790  0.286071  0.048725  1.002440  1.276582  0.054399  0.241963 -0.47178
4 -0.376280  0.511936 -0.116412 -0.625256 -0.550627  1.261433 -0.552429  1.695803 -1.025917 -0.91094

[5 rows x 16 columns]
```

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

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


In [40]: wide_frame
Out[40]:
         0         1         2  \
0  2.520045  1.570114 -0.360875
1  0.422194  0.288403 -0.487393
2  0.585174 -0.568825 -0.719412
3  1.218080 -0.564705 -0.581790
4 -0.376280  0.511936 -0.116412

         3         4         5  \
0 -0.880096  0.235532  0.207232
1 -0.777639  0.055865  1.383381
2  1.191340 -0.456362  0.089931
3  0.286071  0.048725  1.002440
4 -0.625256 -0.550627  1.261433

         6         7         8  \
0 -1.983857 -1.702547 -1.621234
```

```
1  0.085638  0.246392  0.965887
2  0.776079  0.752889 -1.195795
3  1.276582  0.054399  0.241963
4 -0.552429  1.695803 -1.025917

          9         10         11  \
0 -0.906840  1.014601 -0.475108
1  0.246354 -0.727728 -0.094414
2 -1.425911 -0.548829  0.774225
3 -0.471786  0.314510 -0.059986
4 -0.910942  0.426805 -0.131749

         12         13         14  \
0 -0.358944  1.262942 -0.412451
1 -0.276854  0.158399 -0.277255
2  0.740501  1.510263 -1.642511
3 -2.069319 -1.115104 -0.369325
4  0.432600  0.044671 -0.341265

         15
0 -0.462580
1  1.331263
2  0.432560
3 -1.502617
4  1.844536

[5 rows x 16 columns]
```

1.14.5 Updated PyTables Support

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

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

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

In [43]: df
Out[43]:
                   A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]

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

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

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

In [47]: store.append('df', df2)

In [48]: store
Out[48]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# selecting the entire store
In [49]: store.select('df')
Out[49]:
                   A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]

In [50]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   ....:         major_axis=date_range('1/1/2000', periods=5),
   ....:         minor_axis=['A', 'B', 'C', 'D'])
   ....:

In [51]: wp
Out[51]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# storing a panel
In [52]: store.append('wp',wp)

# selecting via A QUERY
In [53]: store.select('wp',
   ....:    [ Term('major_axis>20000102'), Term('minor_axis', '=', ['A','B']) ])
   ....:
Out[53]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to B

# removing data from tables
In [54]: store.remove('wp', Term('major_axis>20000103'))
Out[54]: 8

In [55]: store.select('wp')
Out[55]:
```

```
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to D

# deleting a store
In [56]: del store['df']

In [57]: store
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp            wide_table   (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,minor_axis])
```

Enhancements

- added ability to hierarchical keys

```
In [58]: store.put('foo/bar/bah', df)

In [59]: store.append('food/orange', df)

In [60]: store.append('food/apple',  df)

In [61]: store
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah            frame        (shape->[8,3])
/food/apple             frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/wp                     wide_table   (typ->appendable,nrows->12,ncols->2,indexers->[major_ax

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

In [63]: store
Out[63]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah            frame        (shape->[8,3])
/wp                     wide_table   (typ->appendable,nrows->12,ncols->2,indexers->[major_ax
```

- added mixed-dtype support!

```
In [64]: df['string'] = 'string'

In [65]: df['int']    = 1

In [66]: store.append('df',df)

In [67]: df1 = store.select('df')

In [68]: df1
Out[68]:
                   A         B         C  string  int
2000-01-01 -2.036047  0.000830 -0.955697  string    1
2000-01-02 -0.898872 -0.725411  0.059904  string    1
```

```
2000-01-03 -0.449644  1.082900 -1.221265  string    1
2000-01-04  0.361078  1.330704  0.855932  string    1
2000-01-05 -1.216718  1.488887  0.018993  string    1
2000-01-06 -0.877046  0.045976  0.437274  string    1
2000-01-07 -0.567182 -0.888657 -0.556383  string    1
2000-01-08  0.655457  1.117949 -2.782376  string    1

[8 rows x 5 columns]

In [69]: df1.get_dtype_counts()
Out[69]:
float64    3
int64      1
object     1
dtype: int64
```

- performance improvments 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.

1.14.6 N Dimensional Panels (Experimental)

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

```
In [70]: p4d = Panel4D(randn(2, 2, 5, 4),
   ....:       labels=['Label1','Label2'],
   ....:       items=['Item1', 'Item2'],
   ....:       major_axis=date_range('1/1/2000', periods=5),
```

```
   ....:        minor_axis=['A', 'B', 'C', 'D'])
   ....:

In [71]: p4d
Out[71]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

See the *full release notes* or issue tracker on GitHub for a complete list.

1.15 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.

1.15.1 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 [1]: df = DataFrame(np.random.randint(0, 2, (6, 3)), columns=['A', 'B', 'C'])

In [2]: df.sort(['A', 'B'], ascending=[1, 0])
Out[2]:
   A  B  C
2  0  1  1
3  0  1  1
4  0  0  1
0  1  1  0
1  1  0  1
5  1  0  1

[6 rows x 3 columns]
```

- *DataFrame.rank* now supports additional argument values for the *na_option* parameter so missing values can be assigned either the largest or the smallest rank (GH1508, GH2159)

```
In [3]: df = DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])

In [4]: df.ix[2:4] = np.nan

In [5]: df.rank()
Out[5]:
     A    B    C
0    3    2    1
1    2    1    3
2  NaN  NaN  NaN
3  NaN  NaN  NaN
4  NaN  NaN  NaN
5    1    3    2
```

```
[6 rows x 3 columns]

In [6]: df.rank(na_option='top')
Out[6]:
   A  B  C
0  6  5  4
1  5  4  6
2  2  2  2
3  2  2  2
4  2  2  2
5  4  6  5

[6 rows x 3 columns]

In [7]: df.rank(na_option='bottom')
Out[7]:
   A  B  C
0  3  2  1
1  2  1  3
2  5  5  5
3  5  5  5
4  5  5  5
5  1  3  2

[6 rows x 3 columns]
```

- DataFrame has new *where* and *mask* methods to select values according to a given boolean mask (GH2109, GH2151)

  DataFrame currently supports slicing via a boolean vector the same length as the DataFrame (inside the *[]*). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

  ```
  In [8]: df = DataFrame(np.random.randn(5, 3), columns = ['A','B','C'])

  In [9]: df
  Out[9]:
            A         B         C
  0  0.706220 -1.130744 -0.690308
  1 -0.885387  0.246004  1.986687
  2  0.212595 -1.189832 -0.344258
  3  0.816335 -1.514102  1.298184
  4  0.089527  0.576687 -0.737750

  [5 rows x 3 columns]

  In [10]: df[df['A'] > 0]
  Out[10]:
            A         B         C
  0  0.706220 -1.130744 -0.690308
  2  0.212595 -1.189832 -0.344258
  3  0.816335 -1.514102  1.298184
  4  0.089527  0.576687 -0.737750

  [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 *NaN*. This is accomplished via the new method *DataFrame.where*. In addition, *where* takes an optional *other* argument for replacement.

```
In [11]: df[df>0]
Out[11]:
          A         B         C
0  0.706220       NaN       NaN
1       NaN  0.246004  1.986687
2  0.212595       NaN       NaN
3  0.816335       NaN  1.298184
4  0.089527  0.576687       NaN

[5 rows x 3 columns]

In [12]: df.where(df>0)
Out[12]:
          A         B         C
0  0.706220       NaN       NaN
1       NaN  0.246004  1.986687
2  0.212595       NaN       NaN
3  0.816335       NaN  1.298184
4  0.089527  0.576687       NaN

[5 rows x 3 columns]

In [13]: df.where(df>0,-df)
Out[13]:
          A         B         C
0  0.706220  1.130744  0.690308
1  0.885387  0.246004  1.986687
2  0.212595  1.189832  0.344258
3  0.816335  1.514102  1.298184
4  0.089527  0.576687  0.737750

[5 rows x 3 columns]
```

Furthermore, *where* now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analagous to partial setting via *.ix* (but on the contents rather than the axis labels)

```
In [14]: df2 = df.copy()

In [15]: df2[ df2[1:4] > 0 ] = 3

In [16]: df2
Out[16]:
          A         B         C
0  0.706220 -1.130744 -0.690308
1 -0.885387  3.000000  3.000000
2  3.000000 -1.189832 -0.344258
3  3.000000 -1.514102  3.000000
4  0.089527  0.576687 -0.737750

[5 rows x 3 columns]
```

DataFrame.mask is the inverse boolean operation of *where*.

```
In [17]: df.mask(df<=0)
Out[17]:
```

```
          A         B         C
0  0.706220       NaN       NaN
1       NaN  0.246004  1.986687
2  0.212595       NaN       NaN
3  0.816335       NaN  1.298184
4  0.089527  0.576687       NaN

[5 rows x 3 columns]
```

- Enable referencing of Excel columns by their column names (GH1936)

```
In [18]: xl = ExcelFile('data/test.xls')

In [19]: xl.parse('Sheet1', index_col=0, parse_dates=True,
   ....:          parse_cols='A:D')
   ....:
Out[19]:
                   A         B         C
2000-01-03  0.980269  3.685731 -0.364217
2000-01-04  1.047916 -0.041232 -0.161812
2000-01-05  0.498581  0.731168 -0.537677
2000-01-06  1.120202  1.567621  0.003641
2000-01-07 -0.487094  0.571455 -1.611639
2000-01-10  0.836649  0.246462  0.588543
2000-01-11 -0.157161  1.340307  1.195778

[7 rows x 3 columns]
```

- Added option to disable pandas-style tick locators and formatters using *series.plot(x_compat=True)* or *pandas.plot_params['x_compat'] = True* (GH2205)
- Existing TimeSeries methods *at_time* and *between_time* were added to DataFrame (GH2149)
- DataFrame.dot can now accept ndarrays (GH2042)
- DataFrame.drop now supports non-unique indexes (GH2101)
- Panel.shift now supports negative periods (GH2164)
- DataFrame now support unary ~ operator (GH2110)

1.15.2 API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [20]: prng = period_range('2012Q1', periods=2, freq='Q')

In [21]: s = Series(np.random.randn(len(prng)), prng)

In [22]: s.resample('M')
Out[22]:
2012-01    0.194513
2012-02         NaN
2012-03         NaN
2012-04   -0.854246
2012-05         NaN
2012-06         NaN
Freq: M, dtype: float64
```

- Period.end_time now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```
In [23]: p = Period('2012')

In [24]: p.end_time
Out[24]: Timestamp('2012-12-31 23:59:59.999999999')
```

- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

```
In [25]: data = 'A,B,C\n00001,001,5\n00002,002,6'

In [26]: read_csv(StringIO(data), converters={'A' : lambda x: x.strip()})
Out[26]:
       A  B  C
0  00001  1  5
1  00002  2  6

[2 rows x 3 columns]
```

See the *full release notes* or issue tracker on GitHub for a complete list.

1.16 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.

1.16.1 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)

1.16.2 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:

```
In [1]: data = '0,0,1\n1,1,0\n0,1,0'

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:

```
In [4]: s1 = Series([1, 2, 3])

In [5]: s1
Out[5]:
0    1
1    2
2    3
dtype: int64

In [6]: s2 = Series(s1, index=['foo', 'bar', 'baz'])

In [7]: s2
Out[7]:
foo   NaN
bar   NaN
baz   NaN
dtype: float64
```

- Deprecated `day_of_year` API removed from PeriodIndex, use `dayofyear` (GH1723)
- Don't modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by HDFStore (GH1834, GH1824)
- Legacy cruft removed: pandas.stats.misc.quantileTS
- Use ISO8601 format for Period repr: monthly, daily, and on down (GH1776)
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) (GH1783)
- Setting parts of DataFrame/Panel using ix now aligns input Series/DataFrame (GH1630)
- `first` and `last` methods in `GroupBy` no longer drop non-numeric columns (GH1809)
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly (GH1657)
- `DataFrame.dot` will not do data alignment, and also work with Series (GH1915)

See the *full release notes* or issue tracker on GitHub for a complete list.

1.17 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.

1.17.1 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)

1.17.2 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 improvments

1.18 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.

1.18.1 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)

1.18.2 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.

1.18.3 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_lcoalize` methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to localtime. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as as strings are required. Time zone-aware timestamps are equal if and only if their UTC timestamps match. Operations between time zone-aware time series with different time zones will result in a UTC-indexed time series.
- Time series **string indexing conveniences** / shortcuts: slice years, year and month, and index values with strings
- Enhanced time series **plotting**; adaptation of scikits.timeseries matplotlib-based plotting code
- New `date_range`, `bdate_range`, and `period_range` *factory functions*
- Robust **frequency inference** function *infer_freq* and `inferred_freq` property of DatetimeIndex, with option to infer frequency on construction of DatetimeIndex

- to_datetime function efficiently **parses array of strings** to DatetimeIndex. DatetimeIndex will parse array or list of strings to datetime64
- **Optimized** support for datetime64-dtype data in Series and DataFrame columns
- New NaT (Not-a-Time) type to represent **NA** in timestamp arrays
- Optimize Series.asof for looking up **"as of" values** for arrays of timestamps
- Milli, Micro, Nano date offset objects
- Can index time series with datetime.time objects to select all data at particular **time of day** (`TimeSeries.at_time`) or **between two times** (`TimeSeries.between_time`)
- Add *tshift* method for leading/lagging using the frequency (if any) of the index, as opposed to a naive lead/lag using shift

1.18.4 Other new features

- New *cut* and `qcut` functions (like R's cut function) for computing a categorical variable from a continuous variable by binning values either into value-based (`cut`) or quantile-based (`qcut`) bins
- Rename `Factor` to `Categorical` and add a number of usability features
- Add *limit* argument to fillna/reindex
- More flexible multiple function application in GroupBy, and can pass list (name, function) tuples to get result in particular order with given names
- Add flexible *replace* method for efficiently substituting values
- Enhanced *read_csv/read_table* for reading time series data and converting multiple columns to dates
- Add *comments* option to parser functions: read_csv, etc.
- Add :ref'dayfirst <io.dayfirst>' option to parser functions for parsing international DD/MM/YYYY dates
- Allow the user to specify the CSV reader *dialect* to control quoting etc.
- Handling *thousands* separators in read_csv to improve integer parsing.
- Enable unstacking of multiple levels in one shot. Alleviate `pivot_table` bugs (empty columns being introduced)
- Move to klib-based hash tables for indexing; better performance and less memory usage than Python's dict
- Add first, last, min, max, and prod optimized GroupBy functions
- New *ordered_merge* function
- Add flexible *comparison* instance methods eq, ne, lt, gt, etc. to DataFrame, Series
- Improve *scatter_matrix* plotting function and add histogram or kernel density estimates to diagonal
- Add *'kde'* plot option for density plots
- Support for converting DataFrame to R data.frame through rpy2
- Improved support for complex numbers in Series and DataFrame
- Add *pct_change* method to all data structures
- Add max_colwidth configuration option for DataFrame console output
- *Interpolate* Series values using index values
- Can select multiple columns from GroupBy

- Add *update* methods to Series/DataFrame for updating values in place
- Add `any` and `all` method to DataFrame

1.18.5 New plotting methods

`Series.plot` now supports a `secondary_y` option:

```
In [1]: plt.figure()
Out[1]: <matplotlib.figure.Figure at 0xa9d450ec>

In [2]: fx['FR'].plot(style='g')
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0xa9d450cc>

In [3]: fx['IT'].plot(style='k--', secondary_y=True)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0xa9d45c6c>
```

../_static/whatsnew_secondary_y.png

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, `'kde'` is a new option:

```
In [4]: s = Series(np.concatenate((np.random.randn(1000),
   ...:                            np.random.randn(1000) * 0.5 + 3)))
   ...:

In [5]: plt.figure()
Out[5]: <matplotlib.figure.Figure at 0xac3c2e8c>

In [6]: s.hist(normed=True, alpha=0.2)
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0xa9f4066c>

In [7]: s.plot(kind='kde')
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0xa9f4066c>
```

../_static/whatsnew_kde.png

See *the plotting page* for much more.

1.18.6 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.

1.18.7 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:

```
In [8]: import datetime

In [9]: rng = date_range('1/1/2000', periods=10)

In [10]: rng[5]
Out[10]: Timestamp('2000-01-06 00:00:00', offset='D')

In [11]: isinstance(rng[5], datetime.datetime)
Out[11]: True

In [12]: rng_asarray = np.asarray(rng)

In [13]: scalar_val = rng_asarray[5]

In [14]: type(scalar_val)
Out[14]: numpy.datetime64
```

pandas's `Timestamp` object is a subclass of `datetime.datetime` that has nanosecond support (the `nanosecond` field store the nanosecond value between 0 and 999). It should substitute directly into any code that used `datetime.datetime` values before. Thus, I recommend not casting `DatetimeIndex` to regular NumPy arrays.

If you have code that requires an array of `datetime.datetime` objects, you have a couple of options. First, the `asobject` property of `DatetimeIndex` produces an array of `Timestamp` objects:

```
In [15]: stamp_array = rng.asobject

In [16]: stamp_array
Out[16]:
Index([2000-01-01 00:00:00, 2000-01-02 00:00:00, 2000-01-03 00:00:00,
       2000-01-04 00:00:00, 2000-01-05 00:00:00, 2000-01-06 00:00:00,
       2000-01-07 00:00:00, 2000-01-08 00:00:00, 2000-01-09 00:00:00,
       2000-01-10 00:00:00],
      dtype='object')

In [17]: stamp_array[5]
Out[17]: Timestamp('2000-01-06 00:00:00', offset='D')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```
In [18]: dt_array = rng.to_pydatetime()

In [19]: dt_array
Out[19]:
array([datetime.datetime(2000, 1, 1, 0, 0),
       datetime.datetime(2000, 1, 2, 0, 0),
       datetime.datetime(2000, 1, 3, 0, 0),
       datetime.datetime(2000, 1, 4, 0, 0),
       datetime.datetime(2000, 1, 5, 0, 0),
       datetime.datetime(2000, 1, 6, 0, 0),
       datetime.datetime(2000, 1, 7, 0, 0),
```

```
       datetime.datetime(2000, 1, 8, 0, 0),
       datetime.datetime(2000, 1, 9, 0, 0),
       datetime.datetime(2000, 1, 10, 0, 0)], dtype=object)

In [20]: dt_array[5]
Out[20]: datetime.datetime(2000, 1, 6, 0, 0)
```

matplotlib knows how to handle `datetime.datetime` but not Timestamp objects. While I recommend that you plot time series using `TimeSeries.plot`, you can either use `to_pydatetime` or register a converter for the Timestamp type. See matplotlib documentation for more on this.

Warning: There are bugs in the user-facing API with the nanosecond datetime64 unit in NumPy 1.6. In particular, the string version of the array shows garbage values, and conversion to `dtype=object` is similarly broken.

```
In [21]: rng = date_range('1/1/2000', periods=10)

In [22]: rng
Out[22]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10'],
              dtype='datetime64[ns]', freq='D', tz=None)

In [23]: np.asarray(rng)
Out[23]:
array(['2000-01-01T01:00:00.000000000+0100',
       '2000-01-02T01:00:00.000000000+0100',
       '2000-01-03T01:00:00.000000000+0100',
       '2000-01-04T01:00:00.000000000+0100',
       '2000-01-05T01:00:00.000000000+0100',
       '2000-01-06T01:00:00.000000000+0100',
       '2000-01-07T01:00:00.000000000+0100',
       '2000-01-08T01:00:00.000000000+0100',
       '2000-01-09T01:00:00.000000000+0100',
       '2000-01-10T01:00:00.000000000+0100'], dtype='datetime64[ns]')

In [24]: converted = np.asarray(rng, dtype=object)

In [25]: converted[5]
Out[25]: 947116800000000000L
```

Trust me: don't panic. If you are using NumPy 1.6 and restrict your interaction with `datetime64` values to pandas's API you will be just fine. There is nothing wrong with the data-type (a 64-bit integer internally); all of the important data processing happens in pandas and is heavily tested. I strongly recommend that you **do not work directly with datetime64 arrays in NumPy 1.6** and only use the pandas API.

Support for non-unique indexes: In the latter case, you may have code inside a `try:... catch:` block that failed due to the index not being unique. In many cases it will no longer fail (some method like `append` still check for uniqueness unless disabled). However, all is not lost: you can inspect `index.is_unique` and raise an exception explicitly if it is `False` or go to a different code branch.

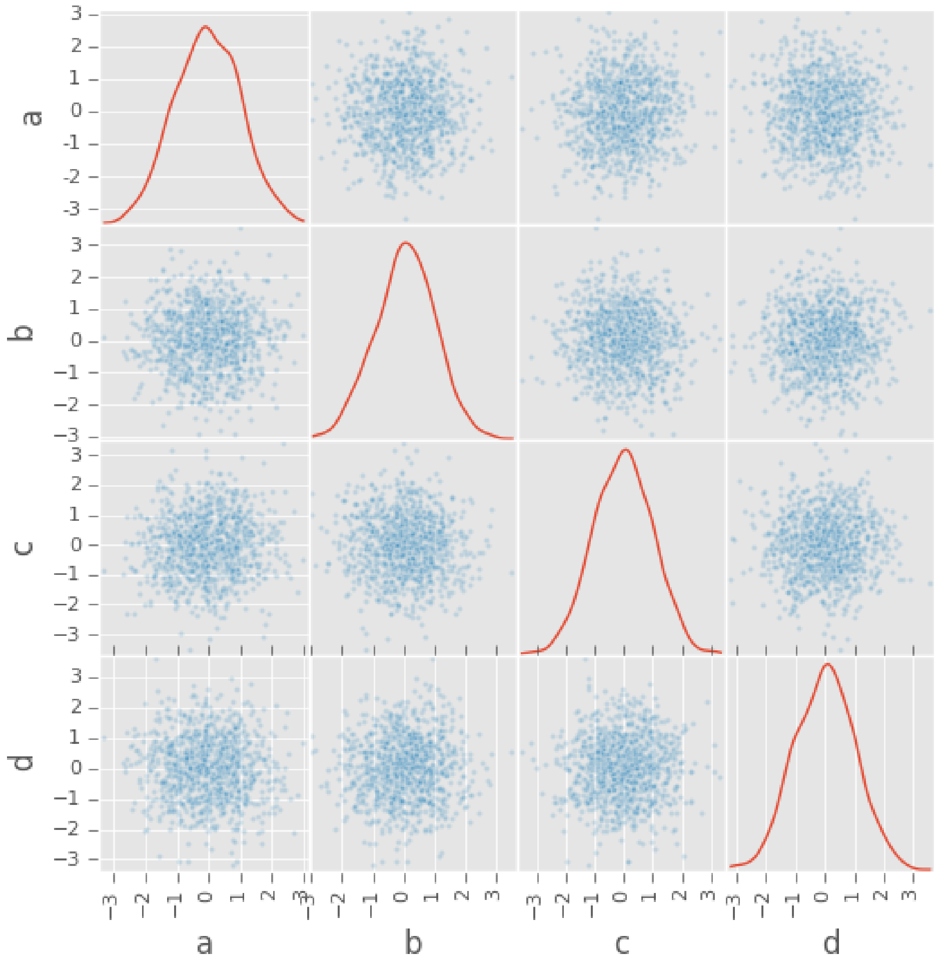
1.19 v.0.7.3 (April 12, 2012)

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.

1.19.1 New features

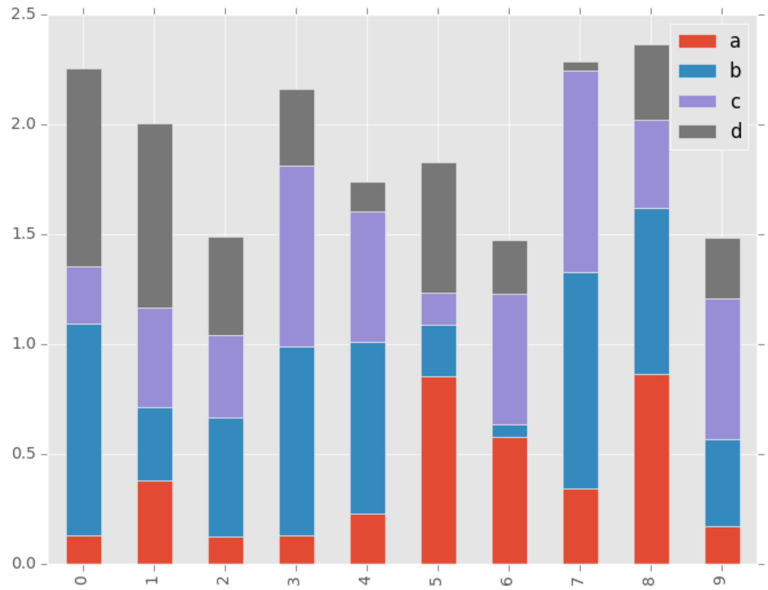
- New *fixed width file reader*, `read_fwf`
- New *scatter_matrix* function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)
```

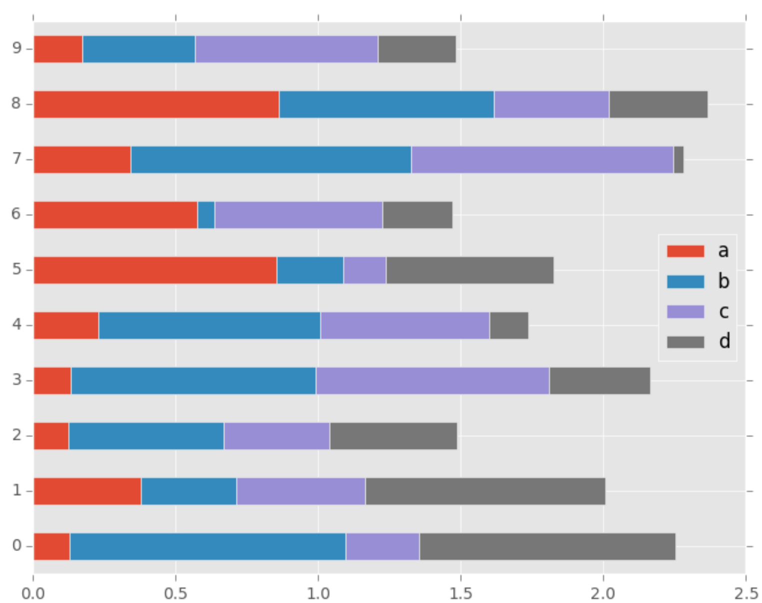


- Add `stacked` argument to Series and DataFrame's `plot` method for *stacked bar plots*.

```
df.plot(kind='bar', stacked=True)
```




```
df.plot(kind='barh', stacked=True)
```



- Add log x and y *scaling options* to `DataFrame.plot` and `Series.plot`
- Add `kurt` methods to Series and DataFrame for computing kurtosis

1.19.2 NA Boolean Comparison API Change

Reverted some changes to how NA values (represented typically as `NaN` or `None`) are handled in non-numeric Series:

```
In [1]: series = Series(['Steve', np.nan, 'Joe'])

In [2]: series == 'Steve'
Out[2]:
0     True
```

```
1    False
2    False
dtype: bool

In [3]: series != 'Steve'
Out[3]:
0    False
1     True
2     True
dtype: bool
```

In comparisons, NA / NaN will always come through as `False` except with `!=` which is `True`. *Be very careful* with boolean arithmetic, especially negation, in the presence of NA data. You may wish to add an explicit NA filter into boolean array operations if you are worried about this:

```
In [4]: mask = series == 'Steve'

In [5]: series[mask & series.notnull()]
Out[5]:
0    Steve
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.

1.19.3 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 [1]: 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 [2]: df
Out[2]:
     A      B         C         D
0  foo    one  0.144909  1.387310
1  bar    one -1.033812  0.063490
2  foo    two  0.197333  1.437656
3  bar  three -0.059730 -0.814844
4  foo    two  0.087205 -0.482060
5  bar    two -1.607906  1.521442
6  foo    one -1.275249  0.882182
7  foo  three -0.054460 -0.108020

[8 rows x 4 columns]

In [3]: grouped = df.groupby('A')['C']

In [4]: grouped.describe()
Out[4]:
```

```
A
bar  count    3.000000
     mean    -0.900483
     std      0.782652
     min     -1.607906
     25%     -1.320859
     50%     -1.033812
     75%     -0.546771
                ...
foo  mean    -0.180052
     std      0.619410
     min     -1.275249
     25%     -0.054460
     50%      0.087205
     75%      0.144909
     max      0.197333
dtype: float64

In [5]: grouped.apply(lambda x: x.order()[-2:]) # top 2 values
Out[5]:
A
bar  1   -1.033812
     3   -0.059730
foo  0    0.144909
     2    0.197333
dtype: float64
```

1.20 v.0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

1.20.1 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)

1.20.2 Performance improvements

- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Intercept __builtin__.sum in groupby (GH885)

1.21 v.0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

1.21.1 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

1.21.2 Performance improvements

- Improve performance and memory usage of fillna on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame (GH787)

1.22 v.0.7.0 (February 9, 2012)

1.22.1 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    0.119046   0.455043  -0.093701  -0.330828
std     0.814006   0.972606   0.948124   0.814913
```

```
min    -0.964456  -0.790943  -1.921164  -1.578003
25%    -0.512550  -0.462622  -0.683389  -0.934434
50%     0.013691   0.415879  -0.061961  -0.343709
75%     0.616168   1.351857   0.671847   0.150746
max     1.507974   1.755240   1.183075   1.051356

[8 rows x 4 columns]
```

- *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.

1.22.2 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    -0.392051
2    -0.189537
4     0.886170
6    -1.125894
8     0.319635
10    0.998222
12    0.091743
14   -2.032047
16   -0.448560
18    0.730510
dtype: float64

In [5]: s[0]
Out[5]: -0.39205110783730307

In [6]: s[2]
Out[6]: -0.18953739573269113

In [7]: s[4]
Out[7]: 0.88617008348573789
```

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
`Series.iget_value(i)`	Retrieve value stored at location `i`
`Series.iget(i)`	Alias for `iget_value`
`DataFrame.irow(i)`	Retrieve the `i`-th row
`DataFrame.icol(j)`	Retrieve the `j`-th column
`DataFrame.iget_value(i, j)`	Retrieve the value at row `i` and column `j`

1.22.3 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 [8]: s = Series(randn(6), index=list('gmkaec'))

In [9]: s
Out[9]:
g    1.269713
m    1.209524
k    2.160843
a    0.533532
e   -2.371548
c    0.562726
dtype: float64
```

Then this is OK:

```
In [10]: s.ix['k':'e']
Out[10]:
k    2.160843
a    0.533532
e   -2.371548
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 [11]: s2 = s.sort_index()

In [12]: s2
Out[12]:
a    0.533532
c    0.562726
e   -2.371548
g    1.269713
k    2.160843
m    1.209524
dtype: float64

In [13]: s2.ix['b':'h']
Out[13]:
c    0.562726
e   -2.371548
g    1.269713
dtype: float64
```

1.22.4 Changes to Series [] operator

As as notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via [] (i.e. the __getitem__ and __setitem__ methods). The behavior will be the same as passing similar input to ix **except in the case of integer indexing**:

```
In [14]: s = Series(randn(6), index=list('acegkm'))

In [15]: s
Out[15]:
a    2.031757
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
m    0.945588
dtype: float64

In [16]: s[['m', 'a', 'c', 'e']]
Out[16]:
m    0.945588
a    2.031757
c    0.851077
e    0.660056
dtype: float64

In [17]: s['b':'l']
Out[17]:
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
dtype: float64

In [18]: s['c':'k']
Out[18]:
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing ndarray):

```
In [19]: s = Series(randn(6), index=range(0, 12, 2))

In [20]: s[[4, 0, 2]]
Out[20]:
4   -1.263534
0   -0.414691
2    2.108285
dtype: float64

In [21]: s[1:5]
Out[21]:
2    2.108285
4   -1.263534
6    2.617801
8    1.967592
```

```
dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

1.22.5 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)

1.22.6 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)

1.23 v.0.6.1 (December 13, 2011)

1.23.1 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*

1.23.2 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)

1.24 v.0.6.0 (November 25, 2011)

1.24.1 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)

1.24.2 Performance Enhancements

- VBENCH Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the codebase (GH361)
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than *np.apply_along_axis* (GH309)
- VBENCH Improved performance of `MultiIndex.from_tuples`
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations
- VBENCH + DOCUMENT Add `raw` option to `DataFrame.apply` for getting better performance when
- VBENCH Faster cythonized count by level in Series and DataFrame (GH341)

- VBENCH? Significant GroupBy performance enhancement with multiple keys with many "empty" combinations
- VBENCH New Cython vectorized function `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)

1.25 v.0.5.0 (October 24, 2011)

1.25.1 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

1.25.2 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

1.26 v.0.4.3 through v0.4.1 (September 25 - October 9, 2011)

1.26.1 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)

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

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

2.1 Python version support

Officially Python 2.6, 2.7, 3.2, 3.3, and 3.4.

2.2 Installing pandas

2.2.1 Trying out pandas, no installation required!

The easiest way to start experimenting with pandas doesn't involve installing pandas at all.

Wakari is a free service that provides a hosted IPython Notebook service in the cloud.

Simply create an account, and have access to pandas from within your brower via an IPython Notebook in a few minutes.

2.2.2 Installing pandas with Anaconda

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

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

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

Installation instructions for Anaconda can be found here.

A full list of the packages available as part of the Anaconda distribution can be found here.

An additional advantage of installing with Anaconda is that you don't require admin rights to install it, it will install in the user's home directory, and this also makes it trivial to delete Anaconda at a later date (just delete that folder).

2.2.3 Installing pandas with Miniconda

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

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

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

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

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

The next step is to create a new conda environment (these are analogous to a virtualenv but they also allow you to specify precisely which Python version to install also). Run the following commands from a terminal window:

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

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

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

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

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.13.1
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full Anaconda distribution:

```
conda install anaconda
```

If you require any packages that are available to pip but not conda, simply install pip, and use pip to install these packages:

```
conda install pip
pip install django
```

2.2.4 Installing from PyPI

pandas can be installed via pip from PyPI.

```
pip install pandas
```

This will likely require the installation of a number of dependencies, including NumPy, will require a compiler to compile required bits of code, and can take a few minutes to complete.

2.2.5 Installing using your Linux distribution's package manager.

Distribution	Status	Download / Repository Link	Install method
Debian	stable	official Debian repository	`sudo apt-get install python-pandas`
Debian & Ubuntu	unstable (latest packages)	NeuroDebian	`sudo apt-get install python-pandas`
Ubuntu	stable	official Ubuntu repository	`sudo apt-get install python-pandas`
Ubuntu	unstable (daily builds)	PythonXY PPA; activate by: `sudo add-apt-repository ppa:pythonxy/pythonxy-devel && sudo apt-get update`	`sudo apt-get install python-pandas`
OpenSuse & Fedora	stable	OpenSuse Repository	`zypper in python-pandas`

2.2.6 Installing from source

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

2.2.7 Running the test suite

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

```
$ nosetests pandas
..........................................................................
.......................S..................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
.................S........................................................
....
----------------------------------------------------------------------
Ran 818 tests in 21.631s

OK (SKIP=2)
```

2.3 Dependencies

- NumPy: 1.7.0 or higher
- python-dateutil 1.5 or higher
- **pytz**
  - Needed for time zone support

2.3.1 Recommended Dependencies

- numexpr: for accelerating certain numerical operations. `numexpr` uses multiple cores as well as smart chunking and caching to achieve large speedups. If installed, must be Version 2.1 or higher.
- bottleneck: for accelerating certain types of `nan` evaluations. `bottleneck` uses specialized cython routines to achieve large speedups.

Note: You are highly encouraged to install these libraries, as they provide large speedups, especially if working with large data sets.

2.3.2 Optional Dependencies

- Cython: Only necessary to build development version. Version 0.19.1 or higher.
- SciPy: miscellaneous statistical functions
- PyTables: necessary for HDF5-based storage. Version 3.0.0 or higher required, Version 3.2.0 or higher highly recommended.
- SQLAlchemy: for SQL database support. Version 0.8.1 or higher recommended.
- matplotlib: for plotting
- **statsmodels**
  - Needed for parts of `pandas.stats`
- **openpyxl, xlrd/xlwt**
  - openpyxl version 1.6.1 or higher, but lower than 2.0.0
  - Needed for Excel I/O
- **XlsxWriter**
  - Alternative Excel writer.
- boto: necessary for Amazon S3 access.
- blosc: for msgpack compression using `blosc`
- One of PyQt4, PySide, pygtk, xsel, or xclip: necessary to use `read_clipboard()`. Most package managers on Linux distributions will have xclip and/or xsel immediately available for installation.
- Google's python-gflags and google-api-python-client
  - Needed for `gbq`
- **setuptools**
  - Needed for `gbq` (specifically, it utilizes *pkg_resources*)

- **httplib2**
    - Needed for `gbq`
- One of the following combinations of libraries is needed to use the top-level `read_html()` function:
    - BeautifulSoup4 and html5lib (Any recent version of html5lib is okay.)
    - BeautifulSoup4 and lxml
    - BeautifulSoup4 and html5lib and lxml
    - Only lxml, although see *HTML reading gotchas* for reasons as to why you should probably **not** take this approach.

Warning:
- if you install BeautifulSoup4 you must install either lxml or html5lib or both. `read_html()` will **not** work with *only* BeautifulSoup4 installed.
- You are highly encouraged to read *HTML reading gotchas*. It explains issues surrounding the installation and usage of the above three libraries
- **You may need to install an older version of BeautifulSoup4:**
    - Versions 4.2.1, 4.1.3 and 4.0.2 have been confirmed for 64 and 32-bit Ubuntu/Debian
- Additionally, if you're using Anaconda you should definitely read *the gotchas about HTML parsing libraries*

Note:
- if you're on a system with `apt-get` you can do

```
sudo apt-get build-dep python-lxml
```

to get the necessary dependencies for installation of lxml. This will prevent further headaches down the line.

Note: Without the optional dependencies, many useful features will not work. Hence, it is highly recommended that you install these. A packaged distribution like Enthought Canopy may be worth considering.

CHAPTER THREE

CONTRIBUTING TO PANDAS

Table of contents:

3.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements and ideas are welcome.

If you are simply looking to start working with the *pandas* codebase, navigate to the GitHub "issues" tab and start looking through interesting issues. There are a number of issues listed under Docs and Difficulty Novice where you could start out.

Or maybe through using *pandas* you have an idea of you own or are looking for something in the documentation and thinking 'this can be improved'...you can do something about it!

Feel free to ask questions on mailing list

3.2 Bug Reports/Enhancement Requests

Bug reports are an important part of making *pandas* more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. Since many versions of *pandas* are supported, knowing version information will also identify improvements made since previous versions. Often trying the bug-producing code out on the *master* branch is a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can have the code formatted nicely by using GitHub Flavored Markdown:

````
```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...
```
````

2. Include the full version string of *pandas* and its dependencies. In recent (>0.12) versions of *pandas* you can use a built in function:

```
>>> from pandas.util.print_versions import show_versions
>>> show_versions()
```

   and in 0.13.1 onwards:

```
>>> pd.show_versions()
```

3. Explain why the current behavior is wrong/not desired and what you expect instead.

The issue will then show up to the *pandas* community and be open to comments/ideas from others.

3.3 Working with the code

Now that you have an issue you want to fix, enhancement to add, or documentation to improve, you need to learn how to work with GitHub and the *pandas* code base.

3.3.1 Version Control, Git, and GitHub

To the new user, working with Git is one of the more daunting aspects of contributing to *pandas*. It can very quickly become overwhelming, but sticking to the guidelines below will make the process straightforward and will work without much trouble. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on GitHub. To contribute you will need to sign up for a free GitHub account. We use Git for version control to allow many people to work together on the project.

Some great resources for learning git:

- 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 working seamlessly with your local repository and GitHub.

3.3.3 Forking

You will need your own fork to work on the code. Go to the pandas project page and hit the *fork* button. You will want to clone your fork to your machine:

```
git clone git@github.com:your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream git://github.com/pydata/pandas.git
```

This creates the directory *pandas-yourname* and connects your repository to the upstream (main project) *pandas* repository.

The testing suite will run automatically on Travis-CI once your Pull Request is submitted. However, if you wish to run the test suite on a branch prior to submitting the Pull Request, then Travis-CI needs to be hooked up to your GitHub repository. Instructions are for doing so are here.

3.3.4 Creating a Branch

You want your master branch to reflect only production-ready code, so create a feature branch for making your changes. For example:

```
git branch shiny-new-feature
git checkout shiny-new-feature
```

The above can be simplified to:

```
git checkout -b shiny-new-feature
```

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to *pandas*. You can have many shiny-new-features and switch in between them using the git checkout command.

To update this branch, you need to retrieve the changes from the master branch:

```
git fetch upstream
git rebase upstream/master
```

This will replay your commits on top of the lastest pandas git master. If this leads to merge conflicts, you must resolve these before submitting your Pull Request. If you have uncommitted changes, you will need to *stash* them prior to updating. This will effectively store your changes and they can be reapplied after updating.

3.3.5 Creating a Development Environment

An easy way to create a *pandas* development environment is as follows.

- Install either *Install Anaconda* or *Install miniconda*

- Make sure that you have *cloned the repository*
- `cd` to the pandas source directory

Tell `conda` to create a new environment, named `pandas_dev`, or any name you would like for this environment by running:

```
conda create -n pandas_dev --file ci/requirements_dev.txt
```

For a python 3 environment

```
conda create -n pandas_dev python=3 --file ci/requirements_dev.txt
```

If you are on `windows`, then you will need to install the compiler linkages:

```
conda install -n pandas_dev libpython
```

This will create the new environment, and not touch any of your existing environments, nor any existing python installation. It will install all of the basic dependencies of *pandas*, as well as the development and testing tools. If you would like to install other dependencies, you can install them as follows:

```
conda install -n pandas_dev -c pandas pytables scipy
```

To install *all* pandas dependencies you can do the following:

```
conda install -n pandas_dev -c pandas --file ci/requirements_all.txt
```

To work in this environment, `activate` it as follows:

```
activate pandas_dev
```

At which point, the prompt will change to indicate you are in the new development environment.

Note: The above syntax is for `windows` environments. To work on `macosx/linux`, use:

```
source activate pandas_dev
```

To view your environments:

```
conda info -e
```

To return to you home root environment:

```
deactivate
```

See the full `conda` docs here.

At this point you can easily do an *in-place* install, as detailed in the next section.

3.3.6 Making changes

Before making your code changes, it is often necessary to build the code that was just checked out. There are two primary methods of doing this.

1. The best way to develop *pandas* is to build the C extensions in-place by running:

   ```
   python setup.py build_ext --inplace
   ```

   If you startup the Python interpreter in the *pandas* source directory you will call the built C extensions

2. Another very common option is to do a `develop` install of *pandas*:

```
python setup.py develop
```

This makes a symbolic link that tells the Python interpreter to import *pandas* from your development directory. Thus, you can always be using the development version on your system without being inside the clone directory.

3.4 Contributing to the documentation

If you're not the developer type, contributing to the documentation is still of huge value. You don't even have to be an expert on *pandas* to do so! Something as simple as rewriting small passages for clarity as you reference the docs is a simple but effective way to contribute. The next person to read that passage will be in your debt!

Actually, there are sections of the docs that are worse off by being written by experts. If something in the docs doesn't make sense to you, updating the relevant section after you figure it out is a simple way to ensure it will help the next person.

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 the **Numpy Docstring Standard** which is used widely in the Scientific Python community. This standard specifies the format of the different sections of the docstring. See this document for a detailed explanation, or look at some of the existing functions to extend it in a similar manner.

- The tutorials make heavy use of the ipython directive sphinx extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

  ```
  .. ipython:: python

      x = 2
      x**3
  ```

  will be rendered as

  ```
  In [1]: x = 2
  ```

```
In [2]: x**3
Out[2]: 8
```

This means that almost all code examples in the docs are always run (and the output saved) during the doc build. This way, they will always be up to date, but it makes the doc building a bit more complex.

3.4.2 How to build the pandas documentation

Requirements

To build the *pandas* docs there are some extra requirements: you will need to have `sphinx` and `ipython` installed. numpydoc is used to parse the docstrings that follow the Numpy Docstring Standard (see above), but you don't need to install this because a local copy of `numpydoc` is included in the *pandas* source code.

It is easiest to *create a development environment*, then install:

```
conda install -n pandas_dev sphinx ipython
```

Furthermore, it is recommended to have all optional dependencies installed. This is not strictly necessary, but be aware that you will see some error messages. Because all the code in the documentation is executed during the doc build, the examples using this optional dependencies will generate errors. Run `pd.show_versions()` to get an overview of the installed version of all dependencies.

Warning: Sphinx version >= 1.2.2 or the older 1.1.3 is required.

Building the documentation

So how do you build the docs? Navigate to your local the folder `pandas/doc/` directory in the console and run:

```
python make.py html
```

And then you can find the html output in the folder `pandas/doc/build/html/`.

The first time it will take quite a while, because it has to run all the code examples in the documentation and build all generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean
python make.py build
```

Starting with 0.13.1 you can tell `make.py` to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes. You will be prompted to delete *.rst* files that aren't required. This is okay since the prior version can be checked out from git, but make sure to not commit the file deletions.

```
#omit autosummary and API section
python make.py clean
python make.py --no-api

# compile the docs with only a single
# section, that which is in indexing.rst
python make.py clean
python make.py --single indexing
```

For comparison, a full documentation build may take 10 minutes. a `-no-api` build may take 3 minutes and a single section may take 15 seconds. However, subsequent builds only process portions you changed. Now, open the following file in a web browser to see the full documentation you just built:

```
pandas/docs/build/html/index.html
```

And you'll have the satisfaction of seeing your new and improved documentation!

Built Master Branch Documentation

When pull-requests are merged into the pandas *master* branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted here.

3.5 Contributing to the code base

Code Base:

3.5.1 Code Standards

pandas uses the PEP8 standard. There are several tools to ensure you abide by this standard.

We've written a tool to check that your commits are PEP8 great, pip install pep8radius. Look at PEP8 fixes in your branch vs master with:

```
pep8radius master --diff` and make these changes with `pep8radius master --diff --in-place`
```

Alternatively, use flake8 tool for checking the style of your code. Additional standards are outlined on the code style wiki page.

Please try to maintain backward-compatibility. *Pandas* has lots of users with lots of existing code, so don't break it if at all possible. If you think breakage is required clearly state why as part of the Pull Request. Also, be careful when changing method signatures and add deprecation warnings where needed.

3.5.2 Test-driven Development/Writing Code

Pandas is serious about testing and strongly encourages individuals to embrace Test-driven Development (TDD). This development process "relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount of code to pass that test." So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to *pandas*. It is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, *pandas* uses the Nose testing system and the convenient extensions in numpy.testing.

Writing tests

All tests should go into the *tests* subdirectory of the specific package. There are probably many examples already there and looking to these for inspiration is suggested. If you test requires working with files or network connectivity there is more information on the testing page of the wiki.

The `pandas.util.testing` module has many special `assert` functions that make it easier to make statements about whether Series or DataFrame objects are equivalent. The easiest way to verify that your code is correct is to explicitly construct the result you expect, then compare the actual result to the expected correct result:

```
def test_pivot(self):
    data = {
        'index' : ['A', 'B', 'C', 'C', 'B', 'A'],
        'columns' : ['One', 'One', 'One', 'Two', 'Two', 'Two'],
        'values' : [1., 2., 3., 3., 2., 1.]
    }

    frame = DataFrame(data)
    pivoted = frame.pivot(index='index', columns='columns', values='values')

    expected = DataFrame({
        'One' : {'A' : 1., 'B' : 2., 'C' : 3.},
        'Two' : {'A' : 1., 'B' : 2., 'C' : 3.}
    })

    assert_frame_equal(pivoted, expected)
```

Running the test suite

The tests can then be run directly inside your git clone (without having to install *pandas*) by typing::

```
nosetests pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite. This is done using one of the following constructs:

```
nosetests pandas/tests/[test-module].py
nosetests pandas/tests/[test-module].py:[TestClass]
nosetests pandas/tests/[test-module].py:[TestClass].[test_method]
```

Running the performance test suite

Performance matters and it is worth considering that your code has not introduced performance regressions. Currently *pandas* uses the vbench library to enable easy monitoring of the performance of critical *pandas* operations. These benchmarks are all found in the `pandas/vb_suite` directory. vbench currently only works on python2.

To install vbench:

```
pip install git+https://github.com/pydata/vbench
```

Vbench also requires sqlalchemy, gitpython, and psutil which can all be installed using pip. If you need to run a benchmark, change your directory to the *pandas* root and run:

```
./test_perf.sh -b master -t HEAD
```

This will checkout the master revision and run the suite on both master and your commit. Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to past a subset of the results in to the Pull Request to show that the committed changes do not cause unexpected performance regressions.

You can run specific benchmarks using the *-r* flag which takes a regular expression.

See the performance testing wiki for information on how to write a benchmark.

3.5.3 Documenting your code

Changes should be reflected in the release notes located in *doc/source/whatsnew/vx.y.z.txt*. This file contains an ongoing change log for each release. Add an entry to this file to document your fix, enhancement or (unavoidable) breaking change. Make sure to include the GitHub issue number when adding your entry.

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.

3.6 Contributing your changes to *pandas*

3.6.1 Committing your code

Keep style fixes to a separate commit to make your PR more readable.

Once you've made changes, you can see them by typing:

```
git status
```

If you've created a new file, it is not being tracked by git. Add it by typing

```
git add path/to/file-to-be-added.py
```

Doing 'git status' again should give something like

```
# On branch shiny-new-feature
#
#       modified:   /relative/path/to/file-you-added.py
#
```

Finally, commit your changes to your local repository with an explanatory message. *Pandas* uses a convention for commit message prefixes and layout. Here are some common prefixes along with general guidelines for when to use them:

- ENH: Enhancement, new functionality
- BUG: Bug fix
- DOC: Additions/updates to documentation
- TST: Additions/updates to tests
- BLD: Updates to the build process/scripts
- PERF: Performance improvement
- CLN: Code cleanup

The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using *GH1234* or *#1234*. Either style is fine, but the former is generally preferred:

- a subject line with < *80* chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

If you have multiple commits, it is common to want to combine them into one commit, often referred to as "squashing" or "rebasing". This is a common request by package maintainers when submitting a Pull Request as it maintains a more compact commit history. To rebase your commits:

```
git rebase -i HEAD~#
```

Where # is the number of commits you want to combine. Then you can pick the relevant commit message and discard others.

3.6.2 Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch's commits

```
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/pydata/pandas.git (fetch)
upstream        git://github.com/pydata/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the *pandas* project. For that to happen, a Pull Request needs to be submitted on GitHub.

3.6.3 Review your code

When you're ready to ask for a code review, you will file a Pull Request. Before you do, again make sure you've followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based off of:

1. Navigate to your repository on GitHub–https://github.com/your-user-name/pandas.
2. Click on *Branches*.
3. Click on the *Compare* button for your feature branch.
4. Select the *base* and *compare* branches, if necessary. This will be *master* and *shiny-new-feature*, respectively.

3.6.4 Finally, make the Pull Request

If everything looks good you are ready to make a Pull Request. A Pull Request is how code from a local repository becomes available to the GitHub community and can be looked at and eventually merged into the master version. This Pull Request and its associated changes will eventually be committed to the master branch and available in the next release. To submit a Pull Request:

1. Navigate to your repository on GitHub.
2. Click on the *Pull Request* button.
3. You can then click on *Commits* and *Files Changed* to make sure everything looks okay one last time.
4. Write a description of your changes in the *Preview Discussion* tab.
5. Click *Send Pull Request*.

This request then appears to the repository maintainers, and they will review the code. If you need to make more changes, you can make them in your branch, push them to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push -f origin shiny-new-feature
```

This will automatically update your Pull Request with the latest code and restart the Travis-CI tests.

3.6.5 Delete your merged branch (optional)

Once your feature branch is accepted into upstream, you'll probably want to get rid of the branch. First, merge upstream master into your branch so git knows it is safe to delete your branch

```
git fetch upstream
git checkout master
git merge upstream/master
```

Then you can just do:

```
git branch -d shiny-new-feature
```

Make sure you use a lower-case -d, or else git won't warn you if your feature branch has not actually been merged.

The branch will still exist on GitHub, so to delete it there do

```
git push origin --delete shiny-new-feature
```

CHAPTER

FOUR

FREQUENTLY ASKED QUESTIONS (FAQ)

4.1 DataFrame memory usage

As of pandas version 0.15.0, the memory usage of a dataframe (including the index) is shown when accessing the `info` method of a dataframe. A configuration option, `display.memory_usage` (see *Options and Settings*), specifies if the dataframe's memory usage will be displayed when invoking the `df.info()` method.

For example, the memory usage of the dataframe below is shown when calling `df.info()`:

```
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 = DataFrame(data)

In [5]: df['categorical'] = df['object'].astype('category')

In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool               5000 non-null bool
complex128         5000 non-null complex128
datetime64[ns]     5000 non-null datetime64[ns]
float64            5000 non-null float64
int64              5000 non-null int64
object             5000 non-null object
timedelta64[ns]    5000 non-null timedelta64[ns]
categorical        5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), object(1), time
memory usage: 303.5+ KB
```

The + symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with `dtype=object`.

By default the display option is set to `True` but can be explicitly overridden by passing the `memory_usage` argument when invoking `df.info()`.

The memory usage of each column can be found by calling the `memory_usage` method. This returns a Series with an index represented by column names and memory usage of each column shown in bytes. For the dataframe above, the memory usage of each column and the total memory usage of the dataframe can be found with the memory_usage method:

```
In [7]: df.memory_usage()
Out[7]:
bool                 5000
complex128          80000
datetime64[ns]      40000
float64             40000
int64               40000
object              20000
timedelta64[ns]     40000
categorical          5800
dtype: int64

# total memory usage of dataframe
In [8]: df.memory_usage().sum()
Out[8]: 270800
```

By default the memory usage of the dataframe's index is not shown in the returned Series, the memory usage of the index can be shown by passing the `index=True` argument:

```
In [9]: df.memory_usage(index=True)
Out[9]:
Index               40000
bool                 5000
complex128          80000
datetime64[ns]      40000
float64             40000
int64               40000
object              20000
timedelta64[ns]     40000
categorical          5800
dtype: int64
```

The memory usage displayed by the `info` method utilizes the `memory_usage` method to determine the memory usage of a dataframe while also formatting the output in human-readable units (base-2 representation; i.e., 1KB = 1024 bytes).

See also *Categorical Memory Usage*.

4.2 Migrating from scikits.timeseries to pandas >= 0.8.0

Starting with pandas 0.8.0, users of scikits.timeseries should have all of the features that they need to migrate their code to use pandas. Portions of the scikits.timeseries codebase for implementing calendar logic and timespan frequency conversions (but **not** resampling, that has all been implemented from scratch from the ground up) have been ported to the pandas codebase.

The scikits.timeseries notions of `Date` and `DateArray` are responsible for implementing calendar logic:

```
In [16]: dt = ts.Date('Q', '1984Q3')

# sic
In [17]: dt
Out[17]: <Q-DEC : 1984Q1>
```

```
In [18]: dt.asfreq('D', 'start')
Out[18]: <D : 01-Jan-1984>

In [19]: dt.asfreq('D', 'end')
Out[19]: <D : 31-Mar-1984>

In [20]: dt + 3
Out[20]: <Q-DEC : 1984Q4>
```

`Date` and `DateArray` from scikits.timeseries have been reincarnated in pandas `Period` and `PeriodIndex`:

```
In [10]: pnow('D')  # scikits.timeseries.now()
Out[10]: Period('2015-06-13', 'D')

In [11]: Period(year=2007, month=3, day=15, freq='D')
Out[11]: Period('2007-03-15', 'D')

In [12]: p = Period('1984Q3')

In [13]: p
Out[13]: Period('1984Q3', 'Q-DEC')

In [14]: p.asfreq('D', 'start')
Out[14]: Period('1984-07-01', 'D')

In [15]: p.asfreq('D', 'end')
Out[15]: Period('1984-09-30', 'D')

In [16]: (p + 3).asfreq('T') + 6 * 60 + 30
Out[16]: Period('1985-07-01 06:29', 'T')

In [17]: rng = period_range('1990', '2010', freq='A')

In [18]: rng
Out[18]: 
PeriodIndex(['1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997',
             '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
             '2006', '2007', '2008', '2009', '2010'],
            dtype='int64', freq='A-DEC')

In [19]: rng.asfreq('B', 'end') - 3
Out[19]: 
PeriodIndex(['1990-12-26', '1991-12-26', '1992-12-28', '1993-12-28',
             '1994-12-27', '1995-12-26', '1996-12-26', '1997-12-26',
             '1998-12-28', '1999-12-28', '2000-12-26', '2001-12-26',
             '2002-12-26', '2003-12-26', '2004-12-28', '2005-12-27',
             '2006-12-26', '2007-12-26', '2008-12-26', '2009-12-28',
             '2010-12-28'],
            dtype='int64', freq='B')
```

scikits.timeseries	pandas	Notes
Date	Period	A span of time, from yearly through to secondly
DateArray	PeriodIndex	An array of timespans
convert	resample	Frequency conversion in scikits.timeseries
convert_to_annual	pivot_annual	currently supports up to daily frequency, see GH736

4.2.1 PeriodIndex / DateArray properties and functions

The scikits.timeseries `DateArray` had a number of information properties. Here are the pandas equivalents:

scikits.timeseries	pandas	Notes
get_steps	`np.diff(idx.values)`	
has_missing_dates	`not idx.is_full`	
is_full	`idx.is_full`	
is_valid	`idx.is_monotonic and idx.is_unique`	
is_chronological	`is_monotonic`	
`arr.sort_chronologically()`	`idx.order()`	

4.2.2 Frequency conversion

Frequency conversion is implemented using the `resample` method on Series and DataFrame objects with a DatetimeIndex or PeriodIndex. `resample` also works on panels (3D). Here is some code that resamples daily data to montly:

```
In [20]: rng = period_range('Jan-2000', periods=50, freq='M')

In [21]: data = Series(np.random.randn(50), index=rng)

In [22]: data
Out[22]:
2000-01    1.544821
2000-02   -1.708552
2000-03    1.545458
2000-04   -0.735738
2000-05   -0.649091
2000-06   -0.403878
2000-07   -2.474932
             ...
2003-08    1.034493
2003-09    1.269838
2003-10    0.606166
2003-11   -0.827409
2003-12   -0.943863
2004-01    1.041569
2004-02    0.701815
Freq: M, dtype: float64

In [23]: data.resample('A', how=np.mean)
Out[23]:
2000    0.102447
2001   -0.204847
2002    0.210840
2003    0.300564
2004    0.871692
Freq: A-DEC, dtype: float64
```

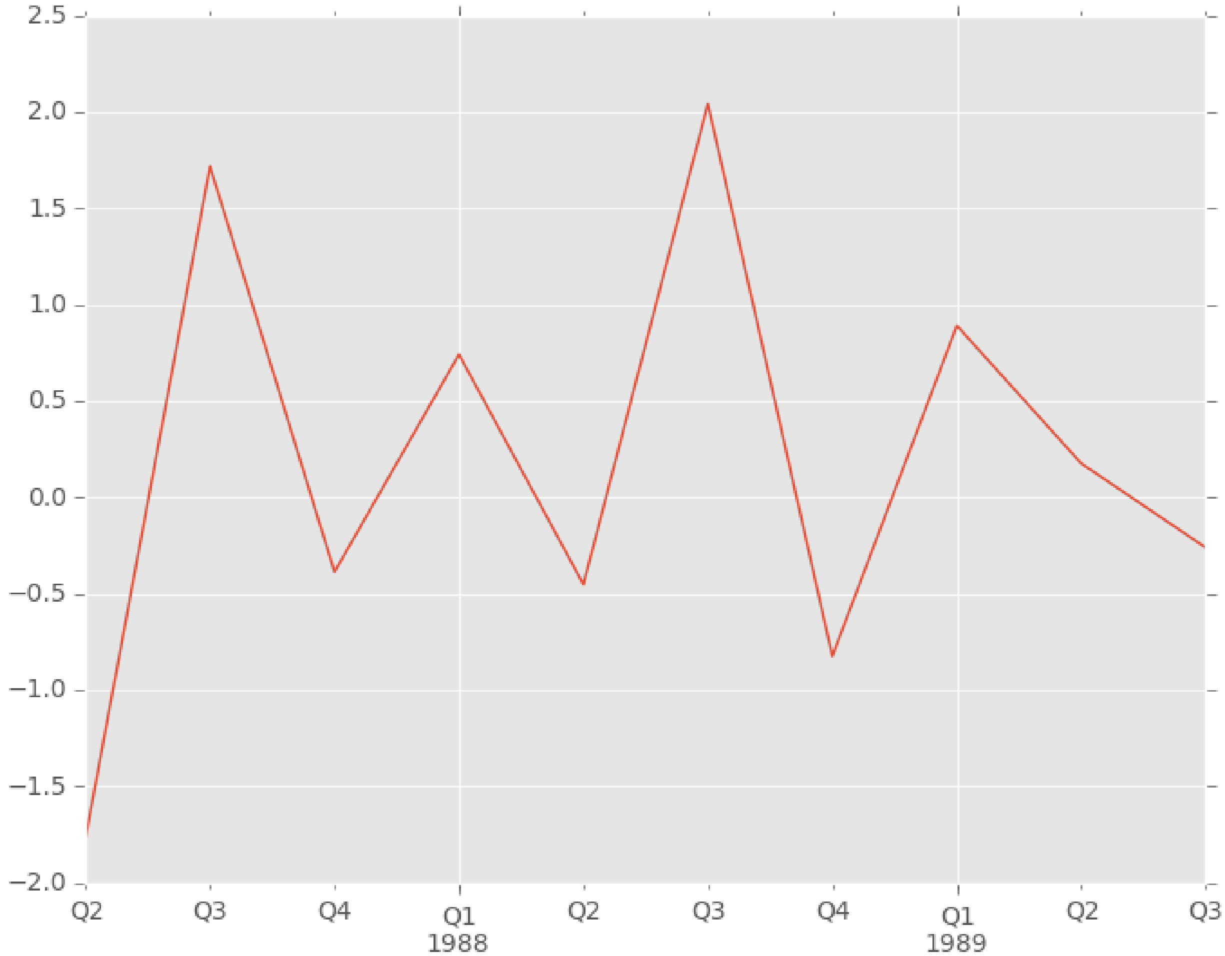
4.2.3 Plotting

Much of the plotting functionality of scikits.timeseries has been ported and adopted to pandas's data structures. For example:

```
In [24]: rng = period_range('1987Q2', periods=10, freq='Q-DEC')

In [25]: data = Series(np.random.randn(10), index=rng)

In [26]: plt.figure(); data.plot()
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0xaa2bb16c>
```



4.2.4 Converting to and from period format

Use the `to_timestamp` and `to_period` instance methods.

4.2.5 Treatment of missing data

Unlike scikits.timeseries, pandas data structures are not based on NumPy's `MaskedArray` object. Missing data is represented as `NaN` in numerical arrays and either as `None` or `NaN` in non-numerical arrays. Implementing a version of pandas's data structures that use MaskedArray is possible but would require the involvement of a dedicated maintainer. Active pandas developers are not interested in this.

4.2.6 Resampling with timestamps and periods

`resample` has a `kind` argument which allows you to resample time series with a DatetimeIndex to PeriodIndex:

```
In [27]: rng = date_range('1/1/2000', periods=200, freq='D')

In [28]: data = Series(np.random.randn(200), index=rng)

In [29]: data[:10]
Out[29]:
2000-01-01   -0.197661
2000-01-02    0.507155
2000-01-03   -0.493913
2000-01-04   -0.994339
2000-01-05   -0.581662
2000-01-06   -0.855251
2000-01-07   -0.256469
2000-01-08   -0.454868
2000-01-09    0.519612
2000-01-10    0.764490
Freq: D, dtype: float64

In [30]: data.index
Out[30]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10',
               ...
               '2000-07-09', '2000-07-10', '2000-07-11', '2000-07-12',
               '2000-07-13', '2000-07-14', '2000-07-15', '2000-07-16',
               '2000-07-17', '2000-07-18'],
              dtype='datetime64[ns]', length=200, freq='D', tz=None)

In [31]: data.resample('M', kind='period')
Out[31]:
2000-01   -0.226155
2000-02    0.056704
2000-03   -0.132553
2000-04   -0.064003
2000-05    0.233736
2000-06   -0.301008
2000-07   -0.584631
Freq: M, dtype: float64
```

Similarly, resampling from periods to timestamps is possible with an optional interval (`'start'` or `'end'`) convention:

```
In [32]: rng = period_range('Jan-2000', periods=50, freq='M')

In [33]: data = Series(np.random.randn(50), index=rng)

In [34]: resampled = data.resample('A', kind='timestamp', convention='end')

In [35]: resampled.index
Out[35]:
DatetimeIndex(['2000-12-31', '2001-12-31', '2002-12-31', '2003-12-31',
               '2004-12-31'],
              dtype='datetime64[ns]', freq='A-DEC', tz=None)
```

4.3 Byte-Ordering Issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to Series/DataFrame/Panel constructors using something similar to the following:

```
In [36]: x = np.array(list(range(10)), '>i4') # big endian

In [37]: newx = x.byteswap().newbyteorder() # force native byteorder

In [38]: s = Series(newx)
```

See the NumPy documentation on byte order for more details.

4.4 Visualizing Data in Qt applications

Warning: The `qt` support is **deprecated and will be removed in a future version**. We refer users to the external package pandas-qt.

There is experimental support for visualizing DataFrames in PyQt4 and PySide applications. At the moment you can display and edit the values of the cells in the DataFrame. Qt will take care of displaying just the portion of the DataFrame that is currently visible and the edits will be immediately saved to the underlying DataFrame

To demonstrate this we will create a simple PySide application that will switch between two editable DataFrames. For this will use the `DataFrameModel` class that handles the access to the DataFrame, and the `DataFrameWidget`, which is just a thin layer around the `QTableView`.

```
import numpy as np
import pandas as pd
from pandas.sandbox.qtpandas import DataFrameModel, DataFrameWidget
from PySide import QtGui, QtCore

# Or if you use PyQt4:
# from PyQt4 import QtGui, QtCore

class MainWidget(QtGui.QWidget):
    def __init__(self, parent=None):
        super(MainWidget, self).__init__(parent)

        # Create two DataFrames
        self.df1 = pd.DataFrame(np.arange(9).reshape(3, 3),
                                columns=['foo', 'bar', 'baz'])
        self.df2 = pd.DataFrame({
                'int': [1, 2, 3],
                'float': [1.5, 2.5, 3.5],
                'string': ['a', 'b', 'c'],
                'nan': [np.nan, np.nan, np.nan]
            }, index=['AAA', 'BBB', 'CCC'],
            columns=['int', 'float', 'string', 'nan'])

        # Create the widget and set the first DataFrame
        self.widget = DataFrameWidget(self.df1)

        # Create the buttons for changing DataFrames
        self.button_first = QtGui.QPushButton('First')
```

```
        self.button_first.clicked.connect(self.on_first_click)
        self.button_second = QtGui.QPushButton('Second')
        self.button_second.clicked.connect(self.on_second_click)

        # Set the layout
        vbox = QtGui.QVBoxLayout()
        vbox.addWidget(self.widget)
        hbox = QtGui.QHBoxLayout()
        hbox.addWidget(self.button_first)
        hbox.addWidget(self.button_second)
        vbox.addLayout(hbox)
        self.setLayout(vbox)

    def on_first_click(self):
        '''Sets the first DataFrame'''
        self.widget.setDataFrame(self.df1)

    def on_second_click(self):
        '''Sets the second DataFrame'''
        self.widget.setDataFrame(self.df2)

if __name__ == '__main__':
    import sys

    # Initialize the application
    app = QtGui.QApplication(sys.argv)
    mw = MainWidget()
    mw.show()
    app.exec_()
```

CHAPTER

FIVE

PACKAGE OVERVIEW

`pandas` consists of the following things

- A set of labeled array data structures, the primary of which are Series and DataFrame
- Index objects enabling both simple axis indexing and multi-level / hierarchical axis indexing
- An integrated group by engine for aggregating and transforming data sets
- Date range generation (date_range) and custom date offsets enabling the implementation of customized frequencies
- Input/Output tools: loading tabular data from flat files (CSV, delimited, Excel 2003), and saving and loading pandas objects from the fast and efficient PyTables/HDF5 format.
- Memory-efficient "sparse" versions of the standard data structures for storing data that is mostly missing or mostly constant (some fixed value)
- Moving window statistics (rolling mean, rolling standard deviation, etc.)
- Static and moving window linear and panel regression

5.1 Data structures at a glance

Dimensions	Name	Description
1	Series	1D labeled homogeneously-typed array
2	DataFrame	General 2D labeled, size-mutable tabular structure with potentially heterogeneously-typed columns
3	Panel	General 3D labeled, also size-mutable array

5.1.1 Why more than 1 data structure?

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

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

For example, with tabular data (DataFrame) it is more semantically helpful to think of the **index** (the rows) and the **columns** rather than axis 0 and axis 1. And iterating through the columns of the DataFrame thus results in more readable code:

```
for col in df.columns:
    series = df[col]
    # do something with series
```

5.2 Mutability and copying of data

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

5.3 Getting Support

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

Longer discussions occur on the developer mailing list, and commercial support inquiries for Lambda Foundry should be sent to: support@lambdafoundry.com

5.4 Credits

pandas development began at AQR Capital Management in April 2008. It was open-sourced at the end of 2009. AQR continued to provide resources for development through the end of 2011, and continues to contribute bug reports today.

Since January 2012, Lambda Foundry, has been providing development resources, as well as commercial support, training, and consulting for pandas.

pandas is only made possible by a group of people around the world like you who have contributed new code, bug reports, fixes, comments and ideas. A complete list can be found on Github.

5.5 Development Team

pandas is a part of the PyData project. The PyData Development Team is a collection of developers focused on the improvement of Python's data libraries. The core team that coordinates development can be found on Github. If you're interested in contributing, please visit the project website.

5.6 License

```
=======
License
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AQR Capital Management began pandas development in 2008. Development was
led by Wes McKinney. AQR released the source under this license in 2009.
Wes is now an employee of Lambda Foundry, and remains the pandas project
lead.

The PyData Development Team is the collection of developers of the PyData
project. This includes all of the PyData sub-projects, including pandas. The
core team that coordinates development on GitHub can be found here:
http://github.com/pydata.

Full credits for pandas contributors can be found in the documentation.

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```

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```

CHAPTER

SIX

10 MINUTES TO PANDAS

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the *Cookbook*

Customarily, we import as follows

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

In [2]: import numpy as np

In [3]: import matplotlib.pyplot as plt
```

6.1 Object Creation

See the *Data Structure Intro section*

Creating a `Series` by passing a list of values, letting pandas create a default integer index:

```
In [4]: s = pd.Series([1,3,5,np.nan,6,8])

In [5]: s
Out[5]:
0     1
1     3
2     5
3   NaN
4     6
5     8
dtype: float64
```

Creating a `DataFrame` by passing a numpy array, with a datetime index and labeled columns:

```
In [6]: dates = pd.date_range('20130101', periods=6)

In [7]: dates
Out[7]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D', tz=None)

In [8]: df = pd.DataFrame(np.random.randn(6,4), index=dates, columns=list('ABCD'))

In [9]: df
Out[9]:
                   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
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
```

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 2013-01-02  1  3   test  foo
1  1 2013-01-02  1  3  train  foo
2  1 2013-01-02  1  3   test  foo
3  1 2013-01-02  1  3  train  foo
```

Having specific *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.boxplot
df2.abs                df2.C
df2.add                df2.clip
df2.add_prefix         df2.clip_lower
df2.add_suffix         df2.clip_upper
df2.align              df2.columns
df2.all                df2.combine
df2.any                df2.combineAdd
df2.append             df2.combine_first
df2.apply              df2.combineMult
df2.applymap           df2.compound
df2.as_blocks          df2.consolidate
df2.asfreq             df2.convert_objects
df2.as_matrix          df2.copy
df2.astype             df2.corr
df2.at                 df2.corrwith
df2.at_time            df2.count
df2.axes               df2.cov
```

```
df2.B                    df2.cummax
df2.between_time         df2.cummin
df2.bfill                df2.cumprod
df2.blocks               df2.cumsum
df2.bool                 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.

6.2 Viewing Data

See the *Basics section*

See the top & 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', tz=None)

In [17]: df.columns
Out[17]: Index([u'A', u'B', u'C', u'D'], dtype='object')

In [18]: df.values
Out[18]:
array([[ 0.4691, -0.2829, -1.5091, -1.1356],
       [ 1.2121, -0.1732,  0.1192, -1.0442],
       [-0.8618, -2.1046, -0.4949,  1.0718],
       [ 0.7216, -0.7068, -1.0396,  0.2719],
       [-0.425 ,  0.567 ,  0.2762, -1.0874],
       [-0.6737,  0.1136, -1.4784,  0.525 ]])
```

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 -0.767252 -0.386188
75%    0.658444  0.041933 -0.034326  0.461706
max    1.212112  0.567020  0.276232  1.071804
```

Transposing your data

```
In [20]: df.T
Out[20]:
   2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  2013-01-06
A    0.469112    1.212112   -0.861849    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
```

Sorting by an axis

```
In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:
                   D         C         B         A
2013-01-01 -1.135632 -1.509059 -0.282863  0.469112
2013-01-02 -1.044236  0.119209 -0.173215  1.212112
2013-01-03  1.071804 -0.494929 -2.104569 -0.861849
2013-01-04  0.271860 -1.039575 -0.706771  0.721555
2013-01-05 -1.087401  0.276232  0.567020 -0.424972
2013-01-06  0.524988 -1.478427  0.113648 -0.673690
```

Sorting by values

```
In [22]: df.sort(columns='B')
Out[22]:
                   A         B         C         D
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
```

6.3 Selection

Note: While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc`, `.iloc` and `.ix`.

See the indexing documentation *Indexing and Selecing Data* and *MultiIndex / Advanced Indexing*

6.3.1 Getting

Selecting a single column, which yields a `Series`, equivalent to `df.A`

```
In [23]: df['A']
Out[23]:
2013-01-01    0.469112
2013-01-02    1.212112
2013-01-03   -0.861849
2013-01-04    0.721555
2013-01-05   -0.424972
2013-01-06   -0.673690
Freq: D, Name: A, dtype: float64
```

Selecting via [], which slices the rows.

```
In [24]: df[0:3]
Out[24]:
                   A         B         C         D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804

In [25]: df['20130102':'20130104']
Out[25]:
                   A         B         C         D
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
```

6.3.2 Selection by Label

See more in *Selection by Label*

For getting a cross section using a label

```
In [26]: df.loc[dates[0]]
Out[26]:
A    0.469112
B   -0.282863
C   -1.509059
D   -1.135632
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label

```
In [27]: df.loc[:,['A','B']]
Out[27]:
                   A         B
2013-01-01  0.469112 -0.282863
2013-01-02  1.212112 -0.173215
2013-01-03 -0.861849 -2.104569
2013-01-04  0.721555 -0.706771
2013-01-05 -0.424972  0.567020
2013-01-06 -0.673690  0.113648
```

Showing label slicing, both endpoints are *included*

```
In [28]: df.loc['20130102':'20130104',['A','B']]
Out[28]:
                   A         B
2013-01-02  1.212112 -0.173215
```

```
2013-01-03 -0.861849 -2.104569
2013-01-04  0.721555 -0.706771
```

Reduction in the dimensions of the returned object

```
In [29]: df.loc['20130102',['A','B']]
Out[29]:
A    1.212112
B   -0.173215
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value

```
In [30]: df.loc[dates[0],'A']
Out[30]: 0.46911229990718628
```

For getting fast access to a scalar (equiv to the prior method)

```
In [31]: df.at[dates[0],'A']
Out[31]: 0.46911229990718628
```

6.3.3 Selection by Position

See more in *Selection by Position*

Select via the position of the passed integers

```
In [32]: df.iloc[3]
Out[32]:
A    0.721555
B   -0.706771
C   -1.039575
D    0.271860
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python

```
In [33]: df.iloc[3:5,0:2]
Out[33]:
                   A         B
2013-01-04  0.721555 -0.706771
2013-01-05 -0.424972  0.567020
```

By lists of integer position locations, similar to the numpy/python style

```
In [34]: df.iloc[[1,2,4],[0,2]]
Out[34]:
                   A         C
2013-01-02  1.212112  0.119209
2013-01-03 -0.861849 -0.494929
2013-01-05 -0.424972  0.276232
```

For slicing rows explicitly

```
In [35]: df.iloc[1:3,:]
Out[35]:
                   A         B         C         D
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
```

For slicing columns explicitly

```
In [36]: df.iloc[:,1:3]
Out[36]:
                   B         C
2013-01-01 -0.282863 -1.509059
2013-01-02 -0.173215  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 (equiv to the prior method)

```
In [38]: df.iat[1,1]
Out[38]: -0.17321464905330858
```

6.3.4 Boolean Indexing

Using a single column's values to select data.

```
In [39]: df[df.A > 0]
Out[39]:
                   A         B         C         D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
```

A `where` operation for getting.

```
In [40]: df[df > 0]
Out[40]:
                   A         B         C         D
2013-01-01  0.469112       NaN       NaN       NaN
2013-01-02  1.212112       NaN  0.119209       NaN
2013-01-03       NaN       NaN       NaN  1.071804
2013-01-04  0.721555       NaN       NaN  0.271860
2013-01-05       NaN  0.567020  0.276232       NaN
2013-01-06       NaN  0.113648       NaN  0.524988
```

Using the `isin()` method for filtering:

```
In [41]: df2 = df.copy()

In [42]: df2['E'] = ['one', 'one','two','three','four','three']

In [43]: df2
Out[43]:
                   A         B         C         D      E
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632    one
2013-01-02  1.212112 -0.173215  0.119209 -1.044236    one
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804    two
2013-01-04  0.721555 -0.706771 -1.039575  0.271860  three
2013-01-05 -0.424972  0.567020  0.276232 -1.087401   four
```

```
2013-01-06 -0.673690  0.113648 -1.478427  0.524988  three

In [44]: df2[df2['E'].isin(['two','four'])]
Out[44]:
                   A         B         C         D     E
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804   two
2013-01-05 -0.424972  0.567020  0.276232 -1.087401  four
```

6.3.5 Setting

Setting a new column automatically aligns the data by the indexes

```
In [45]: s1 = pd.Series([1,2,3,4,5,6], index=pd.date_range('20130102', periods=6))

In [46]: s1
Out[46]:
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]:
                   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
2013-01-03 -0.861849 -2.104569 -0.494929  5   2
2013-01-04  0.721555 -0.706771 -1.039575  5   3
2013-01-05 -0.424972  0.567020  0.276232  5   4
2013-01-06 -0.673690  0.113648 -1.478427  5   5
```

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
2013-01-03 -0.861849 -2.104569 -0.494929 -5  -2
2013-01-04 -0.721555 -0.706771 -1.039575 -5  -3
2013-01-05 -0.424972 -0.567020 -0.276232 -5  -4
2013-01-06 -0.673690 -0.113648 -1.478427 -5  -5
```

6.4 Missing Data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the *Missing Data section*

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])

In [56]: df1.loc[dates[0]:dates[1],'E'] = 1

In [57]: df1
Out[57]: 
                   A         B         C  D   F   E
2013-01-01  0.000000  0.000000 -1.509059  5 NaN   1
2013-01-02  1.212112 -0.173215  0.119209  5   1   1
2013-01-03 -0.861849 -2.104569 -0.494929  5   2 NaN
2013-01-04  0.721555 -0.706771 -1.039575  5   3 NaN
```

To drop any rows that have missing data.

```
In [58]: df1.dropna(how='any')
Out[58]: 
                   A         B         C  D  F  E
2013-01-02  1.212112 -0.173215  0.119209  5  1  1
```

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  1
2013-01-02  1.212112 -0.173215  0.119209  5  1  1
2013-01-03 -0.861849 -2.104569 -0.494929  5  2  5
2013-01-04  0.721555 -0.706771 -1.039575  5  3  5
```

To get the boolean mask where values are `nan`

```
In [60]: pd.isnull(df1)
Out[60]: 
                A      B      C      D      F      E
2013-01-01  False  False  False  False   True  False
2013-01-02  False  False  False  False  False  False
2013-01-03  False  False  False  False  False   True
2013-01-04  False  False  False  False  False   True
```

6.5 Operations

See the *Basic section on Binary Ops*

6.5.1 Stats

Operations in general *exclude* missing data.

Performing a descriptive statistic

```
In [61]: df.mean()
Out[61]:
A   -0.004474
B   -0.383981
C   -0.687758
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis

```
In [62]: df.mean(1)
Out[62]:
2013-01-01    0.872735
2013-01-02    1.431621
2013-01-03    0.707731
2013-01-04    1.395042
2013-01-05    1.883656
2013-01-06    1.592306
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1,3,5,np.nan,6,8], index=dates).shift(2)

In [64]: s
Out[64]:
2013-01-01   NaN
2013-01-02   NaN
2013-01-03     1
2013-01-04     3
2013-01-05     5
2013-01-06   NaN
Freq: D, dtype: float64

In [65]: df.sub(s, axis='index')
Out[65]:
                   A         B         C   D   F
2013-01-01       NaN       NaN       NaN NaN NaN
2013-01-02       NaN       NaN       NaN NaN NaN
2013-01-03 -1.861849 -3.104569 -1.494929   4   1
2013-01-04 -2.278445 -3.706771 -4.039575   2   0
2013-01-05 -5.424972 -4.432980 -4.723768   0  -1
2013-01-06       NaN       NaN       NaN NaN NaN
```

6.5.2 Apply

Applying functions to the data

```
In [66]: df.apply(np.cumsum)
Out[66]:
```

```
                   A         B         C   D   F
2013-01-01  0.000000  0.000000 -1.509059   5 NaN
2013-01-02  1.212112 -0.173215 -1.389850  10   1
2013-01-03  0.350263 -2.277784 -1.884779  15   3
2013-01-04  1.071818 -2.984555 -2.924354  20   6
2013-01-05  0.646846 -2.417535 -2.648122  25  10
2013-01-06 -0.026844 -2.303886 -4.126549  30  15

In [67]: df.apply(lambda x: x.max() - x.min())
Out[67]: 
A    2.073961
B    2.671590
C    1.785291
D    0.000000
F    4.000000
dtype: float64
```

6.5.3 Histogramming

See more at *Histogramming and Discretization*

```
In [68]: s = pd.Series(np.random.randint(0, 7, size=10))

In [69]: s
Out[69]: 
0    4
1    2
2    1
3    2
4    6
5    4
6    4
7    6
8    4
9    4
dtype: int32

In [70]: s.value_counts()
Out[70]: 
4    5
6    2
2    2
1    1
dtype: int64
```

6.5.4 String Methods

Series is equipped with a set of string processing methods in the *str* attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in *str* generally uses regular expressions by default (and in some cases always uses them). See more at *Vectorized String Methods*.

```
In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [72]: s.str.lower()
Out[72]: 
```

```
0       a
1       b
2       c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

6.6 Merge

6.6.1 Concat

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the *Merging section*

Concatenating pandas objects together with `concat()`:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))

In [74]: df
Out[74]:
          0         1         2         3
0 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495

# break it into pieces
In [75]: pieces = [df[:3], df[3:7], df[7:]]

In [76]: pd.concat(pieces)
Out[76]:
          0         1         2         3
0 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495
```

6.6.2 Join

SQL style merges. See the *Database style joining*

```
In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})

In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})

In [79]: left
Out[79]:
   key  lval
0  foo     1
1  foo     2

In [80]: right
Out[80]:
   key  rval
0  foo     4
1  foo     5

In [81]: pd.merge(left, right, on='key')
Out[81]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

6.6.3 Append

Append rows to a dataframe. See the *Appending*

```
In [82]: df = pd.DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])

In [83]: df
Out[83]:
          A         B         C         D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758

In [84]: s = df.iloc[3]

In [85]: df.append(s, ignore_index=True)
Out[85]:
          A         B         C         D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
```

```
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758
8  1.453749  1.208843 -0.080952 -0.264610
```

6.7 Grouping

By "group by" we are referring to a process involving one or more of the following steps

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the *Grouping section*

```
In [86]: df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
   ....:                           'foo', 'bar', 'foo', 'foo'],
   ....:                    'B' : ['one', 'one', 'two', 'three',
   ....:                           'two', 'two', 'one', 'three'],
   ....:                    'C' : np.random.randn(8),
   ....:                    'D' : np.random.randn(8)})
   ....:

In [87]: df
Out[87]:
     A      B         C         D
0  foo    one -1.202872 -0.055224
1  bar    one -1.814470  2.395985
2  foo    two  1.018601  1.552825
3  bar  three -0.595447  0.166599
4  foo    two  1.395433  0.047609
5  bar    two -0.392670 -0.136473
6  foo    one  0.007207 -0.561757
7  foo  three  1.928123 -1.623033
```

Grouping and then applying a function `sum` to the resulting groups.

```
In [88]: df.groupby('A').sum()
Out[88]:
            C        D
A
bar -2.802588  2.42611
foo  3.146492 -0.63958
```

Grouping by multiple columns forms a hierarchical index, which we then apply the function.

```
In [89]: df.groupby(['A','B']).sum()
Out[89]:
                  C         D
A   B
bar one   -1.814470  2.395985
    three -0.595447  0.166599
    two   -0.392670 -0.136473
foo one   -1.195665 -0.616981
    three  1.928123 -1.623033
    two    2.414034  1.600434
```

6.8 Reshaping

See the sections on *Hierarchical Indexing* and *Reshaping*.

6.8.1 Stack

```
In [90]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
   ....:                      'foo', 'foo', 'qux', 'qux'],
   ....:                     ['one', 'two', 'one', 'two',
   ....:                      'one', 'two', 'one', 'two']]))
   ....:

In [91]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [92]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [93]: df2 = df[:4]

In [94]: df2
Out[94]:
                     A         B
first second
bar   one     0.029399 -0.542108
      two     0.282696 -0.087302
baz   one    -1.575170  1.771208
      two     0.816482  1.100230
```

The `stack()` method "compresses" a level in the DataFrame's columns.

```
In [95]: stacked = df2.stack()

In [96]: stacked
Out[96]:
first  second
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 [97]: stacked.unstack()
Out[97]:
                     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 [98]: stacked.unstack(1)
```

```
Out[98]:
second        one       two
first
bar    A  0.029399  0.282696
       B -0.542108 -0.087302
baz    A -1.575170  0.816482
       B  1.771208  1.100230

In [99]: stacked.unstack(0)
Out[99]:
first          bar       baz
second
one     A  0.029399 -1.575170
        B -0.542108  1.771208
two     A  0.282696  0.816482
        B -0.087302  1.100230
```

6.8.2 Pivot Tables

See the section on *Pivot Tables*.

```
In [100]: df = pd.DataFrame({'A' : ['one', 'one', 'two', 'three'] * 3,
   .....:                    'B' : ['A', 'B', 'C'] * 4,
   .....:                    'C' : ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2,
   .....:                    'D' : np.random.randn(12),
   .....:                    'E' : np.random.randn(12)})
   .....:

In [101]: df
Out[101]:
        A  B    C         D         E
0     one  A  foo  1.418757 -0.179666
1     one  B  foo -1.879024  1.291836
2     two  C  foo  0.536826 -0.009614
3   three  A  bar  1.006160  0.392149
4     one  B  bar -0.029716  0.264599
5     one  C  bar -1.146178 -0.057409
6     two  A  foo  0.100900 -1.425638
7   three  B  foo -1.035018  1.024098
8     one  C  foo  0.314665 -0.106062
9     one  A  bar -0.773723  1.824375
10    two  B  bar -1.170653  0.595974
11  three  C  bar  0.648740  1.167115
```

We can produce pivot tables from this data very easily:

```
In [102]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[102]:
C             bar       foo
A     B
one   A -0.773723  1.418757
      B -0.029716 -1.879024
      C -1.146178  0.314665
three A  1.006160       NaN
      B       NaN -1.035018
      C  0.648740       NaN
two   A       NaN  0.100900
```

```
B -1.170653       NaN
C       NaN  0.536826
```

6.9 Time Series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the *Time Series section*

```
In [103]: rng = pd.date_range('1/1/2012', periods=100, freq='S')

In [104]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [105]: ts.resample('5Min', how='sum')
Out[105]:
2012-01-01    25083
Freq: 5T, dtype: int32
```

Time zone representation

```
In [106]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')

In [107]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [108]: ts
Out[108]:
2012-03-06    0.464000
2012-03-07    0.227371
2012-03-08   -0.496922
2012-03-09    0.306389
2012-03-10   -2.290613
Freq: D, dtype: float64

In [109]: ts_utc = ts.tz_localize('UTC')

In [110]: ts_utc
Out[110]:
2012-03-06 00:00:00+00:00    0.464000
2012-03-07 00:00:00+00:00    0.227371
2012-03-08 00:00:00+00:00   -0.496922
2012-03-09 00:00:00+00:00    0.306389
2012-03-10 00:00:00+00:00   -2.290613
Freq: D, dtype: float64
```

Convert to another time zone

```
In [111]: ts_utc.tz_convert('US/Eastern')
Out[111]:
2012-03-05 19:00:00-05:00    0.464000
2012-03-06 19:00:00-05:00    0.227371
2012-03-07 19:00:00-05:00   -0.496922
2012-03-08 19:00:00-05:00    0.306389
2012-03-09 19:00:00-05:00   -2.290613
Freq: D, dtype: float64
```

Converting between time span representations

```
In [112]: rng = pd.date_range('1/1/2012', periods=5, freq='M')

In [113]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [114]: ts
Out[114]:
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 [115]: ps = ts.to_period()

In [116]: ps
Out[116]:
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 [117]: ps.to_timestamp()
Out[117]:
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 [118]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')

In [119]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [120]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9

In [121]: ts.head()
Out[121]:
1990-03-01 09:00   -0.902937
1990-06-01 09:00    0.068159
1990-09-01 09:00   -0.057873
1990-12-01 09:00   -0.368204
1991-03-01 09:00   -1.144073
Freq: H, dtype: float64
```

6.10 Categoricals

Since version 0.15, pandas can include categorical data in a `DataFrame`. For full docs, see the *categorical introduction* and the *API documentation*.

```
In [122]: df = pd.DataFrame({"id":[1,2,3,4,5,6], "raw_grade":['a', 'b', 'b', 'a', 'a', 'e']})
```

Convert the raw grades to a categorical data type.

```
In [123]: df["grade"] = df["raw_grade"].astype("category")

In [124]: df["grade"]
Out[124]:
0    a
1    b
2    b
3    a
4    a
5    e
Name: grade, dtype: category
Categories (3, object): [a, b, e]
```

Rename the categories to more meaningful names (assigning to `Series.cat.categories` is inplace!)

```
In [125]: df["grade"].cat.categories = ["very good", "good", "very bad"]
```

Reorder the categories and simultaneously add the missing categories (methods under `Series .cat` return a new `Series` per default).

```
In [126]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very g

In [127]: df["grade"]
Out[127]:
0    very good
1         good
2         good
3    very good
4    very good
5     very bad
Name: grade, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]
```

Sorting is per order in the categories, not lexical order.

```
In [128]: df.sort("grade")
Out[128]:
   id raw_grade      grade
5   6         e   very bad
1   2         b       good
2   3         b       good
0   1         a  very good
3   4         a  very good
4   5         a  very good
```

Grouping by a categorical column shows also empty categories.

```
In [129]: df.groupby("grade").size()
Out[129]:
grade
very bad      1
bad         NaN
medium      NaN
good          2
very good     3
dtype: float64
```

6.11 Plotting

Plotting docs.

```
In [130]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [131]: ts = ts.cumsum()

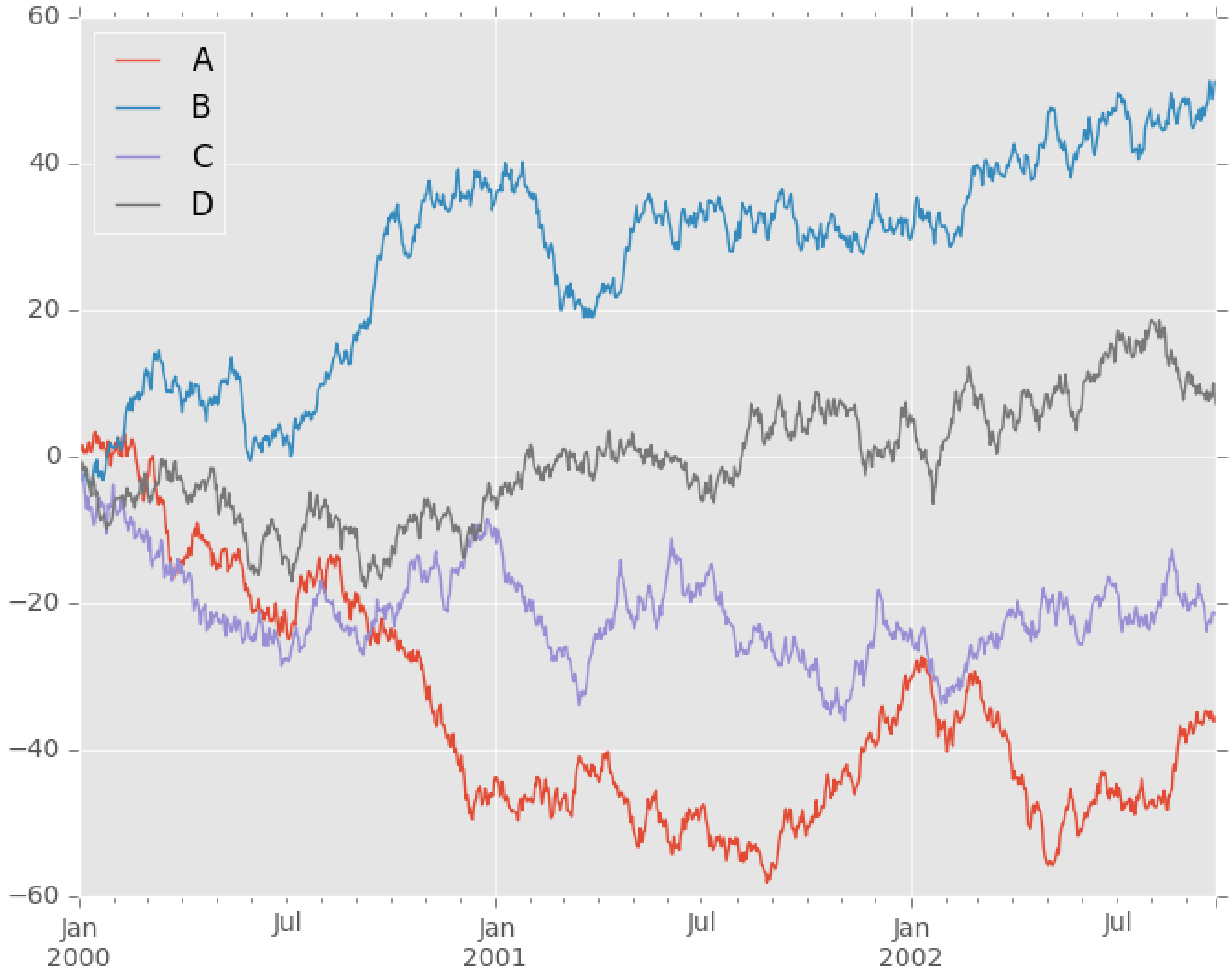
In [132]: ts.plot()
Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0xaf663c8c>
```

On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [133]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
   .....:                   columns=['A', 'B', 'C', 'D'])
   .....:

In [134]: df = df.cumsum()

In [135]: plt.figure(); df.plot(); plt.legend(loc='best')
Out[135]: <matplotlib.legend.Legend at 0xaf5b31cc>
```



6.12 Getting Data In/Out

6.12.1 CSV

Writing to a csv file

```
In [136]: df.to_csv('foo.csv')
```

Reading from a csv file

```
In [137]: pd.read_csv('foo.csv')
Out[137]:
     Unnamed: 0         A         B         C         D
0    2000-01-01  0.266457 -0.399641 -0.219582  1.186860
1    2000-01-02 -1.170732 -0.345873  1.653061 -0.282953
2    2000-01-03 -1.734933  0.530468  2.060811 -0.515536
3    2000-01-04 -1.555121  1.452620  0.239859 -1.156896
4    2000-01-05  0.578117  0.511371  0.103552 -2.428202
5    2000-01-06  0.478344  0.449933 -0.741620 -1.962409
6    2000-01-07  1.235339 -0.091757 -1.543861 -1.084753
..          ...       ...       ...       ...       ...
```

```
993  2002-09-20 -10.628548  -9.153563 -7.883146  28.313940
994  2002-09-21 -10.390377  -8.727491 -6.399645  30.914107
995  2002-09-22  -8.985362  -8.485624 -4.669462  31.367740
996  2002-09-23  -9.558560  -8.781216 -4.499815  30.518439
997  2002-09-24  -9.902058  -9.340490 -4.386639  30.105593
998  2002-09-25 -10.216020  -9.480682 -3.933802  29.758560
999  2002-09-26 -11.856774 -10.671012 -3.216025  29.369368

[1000 rows x 5 columns]
```

6.12.2 HDF5

Reading and writing to *HDFStores*

Writing to a HDF5 Store

```
In [138]: df.to_hdf('foo.h5','df')
```

Reading from a HDF5 Store

```
In [139]: pd.read_hdf('foo.h5','df')
Out[139]:
                    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
...               ...        ...       ...        ...
2002-09-20 -10.628548  -9.153563 -7.883146  28.313940
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
2002-09-24  -9.902058  -9.340490 -4.386639  30.105593
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]
```

6.12.3 Excel

Reading and writing to *MS Excel*

Writing to an excel file

```
In [140]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

Reading from an excel file

```
In [141]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
Out[141]:
                    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
...               ...        ...       ...        ...
2002-09-20 -10.628548  -9.153563 -7.883146  28.313940
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
2002-09-24  -9.902058  -9.340490 -4.386639  30.105593
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]
```

6.13 Gotchas

If you are trying an operation and you 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.

CHAPTER

SEVEN

TUTORIALS

This is a guide to many pandas tutorials, geared mainly for new users.

7.1 Internal Guides

pandas own *10 Minutes to pandas*

More complex recipes are in the *Cookbook*

7.2 pandas Cookbook

The goal of this cookbook (by Julia Evans) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that that entails.

Here are links to the v0.1 release. For an up-to-date table of contents, see the pandas-cookbook GitHub repository. To run the examples in this tutorial, you'll need to clone the GitHub repository and get IPython Notebook running. See How to use this cookbook.

- A quick tour of the IPython Notebook: Shows off IPython's awesome tab completion and magic functions.
- Chapter 1: Reading your data into pandas is pretty much the easiest thing. Even when the encoding is wrong!
- Chapter 2: It's not totally obvious how to select data from a pandas dataframe. Here we explain the basics (how to take slices and get columns)
- Chapter 3: Here we get into serious slicing and dicing and learn how to filter dataframes in complicated ways, really fast.
- Chapter 4: Groupby/aggregate is seriously my favorite thing about pandas and I use it all the time. You should probably read this.
- Chapter 5: Here you get to find out if it's cold in Montreal in the winter (spoiler: yes). Web scraping with pandas is fun! Here we combine dataframes.
- Chapter 6: Strings with pandas are great. It has all these vectorized string operations and they're the best. We will turn a bunch of strings containing "Snow" into vectors of numbers in a trice.
- Chapter 7: Cleaning up messy data is never a joy, but with pandas it's easier.
- Chapter 8: Parsing Unix timestamps is confusing at first but it turns out to be really easy.

7.3 Lessons for New pandas Users

For more resources, please visit the main repository.

- 01 - Lesson: - Importing libraries - Creating data sets - Creating data frames - Reading from CSV - Exporting to CSV - Finding maximums - Plotting data
- 02 - Lesson: - Reading from TXT - Exporting to TXT - Selecting top/bottom records - Descriptive statistics - Grouping/sorting data
- 03 - Lesson: - Creating functions - Reading from EXCEL - Exporting to EXCEL - Outliers - Lambda functions - Slice and dice data
- 04 - Lesson: - Adding/deleting columns - Index operations
- 05 - Lesson: - Stack/Unstack/Transpose functions
- 06 - Lesson: - GroupBy function
- 07 - Lesson: - Ways to calculate outliers
- 08 - Lesson: - Read from Microsoft SQL databases
- 09 - Lesson: - Export to CSV/EXCEL/TXT
- 10 - Lesson: - Converting between different kinds of formats
- 11 - Lesson: - Combining data from various sources

7.4 Practical data analysis with Python

This guide is a comprehensive introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as follows:

- Munging Data
- Aggregating Data
- Visualizing Data
- Time Series

7.5 Excel charts with pandas, vincent and xlsxwriter

- Using Pandas and XlsxWriter to create Excel charts

7.6 Various Tutorials

- Wes McKinney's (pandas BDFL) blog
- Statistical analysis made easy in Python with SciPy and pandas DataFrames, by Randal Olson
- Statistical Data Analysis in Python, tutorial videos, by Christopher Fonnesbeck from SciPy 2013
- Financial analysis in python, by Thomas Wiecki
- Intro to pandas data structures, by Greg Reda

- Pandas and Python: Top 10, by Manish Amde
- Pandas Tutorial, by Mikhail Semeniuk

CHAPTER

EIGHT

COOKBOOK

This is a repository for *short and sweet* examples and links for useful pandas recipes. We encourage users to add to this documentation.

Adding interesting links and/or inline examples to this section is a great *First Pull Request*.

Simplified, condensed, new-user friendly, in-line examples have been inserted where possible to augment the 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 3.4. Minor tweaks might be necessary for earlier python versions.

8.1 Idioms

These are some neat pandas `idioms`

if-then/if-then-else on one column, and assignment to another one or more columns:

```
In [1]: df = pd.DataFrame(
   ...:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ...:
Out[1]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50
```

8.1.1 if-then...

An if-then on one column

```
In [2]: df.ix[df.AAA >= 5,'BBB'] = -1; df
Out[2]:
   AAA  BBB  CCC
0    4   10  100
1    5   -1   50
2    6   -1  -30
3    7   -1  -50
```

An if-then with assignment to 2 columns:

```
In [3]: df.ix[df.AAA >= 5,['BBB','CCC']] = 555; df
Out[3]:
   AAA  BBB  CCC
0    4   10  100
1    5  555  555
2    6  555  555
3    7  555  555
```

Add another line with different logic, to do the -else

```
In [4]: df.ix[df.AAA < 5,['BBB','CCC']] = 2000; df
Out[4]:
   AAA   BBB   CCC
0    4  2000  2000
1    5   555   555
2    6   555   555
3    7   555   555
```

Or use pandas where after you've set up a mask

```
In [5]: df_mask = pd.DataFrame({'AAA' : [True] * 4, 'BBB' : [False] * 4,'CCC' : [True,False] * 2})

In [6]: df.where(df_mask,-1000)
Out[6]:
   AAA   BBB   CCC
0    4 -1000  2000
1    5 -1000 -1000
2    6 -1000   555
3    7 -1000 -1000
```

if-then-else using numpy's where()

```
In [7]: df = pd.DataFrame(
   ...:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ...:
Out[7]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [8]: df['logic'] = np.where(df['AAA'] > 5,'high','low'); df
Out[8]:
   AAA  BBB  CCC logic
0    4   10  100   low
1    5   20   50   low
2    6   30  -30  high
3    7   40  -50  high
```

8.1.2 Splitting

Split a frame with a boolean criterion

```
In [9]: df = pd.DataFrame(
   ...:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ...:
Out[9]:
```

```
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [10]: dflow = df[df.AAA <= 5]

In [11]: dfhigh = df[df.AAA > 5]

In [12]: dflow; dfhigh
Out[12]:
   AAA  BBB  CCC
2    6   30  -30
3    7   40  -50
```

8.1.3 Building Criteria

Select with multi-column criteria

```
In [13]: df = pd.DataFrame(
   ....:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ....:
Out[13]:
   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 [14]: newseries = df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']; newseries
Out[14]:
0    4
1    5
Name: AAA, dtype: int64
```

...or (without assignment returns a Series)

```
In [15]: newseries = df.loc[(df['BBB'] > 25) | (df['CCC'] >= -40), 'AAA']; newseries;
```

...or (with assignment modifies the DataFrame.)

```
In [16]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA'] = 0.1; df
Out[16]:
   AAA  BBB  CCC
0  0.1   10  100
1  5.0   20   50
2  0.1   30  -30
3  0.1   40  -50
```

Select rows with data closest to certain value using argsort

```
In [17]: df = pd.DataFrame(
   ....:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ....:
Out[17]:
```

```
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [18]: aValue = 43.0

In [19]: df.ix[(df.CCC-aValue).abs().argsort()]
Out[19]:
   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

```
In [20]: df = pd.DataFrame(
   ....:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ....:
Out[20]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [21]: Crit1 = df.AAA <= 5.5

In [22]: Crit2 = df.BBB == 10.0

In [23]: Crit3 = df.CCC > -40.0
```

One could hard code:

```
In [24]: AllCrit = Crit1 & Crit2 & Crit3
```

...Or it can be done with a list of dynamically built criteria

```
In [25]: CritList = [Crit1,Crit2,Crit3]

In [26]: AllCrit = functools.reduce(lambda x,y: x & y, CritList)

In [27]: df[AllCrit]
Out[27]:
   AAA  BBB  CCC
0    4   10  100
```

8.2 Selection

8.2.1 DataFrames

The *indexing* docs.

Using both row labels and value conditionals

```
In [28]: df = pd.DataFrame(
   ....:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
   ....:
Out[28]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [29]: df[(df.AAA <= 6) & (df.index.isin([0,2,4]))]
Out[29]:
   AAA  BBB  CCC
0    4   10  100
2    6   30  -30
```

Use loc for label-oriented slicing and iloc positional slicing

```
In [30]: data = {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}

In [31]: df = pd.DataFrame(data=data,index=['foo','bar','boo','kar']); df
Out[31]:
     AAA  BBB  CCC
foo    4   10  100
bar    5   20   50
boo    6   30  -30
kar    7   40  -50
```

There are 2 explicit slicing methods, with a third general case

1. Positional-oriented (Python slicing style : exclusive of end)
2. Label-oriented (Non-Python slicing style : inclusive of end)
3. General (Either slicing style : depends on if the slice contains labels or positions)

```
In [32]: df.loc['bar':'kar'] #Label
Out[32]:
     AAA  BBB  CCC
bar    5   20   50
boo    6   30  -30
kar    7   40  -50

#Generic
In [33]: df.ix[0:3] #Same as .iloc[0:3]
Out[33]:
     AAA  BBB  CCC
foo    4   10  100
bar    5   20   50
boo    6   30  -30

In [34]: df.ix['bar':'kar'] #Same as .loc['bar':'kar']
Out[34]:
     AAA  BBB  CCC
bar    5   20   50
boo    6   30  -30
kar    7   40  -50
```

Ambiguity arises when an index consists of integers with a non-zero start or non-unit increment.

```
In [35]: df2 = pd.DataFrame(data=data,index=[1,2,3,4]); #Note index starts at 1.

In [36]: df2.iloc[1:3] #Position-oriented
Out[36]:
   AAA  BBB  CCC
2    5   20   50
3    6   30  -30

In [37]: df2.loc[1:3] #Label-oriented
Out[37]:
   AAA  BBB  CCC
1    4   10  100
2    5   20   50
3    6   30  -30

In [38]: df2.ix[1:3] #General, will mimic loc (label-oriented)
Out[38]:
   AAA  BBB  CCC
1    4   10  100
2    5   20   50
3    6   30  -30

In [39]: df2.ix[0:3] #General, will mimic iloc (position-oriented), as loc[0:3] would raise a KeyErro
Out[39]:
   AAA  BBB  CCC
1    4   10  100
2    5   20   50
3    6   30  -30
```

Using inverse operator (~) to take the complement of a mask

```
In [40]: df = pd.DataFrame(
   ....:      {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}); df
   ....:
Out[40]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [41]: df[~((df.AAA <= 6) & (df.index.isin([0,2,4])))]
Out[41]:
   AAA  BBB  CCC
1    5   20   50
3    7   40  -50
```

8.2.2 Panels

Extend a panel frame by transposing, adding a new dimension, and transposing back to the original dimensions

```
In [42]: rng = pd.date_range('1/1/2013',periods=100,freq='D')

In [43]: data = np.random.randn(100, 4)

In [44]: cols = ['A','B','C','D']
```

```
In [45]: df1, df2, df3 = pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols), pd.DataFrame(d

In [46]: pf = pd.Panel({'df1':df1,'df2':df2,'df3':df3});pf
Out[46]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 4 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to D

#Assignment using Transpose  (pandas < 0.15)
In [47]: pf = pf.transpose(2,0,1)

In [48]: pf['E'] = pd.DataFrame(data, rng, cols)

In [49]: pf = pf.transpose(1,2,0);pf
Out[49]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 5 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to E

#Direct assignment (pandas > 0.15)
In [50]: pf.loc[:,:,'F'] = pd.DataFrame(data, rng, cols);pf
Out[50]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 6 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to F
```

Mask a panel by using np.where and then reconstructing the panel with the new masked values

8.2.3 New Columns

Efficiently and dynamically creating new columns using applymap

```
In [51]: df = pd.DataFrame(
   ....:      {'AAA' : [1,2,1,3], 'BBB' : [1,1,2,2], 'CCC' : [2,1,3,1]}); df
   ....:
Out[51]:
   AAA  BBB  CCC
0    1    1    2
1    2    1    1
2    1    2    3
3    3    2    1

In [52]: source_cols = df.columns # or some subset would work too.

In [53]: new_cols = [str(x) + "_cat" for x in source_cols]

In [54]: categories = {1 : 'Alpha', 2 : 'Beta', 3 : 'Charlie' }

In [55]: df[new_cols] = df[source_cols].applymap(categories.get);df
Out[55]:
   AAA  BBB  CCC  AAA_cat BBB_cat  CCC_cat
```

```
0    1    1    2    Alpha    Alpha     Beta
1    2    1    1     Beta    Alpha    Alpha
2    1    2    3    Alpha     Beta  Charlie
3    3    2    1  Charlie     Beta    Alpha
```

Keep other columns when using min() with groupby

```
In [56]: df = pd.DataFrame(
   ....:      {'AAA' : [1,1,1,2,2,2,3,3], 'BBB' : [2,1,3,4,5,1,2,3]}); df
   ....:
Out[56]:
   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

```
In [57]: df.loc[df.groupby("AAA")["BBB"].idxmin()]
Out[57]:
   AAA  BBB
1    1    1
5    2    1
6    3    2
```

Method 2 : sort then take first of each

```
In [58]: df.sort("BBB").groupby("AAA", as_index=False).first()
Out[58]:
   AAA  BBB
0    1    1
1    2    1
2    3    2
```

Notice the same results, with the exception of the index.

8.3 MultiIndexing

The *multindexing* docs.

Creating a multi-index from a labeled frame

```
In [59]: df = pd.DataFrame({'row' : [0,1,2],
   ....:                    'One_X' : [1.1,1.1,1.1],
   ....:                    'One_Y' : [1.2,1.2,1.2],
   ....:                    'Two_X' : [1.11,1.11,1.11],
   ....:                    'Two_Y' : [1.22,1.22,1.22]}); df
   ....:
Out[59]:
   One_X  One_Y  Two_X  Two_Y  row
0    1.1    1.2   1.11   1.22    0
1    1.1    1.2   1.11   1.22    1
2    1.1    1.2   1.11   1.22    2
```

```
# As Labelled Index
In [60]: df = df.set_index('row');df
Out[60]:
     One_X  One_Y  Two_X  Two_Y
row
0      1.1    1.2   1.11   1.22
1      1.1    1.2   1.11   1.22
2      1.1    1.2   1.11   1.22

# With Heirarchical Columns
In [61]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_')) for c in df.columns]);df
Out[61]:
     One        Two
       X    Y     X     Y
row
0    1.1  1.2  1.11  1.22
1    1.1  1.2  1.11  1.22
2    1.1  1.2  1.11  1.22

# Now stack & Reset
In [62]: df = df.stack(0).reset_index(1);df
Out[62]:
    level_1     X     Y
row
0       One  1.10  1.20
0       Two  1.11  1.22
1       One  1.10  1.20
1       Two  1.11  1.22
2       One  1.10  1.20
2       Two  1.11  1.22

# And fix the labels (Notice the label 'level_1' got added automatically)
In [63]: df.columns = ['Sample','All_X','All_Y'];df
Out[63]:
    Sample  All_X  All_Y
row
0      One   1.10   1.20
0      Two   1.11   1.22
1      One   1.10   1.20
1      Two   1.11   1.22
2      One   1.10   1.20
2      Two   1.11   1.22
```

8.3.1 Arithmetic

Performing arithmetic with a multi-index that needs broadcasting

```
In [64]: cols = pd.MultiIndex.from_tuples([ (x,y) for x in ['A','B','C'] for y in ['O','I']])

In [65]: df = pd.DataFrame(np.random.randn(2,6),index=['n','m'],columns=cols); df
Out[65]:
          A                   B                   C
          O         I         O         I         O         I
n  1.920906 -0.388231 -2.314394  0.665508  0.402562  0.399555
m -1.765956  0.850423  0.388054  0.992312  0.744086 -0.739776
```

```
In [66]: df = df.div(df['C'],level=1); df
Out[66]:
          A                   B            C
          O         I         O         I  O  I
n  4.771702 -0.971660 -5.749162  1.665625  1  1
m -2.373321 -1.149568  0.521518 -1.341367  1  1
```

8.3.2 Slicing

Slicing a multi-index with xs

```
In [67]: coords = [('AA','one'),('AA','six'),('BB','one'),('BB','two'),('BB','six')]

In [68]: index = pd.MultiIndex.from_tuples(coords)

In [69]: df = pd.DataFrame([11,22,33,44,55],index,['MyData']); df
Out[69]:
        MyData
AA one      11
   six      22
BB one      33
   two      44
   six      55
```

To take the cross section of the 1st level and 1st axis the index:

```
In [70]: df.xs('BB',level=0,axis=0)  #Note : level and axis are optional, and default to zero
Out[70]:
     MyData
one      33
two      44
six      55
```

...and now the 2nd level of the 1st axis.

```
In [71]: df.xs('six',level=1,axis=0)
Out[71]:
    MyData
AA      22
BB      55
```

Slicing a multi-index with xs, method #2

```
In [72]: index = list(itertools.product(['Ada','Quinn','Violet'],['Comp','Math','Sci']))

In [73]: headr = list(itertools.product(['Exams','Labs'],['I','II']))

In [74]: indx = pd.MultiIndex.from_tuples(index,names=['Student','Course'])

In [75]: cols = pd.MultiIndex.from_tuples(headr) #Notice these are un-named

In [76]: data = [[70+x+y+(x*y)%3 for x in range(4)] for y in range(9)]

In [77]: df = pd.DataFrame(data,indx,cols); df
Out[77]:
               Exams     Labs
                   I  II    I  II
Student Course
```

```
Ada     Comp      70  71   72  73
        Math      71  73   75  74
        Sci       72  75   75  75
Quinn   Comp      73  74   75  76
        Math      74  76   78  77
        Sci       75  78   78  78
Violet  Comp      76  77   78  79
        Math      77  79   81  80
        Sci       78  81   81  81

In [78]: All = slice(None)

In [79]: df.loc['Violet']
Out[79]:
       Exams      Labs
           I  II     I  II
Course
Comp      76  77    78  79
Math      77  79    81  80
Sci       78  81    81  81

In [80]: df.loc[(All,'Math'),All]
Out[80]:
               Exams      Labs
                   I  II     I  II
Student Course
Ada     Math      71  73    75  74
Quinn   Math      74  76    78  77
Violet  Math      77  79    81  80

In [81]: df.loc[(slice('Ada','Quinn'),'Math'),All]
Out[81]:
               Exams      Labs
                   I  II     I  II
Student Course
Ada     Math      71  73    75  74
Quinn   Math      74  76    78  77

In [82]: df.loc[(All,'Math'),('Exams')]
Out[82]:
                 I  II
Student Course
Ada     Math    71  73
Quinn   Math    74  76
Violet  Math    77  79

In [83]: df.loc[(All,'Math'),(All,'II')]
Out[83]:
               Exams Labs
                  II   II
Student Course
Ada     Math      73   74
Quinn   Math      76   77
Violet  Math      79   80
```

Setting portions of a multi-index with xs

8.3.3 Sorting

Sort by specific column or an ordered list of columns, with a multi-index

```
In [84]: df.sort(('Labs', 'II'), ascending=False)
Out[84]:
               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;

8.3.4 Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

8.3.5 panelnd

The *panelnd* docs.

Construct a 5D panelnd

8.4 Missing Data

The *missing data* docs.

Fill forward a reversed timeseries

```
In [85]: df = pd.DataFrame(np.random.randn(6,1), index=pd.date_range('2013-08-01', periods=6, freq='I

In [86]: df.ix[3,'A'] = np.nan

In [87]: df
Out[87]:
                   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 [88]: df.reindex(df.index[::-1]).ffill()
Out[88]:
```

```
                   A
2013-08-08  0.104050
2013-08-07  1.906684
2013-08-06  1.906684
2013-08-05  0.639589
2013-08-02 -0.179642
2013-08-01 -1.054874
```

cumsum reset at NaN values

8.4.1 Replace

Using replace with backrefs

8.5 Grouping

The *grouping* docs.

Basic grouping with apply

Unlike agg, apply's callable is passed a sub-DataFrame which gives you access to all the columns

```
In [89]: df = pd.DataFrame({'animal': 'cat dog cat fish dog cat cat'.split(),
   ....:                    'size': list('SSMMMLL'),
   ....:                    'weight': [8, 10, 11, 1, 20, 12, 12],
   ....:                    'adult' : [False] * 5 + [True] * 2}); df
   ....:
Out[89]:
   adult animal size  weight
0  False    cat    S       8
1  False    dog    S      10
2  False    cat    M      11
3  False   fish    M       1
4  False    dog    M      20
5   True    cat    L      12
6   True    cat    L      12

#List the size of the animals with the highest weight.
In [90]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])
Out[90]:
animal
cat     L
dog     M
fish    M
dtype: object
```

Using get_group

```
In [91]: gb = df.groupby(['animal'])

In [92]: gb.get_group('cat')
Out[92]:
   adult animal size  weight
0  False    cat    S       8
2  False    cat    M      11
```

```
5    True     cat     L       12
6    True     cat     L       12
```

Apply to different items in a group

```
In [93]: def GrowUp(x):
   ....:     avg_weight =  sum(x[x['size'] == 'S'].weight * 1.5)
   ....:     avg_weight += sum(x[x['size'] == 'M'].weight * 1.25)
   ....:     avg_weight += sum(x[x['size'] == 'L'].weight)
   ....:     avg_weight /= len(x)
   ....:     return pd.Series(['L',avg_weight,True], index=['size', 'weight', 'adult'])
   ....:

In [94]: expected_df = gb.apply(GrowUp)

In [95]: expected_df
Out[95]:
       size   weight adult
animal
cat       L  12.4375  True
dog       L  20.0000  True
fish      L   1.2500  True
```

Expanding Apply

```
In [96]: S = pd.Series([i / 100.0 for i in range(1,11)])

In [97]: def CumRet(x,y):
   ....:     return x * (1 + y)
   ....:

In [98]: def Red(x):
   ....:     return functools.reduce(CumRet,x,1.0)
   ....:

In [99]: pd.expanding_apply(S, Red)
Out[99]:
0    1.010000
1    1.030200
2    1.061106
3    1.103550
4    1.158728
5    1.228251
6    1.314229
7    1.419367
8    1.547110
9    1.701821
dtype: float64
```

Replacing some values with mean of the rest of a group

```
In [100]: df = pd.DataFrame({'A' : [1, 1, 2, 2], 'B' : [1, -1, 1, 2]})

In [101]: gb = df.groupby('A')

In [102]: def replace(g):
   .....:     mask = g < 0
   .....:     g.loc[mask] = g[~mask].mean()
   .....:     return g
```

```
   .....:

In [103]: gb.transform(replace)
Out[103]: 
   B
0  1
1  1
2  1
3  2
```

Sort groups by aggregated data

```
In [104]: df = pd.DataFrame({'code': ['foo', 'bar', 'baz'] * 2,
   .....:                    'data': [0.16, -0.21, 0.33, 0.45, -0.59, 0.62],
   .....:                    'flag': [False, True] * 3})
   .....:

In [105]: code_groups = df.groupby('code')

In [106]: agg_n_sort_order = code_groups[['data']].transform(sum).sort('data')

In [107]: sorted_df = df.ix[agg_n_sort_order.index]

In [108]: sorted_df
Out[108]: 
  code  data   flag
1  bar -0.21   True
4  bar -0.59  False
0  foo  0.16  False
3  foo  0.45   True
2  baz  0.33  False
5  baz  0.62   True
```

Create multiple aggregated columns

```
In [109]: rng = pd.date_range(start="2014-10-07",periods=10,freq='2min')

In [110]: ts = pd.Series(data = list(range(10)), index = rng)

In [111]: def MyCust(x):
   .....:    if len(x) > 2:
   .....:       return x[1] * 1.234
   .....:    return pd.NaT
   .....:

In [112]: mhc = {'Mean' : np.mean, 'Max' : np.max, 'Custom' : MyCust}

In [113]: ts.resample("5min",how = mhc)
Out[113]: 
                     Max Custom  Mean
2014-10-07 00:00:00    2  1.234   1.0
2014-10-07 00:05:00    4    NaN   3.5
2014-10-07 00:10:00    7  7.404   6.0
2014-10-07 00:15:00    9    NaN   8.5

In [114]: ts
Out[114]: 
2014-10-07 00:00:00    0
2014-10-07 00:02:00    1
```

```
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 [115]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),
   .....:                    'Value': [100, 150, 50, 50]}); df
   .....:
Out[115]:
  Color  Value
0   Red    100
1   Red    150
2   Red     50
3  Blue     50

In [116]: df['Counts'] = df.groupby(['Color']).transform(len)

In [117]: df
Out[117]:
  Color  Value  Counts
0   Red    100       3
1   Red    150       3
2   Red     50       3
3  Blue     50       1
```

Shift groups of the values in a column based on the index

```
In [118]: df = pd.DataFrame(
   .....:     {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[118]:
                 beyer  line_race
Last Gunfighter     99         10
Last Gunfighter    102         10
Last Gunfighter    103          8
Paynter            103         10
Paynter             88         10
Paynter            100          8

In [119]: df['beyer_shifted'] = df.groupby(level=0)['beyer'].shift(1)

In [120]: df
Out[120]:
                 beyer  line_race  beyer_shifted
Last Gunfighter     99         10            NaN
Last Gunfighter    102         10             99
Last Gunfighter    103          8            102
Paynter            103         10            NaN
Paynter             88         10            103
```

```
Paynter            100          8            88
```

Select row with maximum value from each group

```
In [121]: df = pd.DataFrame({'host':['other','other','that','this','this'],
   .....:                    'service':['mail','web','mail','mail','web'],
   .....:                    'no':[1, 2, 1, 2, 1]}).set_index(['host', 'service'])
   .....:

In [122]: mask = df.groupby(level=0).agg('idxmax')

In [123]: df_count = df.loc[mask['no']].reset_index()

In [124]: df_count
Out[124]:
    host service  no
0  other     web   2
1   that    mail   1
2   this    mail   2
```

Grouping like Python's itertools.groupby

```
In [125]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])

In [126]: df.A.groupby((df.A != df.A.shift()).cumsum()).groups
Out[126]: {1: [0L], 2: [1L], 3: [2L], 4: [3L, 4L, 5L], 5: [6L], 6: [7L, 8L]}

In [127]: df.A.groupby((df.A != df.A.shift()).cumsum()).cumsum()
Out[127]:
0    0
1    1
2    0
3    1
4    2
5    3
6    0
7    1
8    2
dtype: int64
```

8.5.1 Expanding Data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

8.5.2 Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```
In [128]: df = pd.DataFrame(data={'Case' : ['A','A','A','B','A','A','B','A','A'],
   .....:                         'Data' : np.random.randn(9)})
   .....:
```

```
In [129]: dfs = list(zip(*df.groupby(pd.rolling_median((1*(df['Case']=='B')).cumsum(),3,True))))[-1]

In [130]: dfs[0]
Out[130]:
  Case      Data
0    A  0.174068
1    A -0.439461
2    A -0.741343
3    B -0.079673

In [131]: dfs[1]
Out[131]:
  Case      Data
4    A -0.922875
5    A  0.303638
6    B -0.917368

In [132]: dfs[2]
Out[132]:
  Case      Data
7    A -1.624062
8    A -0.758514
```

8.5.3 Pivot

The *Pivot* docs.

Partial sums and subtotals

```
In [133]: df = pd.DataFrame(data={'Province' : ['ON','QC','BC','AL','AL','MN','ON'],
   .....:                            'City' : ['Toronto','Montreal','Vancouver','Calgary','Edmonton','W
   .....:                            'Sales' : [13,6,16,8,4,3,1]})
   .....:

In [134]: table = pd.pivot_table(df,values=['Sales'],index=['Province'],columns=['City'],aggfunc=np.s

In [135]: table.stack('City')
Out[135]:
                    Sales
Province City
AL       All           12
         Calgary        8
         Edmonton       4
BC       All           16
         Vancouver     16
MN       All            3
         Winnipeg       3
...                   ...
All      Calgary        8
         Edmonton       4
         Montreal       6
         Toronto       13
         Vancouver     16
         Windsor        1
         Winnipeg       3

[20 rows x 1 columns]
```

Frequency table like plyr in R

```
In [136]: grades = [48,99,75,80,42,80,72,68,36,78]

In [137]: df = pd.DataFrame( {'ID': ["x%d" % r for r in range(10)],
   .....:                     'Gender' : ['F', 'M', 'F', 'M', 'F', 'M', 'F', 'M', 'M', 'M'],
   .....:                     'ExamYear': ['2007','2007','2007','2008','2008','2008','2008','2009','2
   .....:                     'Class': ['algebra', 'stats', 'bio', 'algebra', 'algebra', 'stats', 'st
   .....:                     'Participated': ['yes','yes','yes','yes','no','yes','yes','yes','yes',
   .....:                     'Passed': ['yes' if x > 50 else 'no' for x in grades],
   .....:                     'Employed': [True,True,True,False,False,False,False,True,True,False],
   .....:                     'Grade': grades})
   .....:

In [138]: df.groupby('ExamYear').agg({'Participated': lambda x: x.value_counts()['yes'],
   .....:                     'Passed': lambda x: sum(x == 'yes'),
   .....:                     'Employed' : lambda x : sum(x),
   .....:                     'Grade' : lambda x : sum(x) / len(x)})
   .....:
Out[138]:
          Grade  Employed  Participated  Passed
ExamYear
2007         74         3             3       2
2008         68         0             3       3
2009         60         2             3       2
```

8.5.4 Apply

Rolling Apply to Organize - Turning embedded lists into a multi-index frame

```
In [139]: df = pd.DataFrame(data={'A' : [[2,4,8,16],[100,200],[10,20,30]], 'B' : [['a','b','c'],['jj

In [140]: def SeriesFromSubList(aList):
   .....:    return pd.Series(aList)
   .....:

In [141]: df_orgz = pd.concat(dict([ (ind,row.apply(SeriesFromSubList)) for ind,row in df.iterrows()
```

Rolling Apply with a DataFrame returning a Series

Rolling Apply to multiple columns where function calculates a Series before a Scalar from the Series is returned

```
In [142]: df = pd.DataFrame(data=np.random.randn(2000,2)/10000,
   .....:                   index=pd.date_range('2001-01-01',periods=2000),
   .....:                   columns=['A','B']); df
   .....:
Out[142]:
                   A         B
2001-01-01 -0.000056 -0.000059
2001-01-02 -0.000107 -0.000168
2001-01-03  0.000040  0.000061
2001-01-04  0.000039  0.000182
2001-01-05  0.000071 -0.000067
2001-01-06  0.000024  0.000031
2001-01-07  0.000012 -0.000021
...              ...       ...
2006-06-17  0.000129  0.000094
2006-06-18  0.000059  0.000216
```

```
2006-06-19 -0.000069  0.000283
2006-06-20  0.000089  0.000084
2006-06-21  0.000075  0.000041
2006-06-22 -0.000037 -0.000011
2006-06-23 -0.000070 -0.000048

[2000 rows x 2 columns]

In [143]: def gm(aDF,Const):
   .....:     v = ((((aDF.A+aDF.B)+1).cumprod())-1)*Const
   .....:     return (aDF.index[0],v.iloc[-1])
   .....:

In [144]: S = pd.Series(dict([ gm(df.iloc[i:min(i+51,len(df)-1)],5) for i in range(len(df)-50) ])); S
Out[144]:
2001-01-01   -0.003108
2001-01-02   -0.001787
2001-01-03    0.000204
2001-01-04   -0.000166
2001-01-05   -0.002148
2001-01-06   -0.001831
2001-01-07   -0.001663
                 ...
2006-04-28   -0.009152
2006-04-29   -0.006728
2006-04-30   -0.005840
2006-05-01   -0.003650
2006-05-02   -0.003801
2006-05-03   -0.004272
2006-05-04   -0.003839
dtype: float64
```

Rolling apply with a DataFrame returning a Scalar

Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

```
In [145]: rng = pd.date_range(start = '2014-01-01',periods = 100)

In [146]: df = pd.DataFrame({'Open' : np.random.randn(len(rng)),
   .....:                    'Close' : np.random.randn(len(rng)),
   .....:                    'Volume' : np.random.randint(100,2000,len(rng))}, index=rng); df
   .....:
Out[146]:
               Close      Open  Volume
2014-01-01  1.550590  0.458513    1371
2014-01-02 -0.818812 -0.508850    1433
2014-01-03  1.160619  0.257610     645
2014-01-04  0.081521 -1.773393     878
2014-01-05  1.083284 -0.560676    1143
2014-01-06 -0.518721  0.284174    1088
2014-01-07  0.140661  1.146889    1722
...              ...       ...     ...
2014-04-04  0.458193 -0.669474    1768
2014-04-05  0.108502 -1.616315     836
2014-04-06  1.418082 -1.294906     694
2014-04-07  0.486530  1.171647     796
2014-04-08  0.181885  0.501639     265
2014-04-09 -0.707238 -0.361868    1293
2014-04-10  1.211432  1.564429    1088
```

```
[100 rows x 3 columns]

In [147]: def vwap(bars): return ((bars.Close*bars.Volume).sum()/bars.Volume.sum()).round(2)

In [148]: window = 5

In [149]: s = pd.concat([ (pd.Series(vwap(df.iloc[i:i+window]), index=[df.index[i+window]])) for i in
Out[149]:
2014-01-06    0.55
2014-01-07    0.06
2014-01-08    0.32
2014-01-09    0.03
2014-01-10    0.08
2014-01-11   -0.50
2014-01-12   -0.26
              ...
2014-04-04    0.36
2014-04-05    0.48
2014-04-06    0.54
2014-04-07    0.46
2014-04-08    0.45
2014-04-09    0.53
2014-04-10    0.15
dtype: float64
```

8.6 Timeseries

Between times

Using indexer between time

Constructing a datetime range that excludes weekends and includes only certain times

Vectorized Lookup

Turn a matrix with hours in columns and days in rows into a continuous row sequence in the form of a time series. How to rearrange a python pandas DataFrame?

Dealing with duplicates when reindexing a timeseries to a specified frequency

Calculate the first day of the month for each entry in a DatetimeIndex

```
In [150]: dates = pd.date_range('2000-01-01', periods=5)

In [151]: dates.to_period(freq='M').to_timestamp()
Out[151]:
DatetimeIndex(['2000-01-01', '2000-01-01', '2000-01-01', '2000-01-01',
               '2000-01-01'],
              dtype='datetime64[ns]', freq=None, tz=None)
```

8.6.1 Resampling

The *Resample* docs.

TimeGrouping of values grouped across time

TimeGrouping #2

Using TimeGrouper and another grouping to create subgroups, then apply a custom function

Resampling with custom periods

Resample intraday frame without adding new days

Resample minute data

Resample with groupby

8.7 Merge

The *Concat* docs. The *Join* docs.

Append two dataframes with overlapping index (emulate R rbind)

```
In [152]: rng = pd.date_range('2000-01-01', periods=6)

In [153]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C'])

In [154]: df2 = df1.copy()
```

ignore_index is needed in pandas < v0.13, and depending on df construction

```
In [155]: df = df1.append(df2,ignore_index=True); df
Out[155]:
           A         B         C
0  -0.174202 -0.477257  0.239870
1  -0.654455 -1.411456 -1.778457
2   0.351578  0.307871 -0.286865
3   0.565398 -0.185821  0.937593
4   0.446473  0.566368  0.721476
5   1.710685 -0.667054 -0.651191
6  -0.174202 -0.477257  0.239870
7  -0.654455 -1.411456 -1.778457
8   0.351578  0.307871 -0.286865
9   0.565398 -0.185821  0.937593
10  0.446473  0.566368  0.721476
11  1.710685 -0.667054 -0.651191
```

Self Join of a DataFrame

```
In [156]: df = pd.DataFrame(data={'Area' : ['A'] * 5 + ['C'] * 2,
   .....:                         'Bins' : [110] * 2 + [160] * 3 + [40] * 2,
   .....:                         'Test_0' : [0, 1, 0, 1, 2, 0, 1],
   .....:                         'Data' : np.random.randn(7)});df
   .....:
Out[156]:
  Area  Bins      Data  Test_0
0    A   110 -0.399974       0
1    A   110 -1.519206       1
2    A   160  1.678487       0
3    A   160  0.005345       1
4    A   160 -0.534461       2
5    C    40  0.255077       0
6    C    40  1.093310       1

In [157]: df['Test_1'] = df['Test_0'] - 1
```

```
In [158]: pd.merge(df, df, left_on=['Bins', 'Area','Test_0'], right_on=['Bins', 'Area','Test_1'],suf
Out[158]:
  Area  Bins    Data_L  Test_0_L  Test_1_L    Data_R  Test_0_R  Test_1_R
0    A   110 -0.399974         0        -1 -1.519206         1         0
1    A   160  1.678487         0        -1  0.005345         1         0
2    A   160  0.005345         1         0 -0.534461         2         1
3    C    40  0.255077         0        -1  1.093310         1         0
```

How to set the index and join

KDB like asof join

Join with a criteria based on the values

8.8 Plotting

The *Plotting* docs.

Make Matplotlib look like R

Setting x-axis major and minor labels

Plotting multiple charts in an ipython notebook

Creating a multi-line plot

Plotting a heatmap

Annotate a time-series plot

Annotate a time-series plot #2

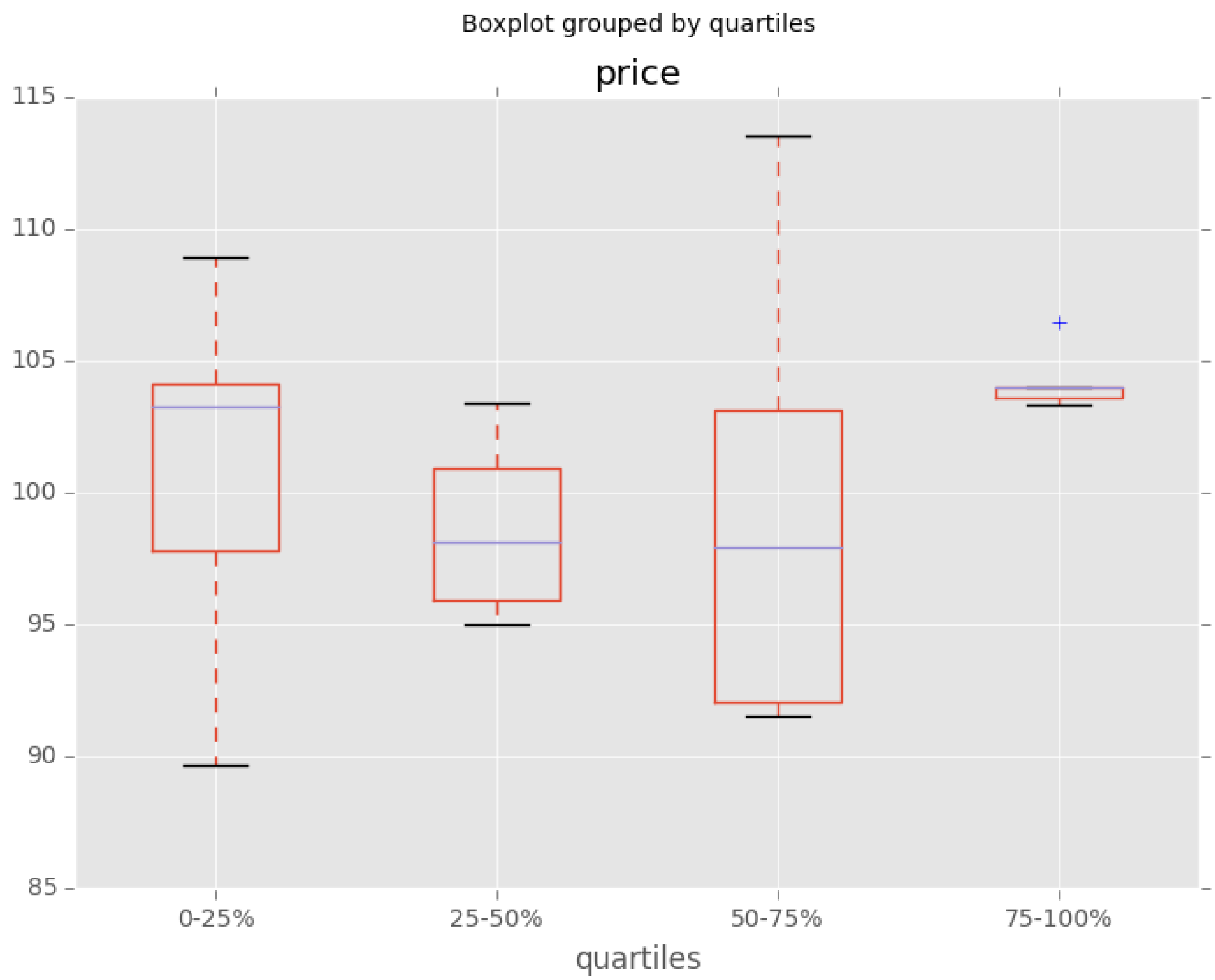
Generate Embedded plots in excel files using Pandas, Vincent and xlsxwriter

Boxplot for each quartile of a stratifying variable

```
In [159]: df = pd.DataFrame(
   .....:      {u'stratifying_var': np.random.uniform(0, 100, 20),
   .....:       u'price': np.random.normal(100, 5, 20)})
   .....:

In [160]: df[u'quartiles'] = pd.qcut(
   .....:     df[u'stratifying_var'],
   .....:     4,
   .....:     labels=[u'0-25%', u'25-50%', u'50-75%', u'75-100%'])
   .....:

In [161]: df.boxplot(column=u'price', by=u'quartiles')
Out[161]: <matplotlib.axes._subplots.AxesSubplot at 0xa98ad08c>
```



8.9 Data In/Out

Performance comparison of SQL vs HDF5

8.9.1 CSV

The *CSV* docs

read_csv in action

appending to a csv

how to read in multiple files, appending to create a single dataframe

Reading a csv chunk-by-chunk

Reading only certain rows of a csv chunk-by-chunk

Reading the first few lines of a frame

Reading a file that is compressed but not by gzip/bz2 (the native compressed formats which read_csv understands). This example shows a WinZipped file, but is a general application of opening the file within a context manager and using that handle to read. See here

Inferring dtypes from a file

Dealing with bad lines

Dealing with bad lines II

Reading CSV with Unix timestamps and converting to local timezone

Write a multi-row index CSV without writing duplicates

Parsing date components in multi-columns is faster with a format

```
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]:
0    20000101
1    20000102
2    20000103
3    20000104
4    20000105
dtype: object

In [36]: %timeit pd.to_datetime(ds)
1 loops, best of 3: 488 ms per loop
```

8.9.2 SQL

The *SQL* docs

Reading from databases with SQL

8.9.3 Excel

The *Excel* docs

Reading from a filelike handle Reading HTML tables from a server that cannot handle the default request header

8.9.4 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

Large Data work flows

Reading in a sequence of files, then providing a global unique index to a store while appending

Groupby on a HDFStore with low group density

Groupby on a HDFStore with high group density

Hierarchical queries on a HDFStore

Counting with a HDFStore

Troubleshoot HDFStore exceptions

Setting min_itemsize with strings

Using ptrepack to create a completely-sorted-index on a store

Storing Attributes to a group node

```
In [162]: df = pd.DataFrame(np.random.randn(8,3))

In [163]: store = pd.HDFStore('test.h5')

In [164]: store.put('df',df)

# you can store an arbitrary python object via pickle
In [165]: store.get_storer('df').attrs.my_attribute = dict(A = 10)

In [166]: store.get_storer('df').attrs.my_attribute
Out[166]: {'A': 10}
```

8.9.5 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;
    }

    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:

```
names = 'count', 'avg', 'scale'

# note that the offsets are larger than the size of the type because of
# struct padding
offsets = 0, 8, 16
formats = 'i4', 'f8', 'f4'
dt = np.dtype({'names': names, 'offsets': offsets, 'formats': formats},
              align=True)
df = pd.DataFrame(np.fromfile('binary.dat', dt))
```

Note: The offsets of the structure elements may be different depending on the architecture of the machine on which the file was created. Using a raw binary file format like this for general data storage is not recommended, as it is not cross platform. We recommended either HDF5 or msgpack, both of which are supported by pandas' IO facilities.

8.10 Computation

Numerical integration (sample-based) of a time series

8.11 Timedeltas

The *Timedeltas* docs.

Using timedeltas

```
In [167]: s  = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))

In [168]: s - s.max()
```

```
Out[168]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [169]: s.max() - s
Out[169]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [170]: s - datetime.datetime(2011,1,1,3,5)
Out[170]:
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [171]: s + datetime.timedelta(minutes=5)
Out[171]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [172]: datetime.datetime(2011,1,1,3,5) - s
Out[172]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [173]: datetime.timedelta(minutes=5) + s
Out[173]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]
```

Adding and subtracting deltas and dates

```
In [174]: deltas = pd.Series([ datetime.timedelta(days=i) for i in range(3) ])

In [175]: df = pd.DataFrame(dict(A = s, B = deltas)); df
Out[175]:
           A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [176]: df['New Dates'] = df['A'] + df['B'];

In [177]: df['Delta'] = df['A'] - df['New Dates']; df
Out[177]:
           A      B  New Dates   Delta
0 2012-01-01 0 days 2012-01-01  0 days
```

```
1 2012-01-02 1 days 2012-01-03 -1 days
2 2012-01-03 2 days 2012-01-05 -2 days

In [178]: df.dtypes
Out[178]:
A              datetime64[ns]
B             timedelta64[ns]
New Dates      datetime64[ns]
Delta         timedelta64[ns]
dtype: object
```

Another example

Values can be set to NaT using np.nan, similar to datetime

```
In [179]: y = s - s.shift(); y
Out[179]:
0       NaT
1    1 days
2    1 days
dtype: timedelta64[ns]

In [180]: y[1] = np.nan; y
Out[180]:
0       NaT
1       NaT
2    1 days
dtype: timedelta64[ns]
```

8.12 Aliasing Axis Names

To globally provide aliases for axis names, one can define these 2 functions:

```
In [181]: def set_axis_alias(cls, axis, alias):
   .....:    if axis not in cls._AXIS_NUMBERS:
   .....:       raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
   .....:    cls._AXIS_ALIASES[alias] = axis
   .....:

In [182]: def clear_axis_alias(cls, axis, alias):
   .....:    if axis not in cls._AXIS_NUMBERS:
   .....:       raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
   .....:    cls._AXIS_ALIASES.pop(alias,None)
   .....:

In [183]: set_axis_alias(pd.DataFrame,'columns', 'myaxis2')

In [184]: df2 = pd.DataFrame(np.random.randn(3,2),columns=['c1','c2'],index=['i1','i2','i3'])

In [185]: df2.sum(axis='myaxis2')
Out[185]:
i1    0.239786
i2    0.259018
i3    0.163470
dtype: float64

In [186]: clear_axis_alias(pd.DataFrame,'columns', 'myaxis2')
```

8.13 Creating Example Data

To create a dataframe from every combination of some given values, like R's `expand.grid()` function, we can create a dict where the keys are column names and the values are lists of the data values:

```
In [187]: def expand_grid(data_dict):
   .....:     rows = itertools.product(*data_dict.values())
   .....:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
   .....:

In [188]: df = expand_grid(
   .....:     {'height': [60, 70],
   .....:      'weight': [100, 140, 180],
   .....:      'sex': ['Male', 'Female']})
   .....:

In [189]: df
Out[189]:
       sex  weight  height
0     Male     100      60
1     Male     100      70
2     Male     140      60
3     Male     140      70
4     Male     180      60
5     Male     180      70
6   Female     100      60
7   Female     100      70
8   Female     140      60
9   Female     140      70
10  Female     180      60
11  Female     180      70
```

CHAPTER

NINE

INTRO TO DATA STRUCTURES

We'll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import numpy and load pandas into your namespace:

```
In [1]: import numpy as np

# will use a lot in examples
In [2]: randn = np.random.randn

In [3]: from pandas import *
```

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.

When using pandas, we recommend the following import convention:

```
import pandas as pd
```

9.1 Series

Warning: In 0.13.0 `Series` has internaly been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similarly to the rest of the pandas containers. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

`Series` is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the **index**. The basic method to create a Series is to call:

```
>>> s = Series(data, index=index)
```

Here, `data` can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed **index** is a list of axis labels. Thus, this separates into a few cases depending on what **data is**:

From ndarray

If `data` is an ndarray, **index** must be the same length as **data**. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```
In [4]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [5]: s
Out[5]:
a   -2.783
b    0.426
c   -0.650
d    1.146
e   -0.663
dtype: float64

In [6]: s.index
Out[6]: Index([u'a', u'b', u'c', u'd', u'e'], dtype='object')

In [7]: Series(randn(5))
Out[7]:
0    0.294
1   -0.405
2    1.167
3    0.842
4    0.540
dtype: float64
```

Note: Starting in v0.8.0, pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

From dict

If `data` is a dict, if **index** is passed the values in data corresponding to the labels in the index will be pulled out. Otherwise, an index will be constructed from the sorted keys of the dict, if possible.

```
In [8]: d = {'a' : 0., 'b' : 1., 'c' : 2.}

In [9]: Series(d)
Out[9]:
a    0
b    1
c    2
dtype: float64

In [10]: Series(d, index=['b', 'c', 'd', 'a'])
Out[10]:
b     1
c     2
d   NaN
a     0
dtype: float64
```

Note: NaN (not a number) is the standard missing data marker used in pandas

From scalar value If `data` is a scalar value, an index must be provided. The value will be repeated to match the length of **index**

```
In [11]: Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[11]:
a    5
b    5
c    5
d    5
e    5
dtype: float64
```

9.1.1 Series is ndarray-like

`Series` acts very similarly to a `ndarray`, and is a valid argument to most NumPy functions. However, things like slicing also slice the index.

```
In [12]: s[0]
Out[12]: -2.7827595933769937

In [13]: s[:3]
Out[13]:
a   -2.783
b    0.426
c   -0.650
dtype: float64

In [14]: s[s > s.median()]
Out[14]:
b    0.426
d    1.146
dtype: float64

In [15]: s[[4, 3, 1]]
Out[15]:
e   -0.663
d    1.146
b    0.426
dtype: float64

In [16]: np.exp(s)
Out[16]:
a    0.062
b    1.532
c    0.522
d    3.147
e    0.515
dtype: float64
```

We will address array-based indexing in a separate *section*.

9.1.2 Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [17]: s['a']
Out[17]: -2.7827595933769937

In [18]: s['e'] = 12.
```

```
In [19]: s
Out[19]:
a    -2.783
b     0.426
c    -0.650
d     1.146
e    12.000
dtype: float64

In [20]: 'e' in s
Out[20]: True

In [21]: 'f' in s
Out[21]: False
```

If a label is not contained, an exception is raised:

```
>>> s['f']
KeyError: 'f'
```

Using the `get` method, a missing label will return None or specified default:

```
In [22]: s.get('f')

In [23]: s.get('f', np.nan)
Out[23]: nan
```

See also the *section on attribute access*.

9.1.3 Vectorized operations and label alignment with Series

When doing data analysis, as with raw NumPy arrays looping through Series value-by-value is usually not necessary. Series can be also be passed into most NumPy methods expecting an ndarray.

```
In [24]: s + s
Out[24]:
a    -5.566
b     0.853
c    -1.301
d     2.293
e    24.000
dtype: float64

In [25]: s * 2
Out[25]:
a    -5.566
b     0.853
c    -1.301
d     2.293
e    24.000
dtype: float64

In [26]: np.exp(s)
Out[26]:
a         0.062
b         1.532
c         0.522
```

```
d         3.147
e    162754.791
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 [27]: s[1:] + s[:-1]
Out[27]:
a      NaN
b    0.853
c   -1.301
d    2.293
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.

9.1.4 Name attribute

Series can also have a `name` attribute:

```
In [28]: s = Series(np.random.randn(5), name='something')

In [29]: s
Out[29]:
0    0.541
1   -1.175
2    0.129
3    0.043
4   -0.429
Name: something, dtype: float64

In [30]: s.name
Out[30]: 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

9.2 DataFrame

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A `Series`
- Another `DataFrame`

Along with the data, you can optionally pass **index** (row labels) and **columns** (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

9.2.1 From dict of Series or dicts

The result **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will be first converted to Series. If no columns are passed, the columns will be the sorted list of dict keys.

```
In [31]: d = {'one' : Series([1., 2., 3.], index=['a', 'b', 'c']),
   ....:      'two' : Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}
   ....:

In [32]: df = DataFrame(d)

In [33]: df
Out[33]:
   one  two
a    1    1
b    2    2
c    3    3
d  NaN    4

In [34]: DataFrame(d, index=['d', 'b', 'a'])
Out[34]:
   one  two
d  NaN    4
b    2    2
a    1    1

In [35]: DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
Out[35]:
   two three
d    4   NaN
b    2   NaN
a    1   NaN
```

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

Note: When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

```
In [36]: df.index
Out[36]: Index([u'a', u'b', u'c', u'd'], dtype='object')

In [37]: df.columns
Out[37]: Index([u'one', u'two'], dtype='object')
```

9.2.2 From dict of ndarrays / lists

The ndarrays must all be the same length. If an index is passed, it must clearly also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where `n` is the array length.

```
In [38]: d = {'one' : [1., 2., 3., 4.],
   ....:      'two' : [4., 3., 2., 1.]}
   ....:

In [39]: DataFrame(d)
Out[39]:
   one  two
0    1    4
1    2    3
2    3    2
3    4    1

In [40]: DataFrame(d, index=['a', 'b', 'c', 'd'])
Out[40]:
   one  two
a    1    4
b    2    3
c    3    2
d    4    1
```

9.2.3 From structured or record array

This case is handled identically to a dict of arrays.

```
In [41]: data = np.zeros((2,),dtype=[('A', 'i4'),('B', 'f4'),('C', 'a10')])

In [42]: data[:] = [(1,2.,'Hello'),(2,3.,"World")]

In [43]: DataFrame(data)
Out[43]:
   A  B      C
0  1  2  Hello
1  2  3  World

In [44]: DataFrame(data, index=['first', 'second'])
Out[44]:
        A  B      C
first   1  2  Hello
second  2  3  World

In [45]: DataFrame(data, columns=['C', 'A', 'B'])
Out[45]:
       C  A  B
0  Hello  1  2
1  World  2  3
```

Note: DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

9.2.4 From a list of dicts

```
In [46]: data2 = [{'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20}]

In [47]: DataFrame(data2)
Out[47]:
   a   b   c
0  1   2 NaN
1  5  10  20

In [48]: DataFrame(data2, index=['first', 'second'])
Out[48]:
        a   b   c
first   1   2 NaN
second  5  10  20

In [49]: DataFrame(data2, columns=['a', 'b'])
Out[49]:
   a   b
0  1   2
1  5  10
```

9.2.5 From a dict of tuples

You can automatically create a multi-indexed frame by passing a tuples dictionary

```
In [50]: 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[50]:
      a           b
      a   b   c   a   b
A B   4   1   5   8  10
  C   3   2   6   7 NaN
  D NaN NaN NaN NaN   9
```

9.2.6 From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

Missing Data

Much more will be said on this topic in the *Missing data* section. To construct a DataFrame with missing data, use `np.nan` for those values which are missing. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

9.2.7 Alternate Constructors

DataFrame.from_dict

DataFrame.from_dict takes a dict of dicts or a dict of array-like sequences and returns a DataFrame. It operates like the DataFrame constructor except for the orient parameter which is 'columns' by default, but which can be set to 'index' in order to use the dict keys as row labels. **DataFrame.from_records**

DataFrame.from_records takes a list of tuples or an ndarray with structured dtype. Works analogously to the normal DataFrame constructor, except that index maybe be a specific field of the structured dtype to use as the index. For example:

```
In [51]: data
Out[51]:
array([(1, 2.0, 'Hello'), (2, 3.0, 'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [52]: DataFrame.from_records(data, index='C')
Out[52]:
       A  B
C
Hello  1  2
World  2  3
```

DataFrame.from_items

DataFrame.from_items works analogously to the form of the dict constructor that takes a sequence of (key, value) pairs, where the keys are column (or row, in the case of orient='index') names, and the value are the column values (or row values). This can be useful for constructing a DataFrame with the columns in a particular order without having to pass an explicit list of columns:

```
In [53]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])])
Out[53]:
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass orient='index', the keys will be the row labels. But in this case you must also pass the desired column names:

```
In [54]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])],
   ....:                      orient='index', columns=['one', 'two', 'three'])
   ....:
Out[54]:
   one  two  three
A    1    2      3
B    4    5      6
```

9.2.8 Column selection, addition, deletion

You can treat a DataFrame semantically like a dict of like-indexed Series objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```
In [55]: df['one']
Out[55]:
a      1
b      2
c      3
d    NaN
Name: one, dtype: float64
```

```
In [56]: df['three'] = df['one'] * df['two']

In [57]: df['flag'] = df['one'] > 2

In [58]: df
Out[58]:
   one  two  three   flag
a    1    1      1  False
b    2    2      4  False
c    3    3      9   True
d  NaN    4    NaN  False
```

Columns can be deleted or popped like with a dict:

```
In [59]: del df['two']

In [60]: three = df.pop('three')

In [61]: df
Out[61]:
   one   flag
a    1  False
b    2  False
c    3   True
d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [62]: df['foo'] = 'bar'

In [63]: df
Out[63]:
   one   flag  foo
a    1  False  bar
b    2  False  bar
c    3   True  bar
d  NaN  False  bar
```

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame's index:

```
In [64]: df['one_trunc'] = df['one'][:2]

In [65]: df
Out[65]:
   one   flag  foo  one_trunc
a    1  False  bar          1
b    2  False  bar          2
c    3   True  bar        NaN
d  NaN  False  bar        NaN
```

You can insert raw ndarrays but their length must match the length of the DataFrame's index.

By default, columns get inserted at the end. The `insert` function is available to insert at a particular location in the columns:

```
In [66]: df.insert(1, 'bar', df['one'])

In [67]: df
Out[67]:
```

```
   one  bar   flag  foo  one_trunc
a    1    1  False  bar          1
b    2    2  False  bar          2
c    3    3   True  bar        NaN
d  NaN  NaN  False  bar        NaN
```

9.2.9 Assigning New Columns in Method Chains

New in version 0.16.0.

Inspired by dplyr's `mutate` verb, DataFrame has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [68]: iris = read_csv('data/iris.data')

In [69]: iris.head()
Out[69]:
   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 [70]: (iris.assign(sepal_ratio = iris['SepalWidth'] / iris['SepalLength'])
   ....:      .head())
   ....:
Out[70]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa        0.686
1          4.9         3.0          1.4         0.2  Iris-setosa        0.612
2          4.7         3.2          1.3         0.2  Iris-setosa        0.681
3          4.6         3.1          1.5         0.2  Iris-setosa        0.674
4          5.0         3.6          1.4         0.2  Iris-setosa        0.720
```

Above was an example of inserting a precomputed value. We can also pass in a function of one argument to be evalutated on the DataFrame being assigned to.

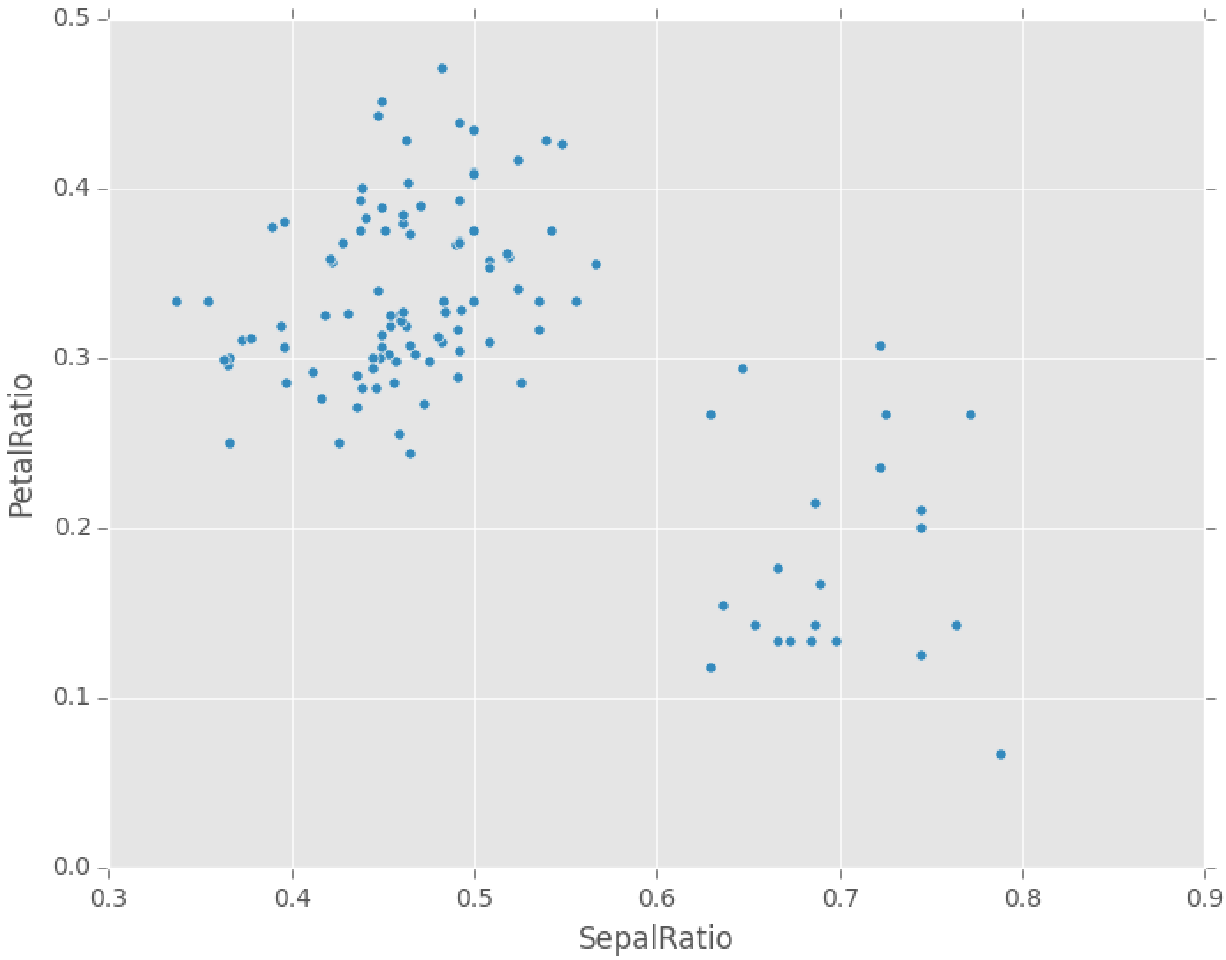
```
In [71]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] /
   ....:                                      x['SepalLength'])).head()
   ....:
Out[71]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa        0.686
1          4.9         3.0          1.4         0.2  Iris-setosa        0.612
2          4.7         3.2          1.3         0.2  Iris-setosa        0.681
3          4.6         3.1          1.5         0.2  Iris-setosa        0.674
4          5.0         3.6          1.4         0.2  Iris-setosa        0.720
```

`assign` **always** returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don't have a reference to the DataFrame at hand. This is common when using `assign` in chains of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:

```
In [72]: (iris.query('SepalLength > 5')
   ....:      .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
   ....:              PetalRatio = lambda x: x.PetalWidth / x.PetalLength)
```

```
   ....:       .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
   ....:
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0xa63e2c4c>
```



Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that's been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn't have a reference to the *filtered* DataFrame available.

The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. A *copy* of the original DataFrame is returned, with the new values inserted.

Warning: Since the function signature of `assign` is `**kwargs`, a dictionary, the order of the new columns in the resulting DataFrame cannot be guaranteed to match the order you pass in. To make things predictable, items are inserted alphabetically (by key) at the end of the DataFrame.

All expressions are computed first, and then assigned. So you can't refer to another column being assigned in the same call to `assign`. For example:

```
In [73]: # Don't do this, bad reference to `C`
        df.assign(C = lambda x: x['A'] + x['B'],
                  D = lambda x: x['A'] + x['C'])
In [2]: # Instead, break it into two assigns
        (df.assign(C = lambda x: x['A'] + x['B'])
           .assign(D = lambda x: x['A'] + x['C']))
```

9.2.10 Indexing / Selection

The basics of indexing are as follows:

Operation	Syntax	Result
Select column	`df[col]`	Series
Select row by label	`df.loc[label]`	Series
Select row by integer location	`df.iloc[loc]`	Series
Slice rows	`df[5:10]`	DataFrame
Select rows by boolean vector	`df[bool_vec]`	DataFrame

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```
In [74]: df.loc['b']
Out[74]:
one              2
bar              2
flag         False
foo            bar
one_trunc        2
Name: b, dtype: object

In [75]: df.iloc[2]
Out[75]:
one             3
bar             3
flag         True
foo           bar
one_trunc     NaN
Name: c, dtype: object
```

For a more exhaustive treatment of more sophisticated label-based indexing and slicing, see the *section on indexing*. We will address the fundamentals of reindexing / conforming to new sets of labels in the *section on reindexing*.

9.2.11 Data alignment and arithmetic

Data alignment between DataFrame objects automatically align on **both the columns and the index (row labels)**. Again, the resulting object will have the union of the column and row labels.

```
In [76]: df = DataFrame(randn(10, 4), columns=['A', 'B', 'C', 'D'])
```

```
In [77]: df2 = DataFrame(randn(7, 3), columns=['A', 'B', 'C'])

In [78]: df + df2
Out[78]:
       A      B          C   D
0 -1.916 -0.986 -2.421e+00 NaN
1  0.965  1.677  3.298e-01 NaN
2 -1.662  2.197 -1.917e+00 NaN
3 -0.189  0.765 -9.522e-04 NaN
4 -1.076  0.397 -1.177e+00 NaN
5  2.810 -0.179 -5.705e-01 NaN
6 -1.227  0.196  5.312e-01 NaN
7    NaN    NaN        NaN NaN
8    NaN    NaN        NaN NaN
9    NaN    NaN        NaN NaN
```

When doing an operation between DataFrame and Series, the default behavior is to align the Series **index** on the DataFrame **columns**, thus broadcasting row-wise. For example:

```
In [79]: df - df.iloc[0]
Out[79]:
       A      B      C      D
0  0.000  0.000  0.000  0.000
1  2.386  1.358  1.223 -2.107
2  2.105  1.700  1.327 -0.689
3  1.874  2.718  2.382 -0.760
4  2.199  0.966  0.826  0.093
5  4.997  1.197  1.330 -0.285
6  1.263  0.578  1.071 -0.525
7  3.463  0.632  1.063 -0.443
8  2.680  3.163  1.298 -1.818
9  1.304  0.196  3.590 -0.867
```

In the special case of working with time series data, and the DataFrame index also contains dates, the broadcasting will be column-wise:

```
In [80]: index = date_range('1/1/2000', periods=8)

In [81]: df = DataFrame(randn(8, 3), index=index, columns=list('ABC'))

In [82]: df
Out[82]:
                A      B      C
2000-01-01  0.063 -0.028  0.444
2000-01-02 -0.269 -1.578  1.850
2000-01-03  0.638 -0.557 -0.071
2000-01-04 -0.511  0.156 -1.076
2000-01-05  1.664 -0.438 -0.077
2000-01-06  0.029  0.179  1.740
2000-01-07 -0.729 -0.898 -0.314
2000-01-08 -0.048 -0.876  0.169

In [83]: type(df['A'])
Out[83]: pandas.core.series.Series

In [84]: df - df['A']
Out[84]:
            A      B      C
2000-01-01  0 -0.091  0.381
```

```
2000-01-02  0 -1.309  2.119
2000-01-03  0 -1.195 -0.709
2000-01-04  0  0.668 -0.564
2000-01-05  0 -2.101 -1.741
2000-01-06  0  0.150  1.711
2000-01-07  0 -0.169  0.415
2000-01-08  0 -0.828  0.217
```

Warning:

```
df - df['A']
```

is now deprecated and will be removed in a future release. The preferred way to replicate this behavior is

```
df.sub(df['A'], axis=0)
```

For explicit control over the matching and broadcasting behavior, see the section on *flexible binary operations*.

Operations with scalars are just as you would expect:

```
In [85]: df * 5 + 2
Out[85]:
                 A      B       C
2000-01-01   2.314  1.858   4.218
2000-01-02   0.656 -5.888  11.251
2000-01-03   5.190 -0.783   1.644
2000-01-04  -0.557  2.781  -3.378
2000-01-05  10.318 -0.189   1.613
2000-01-06   2.146  2.895  10.700
2000-01-07  -1.645 -2.490   0.429
2000-01-08   1.760 -2.378   2.846

In [86]: 1 / df
Out[86]:
                 A       B       C
2000-01-01  15.948 -35.193   2.255
2000-01-02  -3.721  -0.634   0.540
2000-01-03   1.567  -1.797 -14.039
2000-01-04  -1.955   6.398  -0.930
2000-01-05   0.601  -2.285 -12.936
2000-01-06  34.257   5.586   0.575
2000-01-07  -1.372  -1.114  -3.183
2000-01-08 -20.802  -1.142   5.913

In [87]: df ** 4
Out[87]:
                    A          B          C
2000-01-01  1.546e-05  6.519e-07  3.871e-02
2000-01-02  5.219e-03  6.195e+00  1.172e+01
2000-01-03  1.657e-01  9.598e-02  2.574e-05
2000-01-04  6.841e-02  5.966e-04  1.339e+00
2000-01-05  7.660e+00  3.671e-02  3.571e-05
2000-01-06  7.261e-07  1.027e-03  9.168e+00
2000-01-07  2.825e-01  6.503e-01  9.747e-03
2000-01-08  5.341e-06  5.878e-01  8.178e-04
```

Boolean operators work as well:

```
In [88]: df1 = DataFrame({'a' : [1, 0, 1], 'b' : [0, 1, 1] }, dtype=bool)

In [89]: df2 = DataFrame({'a' : [0, 1, 1], 'b' : [1, 1, 0] }, dtype=bool)

In [90]: df1 & df2
Out[90]:
       a      b
0  False  False
1  False   True
2   True  False

In [91]: df1 | df2
Out[91]:
      a     b
0  True  True
1  True  True
2  True  True

In [92]: df1 ^ df2
Out[92]:
       a      b
0   True   True
1   True  False
2  False   True

In [93]: -df1
Out[93]:
       a      b
0  False   True
1   True  False
2  False  False
```

9.2.12 Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an ndarray:

```
# only show the first 5 rows
In [94]: df[:5].T
Out[94]:
   2000-01-01  2000-01-02  2000-01-03  2000-01-04  2000-01-05
A       0.063      -0.269       0.638      -0.511       1.664
B      -0.028      -1.578      -0.557       0.156      -0.438
C       0.444       1.850      -0.071      -1.076      -0.077
```

9.2.13 DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on DataFrame, assuming the data within are numeric:

```
In [95]: np.exp(df)
Out[95]:
                A      B      C
2000-01-01  1.065  0.972  1.558
2000-01-02  0.764  0.206  6.361
2000-01-03  1.893  0.573  0.931
2000-01-04  0.600  1.169  0.341
```

```
2000-01-05  5.278  0.646  0.926
2000-01-06  1.030  1.196  5.698
2000-01-07  0.482  0.407  0.730
2000-01-08  0.953  0.417  1.184

In [96]: np.asarray(df)
Out[96]:
array([[ 0.0627, -0.0284,  0.4436],
       [-0.2688, -1.5776,  1.8502],
       [ 0.6381, -0.5566, -0.0712],
       [-0.5114,  0.1563, -1.0756],
       [ 1.6636, -0.4377, -0.0773],
       [ 0.0292,  0.179 ,  1.7401],
       [-0.729 , -0.898 , -0.3142],
       [-0.0481, -0.8756,  0.1691]])
```

The dot method on DataFrame implements matrix multiplication:

```
In [97]: df.T.dot(df)
Out[97]:
       A      B      C
A  4.047 -0.039  0.178
B -0.039  4.621 -2.581
C  0.178 -2.581  7.943
```

Similarly, the dot method on Series implements dot product:

```
In [98]: s1 = Series(np.arange(5,10))

In [99]: s1.dot(s1)
Out[99]: 255
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics are quite different in places from a matrix.

9.2.14 Console display

Very large DataFrames will be truncated to display them in the console. You can also get a summary using `info()`. (Here I am reading a CSV version of the **baseball** dataset from the **plyr** R package):

```
In [100]: baseball = read_csv('data/baseball.csv')

In [101]: print(baseball)
       id     player  year  stint  ...  hbp  sh  sf  gidp
0   88641  womacto01  2006      2  ...    0   3   0     0
1   88643  schilcu01  2006      1  ...    0   0   0     0
..    ...        ...   ...    ...  ...   ..  ..  ..   ...
98  89533   aloumo01  2007      1  ...    2   0   3    13
99  89534  alomasa02  2007      1  ...    0   0   0     0

[100 rows x 23 columns]

In [102]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 0 to 99
Data columns (total 23 columns):
id        100 non-null int64
player    100 non-null object
```

```
year        100 non-null int64
stint       100 non-null int64
team        100 non-null object
lg          100 non-null object
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
ibb         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: 17.6+ 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:

```
In [103]: print(baseball.iloc[-20:, :12].to_string())
       id     player  year  stint team  lg    g   ab   r    h  X2b  X3b
80  89474  finlest01  2007      1  COL  NL   43   94   9   17    3    0
81  89480  embreal01  2007      1  OAK  AL    4    0   0    0    0    0
82  89481  edmonji01  2007      1  SLN  NL  117  365  39   92   15    2
83  89482  easleda01  2007      1  NYN  NL   76  193  24   54    6    0
84  89489  delgaca01  2007      1  NYN  NL  139  538  71  139   30    0
85  89493  cormirh01  2007      1  CIN  NL    6    0   0    0    0    0
86  89494  coninje01  2007      2  NYN  NL   21   41   2    8    2    0
87  89495  coninje01  2007      1  CIN  NL   80  215  23   57   11    1
88  89497  clemero02  2007      1  NYA  AL    2    2   0    1    0    0
89  89498  claytro01  2007      2  BOS  AL    8    6   1    0    0    0
90  89499  claytro01  2007      1  TOR  AL   69  189  23   48   14    0
91  89501  cirilje01  2007      2  ARI  NL   28   40   6    8    4    0
92  89502  cirilje01  2007      1  MIN  AL   50  153  18   40    9    2
93  89521  bondsba01  2007      1  SFN  NL  126  340  75   94   14    0
94  89523  biggicr01  2007      1  HOU  NL  141  517  68  130   31    3
95  89525  benitar01  2007      2  FLO  NL   34    0   0    0    0    0
96  89526  benitar01  2007      1  SFN  NL   19    0   0    0    0    0
97  89530  ausmubr01  2007      1  HOU  NL  117  349  38   82   16    3
98  89533   aloumo01  2007      1  NYN  NL   87  328  51  112   19    1
99  89534  alomasa02  2007      1  NYN  NL    8   22   1    3    1    0
```

New since 0.10.0, wide DataFrames will now be printed across multiple rows by default:

```
In [104]: DataFrame(randn(3, 12))
Out[104]:
          0         1         2         3         4         5         6   \
0  1.225021 -0.528620  0.448676  0.619107 -1.199110 -0.949097  2.169523
1 -1.753617  0.992384 -0.505601 -0.599848  0.133585  0.008836 -1.767710
2 -0.461585 -1.321106  1.745476  1.445100  0.991037 -0.860733 -0.870661
```

```
         7         8         9        10        11
0  0.302230  0.919516  0.657436  0.262574 -0.804798
1  0.700112 -0.020773 -0.302481  0.347869  0.179123
2 -0.117845 -0.046266  2.095649 -0.524324 -0.610555
```

You can change how much to print on a single row by setting the `display.width` option:

```
In [105]: set_option('display.width', 40) # default is 80

In [106]: DataFrame(randn(3, 12))
Out[106]:
         0         1         2   \
0 -1.280951  1.472585 -1.001914
1  0.130529 -1.603771 -0.128830
2 -1.084566 -0.515272  1.367586

         3         4         5   \
0  1.044770 -0.050668 -0.013289
1 -1.869301 -0.232977 -0.139801
2  0.963500  0.224105 -0.020051

         6         7         8   \
0 -0.291893  2.029038 -1.117195
1 -1.083341 -0.357234 -0.818199
2  0.524663  0.351081 -1.574209

         9         10        11
0  1.598577 -0.397325  0.151653
1 -0.886885  1.238885 -1.639274
2 -0.486856 -0.545888 -0.927076
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

9.2.15 DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like attributes:

```
In [107]: df = DataFrame({'foo1' : np.random.randn(5),
   .....:                 'foo2' : np.random.randn(5)})
   .....:

In [108]: df
Out[108]:
       foo1      foo2
0  0.909160  1.360298
1 -0.667763 -1.603624
2 -0.101656 -1.648929
3  1.189682  0.145121
4 -0.090648 -2.536359

In [109]: df.foo1
Out[109]:
0    0.909160
1   -0.667763
2   -0.101656
3    1.189682
4   -0.090648
Name: foo1, dtype: float64
```

The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```
In [5]: df.fo<TAB>
df.foo1  df.foo2
```

9.3 Panel

Panel is a somewhat less-used, but still important container for 3-dimensional data. The term panel data is derived from econometrics and is partially responsible for the name pandas: pan(el)-da(ta)-s. The names for the 3 axes are intended to give some semantic meaning to describing operations involving panel data and, in particular, econometric analysis of panel data. However, for the strict purposes of slicing and dicing a collection of DataFrame objects, you may find the axis names slightly arbitrary:

- **items**: axis 0, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1, it is the **index** (rows) of each of the DataFrames
- **minor_axis**: axis 2, it is the **columns** of each of the DataFrames

Construction of Panels works about like you would expect:

9.3.1 From 3D ndarray with optional axis labels

```
In [110]: 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 [111]: wp
Out[111]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

9.3.2 From dict of DataFrame objects

```
In [112]: data = {'Item1' : DataFrame(randn(4, 3)),
   .....:         'Item2' : DataFrame(randn(4, 2))}
   .....:

In [113]: Panel(data)
Out[113]:
<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:

Parameter	Default	Description
intersect	False	drops elements whose indices do not align
orient	items	use minor to use DataFrames' columns as panel items

For example, compare to the construction above:

```
In [114]: Panel.from_dict(data, orient='minor')
Out[114]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: 0 to 2
Major_axis axis: 0 to 3
Minor_axis axis: Item1 to Item2
```

Orient is especially useful for mixed-type DataFrames. If you pass a dict of DataFrame objects with mixed-type columns, all of the data will get upcasted to dtype=object unless you pass orient='minor':

```
In [115]: df = DataFrame({'a': ['foo', 'bar', 'baz'],
   .....:                 'b': np.random.randn(3)})
   .....:

In [116]: df
Out[116]:
     a         b
0  foo -1.264356
1  bar -0.497629
2  baz  1.789719

In [117]: data = {'item1': df, 'item2': df}

In [118]: panel = Panel.from_dict(data, orient='minor')

In [119]: panel['a']
Out[119]:
  item1 item2
0   foo   foo
1   bar   bar
2   baz   baz

In [120]: panel['b']
Out[120]:
      item1     item2
0 -1.264356 -1.264356
1 -0.497629 -0.497629
2  1.789719  1.789719

In [121]: panel['b'].dtypes
Out[121]:
item1    float64
item2    float64
dtype: object
```

Note: Unfortunately Panel, being less commonly used than Series and DataFrame, has been slightly neglected feature-wise. A number of methods and options available in DataFrame are not available in Panel. This will get worked on, of course, in future releases. And faster if you join me in working on the codebase.

9.3.3 From DataFrame using `to_panel` method

This method was introduced in v0.7 to replace `LongPanel.to_long`, and converts a DataFrame with a two-level index to a Panel.

```
In [122]: midx = MultiIndex(levels=[['one', 'two'], ['x','y']], labels=[[1,1,0,0],[1,0,1,0]])

In [123]: df = DataFrame({'A' : [1, 2, 3, 4], 'B': [5, 6, 7, 8]}, index=midx)

In [124]: df.to_panel()
Out[124]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: A to B
Major_axis axis: one to two
Minor_axis axis: x to y
```

9.3.4 Item selection / addition / deletion

Similar to DataFrame functioning as a dict of Series, Panel is like a dict of DataFrames:

```
In [125]: wp['Item1']
Out[125]:
                   A         B         C         D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02 -0.354356  2.090183 -0.736019 -1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093 -1.229749  2.295679 -1.016910

In [126]: wp['Item3'] = wp['Item1'] / wp['Item2']
```

The API for insertion and deletion is the same as for DataFrame. And as with DataFrame, if the item is a valid python identifier, you can access it as an attribute and tab-complete it in IPython.

9.3.5 Transposing

A Panel can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [127]: wp.transpose(2, 0, 1)
Out[127]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 5 (minor_axis)
Items axis: A to D
Major_axis axis: Item1 to Item3
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

9.3.6 Indexing / Selection

Operation	Syntax	Result
Select item	`wp[item]`	DataFrame
Get slice at major_axis label	`wp.major_xs(val)`	DataFrame
Get slice at minor_axis label	`wp.minor_xs(val)`	DataFrame

For example, using the earlier example data, we could do:

```
In [128]: wp['Item1']
Out[128]:
                   A         B         C         D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02 -0.354356  2.090183 -0.736019 -1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093 -1.229749  2.295679 -1.016910

In [129]: wp.major_xs(wp.major_axis[2])
Out[129]:
      Item1     Item2     Item3
A -0.581326 -1.271582  0.457167
B -0.244477 -0.861256  0.283861
C  0.917119 -0.597879 -1.533955
D  0.611695 -0.118700 -5.153265

In [130]: wp.minor_axis
Out[130]: Index([u'A', u'B', u'C', u'D'], dtype='object')

In [131]: wp.minor_xs('C')
Out[131]:
               Item1     Item2      Item3
2000-01-01 -0.173710  2.381645  -0.072937
2000-01-02 -0.736019 -2.413161   0.305002
2000-01-03  0.917119 -0.597879  -1.533955
2000-01-04 -0.704643 -1.536019   0.458746
2000-01-05  2.295679  0.181524  12.646732
```

9.3.7 Squeezing

Another way to change the dimensionality of an object is to `squeeze` a 1-len object, similar to `wp['Item1']`

```
In [132]: wp.reindex(items=['Item1']).squeeze()
Out[132]:
                   A         B         C         D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02 -0.354356  2.090183 -0.736019 -1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093 -1.229749  2.295679 -1.016910

In [133]: wp.reindex(items=['Item1'],minor=['B']).squeeze()
Out[133]:
2000-01-01   -0.621868
2000-01-02    2.090183
2000-01-03   -0.244477
2000-01-04   -0.528562
2000-01-05   -1.229749
Freq: D, Name: B, dtype: float64
```

9.3.8 Conversion to DataFrame

A Panel can be represented in 2D form as a hierarchically indexed DataFrame. See the section *hierarchical indexing* for more on this. To convert a Panel to a DataFrame, use the `to_frame` method:

```
In [134]: panel = Panel(np.random.randn(3, 5, 4), items=['one', 'two', 'three'],
   .....:               major_axis=date_range('1/1/2000', periods=5),
   .....:               minor_axis=['a', 'b', 'c', 'd'])
   .....:

In [135]: panel.to_frame()
Out[135]:
                        one       two     three
major      minor
2000-01-01 a       0.445900 -1.286198 -1.023189
           b      -0.574496 -0.407154  0.591682
           c       0.872979  0.068084 -0.008919
           d       0.297255 -2.157051 -0.415572
2000-01-02 a      -1.022617 -0.443982 -0.772683
           b       1.091870 -0.881639 -0.516197
           c       1.831444  0.851834  0.626655
           d       1.271808 -1.352515  0.269623
2000-01-03 a      -0.472876  0.228761  1.709250
           b      -0.279340  0.416858 -0.830728
           c       0.495966  0.301709 -0.290244
           d       0.367858  0.569010 -1.588782
2000-01-04 a      -1.530917 -0.047619  0.639406
           b      -0.285890  0.413370  1.055533
           c       0.943062  0.573056 -0.260898
           d       1.361752 -0.154419 -0.289725
2000-01-05 a       0.210373  0.987044  0.279621
           b      -1.945608  0.063191  0.454423
           c       2.532409  0.439086 -0.065750
           d       0.373819  1.657475  1.465709
```

9.4 Panel4D (Experimental)

`Panel4D` is a 4-Dimensional named container very much like a `Panel`, but having 4 named dimensions. It is intended as a test bed for more N-Dimensional named containers.

- **labels**: axis 0, each item corresponds to a Panel contained inside
- **items**: axis 1, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 2, it is the **index** (rows) of each of the DataFrames
- **minor_axis**: axis 3, it is the **columns** of each of the DataFrames

`Panel4D` is a sub-class of `Panel`, so most methods that work on Panels are applicable to Panel4D. The following methods are disabled:

- `join` , `to_frame` , `to_excel` , `to_sparse` , `groupby`

Construction of Panel4D works in a very similar manner to a `Panel`

9.4.1 From 4D ndarray with optional axis labels

```
In [136]: 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 [137]: p4d
Out[137]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

9.4.2 From dict of Panel objects

```
In [138]: data = { 'Label1' : Panel({ 'Item1' : DataFrame(randn(4, 3)) }),
   .....:          'Label2' : Panel({ 'Item2' : DataFrame(randn(4, 2)) }) }
   .....:

In [139]: Panel4D(data)
Out[139]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 4 (major_axis) x 3 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be **convertible to Panels**. Thus, they can be any of the other valid inputs to Panel as per above.

9.4.3 Slicing

Slicing works in a similar manner to a Panel. `[]` slices the first dimension. `.ix` allows you to slice arbitrarily and get back lower dimensional objects

```
In [140]: p4d['Label1']
Out[140]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

4D -> Panel

```
In [141]: p4d.ix[:,:,:,'A']
Out[141]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 5 (minor_axis)
Items axis: Label1 to Label2
```

```
Major_axis axis: Item1 to Item2
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

4D -> DataFrame

```
In [142]: p4d.ix[:,:,0,'A']
Out[142]:
         Label1    Label2
Item1  1.127489  0.015494
Item2 -1.650400  0.130533
```

4D -> Series

```
In [143]: p4d.ix[:,0,0,'A']
Out[143]:
Label1    1.127489
Label2    0.015494
Name: A, dtype: float64
```

9.4.4 Transposing

A Panel4D can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [144]: p4d.transpose(3, 2, 1, 0)
Out[144]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 4 (labels) x 5 (items) x 2 (major_axis) x 2 (minor_axis)
Labels axis: A to D
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: Item1 to Item2
Minor_axis axis: Label1 to Label2
```

9.5 PanelND (Experimental)

PanelND is a module with a set of factory functions to enable a user to construct N-dimensional named containers like Panel4D, with a custom set of axis labels. Thus a domain-specific container can easily be created.

The following creates a Panel5D. A new panel type object must be sliceable into a lower dimensional object. Here we slice to a Panel4D.

```
In [145]: from pandas.core import panelnd

In [146]: Panel5D = panelnd.create_nd_panel_factory(
   .....:     klass_name   = 'Panel5D',
   .....:     orders  = [ 'cool', 'labels','items','major_axis','minor_axis'],
   .....:     slices  = { 'labels' : 'labels', 'items' : 'items',
   .....:                 'major_axis' : 'major_axis', 'minor_axis' : 'minor_axis' },
   .....:     slicer  = Panel4D,
   .....:     aliases = { 'major' : 'major_axis', 'minor' : 'minor_axis' },
   .....:     stat_axis    = 2)
   .....:

In [147]: p5d = Panel5D(dict(C1 = p4d))
```

```
In [148]: p5d
Out[148]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 1 (cool) x 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Cool axis: C1 to C1
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# print a slice of our 5D
In [149]: p5d.ix['C1',:,:,0:3,:]
Out[149]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 3 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to D

# transpose it
In [150]: p5d.transpose(1,2,3,4,0)
Out[150]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 2 (cool) x 2 (labels) x 5 (items) x 4 (major_axis) x 1 (minor_axis)
Cool axis: Label1 to Label2
Labels axis: Item1 to Item2
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: A to D
Minor_axis axis: C1 to C1

# look at the shape & dim
In [151]: p5d.shape
Out[151]: (1, 2, 2, 5, 4)

In [152]: p5d.ndim
Out[152]: 5
```

CHAPTER

TEN

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'])
   ...:
```

10.1 Head and Tail

To view a small sample of a Series or DataFrame object, use the `head()` and `tail()` methods. The default number of elements to display is five, but you may pass a custom number.

```
In [5]: long_series = pd.Series(np.random.randn(1000))

In [6]: long_series.head()
Out[6]:
0   -0.305384
1   -0.479195
2    0.095031
3   -0.270099
4   -0.707140
dtype: float64

In [7]: long_series.tail(3)
Out[7]:
997    0.588446
998    0.026465
999   -1.728222
dtype: float64
```

10.2 Attributes and the raw ndarray(s)

pandas objects have a number of attributes enabling you to access the metadata

- **shape**: gives the axis dimensions of the object, consistent with ndarray
- Axis labels
  - **Series**: *index* (only axis)
  - **DataFrame**: *index* (rows) and *columns*
  - **Panel**: *items*, *major_axis*, and *minor_axis*

Note, **these attributes can be safely assigned to**!

```
In [8]: df[:2]
Out[8]:
                   A         B         C
2000-01-01  0.187483 -1.933946  0.377312
2000-01-02  0.734122  2.141616 -0.011225

In [9]: df.columns = [x.lower() for x in df.columns]

In [10]: df
Out[10]:
                   a         b         c
2000-01-01  0.187483 -1.933946  0.377312
2000-01-02  0.734122  2.141616 -0.011225
2000-01-03  0.048869 -1.360687 -0.479010
2000-01-04 -0.859661 -0.231595 -0.527750
2000-01-05 -1.296337  0.150680  0.123836
2000-01-06  0.571764  1.555563 -0.823761
2000-01-07  0.535420 -1.032853  1.469725
2000-01-08  1.304124  1.449735  0.203109
```

To get the actual data inside a data structure, one need only access the **values** property:

```
In [11]: s.values
Out[11]: array([ 0.1122,  0.8717, -0.8161, -0.7849,  1.0307])

In [12]: df.values
Out[12]:
array([[ 0.1875, -1.9339,  0.3773],
       [ 0.7341,  2.1416, -0.0112],
       [ 0.0489, -1.3607, -0.479 ],
       [-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]])

In [13]: wp.values
Out[13]:
array([[[-1.032 ,  0.9698, -0.9627,  1.3821],
        [-0.9388,  0.6691, -0.4336, -0.2736],
        [ 0.6804, -0.3084, -0.2761, -1.8212],
        [-1.9936, -1.9274, -2.0279,  1.625 ],
        [ 0.5511,  3.0593,  0.4553, -0.0307]],

       [[ 0.9357,  1.0612, -2.1079,  0.1999],
```

```
[ 0.3236, -0.6416, -0.5875,  0.0539],
[ 0.1949, -0.382 ,  0.3186,  2.0891],
[-0.7283, -0.0903, -0.7482,  1.3189],
[-2.0298,  0.7927,  0.461 , -0.5427]]])
```

If a DataFrame or Panel contains homogeneously-typed data, the ndarray can actually be modified in-place, and the changes will be reflected in the data structure. For heterogeneous data (e.g. some of the DataFrame's columns are not all the same dtype), this will not be the case. The values attribute itself, unlike the axis labels, cannot be assigned to.

Note: When working with heterogeneous data, the dtype of the resulting ndarray will be chosen to accommodate all of the data involved. For example, if strings are involved, the result will be of object dtype. If there are only floats and integers, the resulting array will be of float dtype.

10.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library (starting in 0.11.0) and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have `nans`.

Here is a sample (using 100 column x 100,000 row `DataFrames`):

Operation	0.11.0 (ms)	Prior Version (ms)	Ratio to Prior
`df1 > df2`	13.32	125.35	0.1063
`df1 * df2`	21.71	36.63	0.5928
`df1 + df2`	22.04	36.50	0.6039

You are highly encouraged to install both libraries. See the section *Recommended Dependencies* for more installation info.

10.4 Flexible binary operations

With binary operations between pandas data structures, there are two key points of interest:

- Broadcasting behavior between higher- (e.g. DataFrame) and lower-dimensional (e.g. Series) objects.
- Missing data in computations

We will demonstrate how to manage these issues independently, though they can be handled simultaneously.

10.4.1 Matching / broadcasting behavior

DataFrame has the methods `add()`, `sub()`, `mul()`, `div()` and related functions `radd()`, `rsub()`, ... for carrying out binary operations. For broadcasting behavior, Series input is of primary interest. Using these functions, you can use to either match on the *index* or *columns* via the **axis** keyword:

```
In [14]: df = pd.DataFrame({'one' : pd.Series(np.random.randn(3), index=['a', 'b', 'c']),
   ....:                    'two' : pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd']),
   ....:                    'three' : pd.Series(np.random.randn(3), index=['b', 'c', 'd'])})
   ....:
```

```
In [15]: df
Out[15]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [16]: row = df.ix[1]

In [17]: column = df['two']

In [18]: df.sub(row, axis='columns')
Out[18]:
        one     three       two
a -0.487650       NaN -1.487837
b  0.000000  0.000000  0.000000
c  0.150512  0.639504 -1.585038
d       NaN  1.301762 -2.237808

In [19]: df.sub(row, axis=1)
Out[19]:
        one     three       two
a -0.487650       NaN -1.487837
b  0.000000  0.000000  0.000000
c  0.150512  0.639504 -1.585038
d       NaN  1.301762 -2.237808

In [20]: df.sub(column, axis='index')
Out[20]:
        one     three  two
a -0.274957       NaN    0
b -1.275144 -1.313539    0
c  0.460406  0.911003    0
d       NaN  2.226031    0

In [21]: df.sub(column, axis=0)
Out[21]:
        one     three  two
a -0.274957       NaN    0
b -1.275144 -1.313539    0
c  0.460406  0.911003    0
d       NaN  2.226031    0
```

Furthermore you can align a level of a multi-indexed DataFrame with a Series.

```
In [22]: dfmi = df.copy()

In [23]: dfmi.index = pd.MultiIndex.from_tuples([(1,'a'),(1,'b'),(1,'c'),(2,'a')],
   ....:                                        names=['first','second'])
   ....:

In [24]: dfmi.sub(column, axis=0, level='second')
Out[24]:
                   one     three       two
first second
1     a      -0.274957       NaN  0.000000
      b      -1.275144 -1.313539  0.000000
      c       0.460406  0.911003  0.000000
```

```
2     a            NaN  1.476060 -0.749971
```

With Panel, describing the matching behavior is a bit more difficult, so the arithmetic methods instead (and perhaps confusingly?) give you the option to specify the *broadcast axis*. For example, suppose we wished to demean the data over a particular axis. This can be accomplished by taking the mean over an axis and broadcasting over the same axis:

```
In [25]: major_mean = wp.mean(axis='major')

In [26]: major_mean
Out[26]:
      Item1     Item2
A -0.546569 -0.260774
B  0.492478  0.147993
C -0.649010 -0.532794
D  0.176307  0.623812

In [27]: wp.sub(major_mean, axis='major')
Out[27]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

And similarly for `axis="items"` and `axis="minor"`.

Note: I could be convinced to make the **axis** argument in the DataFrame methods match the broadcasting behavior of Panel. Though it would require a transition period so users can change their code...

10.4.2 Missing data / operations with fill values

In Series and DataFrame (though not yet in Panel), the arithmetic functions have the option of inputting a *fill_value*, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using `fillna` if you wish).

```
In [28]: df
Out[28]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [29]: df2
Out[29]:
        one     three       two
a -0.626544  1.000000 -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [30]: df + df2
Out[30]:
        one     three       two
a -1.253088       NaN -0.703174
```

```
b -0.277789 -0.354579  2.272499
c  0.023235  0.924429 -0.897577
d       NaN  2.248945 -2.203116

In [31]: df.add(df2, fill_value=0)
Out[31]:
        one     three       two
a -1.253088  1.000000 -0.703174
b -0.277789 -0.354579  2.272499
c  0.023235  0.924429 -0.897577
d       NaN  2.248945 -2.203116
```

10.4.3 Flexible Comparisons

Starting in v0.8, pandas introduced binary comparison methods eq, ne, lt, gt, le, and ge to Series and DataFrame whose behavior is analogous to the binary arithmetic operations described above:

```
In [32]: df.gt(df2)
Out[32]:
     one  three    two
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False

In [33]: df2.ne(df)
Out[33]:
     one  three    two
a  False   True  False
b  False  False  False
c  False  False  False
d   True  False  False
```

These operations produce a pandas object the same type as the left-hand-side input that if of dtype `bool`. These `boolean` objects can be used in indexing operations, see *here*

10.4.4 Boolean Reductions

You can apply the reductions: `empty`, `any()`, `all()`, and `bool()` to provide a way to summarize a boolean result.

```
In [34]: (df>0).all()
Out[34]:
one      False
three    False
two      False
dtype: bool

In [35]: (df>0).any()
Out[35]:
one      True
three    True
two      True
dtype: bool
```

You can reduce to a final boolean value.

```
In [36]: (df>0).any().any()
Out[36]: True
```

You can test if a pandas object is empty, via the `empty` property.

```
In [37]: df.empty
Out[37]: False

In [38]: pd.DataFrame(columns=list('ABC')).empty
Out[38]: True
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

```
In [39]: pd.Series([True]).bool()
Out[39]: True

In [40]: pd.Series([False]).bool()
Out[40]: False

In [41]: pd.DataFrame([[True]]).bool()
Out[41]: True

In [42]: pd.DataFrame([[False]]).bool()
Out[42]: False
```

Warning: You might be tempted to do the following:

```
>>>if df:
     ...
```

Or

```
>>> df and df2
```

These both will raise as you are trying to compare multiple values.

```
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See *gotchas* for a more detailed discussion.

10.4.5 Comparing if objects are equivalent

Often you may find there is more than one way to compute the same result. As a simple example, consider `df+df` and `df*2`. To test that these two computations produce the same result, given the tools shown above, you might imagine using `(df+df == df*2).all()`. But in fact, this expression is False:

```
In [43]: df+df == df*2
Out[43]:
     one  three   two
a   True  False  True
b   True   True  True
c   True   True  True
d  False   True  True

In [44]: (df+df == df*2).all()
Out[44]:
one      False
```

```
three    False
two       True
dtype: bool
```

Notice that the boolean DataFrame `df+df == df*2` contains some False values! That is because NaNs do not compare as equals:

```
In [45]: np.nan == np.nan
Out[45]: False
```

So, as of v0.13.1, NDFrames (such as Series, DataFrames, and Panels) have an `equals()` method for testing equality, with NaNs in corresponding locations treated as equal.

```
In [46]: (df+df).equals(df*2)
Out[46]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```
In [47]: df1 = pd.DataFrame({'col':['foo', 0, np.nan]})

In [48]: df2 = pd.DataFrame({'col':[np.nan, 0, 'foo']}, index=[2,1,0])

In [49]: df1.equals(df2)
Out[49]: False

In [50]: df1.equals(df2.sort())
Out[50]: True
```

10.4.6 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 [51]: df1 = pd.DataFrame({'A' : [1., np.nan, 3., 5., np.nan],
   ....:                      'B' : [np.nan, 2., 3., np.nan, 6.]})
   ....:

In [52]: df2 = pd.DataFrame({'A' : [5., 2., 4., np.nan, 3., 7.],
   ....:                      'B' : [np.nan, np.nan, 3., 4., 6., 8.]})
   ....:

In [53]: df1
Out[53]:
    A   B
0   1 NaN
1 NaN   2
2   3   3
3   5 NaN
4 NaN   6

In [54]: df2
Out[54]:
    A   B
```

```
0    5 NaN
1    2 NaN
2    4   3
3  NaN   4
4    3   6
5    7   8

In [55]: df1.combine_first(df2)
Out[55]:
   A   B
0  1 NaN
1  2   2
2  3   3
3  5   4
4  3   6
5  7   8
```

10.4.7 General DataFrame Combine

The `combine_first()` method above calls the more general DataFrame method `combine()`. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (i.e., columns whose names are the same).

So, for instance, to reproduce `combine_first()` as above:

```
In [56]: combiner = lambda x, y: np.where(pd.isnull(x), y, x)

In [57]: df1.combine(df2, combiner)
Out[57]:
   A   B
0  1 NaN
1  2   2
2  3   3
3  5   4
4  3   6
5  7   8
```

10.5 Descriptive statistics

A large number of methods for computing descriptive statistics and other related operations on *Series*, *DataFrame*, and *Panel*. Most of these are aggregations (hence producing a lower-dimensional result) like `sum()`, `mean()`, and `quantile()`, but some of them, like `cumsum()` and `cumprod()`, produce an object of the same size. Generally speaking, these methods take an **axis** argument, just like *ndarray.{sum, std, ...}*, but the axis can be specified by name or integer:

- **Series**: no axis argument needed
- **DataFrame**: "index" (axis=0, default), "columns" (axis=1)
- **Panel**: "items" (axis=0), "major" (axis=1, default), "minor" (axis=2)

For example:

```
In [58]: df
Out[58]:
        one     three       two
```

```
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [59]: df.mean(0)
Out[59]:
one     -0.251274
three    0.469799
two     -0.191421
dtype: float64

In [60]: df.mean(1)
Out[60]:
a   -0.489066
b    0.273355
c    0.008348
d    0.011457
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (`True` by default):

```
In [61]: df.sum(0, skipna=False)
Out[61]:
one           NaN
three         NaN
two     -0.765684
dtype: float64

In [62]: df.sum(axis=1, skipna=True)
Out[62]:
a   -0.978131
b    0.820066
c    0.025044
d    0.022914
dtype: float64
```

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

```
In [63]: ts_stand = (df - df.mean()) / df.std()

In [64]: ts_stand.std()
Out[64]:
one      1
three    1
two      1
dtype: float64

In [65]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)

In [66]: xs_stand.std(1)
Out[66]:
a    1
b    1
c    1
d    1
dtype: float64
```

Note that methods like `cumsum()` and `cumprod()` preserve the location of NA values:

```
In [67]: df.cumsum()
Out[67]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.765438 -0.177289  0.784662
c -0.753821  0.284925  0.335874
d       NaN  1.409398 -0.765684
```

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*.

Function	Description
`count`	Number of non-null observations
`sum`	Sum of values
`mean`	Mean of values
`mad`	Mean absolute deviation
`median`	Arithmetic median of values
`min`	Minimum
`max`	Maximum
`mode`	Mode
`abs`	Absolute Value
`prod`	Product of values
`std`	Unbiased standard deviation
`var`	Unbiased variance
`sem`	Unbiased standard error of the mean
`skew`	Unbiased skewness (3rd moment)
`kurt`	Unbiased kurtosis (4th moment)
`quantile`	Sample quantile (value at %)
`cumsum`	Cumulative sum
`cumprod`	Cumulative product
`cummax`	Cumulative maximum
`cummin`	Cumulative minimum

Note that by chance some NumPy methods, like `mean`, `std`, and `sum`, will exclude NAs on Series input by default:

```
In [68]: np.mean(df['one'])
Out[68]: -0.25127365175839511

In [69]: np.mean(df['one'].values)
Out[69]: nan
```

`Series` also has a method `nunique()` which will return the number of unique non-null values:

```
In [70]: series = pd.Series(np.random.randn(500))

In [71]: series[20:500] = np.nan

In [72]: series[10:20]  = 5

In [73]: series.nunique()
Out[73]: 11
```

10.5.1 Summarizing data: describe

There is a convenient `describe()` function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```
In [74]: series = pd.Series(np.random.randn(1000))

In [75]: series[::2] = np.nan

In [76]: series.describe()
Out[76]:
count    500.000000
mean      -0.039663
std        1.069371
min       -3.463789
25%       -0.731101
50%       -0.058918
75%        0.672758
max        3.120271
dtype: float64

In [77]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [78]: frame.ix[::2] = np.nan

In [79]: frame.describe()
Out[79]:
                a           b           c           d           e
count  500.000000  500.000000  500.000000  500.000000  500.000000
mean     0.000954   -0.044014    0.075936   -0.003679    0.020751
std      1.005133    0.974882    0.967432    1.004732    0.963812
min     -3.010899   -2.782760   -3.401252   -2.944925   -3.794127
25%     -0.682900   -0.681161   -0.528190   -0.663503   -0.615717
50%     -0.001651   -0.006279    0.040098   -0.003378    0.006282
75%      0.656439    0.632852    0.717919    0.687214    0.653423
max      3.007143    2.627688    2.702490    2.850852    3.072117
```

You can select specific percentiles to include in the output:

```
In [80]: series.describe(percentiles=[.05, .25, .75, .95])
Out[80]:
count    500.000000
mean      -0.039663
std        1.069371
min       -3.463789
5%        -1.741334
25%       -0.731101
50%       -0.058918
75%        0.672758
95%        1.854383
max        3.120271
dtype: float64
```

By default, the median is always included.

For a non-numerical Series object, `describe()` will give a simple summary of the number of unique values and most frequently occurring values:

```
In [81]: s = pd.Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])

In [82]: s.describe()
Out[82]:
count      9
unique     4
top        a
freq       5
dtype: object
```

Note that on a mixed-type DataFrame object, `describe()` will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```
In [83]: frame = pd.DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})

In [84]: frame.describe()
Out[84]:
              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:

```
In [85]: frame.describe(include=['object'])
Out[85]:
         a
count    4
unique   2
top     No
freq     2

In [86]: frame.describe(include=['number'])
Out[86]:
              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 [87]: frame.describe(include='all')
Out[87]:
          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.

10.5.2 Index of Min/Max Values

The `idxmin()` and `idxmax()` functions on Series and DataFrame compute the index labels with the minimum and maximum corresponding values:

```
In [88]: s1 = pd.Series(np.random.randn(5))

In [89]: s1
Out[89]:
0   -0.872725
1    1.522411
2    0.080594
3   -1.676067
4    0.435804
dtype: float64

In [90]: s1.idxmin(), s1.idxmax()
Out[90]: (3, 1)

In [91]: df1 = pd.DataFrame(np.random.randn(5,3), columns=['A','B','C'])

In [92]: df1
Out[92]:
          A         B         C
0  0.445734 -1.649461  0.169660
1  1.246181  0.131682 -2.001988
2 -1.273023  0.870502  0.214583
3  0.088452 -0.173364  1.207466
4  0.546121  0.409515 -0.310515

In [93]: df1.idxmin(axis=0)
Out[93]:
A    2
B    0
C    1
dtype: int64

In [94]: df1.idxmax(axis=1)
Out[94]:
0    A
1    A
2    B
3    C
4    A
dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin()` and `idxmax()` return the first matching index:

```
In [95]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [96]: df3
Out[96]:
    A
e   2
d   1
c   1
b   3
a NaN

In [97]: df3['A'].idxmin()
Out[97]: 'd'
```

Note: `idxmin` and `idxmax` are called `argmin` and `argmax` in NumPy.

10.5.3 Value counts (histogramming) / Mode

The `value_counts()` Series method and top-level function computes a histogram of a 1D array of values. It can also be used as a function on regular arrays:

```
In [98]: data = np.random.randint(0, 7, size=50)

In [99]: data
Out[99]:
array([5, 3, 2, 2, 1, 4, 0, 4, 0, 2, 0, 6, 4, 1, 6, 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])

In [100]: s = pd.Series(data)

In [101]: s.value_counts()
Out[101]:
0    11
3    10
6     7
5     7
4     5
2     5
1     5
dtype: int64

In [102]: pd.value_counts(data)
Out[102]:
0    11
3    10
6     7
5     7
4     5
2     5
1     5
dtype: int64
```

Similarly, you can get the most frequently occurring value(s) (the mode) of the values in a Series or DataFrame:

```
In [103]: s5 = pd.Series([1, 1, 3, 3, 3, 5, 5, 7, 7, 7])

In [104]: s5.mode()
Out[104]:
0    3
1    7
dtype: int64

In [105]: df5 = pd.DataFrame({"A": np.random.randint(0, 7, size=50),
   .....:                     "B": np.random.randint(-10, 15, size=50)})
   .....:

In [106]: df5.mode()
Out[106]:
   A  B
0  1 -5
```

10.5.4 Discretization and quantiling

Continuous values can be discretized using the `cut()` (bins based on values) and `qcut()` (bins based on sample quantiles) functions:

```
In [107]: arr = np.random.randn(20)

In [108]: factor = pd.cut(arr, 4)

In [109]: factor
Out[109]:
[(-0.645, 0.336], (-2.61, -1.626], (-1.626, -0.645], (-1.626, -0.645], (-1.626, -0.645], ..., (0.336,
Length: 20
Categories (4, object): [(-2.61, -1.626] < (-1.626, -0.645] < (-0.645, 0.336] < (0.336, 1.316]]

In [110]: factor = pd.cut(arr, [-5, -1, 0, 1, 5])

In [111]: factor
Out[111]:
[(-1, 0], (-5, -1], (-1, 0], (-5, -1], (-1, 0], ..., (0, 1], (1, 5], (0, 1], (0, 1], (-5, -1]]
Length: 20
Categories (4, object): [(-5, -1] < (-1, 0] < (0, 1] < (1, 5]]
```

`qcut()` computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```
In [112]: arr = np.random.randn(30)

In [113]: factor = pd.qcut(arr, [0, .25, .5, .75, 1])

In [114]: factor
Out[114]:
[(-0.139, 1.00736], (1.00736, 1.976], (1.00736, 1.976], [-1.0705, -0.439], [-1.0705, -0.439], ..., (
Length: 30
Categories (4, object): [[-1.0705, -0.439] < (-0.439, -0.139] < (-0.139, 1.00736] < (1.00736, 1.976]

In [115]: pd.value_counts(factor)
Out[115]:
(1.00736, 1.976]     8
[-1.0705, -0.439]    8
```

```
(-0.139, 1.00736]    7
(-0.439, -0.139]     7
dtype: int64
```

We can also pass infinite values to define the bins:

```
In [116]: arr = np.random.randn(20)

In [117]: factor = pd.cut(arr, [-np.inf, 0, np.inf])

In [118]: factor
Out[118]:
[(-inf, 0], (0, inf], (0, inf], (0, inf], (-inf, 0], ..., (-inf, 0], (0, inf], (-inf, 0], (-inf, 0],
Length: 20
Categories (2, object): [(-inf, 0] < (0, inf]]
```

10.6 Function application

To apply your own or another library's functions to pandas objects, you should be aware of the three methods below. The appropriate method to use depends on whether your function expects to operate on an entire `DataFrame` or `Series`, row- or column-wise, or elementwise.

1. Tablewise Function Application: `pipe()`
2. Row or Column-wise Function Application: `apply()`
3. Elementwise function application: `applymap()`

10.6.1 Tablewise Function Application

New in version 0.16.2.

`DataFrames` and `Series` can of course just be passed into functions. However, if the function needs to be called in a chain, consider using the `pipe()` method. Compare the following

```
# 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)`. `.pipe` will route the `DataFrame` to the argument specified in the tuple.

For example, we can fit a regression using statsmodels. Their API expects a formula first and a `DataFrame` as the second argument, `data`. We pass in the function, keyword pair `(sm.poisson, 'data')` to `pipe`:

```
In [119]: import statsmodels.formula.api as sm

In [120]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [121]: (bb.query('h > 0')
   .....:     .assign(ln_h = lambda df: np.log(df.h))
   .....:     .pipe((sm.poisson, 'data'), 'hr ~ ln_h + year + g + C(lg)')
   .....:     .fit()
   .....:     .summary()
   .....: )
   .....:
Optimization terminated successfully.
         Current function value: 2.116284
         Iterations 24
Out[121]:
<class 'statsmodels.iolib.summary.Summary'>
"""
                          Poisson Regression Results
==============================================================================
Dep. Variable:                     hr   No. Observations:                   68
Model:                        Poisson   Df Residuals:                       63
Method:                           MLE   Df Model:                            4
Date:                Sat, 13 Jun 2015   Pseudo R-squ.:                  0.6878
Time:                        14:04:05   Log-Likelihood:                -143.91
converged:                       True   LL-Null:                       -460.91
                                        LLR p-value:                6.774e-136
===============================================================================
                  coef    std err          z      P>|z|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------
Intercept   -1267.3636    457.867     -2.768      0.006     -2164.767  -369.960
C(lg)[T.NL]    -0.2057      0.101     -2.044      0.041        -0.403    -0.008
ln_h            0.9280      0.191      4.866      0.000         0.554     1.302
year            0.6301      0.228      2.762      0.006         0.183     1.077
g               0.0099      0.004      2.754      0.006         0.003     0.017
===============================================================================
"""
```

The pipe method is inspired by unix pipes and more recently dplyr and magrittr, which have introduced the popular (%>%) (read pipe) operator for R. The implementation of pipe here is quite clean and feels right at home in python. We encourage you to view the source code (pd.DataFrame.pipe?? in IPython).

10.6.2 Row or Column-wise Function Application

Arbitrary functions can be applied along the axes of a DataFrame or Panel using the apply() method, which, like the descriptive statistics methods, take an optional axis argument:

```
In [122]: df.apply(np.mean)
Out[122]:
one     -0.251274
three    0.469799
two     -0.191421
dtype: float64

In [123]: df.apply(np.mean, axis=1)
Out[123]:
a   -0.489066
b    0.273355
```

```
c    0.008348
d    0.011457
dtype: float64

In [124]: df.apply(lambda x: x.max() - x.min())
Out[124]:
one      0.638161
three    1.301762
two      2.237808
dtype: float64

In [125]: df.apply(np.cumsum)
Out[125]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.765438 -0.177289  0.784662
c -0.753821  0.284925  0.335874
d       NaN  1.409398 -0.765684

In [126]: df.apply(np.exp)
Out[126]:
        one     three       two
a  0.534436       NaN  0.703570
b  0.870320  0.837537  3.115063
c  1.011685  1.587586  0.638401
d       NaN  3.078592  0.332353
```

Depending on the return type of the function passed to `apply()`, the result will either be of lower dimension or the same dimension.

`apply()` combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

```
In [127]: tsdf = pd.DataFrame(np.random.randn(1000, 3), columns=['A', 'B', 'C'],
   .....:                     index=pd.date_range('1/1/2000', periods=1000))
   .....:

In [128]: tsdf.apply(lambda x: x.idxmax())
Out[128]:
A   2001-04-27
B   2002-06-02
C   2000-04-02
dtype: datetime64[ns]
```

You may also pass additional arguments and keyword arguments to the `apply()` method. For instance, consider the following function you would like to apply:

```
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 [129]: tsdf
Out[129]:
                   A         B         C
2000-01-01  1.796883 -0.930690  3.542846
```

```
2000-01-02 -1.242888 -0.695279 -1.000884
2000-01-03 -0.720299  0.546303 -0.082042
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08 -0.527402  0.933507  0.129646
2000-01-09 -0.338903 -1.265452 -1.969004
2000-01-10  0.532566  0.341548  0.150493

In [130]: tsdf.apply(pd.Series.interpolate)
Out[130]:
                   A         B         C
2000-01-01  1.796883 -0.930690  3.542846
2000-01-02 -1.242888 -0.695279 -1.000884
2000-01-03 -0.720299  0.546303 -0.082042
2000-01-04 -0.681720  0.623743 -0.039704
2000-01-05 -0.643140  0.701184  0.002633
2000-01-06 -0.604561  0.778625  0.044971
2000-01-07 -0.565982  0.856066  0.087309
2000-01-08 -0.527402  0.933507  0.129646
2000-01-09 -0.338903 -1.265452 -1.969004
2000-01-10  0.532566  0.341548  0.150493
```

Finally, `apply()` takes an argument `raw` which is False by default, which converts each row or column into a Series before applying the function. When set to True, the passed function will instead receive an ndarray object, which has positive performance implications if you do not need the indexing functionality.

See also:

The section on *GroupBy* demonstrates related, flexible functionality for grouping by some criterion, applying, and combining the results into a Series, DataFrame, etc.

10.6.3 Applying elementwise Python functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods `applymap()` on DataFrame and analogously `map()` on Series accept any Python function taking a single value and returning a single value. For example:

```
In [131]: df4
Out[131]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [132]: f = lambda x: len(str(x))

In [133]: df4['one'].map(f)
Out[133]:
a    14
b    15
c    15
d     3
Name: one, dtype: int64

In [134]: df4.applymap(f)
```

```
Out[134]:
   one  three  two
a   14      3   15
b   15     15   11
c   15     14   15
d    3     13   14
```

Series.map() has an additional feature which is that it can be used to easily "link" or "map" values defined by a secondary series. This is closely related to *merging/joining functionality*:

```
In [135]: s = pd.Series(['six', 'seven', 'six', 'seven', 'six'],
   .....:               index=['a', 'b', 'c', 'd', 'e'])
   .....:

In [136]: t = pd.Series({'six' : 6., 'seven' : 7.})

In [137]: s
Out[137]:
a      six
b    seven
c      six
d    seven
e      six
dtype: object

In [138]: s.map(t)
Out[138]:
a    6
b    7
c    6
d    7
e    6
dtype: float64
```

10.6.4 Applying with a Panel

Applying with a Panel will pass a Series to the applied function. If the applied function returns a Series, the result of the application will be a Panel. If the applied function reduces to a scalar, the result of the application will be a DataFrame.

Note: Prior to 0.13.1 apply on a Panel would only work on ufuncs (e.g. np.sum/np.max).

```
In [139]: import pandas.util.testing as tm

In [140]: panel = tm.makePanel(5)

In [141]: panel
Out[141]:
<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 [142]: panel['ItemA']
Out[142]:
```

```
                   A         B         C         D
2000-01-03  0.330418  1.893177  0.801111  0.528154
2000-01-04  1.761200  0.170247  0.445614 -0.029371
2000-01-05  0.567133 -0.916844  1.453046 -0.631117
2000-01-06 -0.251020  0.835024  2.430373 -0.172441
2000-01-07  1.020099  1.259919  0.653093 -1.020485
```

A transformational apply.

```
In [143]: result = panel.apply(lambda x: x*2, axis='items')

In [144]: result
Out[144]:
<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 [145]: result['ItemA']
Out[145]:
                   A         B         C         D
2000-01-03  0.660836  3.786354  1.602222  1.056308
2000-01-04  3.522400  0.340494  0.891228 -0.058742
2000-01-05  1.134266 -1.833689  2.906092 -1.262234
2000-01-06 -0.502039  1.670047  4.860747 -0.344882
2000-01-07  2.040199  2.519838  1.306185 -2.040969
```

A reduction operation.

```
In [146]: panel.apply(lambda x: x.dtype, axis='items')
Out[146]:
                  A        B        C        D
2000-01-03  float64  float64  float64  float64
2000-01-04  float64  float64  float64  float64
2000-01-05  float64  float64  float64  float64
2000-01-06  float64  float64  float64  float64
2000-01-07  float64  float64  float64  float64
```

A similar reduction type operation

```
In [147]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[147]:
      ItemA     ItemB     ItemC
A  3.427831 -2.581431  0.840809
B  3.241522 -1.409935 -1.114512
C  5.783237  0.319672 -0.431906
D -1.325260 -2.914834  0.857043
```

This last reduction is equivalent to

```
In [148]: panel.sum('major_axis')
Out[148]:
      ItemA     ItemB     ItemC
A  3.427831 -2.581431  0.840809
B  3.241522 -1.409935 -1.114512
C  5.783237  0.319672 -0.431906
D -1.325260 -2.914834  0.857043
```

A transformation operation that returns a `Panel`, but is computing the z-score across the `major_axis`.

```
In [149]: result = panel.apply(
   .....:              lambda x: (x-x.mean())/x.std(),
   .....:              axis='major_axis')
   .....:

In [150]: result
Out[150]:
<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 [151]: result['ItemA']
Out[151]:
                   A         B         C         D
2000-01-03 -0.469761  1.156225 -0.441347  1.341731
2000-01-04  1.422763 -0.444015 -0.882647  0.398661
2000-01-05 -0.156654 -1.453694  0.367936 -0.619210
2000-01-06 -1.238841  0.173423  1.581149  0.156654
2000-01-07  0.442494  0.568061 -0.625091 -1.277837
```

Apply can also accept multiple axes in the `axis` argument. This will pass a `DataFrame` of the cross-section to the applied function.

```
In [152]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T

In [153]: result = panel.apply(f, axis = ['items','major_axis'])

In [154]: result
Out[154]:
<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 [155]: result.loc[:,:,'ItemA']
Out[155]:
                   A         B         C         D
2000-01-03  0.864236  1.132969  0.557316  0.575106
2000-01-04  0.795745  0.652527  0.534808 -0.070674
2000-01-05 -0.310864  0.558627  1.086688 -1.051477
2000-01-06 -0.001065  0.832460  0.846006  0.043602
2000-01-07  1.128946  1.152469 -0.218186 -0.891680
```

This is equivalent to the following

```
In [156]: result = pd.Panel(dict([ (ax, f(panel.loc[:,:,ax]))
   .....:                         for ax in panel.minor_axis ]))
   .....:

In [157]: result
Out[157]:
<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 [158]: result.loc[:,:,'ItemA']
Out[158]:
                   A         B         C         D
2000-01-03  0.864236  1.132969  0.557316  0.575106
2000-01-04  0.795745  0.652527  0.534808 -0.070674
2000-01-05 -0.310864  0.558627  1.086688 -1.051477
2000-01-06 -0.001065  0.832460  0.846006  0.043602
2000-01-07  1.128946  1.152469 -0.218186 -0.891680
```

10.7 Reindexing and altering labels

`reindex()` is the fundamental data alignment method in pandas. It is used to implement nearly all other features relying on label-alignment functionality. To *reindex* means to conform the data to match a given set of labels along a particular axis. This accomplishes several things:

- Reorders the existing data to match a new set of labels
- Inserts missing value (NA) markers in label locations where no data for that label existed
- If specified, **fill** data for missing labels using logic (highly relevant to working with time series data)

Here is a simple example:

```
In [159]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [160]: s
Out[160]:
a   -1.010924
b   -0.672504
c   -1.139222
d    0.354653
e    0.563622
dtype: float64

In [161]: s.reindex(['e', 'b', 'f', 'd'])
Out[161]:
e    0.563622
b   -0.672504
f         NaN
d    0.354653
dtype: float64
```

Here, the `f` label was not contained in the Series and hence appears as `NaN` in the result.

With a DataFrame, you can simultaneously reindex the index and columns:

```
In [162]: df
Out[162]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [163]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])
Out[163]:
      three       two       one
```

```
c  0.462215 -0.448789  0.011617
f       NaN       NaN       NaN
b -0.177289  1.136249 -0.138894
```

For convenience, you may utilize the `reindex_axis()` method, which takes the labels and a keyword `axis` parameter.

Note that the `Index` objects containing the actual axis labels can be **shared** between objects. So if we have a Series and a DataFrame, the following can be done:

```
In [164]: rs = s.reindex(df.index)

In [165]: rs
Out[165]:
a   -1.010924
b   -0.672504
c   -1.139222
d    0.354653
dtype: float64

In [166]: rs.index is df.index
Out[166]: True
```

This means that the reindexed Series's index is the same Python object as the DataFrame's index.

See also:

MultiIndex / Advanced Indexing is an even more concise way of doing reindexing.

Note: When writing performance-sensitive code, there is a good reason to spend some time becoming a reindexing ninja: **many operations are faster on pre-aligned data**. Adding two unaligned DataFrames internally triggers a reindexing step. For exploratory analysis you will hardly notice the difference (because `reindex` has been heavily optimized), but when CPU cycles matter sprinkling a few explicit `reindex` calls here and there can have an impact.

10.7.1 Reindexing to align with another object

You may wish to take an object and reindex its axes to be labeled the same as another object. While the syntax for this is straightforward albeit verbose, it is a common enough operation that the `reindex_like()` method is available to make this simpler:

```
In [167]: df2
Out[167]:
        one       two
a -0.626544 -0.351587
b -0.138894  1.136249
c  0.011617 -0.448789

In [168]: df3
Out[168]:
        one       two
a -0.375270 -0.463545
b  0.112379  1.024292
c  0.262891 -0.560746

In [169]: df.reindex_like(df2)
Out[169]:
        one       two
```

```
a -0.626544 -0.351587
b -0.138894  1.136249
c  0.011617 -0.448789
```

10.7.2 Aligning objects with each other with `align`

The `align()` method is the fastest way to simultaneously align two objects. It supports a `join` argument (related to *joining and merging*):

- `join='outer'`: take the union of the indexes (default)
- `join='left'`: use the calling object's index
- `join='right'`: use the passed object's index
- `join='inner'`: intersect the indexes

It returns a tuple with both of the reindexed Series:

```
In [170]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [171]: s1 = s[:4]

In [172]: s2 = s[1:]

In [173]: s1.align(s2)
Out[173]:
(a   -0.365106
 b    1.092702
 c   -1.481449
 d    1.781190
 e         NaN
 dtype: float64, a         NaN
 b    1.092702
 c   -1.481449
 d    1.781190
 e   -0.031543
 dtype: float64)

In [174]: s1.align(s2, join='inner')
Out[174]:
(b    1.092702
 c   -1.481449
 d    1.781190
 dtype: float64, b    1.092702
 c   -1.481449
 d    1.781190
 dtype: float64)

In [175]: s1.align(s2, join='left')
Out[175]:
(a   -0.365106
 b    1.092702
 c   -1.481449
 d    1.781190
 dtype: float64, a         NaN
 b    1.092702
 c   -1.481449
```

```
d    1.781190
dtype: float64)
```

For DataFrames, the join method will be applied to both the index and the columns by default:

```
In [176]: df.align(df2, join='inner')
Out[176]:
(        one       two
 a -0.626544 -0.351587
 b -0.138894  1.136249
 c  0.011617 -0.448789,          one       two
 a -0.626544 -0.351587
 b -0.138894  1.136249
 c  0.011617 -0.448789)
```

You can also pass an `axis` option to only align on the specified axis:

```
In [177]: df.align(df2, join='inner', axis=0)
Out[177]:
(        one     three       two
 a -0.626544       NaN -0.351587
 b -0.138894 -0.177289  1.136249
 c  0.011617  0.462215 -0.448789,          one       two
 a -0.626544 -0.351587
 b -0.138894  1.136249
 c  0.011617 -0.448789)
```

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 [178]: df.align(df2.ix[0], axis=1)
Out[178]:
(        one     three       two
 a -0.626544       NaN -0.351587
 b -0.138894 -0.177289  1.136249
 c  0.011617  0.462215 -0.448789
 d       NaN  1.124472 -1.101558, one     -0.626544
 three          NaN
 two     -0.351587
 Name: a, dtype: float64)
```

10.7.3 Filling while reindexing

`reindex()` takes an optional parameter `method` which is a filling method chosen from the following table:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward
nearest	Fill from the nearest index value

We illustrate these fill methods on a simple Series:

```
In [179]: rng = pd.date_range('1/3/2000', periods=8)

In [180]: ts = pd.Series(np.random.randn(8), index=rng)

In [181]: ts2 = ts[[0, 3, 6]]
```

```
In [182]: ts
Out[182]:
2000-01-03    0.480993
2000-01-04    0.604244
2000-01-05   -0.487265
2000-01-06    1.990533
2000-01-07    0.327007
2000-01-08    1.053639
2000-01-09   -2.927808
2000-01-10    0.082065
Freq: D, dtype: float64

In [183]: ts2
Out[183]:
2000-01-03    0.480993
2000-01-06    1.990533
2000-01-09   -2.927808
dtype: float64

In [184]: ts2.reindex(ts.index)
Out[184]:
2000-01-03    0.480993
2000-01-04         NaN
2000-01-05         NaN
2000-01-06    1.990533
2000-01-07         NaN
2000-01-08         NaN
2000-01-09   -2.927808
2000-01-10         NaN
Freq: D, dtype: float64

In [185]: ts2.reindex(ts.index, method='ffill')
Out[185]:
2000-01-03    0.480993
2000-01-04    0.480993
2000-01-05    0.480993
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08    1.990533
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64

In [186]: ts2.reindex(ts.index, method='bfill')
Out[186]:
2000-01-03    0.480993
2000-01-04    1.990533
2000-01-05    1.990533
2000-01-06    1.990533
2000-01-07   -2.927808
2000-01-08   -2.927808
2000-01-09   -2.927808
2000-01-10         NaN
Freq: D, dtype: float64

In [187]: ts2.reindex(ts.index, method='nearest')
Out[187]:
2000-01-03    0.480993
```

```
2000-01-04    0.480993
2000-01-05    1.990533
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08   -2.927808
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64
```

These methods require that the indexes are **ordered** increasing or decreasing.

Note that the same result could have been achieved using *fillna* (except for `method='nearest'`) or *interpolate*:

```
In [188]: ts2.reindex(ts.index).fillna(method='ffill')
Out[188]:
2000-01-03    0.480993
2000-01-04    0.480993
2000-01-05    0.480993
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08    1.990533
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64
```

`reindex()` will raise a ValueError if the index is not monotonic increasing or descreasing. `fillna()` and `interpolate()` will not make any checks on the order of the index.

10.7.4 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 [189]: df
Out[189]:
        one     three       two
a -0.626544       NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d       NaN  1.124472 -1.101558

In [190]: df.drop(['a', 'd'], axis=0)
Out[190]:
        one     three       two
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789

In [191]: df.drop(['one'], axis=1)
Out[191]:
      three       two
a       NaN -0.351587
b -0.177289  1.136249
c  0.462215 -0.448789
d  1.124472 -1.101558
```

Note that the following also works, but is a bit less obvious / clean:

```
In [192]: df.reindex(df.index.difference(['a', 'd']))
Out[192]:
```

```
        one     three       two
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
```

10.7.5 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 [193]: s
Out[193]:
a   -0.365106
b    1.092702
c   -1.481449
d    1.781190
e   -0.031543
dtype: float64

In [194]: s.rename(str.upper)
Out[194]:
A   -0.365106
B    1.092702
C   -1.481449
D    1.781190
E   -0.031543
dtype: float64
```

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). But if you pass a dict or Series, it need only contain a subset of the labels as keys:

```
In [195]: df.rename(columns={'one' : 'foo', 'two' : 'bar'},
   .....:           index={'a' : 'apple', 'b' : 'banana', 'd' : 'durian'})
   .....:
Out[195]:
             foo     three       bar
apple  -0.626544       NaN -0.351587
banana -0.138894 -0.177289  1.136249
c       0.011617  0.462215 -0.448789
durian       NaN  1.124472 -1.101558
```

The `rename()` method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place. The Panel class has a related `rename_axis()` class which can rename any of its three axes.

10.8 Iteration

Because Series is array-like, basic iteration produces the values. Other data structures follow the dict-like convention of iterating over the "keys" of the objects. In short:

- **Series**: values
- **DataFrame**: column labels
- **Panel**: item labels

Thus, for example:

```
In [196]: for col in df:
   .....:     print(col)
   .....:
one
three
two
```

10.8.1 iteritems

Consistent with the dict-like interface, `iteritems()` iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs
- **Panel**: (item, DataFrame) pairs

For example:

```
In [197]: for item, frame in wp.iteritems():
   .....:     print(item)
   .....:     print(frame)
   .....:
Item1
                   A         B         C         D
2000-01-01 -1.032011  0.969818 -0.962723  1.382083
2000-01-02 -0.938794  0.669142 -0.433567 -0.273610
2000-01-03  0.680433 -0.308450 -0.276099 -1.821168
2000-01-04 -1.993606 -1.927385 -2.027924  1.624972
2000-01-05  0.551135  3.059267  0.455264 -0.030740
Item2
                   A         B         C         D
2000-01-01  0.935716  1.061192 -2.107852  0.199905
2000-01-02  0.323586 -0.641630 -0.587514  0.053897
2000-01-03  0.194889 -0.381994  0.318587  2.089075
2000-01-04 -0.728293 -0.090255 -0.748199  1.318931
2000-01-05 -2.029766  0.792652  0.461007 -0.542749
```

10.8.2 iterrows

New in v0.7 is the ability to iterate efficiently through rows of a DataFrame with `iterrows()`. It returns an iterator yielding each index value along with a Series containing the data in each row:

```
In [198]: for row_index, row in df2.iterrows():
   .....:     print('%s\n%s' % (row_index, row))
   .....:
a
one   -0.626544
two   -0.351587
Name: a, dtype: float64
b
one   -0.138894
two    1.136249
Name: b, dtype: float64
c
one    0.011617
```

```
two   -0.448789
Name: c, dtype: float64
```

For instance, a contrived way to transpose the DataFrame would be:

```
In [199]: df2 = pd.DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})

In [200]: print(df2)
   x  y
0  1  4
1  2  5
2  3  6

In [201]: print(df2.T)
   0  1  2
x  1  2  3
y  4  5  6

In [202]: df2_t = pd.DataFrame(dict((idx,values) for idx, values in df2.iterrows()))

In [203]: print(df2_t)
   0  1  2
x  1  2  3
y  4  5  6
```

Note: `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
In [204]: df_iter = pd.DataFrame([[1, 1.0]], columns=['x', 'y'])

In [205]: row = next(df_iter.iterrows())[1]

In [206]: print(row['x'].dtype)
float64

In [207]: print(df_iter['x'].dtype)
int64
```

10.8.3 itertuples

The `itertuples()` method will return an iterator yielding a tuple for each row in the DataFrame. The first element of the tuple will be the row's corresponding index value, while the remaining values are the row values proper.

For instance,

```
In [208]: for r in df2.itertuples():
   .....:     print(r)
   .....:
(0, 1, 4)
(1, 2, 5)
(2, 3, 6)
```

10.8.4 .dt accessor

`Series` has an accessor to succinctly return datetime like properties for the *values* of the Series, if its a datetime/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [209]: s = pd.Series(pd.date_range('20130101 09:10:12',periods=4))

In [210]: s
Out[210]:
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 [211]: s.dt.hour
Out[211]:
0    9
1    9
2    9
3    9
dtype: int64

In [212]: s.dt.second
Out[212]:
0    12
1    12
2    12
3    12
dtype: int64

In [213]: s.dt.day
Out[213]:
0    1
1    2
2    3
3    4
dtype: int64
```

This enables nice expressions like this:

```
In [214]: s[s.dt.day==2]
Out[214]:
1   2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produces tz aware transformations:

```
In [215]: stz = s.dt.tz_localize('US/Eastern')

In [216]: stz
Out[216]:
0    2013-01-01 09:10:12-05:00
1    2013-01-02 09:10:12-05:00
2    2013-01-03 09:10:12-05:00
3    2013-01-04 09:10:12-05:00
dtype: object
```

```
In [217]: stz.dt.tz
Out[217]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [218]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[218]:
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: object
```

The `.dt` accessor works for period and timedelta dtypes.

```
# period
In [219]: s = pd.Series(pd.period_range('20130101', periods=4,freq='D'))

In [220]: s
Out[220]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: object

In [221]: s.dt.year
Out[221]:
0    2013
1    2013
2    2013
3    2013
dtype: int64

In [222]: s.dt.day
Out[222]:
0    1
1    2
2    3
3    4
dtype: int64

# timedelta
In [223]: s = pd.Series(pd.timedelta_range('1 day 00:00:05',periods=4,freq='s'))

In [224]: s
Out[224]:
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 [225]: s.dt.days
Out[225]:
0    1
1    1
2    1
3    1
```

```
dtype: int64

In [226]: s.dt.seconds
Out[226]:
0    5
1    6
2    7
3    8
dtype: int64

In [227]: s.dt.components
Out[227]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     1      0        0        5             0             0            0
1     1      0        0        6             0             0            0
2     1      0        0        7             0             0            0
3     1      0        0        8             0             0            0
```

Note: `Series.dt` will raise a `TypeError` if you access with a non-datetimelike values

10.9 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 [228]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [229]: s.str.lower()
Out[229]:
0       a
1       b
2       c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

Powerful pattern-matching methods are provided as well, but note that pattern-matching generally uses regular expressions by default (and in some cases always uses them).

Please see *Vectorized String Methods* for a complete description.

10.10 Sorting by index and value

There are two obvious kinds of sorting that you may be interested in: sorting by label and sorting by actual values. The primary method for sorting axis labels (indexes) across data structures is the `sort_index()` method.

```
In [230]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
   .....:                          columns=['three', 'two', 'one'])
```

```
   .....:

In [231]: unsorted_df.sort_index()
Out[231]: 
      three       two       one
a       NaN -0.351587 -0.626544
b -0.177289  1.136249 -0.138894
c  0.462215 -0.448789  0.011617
d  1.124472 -1.101558       NaN

In [232]: unsorted_df.sort_index(ascending=False)
Out[232]: 
      three       two       one
d  1.124472 -1.101558       NaN
c  0.462215 -0.448789  0.011617
b -0.177289  1.136249 -0.138894
a       NaN -0.351587 -0.626544

In [233]: unsorted_df.sort_index(axis=1)
Out[233]: 
        one     three       two
a -0.626544       NaN -0.351587
d       NaN  1.124472 -1.101558
c  0.011617  0.462215 -0.448789
b -0.138894 -0.177289  1.136249
```

`DataFrame.sort_index()` can accept an optional `by` argument for `axis=0` which will use an arbitrary vector or a column name of the DataFrame to determine the sort order:

```
In [234]: df1 = pd.DataFrame({'one':[2,1,1,1],'two':[1,3,2,4],'three':[5,4,3,2]})

In [235]: df1.sort_index(by='two')
Out[235]: 
   one  three  two
0    2      5    1
2    1      3    2
1    1      4    3
3    1      2    4
```

The `by` argument can take a list of column names, e.g.:

```
In [236]: df1[['one', 'two', 'three']].sort_index(by=['one','two'])
Out[236]: 
   one  two  three
2    1    2      3
1    1    3      4
3    1    4      2
0    2    1      5
```

Series has the method `order()` (analogous to R's order function) which sorts by value, with special treatment of NA values via the `na_position` argument:

```
In [237]: s[2] = np.nan

In [238]: s.order()
Out[238]: 
0       A
3    Aaba
1       B
4    Baca
```

```
6    CABA
8     cat
7     dog
2     NaN
5     NaN
dtype: object

In [239]: s.order(na_position='first')
Out[239]:
2     NaN
5     NaN
0       A
3    Aaba
1       B
4    Baca
6    CABA
8     cat
7     dog
dtype: object
```

Note: `Series.sort()` sorts a Series by value in-place. This is to provide compatibility with NumPy methods which expect the `ndarray.sort` behavior. `Series.order()` returns a copy of the sorted data.

Series has the `searchsorted()` method, which works similar to `numpy.ndarray.searchsorted()`.

```
In [240]: ser = pd.Series([1, 2, 3])

In [241]: ser.searchsorted([0, 3])
Out[241]: array([0, 2])

In [242]: ser.searchsorted([0, 4])
Out[242]: array([0, 3])

In [243]: ser.searchsorted([1, 3], side='right')
Out[243]: array([1, 3])

In [244]: ser.searchsorted([1, 3], side='left')
Out[244]: array([0, 2])

In [245]: ser = pd.Series([3, 1, 2])

In [246]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[246]: array([0, 2])
```

10.10.1 smallest / largest values

New in version 0.14.0.

`Series` has the `nsmallest()` and `nlargest()` methods which return the smallest or largest n values. For a large `Series` this can be much faster than sorting the entire Series and calling `head(n)` on the result.

```
In [247]: s = pd.Series(np.random.permutation(10))

In [248]: s
Out[248]:
0    7
```

```
1    5
2    4
3    6
4    1
5    8
6    9
7    2
8    0
9    3
dtype: int32

In [249]: s.order()
Out[249]:
8    0
4    1
7    2
9    3
2    4
1    5
3    6
0    7
5    8
6    9
dtype: int32

In [250]: s.nsmallest(3)
Out[250]:
8    0
4    1
7    2
dtype: int32

In [251]: s.nlargest(3)
Out[251]:
6    9
5    8
0    7
dtype: int32
```

10.10.2 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`.

```
In [252]: df1.columns = pd.MultiIndex.from_tuples([('a','one'),('a','two'),('b','three')])

In [253]: df1.sort_index(by=('a','two'))
Out[253]:
    a          b
  one two three
3   1   2     4
2   1   3     2
1   1   4     3
0   2   5     1
```

10.11 Copying

The copy() method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that **it is seldom necessary to copy objects**. For example, there are only a handful of ways to alter a DataFrame *in-place*:

- Inserting, deleting, or modifying a column
- Assigning to the index or columns attributes
- For homogeneous data, directly modifying the values via the values attribute or advanced indexing

To be clear, no pandas methods have the side effect of modifying your data; almost all methods return new objects, leaving the original object untouched. If data is modified, it is because you did so explicitly.

10.12 dtypes

The main types stored in pandas objects are float, int, bool, datetime64[ns], timedelta[ns] and object. In addition these dtypes have item sizes, e.g. int64 and int32. A convenient dtypes` attribute for DataFrames returns a Series with the data type of each column.

```
In [254]: dft = pd.DataFrame(dict(A = np.random.rand(3),
   .....:                        B = 1,
   .....:                        C = 'foo',
   .....:                        D = pd.Timestamp('20010102'),
   .....:                        E = pd.Series([1.0]*3).astype('float32'),
   .....:                                    F = False,
   .....:                                    G = pd.Series([1]*3,dtype='int8')))
   .....:

In [255]: dft
Out[255]:
          A  B    C          D  E      F  G
0  0.028931  1  foo 2001-01-02  1  False  1
1  0.936706  1  foo 2001-01-02  1  False  1
2  0.831782  1  foo 2001-01-02  1  False  1

In [256]: dft.dtypes
Out[256]:
A           float64
B             int64
C            object
D    datetime64[ns]
E           float32
F              bool
G              int8
dtype: object
```

On a Series use the dtype attribute.

```
In [257]: dft['A'].dtype
Out[257]: dtype('float64')
```

If a pandas object contains data multiple dtypes *IN A SINGLE COLUMN*, the dtype of the column will be chosen to accommodate all of the data types (object is the most general).

```
# these ints are coerced to floats
In [258]: pd.Series([1, 2, 3, 4, 5, 6.])
Out[258]:
0    1
1    2
2    3
3    4
4    5
5    6
dtype: float64

# string data forces an ``object`` dtype
In [259]: pd.Series([1, 2, 3, 6., 'foo'])
Out[259]:
0      1
1      2
2      3
3      6
4    foo
dtype: object
```

The method `get_dtype_counts()` will return the number of columns of each type in a `DataFrame`:

```
In [260]: dft.get_dtype_counts()
Out[260]:
bool              1
datetime64[ns]    1
float32           1
float64           1
int64             1
int8              1
object            1
dtype: int64
```

Numeric dtypes will propagate and can coexist in DataFrames (starting in v0.11.0). If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [261]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [262]: df1
Out[262]:
          A
0  1.213978
1 -0.505425
2  0.254678
3 -0.744834
4  0.647650
5  0.822993
6  1.778703
7 -1.543048

In [263]: df1.dtypes
Out[263]:
A    float32
dtype: object

In [264]: 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 [265]: df2
Out[265]:
          A         B    C
0 -0.123230 -1.508174    0
1  2.240234 -0.502623    0
2 -0.143799  0.529008    0
3 -2.884766  0.590536    1
4  0.027588  0.296947    0
5 -1.150391  0.007045  255
6  0.246460  0.707877    1
7 -0.455078  0.950661    0

In [266]: df2.dtypes
Out[266]:
A    float16
B    float64
C      uint8
dtype: object
```

10.12.1 defaults

By default integer types are `int64` and float types are `float64`, *REGARDLESS* of platform (32-bit or 64-bit). The following will all result in `int64` dtypes.

```
In [267]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[267]:
a    int64
dtype: object

In [268]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[268]:
a    int64
dtype: object

In [269]: pd.DataFrame({'a': 1 }, index=list(range(2))).dtypes
Out[269]:
a    int64
dtype: object
```

Numpy, however will choose *platform-dependent* types when creating arrays. The following **WILL** result in `int32` on 32-bit platform.

```
In [270]: frame = pd.DataFrame(np.array([1, 2]))
```

10.12.2 upcasting

Types can potentially be *upcasted* when combined with other types, meaning they are promoted from the current type (say `int` to `float`)

```
In [271]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [272]: df3
```

```
Out[272]:
          A         B    C
0  1.090748 -1.508174    0
1  1.734810 -0.502623    0
2  0.110879  0.529008    0
3 -3.629600  0.590536    1
4  0.675238  0.296947    0
5 -0.327398  0.007045  255
6  2.025163  0.707877    1
7 -1.998126  0.950661    0

In [273]: df3.dtypes
Out[273]:
A    float32
B    float64
C    float64
dtype: object
```

The `values` attribute on a DataFrame return the *lower-common-denominator* of the dtypes, meaning the dtype that can accommodate **ALL** of the types in the resulting homogeneous dtyped numpy array. This can force some *upcasting*.

```
In [274]: df3.values.dtype
Out[274]: dtype('float64')
```

10.12.3 astype

You can use the `astype()` method to explicitly convert dtypes from one to another. These will by default return a copy, even if the dtype was unchanged (pass `copy=False` to change this behavior). In addition, they will raise an exception if the astype operation is invalid.

Upcasting is always according to the **numpy** rules. If two different dtypes are involved in an operation, then the more *general* one will be used as the result of the operation.

```
In [275]: df3
Out[275]:
          A         B    C
0  1.090748 -1.508174    0
1  1.734810 -0.502623    0
2  0.110879  0.529008    0
3 -3.629600  0.590536    1
4  0.675238  0.296947    0
5 -0.327398  0.007045  255
6  2.025163  0.707877    1
7 -1.998126  0.950661    0

In [276]: df3.dtypes
Out[276]:
A    float32
B    float64
C    float64
dtype: object

# conversion of dtypes
In [277]: df3.astype('float32').dtypes
Out[277]:
A    float32
B    float32
```

```
C    float32
dtype: object
```

10.12.4 object conversion

`convert_objects()` is a method to try to force conversion of types from the `object` dtype to other types. To force conversion of specific types that are *number like*, e.g. could be a string that represents a number, pass `convert_numeric=True`. This will force strings and numbers alike to be numbers if possible, otherwise they will be set to `np.nan`.

```
In [278]: df3['D'] = '1.'

In [279]: df3['E'] = '1'

In [280]: df3.convert_objects(convert_numeric=True).dtypes
Out[280]:
A    float32
B    float64
C    float64
D    float64
E      int64
dtype: object

# same, but specific dtype conversion
In [281]: df3['D'] = df3['D'].astype('float16')

In [282]: df3['E'] = df3['E'].astype('int32')

In [283]: df3.dtypes
Out[283]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

To force conversion to `datetime64[ns]`, pass `convert_dates='coerce'`. This will convert any datetime-like object to dates, forcing other values to `NaT`. This might be useful if you are reading in data which is mostly dates, but occasionally has non-dates intermixed and you want to represent as missing.

```
In [284]: import datetime

In [285]: s = pd.Series([datetime.datetime(2001,1,1,0,0),
   .....:                'foo', 1.0, 1, pd.Timestamp('20010104'),
   .....:                '20010105'], dtype='O')
   .....:

In [286]: s
Out[286]:
0    2001-01-01 00:00:00
1                    foo
2                      1
3                      1
4    2001-01-04 00:00:00
5               20010105
dtype: object
```

```
In [287]: s.convert_objects(convert_dates='coerce')
Out[287]:
0   2001-01-01
1          NaT
2          NaT
3          NaT
4   2001-01-04
5   2001-01-05
dtype: datetime64[ns]
```

In addition, `convert_objects()` will attempt the *soft* conversion of any *object* dtypes, meaning that if all the objects in a Series are of the same type, the Series will have that dtype.

10.12.5 gotchas

Performing selection operations on `integer` type data can easily upcast the data to `floating`. The dtype of the input data will be preserved in cases where `nans` are not introduced (starting in 0.11.0) See also *integer na gotchas*

```
In [288]: dfi = df3.astype('int32')

In [289]: dfi['E'] = 1

In [290]: dfi
Out[290]:
   A  B    C  D  E
0  1 -1    0  1  1
1  1  0    0  1  1
2  0  0    0  1  1
3 -3  0    1  1  1
4  0  0    0  1  1
5  0  0  255  1  1
6  2  0    1  1  1
7 -1  0    0  1  1

In [291]: dfi.dtypes
Out[291]:
A    int32
B    int32
C    int32
D    int32
E    int64
dtype: object

In [292]: casted = dfi[dfi>0]

In [293]: casted
Out[293]:
    A   B    C  D  E
0   1 NaN  NaN  1  1
1   1 NaN  NaN  1  1
2 NaN NaN  NaN  1  1
3 NaN NaN    1  1  1
4 NaN NaN  NaN  1  1
5 NaN NaN  255  1  1
6   2 NaN    1  1  1
7 NaN NaN  NaN  1  1
```

```
In [294]: casted.dtypes
Out[294]:
A    float64
B    float64
C    float64
D      int32
E      int64
dtype: object
```

While float dtypes are unchanged.

```
In [295]: dfa = df3.copy()

In [296]: dfa['A'] = dfa['A'].astype('float32')

In [297]: dfa.dtypes
Out[297]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object

In [298]: casted = dfa[df2>0]

In [299]: casted
Out[299]:
          A         B    C   D   E
0       NaN       NaN  NaN NaN NaN
1  1.734810       NaN  NaN NaN NaN
2       NaN  0.529008  NaN NaN NaN
3       NaN  0.590536    1 NaN NaN
4  0.675238  0.296947  NaN NaN NaN
5       NaN  0.007045  255 NaN NaN
6  2.025163  0.707877    1 NaN NaN
7       NaN  0.950661  NaN NaN NaN

In [300]: casted.dtypes
Out[300]:
A    float32
B    float64
C    float64
D    float16
E    float64
dtype: object
```

10.13 Selecting columns based on `dtype`

New in version 0.14.1.

The `select_dtypes()` method implements subsetting of columns based on their `dtype`.

First, let's create a `DataFrame` with a slew of different dtypes:

```
In [301]: df = pd.DataFrame({'string': list('abc'),
   .....:                    'int64': list(range(1, 4)),
```

```
   .....:                         'uint8': np.arange(3, 6).astype('u1'),
   .....:                         'float64': np.arange(4.0, 7.0),
   .....:                         'bool1': [True, False, True],
   .....:                         'bool2': [False, True, False],
   .....:                         'dates': pd.date_range('now', periods=3).values,
   .....:                         'category': pd.Series(list("ABC")).astype('category')})
   .....:

In [302]: df['tdeltas'] = df.dates.diff()

In [303]: df['uint64'] = np.arange(3, 6).astype('u8')

In [304]: df['other_dates'] = pd.date_range('20130101', periods=3).values

In [305]: df
Out[305]:
   bool1  bool2 category                      dates  float64  int64 string  \
0   True  False        A 2015-06-13 14:04:30.984801        4      1      a
1  False   True        B 2015-06-14 14:04:30.984801        5      2      b
2   True  False        C 2015-06-15 14:04:30.984801        6      3      c

   uint8  tdeltas  uint64 other_dates
0      3      NaT       3  2013-01-01
1      4   1 days       4  2013-01-02
2      5   1 days       5  2013-01-03
```

`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 [306]: df.select_dtypes(include=[bool])
Out[306]:
   bool1  bool2
0   True  False
1  False   True
2   True  False
```

You can also pass the name of a dtype in the numpy dtype hierarchy:

```
In [307]: df.select_dtypes(include=['bool'])
Out[307]:
   bool1  bool2
0   True  False
1  False   True
2   True  False
```

`select_dtypes()` also works with generic dtypes as well.

For example, to select all numeric and boolean columns while excluding unsigned integers

```
In [308]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
Out[308]:
   bool1  bool2  float64  int64  tdeltas
0   True  False        4      1      NaT
1  False   True        5      2   1 days
2   True  False        6      3   1 days
```

To select string columns you must use the `object` dtype:

```
In [309]: df.select_dtypes(include=['object'])
Out[309]:
  string
0      a
1      b
2      c
```

To see all the child dtypes of a generic `dtype` like `numpy.number` you can define a function that returns a tree of child dtypes:

```
In [310]: 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`:

```
In [311]: subdtypes(np.generic)
Out[311]:
[numpy.generic,
 [[numpy.number,
   [[numpy.integer,
     [[numpy.signedinteger,
       [numpy.int8,
        numpy.int16,
        numpy.int32,
        numpy.int32,
        numpy.int64,
        numpy.timedelta64]],
      [numpy.unsignedinteger,
       [numpy.uint8,
        numpy.uint16,
        numpy.uint32,
        numpy.uint32,
        numpy.uint64]]]],
    [numpy.inexact,
     [[numpy.floating,
       [numpy.float16, numpy.float32, numpy.float64, numpy.float96]],
      [numpy.complexfloating,
       [numpy.complex64, numpy.complex128, numpy.complex192]]]]]],
  [numpy.flexible,
   [[numpy.character, [numpy.string_, numpy.unicode_]],
    [numpy.void, [numpy.core.records.record]]]],
  numpy.bool_,
  numpy.datetime64,
  numpy.object_]]
```

Note: Pandas also defines an additional `category` dtype, which is not integrated into the normal numpy hierarchy and wont show up with the above function.

Note: The `include` and `exclude` parameters must be non-string sequences.

CHAPTER ELEVEN

WORKING WITH TEXT DATA

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 = 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
1     1
2     1
3     4
4     4
5   NaN
6     4
7     3
8     3
dtype: float64
```

```
In [5]: idx = Index([' jack', 'jill ', ' jesse ', 'frank'])

In [6]: idx.str.strip()
Out[6]: Index([u'jack', u'jill', u'jesse', u'frank'], dtype='object')

In [7]: idx.str.lstrip()
Out[7]: Index([u'jack', u'jill ', u'jesse ', u'frank'], dtype='object')

In [8]: idx.str.rstrip()
Out[8]: Index([u' jack', u'jill', u' jesse', u'frank'], dtype='object')
```

The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

```
In [9]: df = DataFrame(randn(3, 2), columns=[' Column A ', ' Column B '],
   ...:                 index=range(3))
   ...:

In [10]: df
Out[10]:
    Column A    Column B
0    0.017428    0.039049
1   -2.240248    0.847859
2   -1.342107    0.368828
```

Since `df.columns` is an Index object, we can use the `.str` accessor

```
In [11]: df.columns.str.strip()
Out[11]: Index([u'Column A', u'Column B'], dtype='object')

In [12]: df.columns.str.lower()
Out[12]: Index([u' column a ', u' column b '], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing whitespaces, lowercasing all names, and replacing any remaining whitespaces with underscores:

```
In [13]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')

In [14]: df
Out[14]:
   column_a  column_b
0  0.017428  0.039049
1 -2.240248  0.847859
2 -1.342107  0.368828
```

11.1 Splitting and Replacing Strings

Methods like `split` return a Series of lists:

```
In [15]: s2 = 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('_').str[1]
Out[18]: 
0      b
1      d
2    NaN
3      g
dtype: object
```

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  None  None
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
2  NaN  None
3    f   g_h
```

`rsplit` is similar to `split` except it works in the reverse direction, i.e., from the end of the string to the beginning of the string:

```
In [21]: s2.str.rsplit('_', expand=True, n=1)
Out[21]: 
     0     1
0  a_b     c
1  c_d     e
2  NaN  None
3  f_g     h
```

Methods like `replace` and `findall` take regular expressions, too:

```
In [22]: s3 = Series(['A', 'B', 'C', 'Aaba', 'Baca',
   ....:              '', np.nan, 'CABA', 'dog', 'cat'])
   ....: 

In [23]: s3
Out[23]: 
```

```
0       A
1       B
2       C
3    Aaba
4    Baca
5
6     NaN
7    CABA
8     dog
9     cat
dtype: object

In [24]: s3.str.replace('^.a|dog', 'XX-XX ', case=False)
Out[24]:
0           A
1           B
2           C
3    XX-XX ba
4    XX-XX ca
5
6         NaN
7    XX-XX BA
8      XX-XX
9     XX-XX t
dtype: object
```

Some caution must be taken to keep regular expressions in mind! For example, the following code will cause trouble because of the regular expression meaning of *$*:

```
# Consider the following badly formatted financial data
In [25]: dollars = Series(['12', '-$10', '$10,000'])

# This does what you'd naively expect:
In [26]: dollars.str.replace('$', '')
Out[26]:
0        12
1       -10
2    10,000
dtype: object

# But this doesn't:
In [27]: dollars.str.replace('-$', '-')
Out[27]:
0         12
1       -$10
2    $10,000
dtype: object

# We need to escape the special character (for >1 len patterns)
In [28]: dollars.str.replace(r'-\$', '-')
Out[28]:
0         12
1        -10
2    $10,000
dtype: object
```

11.2 Indexing with .str

You can use [] notation to directly index by position locations. If you index past the end of the string, the result will be a NaN.

```
In [29]: s = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan,
   ....:             'CABA', 'dog', 'cat'])
   ....:

In [30]: s.str[0]
Out[30]:
0      A
1      B
2      C
3      A
4      B
5    NaN
6      C
7      d
8      c
dtype: object

In [31]: s.str[1]
Out[31]:
0    NaN
1    NaN
2    NaN
3      a
4      a
5    NaN
6      A
7      o
8      a
dtype: object
```

11.3 Extracting Substrings

The method extract (introduced in version 0.13) accepts regular expressions with match groups. Extracting a regular expression with one group returns a Series of strings.

```
In [32]: Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
Out[32]:
0      1
1      2
2    NaN
dtype: object
```

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

```
In [33]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
Out[33]:
     0    1
0    a    1
1    b    2
2  NaN  NaN
```

Elements that do not match return a row filled with `NaN`. Thus, a Series of messy strings can be “converted” into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects.

The results dtype always is object, even if no match is found and the result only contains `NaN`.

Named groups like

```
In [34]: Series(['a1', 'b2', 'c3']).str.extract('(?P<letter>[ab])(?P<digit>\d)')
Out[34]:
  letter digit
0      a     1
1      b     2
2    NaN   NaN
```

and optional groups like

```
In [35]: Series(['a1', 'b2', '3']).str.extract('(?P<letter>[ab])?(?P<digit>\d)')
Out[35]:
  letter digit
0      a     1
1      b     2
2    NaN     3
```

can also be used.

11.3.1 Testing for Strings that Match or Contain a Pattern

You can check whether elements contain a pattern:

```
In [36]: pattern = r'[a-z][0-9]'

In [37]: Series(['1', '2', '3a', '3b', '03c']).str.contains(pattern)
Out[37]:
0    False
1    False
2    False
3    False
4    False
dtype: bool
```

or match a pattern:

```
In [38]: Series(['1', '2', '3a', '3b', '03c']).str.match(pattern, as_indexer=True)
Out[38]:
0    False
1    False
2    False
3    False
4    False
dtype: bool
```

The distinction between `match` and `contains` is strictness: `match` relies on strict `re.match`, while `contains` relies on `re.search`.

Warning: In previous versions, `match` was for *extracting* groups, returning a not-so-convenient Series of tuples. The new method `extract` (described in the previous section) is now preferred.
This old, deprecated behavior of `match` is still the default. As demonstrated above, use the new behavior by setting `as_indexer=True`. In this mode, `match` is analogous to `contains`, returning a boolean Series. The new behavior will become the default behavior in a future release.

Methods like `match`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```
In [39]: s4 = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [40]: s4.str.contains('A', na=False)
Out[40]:
0     True
1    False
2    False
3     True
4    False
5    False
6     True
7    False
8    False
dtype: bool
```

11.3.2 Creating Indicator Variables

You can extract dummy variables from string columns. For example if they are separated by a `'|'`:

```
In [41]: s = Series(['a', 'a|b', np.nan, 'a|c'])

In [42]: s.str.get_dummies(sep='|')
Out[42]:
   a  b  c
0  1  0  0
1  1  1  0
2  0  0  0
3  1  0  1
```

See also `get_dummies()`.

11.4 Method Summary

Method	Description
`cat()`	Concatenate strings
`split()`	Split strings on delimiter
`rsplit()`	Split strings on delimiter working from the end of the string
`get()`	Index into each element (retrieve i-th element)
`join()`	Join strings in each element of the Series with passed separator
`contains()`	Return boolean array if each string contains pattern/regex
`replace()`	Replace occurrences of pattern/regex with some other string
`repeat()`	Duplicate values (`s.str.repeat(3)` equivalent to `x * 3`)
`pad()`	Add whitespace to left, right, or both sides of strings

Continued on next page

Table 11.1 – continued from previous page

Method	Description
center()	Equivalent to str.center
ljust()	Equivalent to str.ljust
rjust()	Equivalent to str.rjust
zfill()	Equivalent to str.zfill
wrap()	Split long strings into lines with length less than a given width
slice()	Slice each string in the Series
slice_replace()	Replace slice in each string with passed value
count()	Count occurrences of pattern
startswith()	Equivalent to str.startswith(pat) for each element
endswith()	Equivalent to str.endswith(pat) for each element
findall()	Compute list of all occurrences of pattern/regex for each string
match()	Call re.match on each element, returning matched groups as list
extract()	Call re.match on each element, as match does, but return matched groups as strings for convenience.
len()	Compute string lengths
strip()	Equivalent to str.strip
rstrip()	Equivalent to str.rstrip
lstrip()	Equivalent to str.lstrip
partition()	Equivalent to str.partition
rpartition()	Equivalent to str.rpartition
lower()	Equivalent to str.lower
upper()	Equivalent to str.upper
find()	Equivalent to str.find
rfind()	Equivalent to str.rfind
index()	Equivalent to str.index
rindex()	Equivalent to str.rindex
capitalize()	Equivalent to str.capitalize
swapcase()	Equivalent to str.swapcase
normalize()	Return Unicode normal form. Equivalent to unicodedata.normalize
translate()	Equivalent to str.translate
isalnum()	Equivalent to str.isalnum
isalpha()	Equivalent to str.isalpha
isdigit()	Equivalent to str.isdigit
isspace()	Equivalent to str.isspace
islower()	Equivalent to str.islower
isupper()	Equivalent to str.isupper
istitle()	Equivalent to str.istitle
isnumeric()	Equivalent to str.isnumeric
isdecimal()	Equivalent to str.isdecimal

CHAPTER

TWELVE

OPTIONS AND SETTINGS

12.1 Overview

pandas has an options system that lets you customize some aspects of its behaviour, display-related options being those the user is most likely to adjust.

Options have a full "dotted-style", case-insensitive name (e.g. `display.max_rows`). You can get/set options directly as attributes of the top-level `options` attribute:

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

In [2]: pd.options.display.max_rows
Out[2]: 15

In [3]: pd.options.display.max_rows = 999

In [4]: pd.options.display.max_rows
Out[4]: 999
```

There is also an API composed of 5 relevant functions, available directly from the `pandas` namespace:

- `get_option()` / `set_option()` - get/set the value of a single option.
- `reset_option()` - reset one or more options to their default value.
- `describe_option()` - print the descriptions of one or more options.
- `option_context()` - execute a codeblock with a set of options that revert to prior settings after execution.

Note: developers can check out pandas/core/config.py for more info.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous :

```
In [5]: pd.get_option("display.max_rows")
Out[5]: 999

In [6]: pd.set_option("display.max_rows",101)

In [7]: pd.get_option("display.max_rows")
Out[7]: 101

In [8]: pd.set_option("max_r",102)

In [9]: pd.get_option("display.max_rows")
Out[9]: 102
```

The following will **not work** because it matches multiple option names, e.g. `display.max_colwidth`, `display.max_rows`, `display.max_columns`:

```
In [10]: try:
   ....:     pd.get_option("column")
   ....: except KeyError as e:
   ....:     print(e)
   ....:
'Pattern matched multiple keys'
```

Note: Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out the descriptions for all available options.

12.2 Getting and Setting Options

As described above, `get_option()` and `set_option()` are available from the pandas namespace. To change an option, call `set_option('option regex', new_value)`

```
In [11]: pd.get_option('mode.sim_interactive')
Out[11]: False

In [12]: pd.set_option('mode.sim_interactive', True)

In [13]: pd.get_option('mode.sim_interactive')
Out[13]: True
```

Note: that the option 'mode.sim_interactive' is mostly used for debugging purposes.

All options also have a default value, and you can use `reset_option` to do just that:

```
In [14]: pd.get_option("display.max_rows")
Out[14]: 60

In [15]: pd.set_option("display.max_rows",999)

In [16]: pd.get_option("display.max_rows")
Out[16]: 999

In [17]: pd.reset_option("display.max_rows")

In [18]: pd.get_option("display.max_rows")
Out[18]: 60
```

It's also possible to reset multiple options at once (using a regex):

```
In [19]: pd.reset_option("^display")
height has been deprecated.

line_width has been deprecated, use display.width instead (currently both are
identical)
```

`option_context` context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the *with* block:

```
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"))
   ....:
10
5

In [21]: print(pd.get_option("display.max_rows"))
60

In [22]: print(pd.get_option("display.max_columns"))
20
```

12.3 Setting Startup Options in python/ipython Environment

Using startup scripts for the python/ipython environment to import pandas and set options makes working with pandas more efficient. To do this, create a .py or .ipy script in the startup directory of the desired profile. An example where the startup folder is in a default ipython profile can be found at:

```
$IPYTHONDIR/profile_default/startup
```

More information can be found in the ipython documentation. An example startup script for pandas is displayed below:

```
import pandas as pd
pd.set_option('display.max_rows', 999)
pd.set_option('precision', 5)
```

12.4 Frequently Used Options

The following is a walkthrough of the more frequently used display options.

`display.max_rows` and `display.max_columns` sets the maximum number of rows and columns displayed when a frame is pretty-printed. Truncated lines are replaced by an ellipsis.

```
In [23]: df=pd.DataFrame(np.random.randn(7,2))

In [24]: pd.set_option('max_rows', 7)

In [25]: df
Out[25]:
          0         1
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
3  0.119209 -1.044236
4 -0.861849 -2.104569
5 -0.494929  1.071804
6  0.721555 -0.706771

In [26]: pd.set_option('max_rows', 5)

In [27]: df
Out[27]:
```

```
          0         1
0   0.469112 -0.282863
1  -1.509059 -1.135632
..       ...       ...
5  -0.494929  1.071804
6   0.721555 -0.706771

[7 rows x 2 columns]

In [28]: pd.reset_option('max_rows')
```

`display.expand_frame_repr` allows for the the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

```
In [29]: df=pd.DataFrame(np.random.randn(5,10))

In [30]: pd.set_option('expand_frame_repr', True)

In [31]: df
Out[31]:
          0         1         2         3         4         5         6  \
0 -1.039575  0.271860 -0.424972  0.567020  0.276232 -1.087401 -0.673690
1  0.404705  0.577046 -1.715002 -1.039268 -0.370647 -1.157892 -1.344312
2  1.643563 -1.469388  0.357021 -0.674600 -1.776904 -0.968914 -1.294524
3 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
4 -1.170299 -0.226169  0.410835  0.813850  0.132003 -0.827317 -0.076467

          7         8         9
0  0.113648 -1.478427  0.524988
1  0.844885  1.075770 -0.109050
2  0.413738  0.276662 -0.472035
3  2.565646  1.431256  1.340309
4 -1.187678  1.130127 -1.436737

In [32]: pd.set_option('expand_frame_repr', False)

In [33]: df
Out[33]:
          0         1         2         3         4         5         6         7         8         9
0 -1.039575  0.271860 -0.424972  0.567020  0.276232 -1.087401 -0.673690  0.113648 -1.478427  0.524988
1  0.404705  0.577046 -1.715002 -1.039268 -0.370647 -1.157892 -1.344312  0.844885  1.075770 -0.109050
2  1.643563 -1.469388  0.357021 -0.674600 -1.776904 -0.968914 -1.294524  0.413738  0.276662 -0.472035
3 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309
4 -1.170299 -0.226169  0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737

In [34]: pd.reset_option('expand_frame_repr')
```

`display.large_repr` lets you select whether to display dataframes that exceed `max_columns` or `max_rows` as a truncated frame, or as a summary.

```
In [35]: df=pd.DataFrame(np.random.randn(10,10))

In [36]: pd.set_option('max_rows', 5)

In [37]: pd.set_option('large_repr', 'truncate')

In [38]: df
Out[38]:
          0         1         2         3         4         5         6  \
```

```
0  -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466
1   0.545952 -1.219217 -1.226825  0.769804 -1.281247 -0.727707 -0.121306
..       ...       ...       ...       ...       ...       ...       ...
8  -2.484478 -0.281461  0.030711  0.109121  1.126203 -0.977349  1.474071
9  -1.071357  0.441153  2.353925  0.583787  0.221471 -0.744471  0.758527

           7         8         9
0  -2.006747 -0.410001 -0.078638
1  -0.097883  0.695775  0.341734
..       ...       ...       ...
8  -0.064034 -1.282782  0.781836
9   1.729689 -0.964980 -0.845696

[10 rows x 10 columns]

In [39]: pd.set_option('large_repr', 'info')

In [40]: df
Out[40]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0    10 non-null float64
1    10 non-null float64
2    10 non-null float64
3    10 non-null float64
4    10 non-null float64
5    10 non-null float64
6    10 non-null float64
7    10 non-null float64
8    10 non-null float64
9    10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [41]: pd.reset_option('large_repr')

In [42]: pd.reset_option('max_rows')
```

`display.max_columnwidth` 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'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0    10 non-null float64
1    10 non-null float64
2    10 non-null float64
3    10 non-null float64
4    10 non-null float64
5    10 non-null float64
6    10 non-null float64
7    10 non-null float64
8    10 non-null float64
9    10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [52]: pd.set_option('max_info_columns', 5)

In [53]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 880.0 bytes

In [54]: pd.reset_option('max_info_columns')
```

`display.max_info_rows`: `df.info()` will usually show null-counts for each column. For large frames this can be quite slow. `max_info_rows` and `max_info_cols` limit this null check only to frames with smaller dimensions then specified. Note that you can specify the option `df.info(null_counts=True)` to override on showing a particular frame.

```
In [55]: df=pd.DataFrame(np.random.choice([0,1,np.nan],size=(10,10)))

In [56]: df
Out[56]:
    0    1    2    3    4    5    6    7    8    9
0   0    1    1    0    1    1    0  NaN    1  NaN
1   1  NaN    0    0    1    1  NaN    1    0    1
2 NaN  NaN  NaN    1    1    0  NaN    0    1  NaN
3   0    1    1  NaN    0  NaN    1  NaN  NaN    0
4   0    1    0    0    1    0    0  NaN    0    0
5   0  NaN    1  NaN  NaN  NaN  NaN    0    1  NaN
6   0    1    0    0  NaN    1  NaN  NaN    0  NaN
7   0  NaN    1    1  NaN    1    1    1    1  NaN
8   0    0  NaN    0  NaN    1    0    0  NaN  NaN
```

```
9 NaN NaN   0 NaN NaN NaN   0   1   1 NaN

In [57]: pd.set_option('max_info_rows', 11)

In [58]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0    8 non-null float64
1    5 non-null float64
2    8 non-null float64
3    7 non-null float64
4    5 non-null float64
5    7 non-null float64
6    6 non-null float64
7    6 non-null float64
8    8 non-null float64
9    3 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [59]: pd.set_option('max_info_rows', 5)

In [60]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0    float64
1    float64
2    float64
3    float64
4    float64
5    float64
6    float64
7    float64
8    float64
9    float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [61]: pd.reset_option('max_info_rows')
```

`display.precision` sets the output display precision. This is only a suggestion.

```
In [62]: df=pd.DataFrame(np.random.randn(5,5))

In [63]: pd.set_option('precision',7)

In [64]: df
Out[64]:
          0         1         2         3         4
0 -2.049028  2.846612 -1.208049 -0.450392  2.423905
1  0.121108  0.266916  0.843826 -0.222540  2.021981
2 -0.716789 -2.224485 -1.061137 -0.232825  0.430793
3 -0.665478  1.829807 -1.406509  1.078248  0.322774
4  0.200324  0.890024  0.194813  0.351633  0.448881

In [65]: pd.set_option('precision',4)
```

```
In [66]: df
Out[66]:
       0      1      2      3      4
0 -2.049  2.847 -1.208 -0.450  2.424
1  0.121  0.267  0.844 -0.223  2.022
2 -0.717 -2.224 -1.061 -0.233  0.431
3 -0.665  1.830 -1.407  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. Note, this does not effect the precision at which the number is stored.

```
In [67]: df=pd.DataFrame(np.random.randn(6,6))

In [68]: pd.set_option('chop_threshold', 0)

In [69]: df
Out[69]:
       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  0.925 -0.006 -0.820 -0.601 -1.039  0.825
3 -0.824 -0.338 -0.928 -0.840  0.249 -0.109
4  0.432 -0.461  0.337 -3.208 -1.536  0.410
5 -0.673 -0.741 -0.111 -2.673  0.864  0.061

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  0.000 -1.144 -0.633
2  0.925  0.000 -0.820 -0.601 -1.039  0.825
3 -0.824  0.000 -0.928 -0.840  0.000  0.000
4  0.000  0.000  0.000 -3.208 -1.536  0.000
5 -0.673 -0.741  0.000 -2.673  0.864  0.000

In [72]: pd.reset_option('chop_threshold')
```

`display.colheader_justify` controls the justification of the headers. Options are 'right', and 'left'.

```
In [73]: df=pd.DataFrame(np.array([np.random.randn(6), np.random.randint(1,9,6)*.1, np.zeros(6)]).T,

In [74]: pd.set_option('colheader_justify', 'right')

In [75]: df
Out[75]:
       A    B  C
0  0.933  0.3  0
1  0.289  0.2  0
2  1.325  0.2  0
3  0.589  0.7  0
4  0.531  0.1  0
5 -1.199  0.7  0

In [76]: pd.set_option('colheader_justify', 'left')
```

```
In [77]: df
Out[77]:
   A      B    C
0  0.933  0.3  0
1  0.289  0.2  0
2  1.325  0.2  0
3  0.589  0.7  0
4  0.531  0.1  0
5 -1.199  0.7  0

In [78]: pd.reset_option('colheader_justify')
```

12.5 List of Options

Option	Default	Function
display.chop_threshold	None	If set to a float value, all float values smaller then the given threshold will be displayed as e
display.colheader_justify	right	Controls the justification of column headers. used by DataFrameFormatter.
display.column_space	12	No description available.
display.date_dayfirst	False	When True, prints and parses dates with the day first, eg 20/01/2005
display.date_yearfirst	False	When True, prints and parses dates with the year first, eg 2005/01/20
display.encoding	UTF-8	Defaults to the detected encoding of the console. Specifies the encoding to be used for stri
display.expand_frame_repr	True	Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *m*
display.float_format	None	The callable should accept a floating point number and return a string with the desired forr
display.height	60	Deprecated. Use *display.max_rows* instead.
display.large_repr	truncate	For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a tru
display.line_width	80	Deprecated. Use *display.width* instead.
display.max_columns	20	max_rows and max_columns are used in __repr__() methods to decide if to_string() or inf
display.max_colwidth	50	The maximum width in characters of a column in the repr of a pandas data structure. Wher
display.max_info_columns	100	max_info_columns is used in DataFrame.info method to decide if per column information
display.max_info_rows	1690785	df.info() will usually show null-counts for each column. For large frames this can be quite
display.max_rows	60	This sets the maximum number of rows pandas should output when printing out various ou
display.max_seq_items	100	when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If item
display.memory_usage	True	This specifies if the memory usage of a DataFrame should be displayed when the df.info()
display.mpl_style	None	Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more p
display.multi_sparse	True	"Sparsify" MultiIndex display (don't display repeated elements in outer levels within grou
display.notebook_repr_html	True	When True, IPython notebook will use html representation for pandas objects (if it is avail
display.pprint_nest_depth	3	Controls the number of nested levels to process when pretty-printing
display.precision	7	Floating point output precision (number of significant digits). This is only a suggestion
display.show_dimensions	truncate	Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, on
display.width	80	Width of the display in characters. In case python/IPython is running in a terminal this can
io.excel.xls.writer	xlwt	The default Excel writer engine for 'xls' files.
io.excel.xlsm.writer	openpyxl	The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default
io.excel.xlsx.writer	openpyxl	The default Excel writer engine for 'xlsx' files.
io.hdf.default_format	None	default format writing format, if None, then put will default to 'fixed' and append will defa
io.hdf.dropna_table	True	drop ALL nan rows when appending to a table
mode.chained_assignment	warn	Raise an exception, warn, or no action if trying to use chained assignment, The default is w
mode.sim_interactive	False	Whether to simulate interactive mode for purposes of testing
mode.use_inf_as_null	False	True means treat None, NaN, -INF, INF as null (old way), False means None and NaN are

12.6 Number Formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the `set_options` API.

Use the `set_eng_float_format` function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```
In [79]: import numpy as np

In [80]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)

In [81]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [82]: s/1.e3
Out[82]:
a   -236.866u
b    846.974u
c   -685.597u
d    609.099u
e   -303.961u
dtype: float64

In [83]: s/1.e6
Out[83]:
a   -236.866n
b    846.974n
c   -685.597n
d    609.099n
e   -303.961n
dtype: float64
```

CHAPTER

THIRTEEN

INDEXING AND SELECTING DATA

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides *metadata*) using known indicators, important for analysis, visualization, and interactive console display
- Enables automatic and explicit data alignment
- Allows intuitive getting and setting of subsets of the data set

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area. Expect more work to be invested in higher-dimensional data structures (including `Panel`) in the future, especially in label-based advanced indexing.

Note: The Python and NumPy indexing operators `[]` and attribute operator `.` provide quick and easy access to pandas data structures across a wide range of use cases. This makes interactive work intuitive, as there's little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn't known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*

Warning: In 0.15.0 `Index` has internally been refactored to no longer subclass `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

See the *MultiIndex / Advanced Indexing* for `MultiIndex` and more advanced indexing documentation.

See the *cookbook* for some advanced strategies

13.1 Different Choices for Indexing

New in version 0.11.0.

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. pandas now supports three types of multi-axis indexing.

- `.loc` is primarily label based, but may also be used with a boolean array. `.loc` will raise `KeyError` when the items are not found. Allowed inputs are:

  - A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index. This use is **not** an integer position along the index)
  - A list or array of labels `['a', 'b', 'c']`
  - A slice object with labels `'a':'f'`, (note that contrary to usual python slices, **both** the start and the stop are included!)
  - A boolean array

  See more at *Selection by Label*

- `.iloc` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing. (this conforms with python/numpy *slice* semantics). Allowed inputs are:
  - An integer e.g. `5`
  - A list or array of integers `[4, 3, 0]`
  - A slice object with ints `1:7`
  - A boolean array

  See more at *Selection by Position*

- `.ix` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type. `.ix` is the most general and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

  However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

  See more at *Advanced Indexing* and *Advanced Hierarchical*.

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but applies to `.iloc` and `.ix` as well). Any of the axes accessors may be the null slice `:`. Axes left out of the specification are assumed to be `:`. (e.g. `p.loc['a']` is equiv to `p.loc['a', :, :]`)

Object Type	Indexers
Series	`s.loc[indexer]`
DataFrame	`df.loc[row_indexer,column_indexer]`
Panel	`p.loc[item_indexer,major_indexer,minor_indexer]`

13.2 Deprecations

Beginning with version 0.11.0, it's recommended that you transition away from the following methods as they *may* be deprecated in future versions.

- `irow`
- `icol`
- `iget_value`

See the section *Selection by Position* for substitutes.

13.3 Basics

As mentioned when introducing the data structures in the *last section*, the primary function of indexing with `[]` (a.k.a. `__getitem__` for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. Thus,

Object Type	Selection	Return Value Type
Series	`series[label]`	scalar value
DataFrame	`frame[colname]`	`Series` corresponding to colname
Panel	`panel[itemname]`	`DataFrame` corresponing to the itemname

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [1]: dates = date_range('1/1/2000', periods=8)

In [2]: df = DataFrame(randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])

In [3]: df
Out[3]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [4]: panel = Panel({'one' : df, 'two' : df - df.mean()})

In [5]: panel
Out[5]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 8 (major_axis) x 4 (minor_axis)
Items axis: one to two
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-08 00:00:00
Minor_axis axis: A to D
```

Note: None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using `[]`:

```
In [6]: s = df['A']

In [7]: s[dates[5]]
Out[7]: -0.67368970808837025

In [8]: panel['two']
Out[8]:
                   A         B         C         D
2000-01-01  0.409571  0.113086 -0.610826 -0.936507
2000-01-02  1.152571  0.222735  1.017442 -0.845111
2000-01-03 -0.921390 -1.708620  0.403304  1.270929
2000-01-04  0.662014 -0.310822 -0.141342  0.470985
2000-01-05 -0.484513  0.962970  1.174465 -0.888276
2000-01-06 -0.733231  0.509598 -0.580194  0.724113
2000-01-07  0.345164  0.972995 -0.816769 -0.840143
```

```
2000-01-08 -0.430188 -0.761943 -0.446079  1.044010
```

You can pass a list of columns to `[]` to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```
In [9]: df
Out[9]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [10]: df[['B', 'A']] = df[['A', 'B']]

In [11]: df
Out[11]:
                   A         B         C         D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
```

You may find this useful for applying a transform (in-place) to a subset of the columns.

13.4 Attribute Access

You may access an index on a `Series`, column on a `DataFrame`, and a item on a `Panel` directly as an attribute:

```
In [12]: sa = Series([1,2,3],index=list('abc'))

In [13]: dfa = df.copy()

In [14]: sa.b
Out[14]: 2

In [15]: dfa.A
Out[15]:
2000-01-01   -0.282863
2000-01-02   -0.173215
2000-01-03   -2.104569
2000-01-04   -0.706771
2000-01-05    0.567020
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08   -1.157892
Freq: D, Name: A, dtype: float64

In [16]: panel.one
```

```
Out[16]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
```

You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it fails silently, creating a new attribute rather than a new column.

```
In [17]: sa.a = 5

In [18]: sa
Out[18]:
a    5
b    2
c    3
dtype: int64

In [19]: dfa.A = list(range(len(dfa.index)))  # ok if A already exists

In [20]: dfa
Out[20]:
            A         B         C         D
2000-01-01  0  0.469112 -1.509059 -1.135632
2000-01-02  1  1.212112  0.119209 -1.044236
2000-01-03  2 -0.861849 -0.494929  1.071804
2000-01-04  3  0.721555 -1.039575  0.271860
2000-01-05  4 -0.424972  0.276232 -1.087401
2000-01-06  5 -0.673690 -1.478427  0.524988
2000-01-07  6  0.404705 -1.715002 -1.039268
2000-01-08  7 -0.370647 -1.344312  0.844885

In [21]: dfa['A'] = list(range(len(dfa.index)))  # use this form to create a new column

In [22]: dfa
Out[22]:
            A         B         C         D
2000-01-01  0  0.469112 -1.509059 -1.135632
2000-01-02  1  1.212112  0.119209 -1.044236
2000-01-03  2 -0.861849 -0.494929  1.071804
2000-01-04  3  0.721555 -1.039575  0.271860
2000-01-05  4 -0.424972  0.276232 -1.087401
2000-01-06  5 -0.673690 -1.478427  0.524988
2000-01-07  6  0.404705 -1.715002 -1.039268
2000-01-08  7 -0.370647 -1.344312  0.844885
```

Warning:

- You can use this access only if the index element is a valid python identifier, e.g. `s.1` is not allowed. See here for an explanation of valid identifiers.
- The attribute will not be available if it conflicts with an existing method name, e.g. `s.min` is not allowed.
- Similarly, the attribute will not be available if it conflicts with any of the following list: `index`, `major_axis`, `minor_axis`, `items`, `labels`.
- In any of these cases, standard indexing will still work, e.g. `s['1']`, `s['min']`, and `s['index']` will access the corresponding element or column.
- The `Series/Panel` accesses are available starting in 0.13.0.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a `dict` to a row of a `DataFrame`:

```
In [23]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})

In [24]: x.iloc[1] = dict(x=9, y=99)

In [25]: x
Out[25]:
   x   y
0  1   3
1  9  99
2  3   5
```

13.5 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the *Selection by Position* section detailing the `.iloc` method. For now, we explain the semantics of slicing using the `[]` operator.

With Series, the syntax works exactly as with an ndarray, returning a slice of the values and the corresponding labels:

```
In [26]: s[:5]
Out[26]:
2000-01-01   -0.282863
2000-01-02   -0.173215
2000-01-03   -2.104569
2000-01-04   -0.706771
2000-01-05    0.567020
Freq: D, Name: A, dtype: float64

In [27]: s[::2]
Out[27]:
2000-01-01   -0.282863
2000-01-03   -2.104569
2000-01-05    0.567020
2000-01-07    0.577046
Freq: 2D, Name: A, dtype: float64

In [28]: s[::-1]
Out[28]:
2000-01-08   -1.157892
2000-01-07    0.577046
2000-01-06    0.113648
2000-01-05    0.567020
2000-01-04   -0.706771
```

```
2000-01-03   -2.104569
2000-01-02   -0.173215
2000-01-01   -0.282863
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [29]: s2 = s.copy()

In [30]: s2[:5] = 0

In [31]: s2
Out[31]:
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08   -1.157892
Freq: D, Name: A, dtype: float64
```

With DataFrame, slicing inside of `[]` **slices the rows**. This is provided largely as a convenience since it is such a common operation.

```
In [32]: df[:3]
Out[32]:
                   A         B         C         D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804

In [33]: df[::-1]
Out[33]:
                   A         B         C         D
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
```

13.6 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 [34]: dfl = DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=date_range('20130101',pe

In [35]: dfl
Out[35]:
                   A         B         C         D
2013-01-01  1.075770 -0.109050  1.643563 -1.469388
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
2013-01-05  0.895717  0.805244 -1.206412  2.565646
```

```
In [4]: dfl.loc[2:3]
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these inde
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [36]: dfl.loc['20130102':'20130104']
Out[36]:
                   A         B         C         D
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
```

pandas provides a suite of methods in order to have **purely label based indexing**. This is a strict inclusion based protocol. **At least 1** of the labels for which you ask, must be in the index or a `KeyError` will be raised! When slicing, the start bound is *included*, **AND** the stop bound is *included*. Integers are valid labels, but they refer to the label **and not the position**.

The `.loc` attribute is the primary access method. The following are valid inputs:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index. This use is **not** an integer position along the index)
- A list or array of labels `['a', 'b', 'c']`
- A slice object with labels `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!)
- A boolean array

```
In [37]: s1 = Series(np.random.randn(6),index=list('abcdef'))

In [38]: s1
Out[38]:
a    1.431256
b    1.340309
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64

In [39]: s1.loc['c':]
Out[39]:
```

```
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64

In [40]: s1.loc['b']
Out[40]: 1.3403088497993827
```

Note that setting works as well:

```
In [41]: s1.loc['c':] = 0

In [42]: s1
Out[42]:
a    1.431256
b    1.340309
c    0.000000
d    0.000000
e    0.000000
f    0.000000
dtype: float64
```

With a DataFrame

```
In [43]: df1 = DataFrame(np.random.randn(6,4),
   ....:                 index=list('abcdef'),
   ....:                 columns=list('ABCD'))
   ....:

In [44]: df1
Out[44]:
          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 [45]: df1.loc[['a','b','d'],:]
Out[45]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
d  0.974466 -2.006747 -0.410001 -0.078638
```

Accessing via label slices

```
In [46]: df1.loc['d':,'A':'C']
Out[46]:
          A         B         C
d  0.974466 -2.006747 -0.410001
e  0.545952 -1.219217 -1.226825
f -1.281247 -0.727707 -0.121306
```

For getting a cross section using a label (equiv to `df.xs('a')`)

```
In [47]: df1.loc['a']
Out[47]:
A    0.132003
B   -0.827317
C   -0.076467
D   -1.187678
Name: a, dtype: float64
```

For getting values with a boolean array

```
In [48]: df1.loc['a']>0
Out[48]:
A     True
B    False
C    False
D    False
Name: a, dtype: bool

In [49]: df1.loc[:,df1.loc['a']>0]
Out[49]:
          A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247
```

For getting a value explicitly (equiv to deprecated `df.get_value('a','A')`)

```
# this is also equivalent to ``df1.at['a','A']``
In [50]: df1.loc['a','A']
Out[50]: 0.13200317033032927
```

13.7 Selection By Position

> **Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*

pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely python and numpy slicing. These are `0-based` indexing. When slicing, the start bounds is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a **valid** label will raise a `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. `5`
- A list or array of integers `[4, 3, 0]`
- A slice object with ints `1:7`
- A boolean array

```
In [51]: s1 = Series(np.random.randn(5),index=list(range(0,10,2)))

In [52]: s1
Out[52]:
```

```
0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64

In [53]: s1.iloc[:3]
Out[53]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64

In [54]: s1.iloc[3]
Out[54]: -1.1103361028911667
```

Note that setting works as well:

```
In [55]: s1.iloc[:3] = 0

In [56]: s1
Out[56]:
0    0.000000
2    0.000000
4    0.000000
6   -1.110336
8   -0.619976
dtype: float64
```

With a DataFrame

```
In [57]: df1 = DataFrame(np.random.randn(6,4),
   ....:                 index=list(range(0,12,2)),
   ....:                 columns=list(range(0,8,2)))
   ....:

In [58]: df1
Out[58]:
           0         2         4         6
0   0.149748 -0.732339  0.687738  0.176444
2   0.403310 -0.154951  0.301624 -2.179861
4  -1.369849 -0.954208  1.462696 -1.743161
6  -0.826591 -0.345352  1.314232  0.690579
8   0.995761  2.396780  0.014871  3.357427
10 -0.317441 -1.236269  0.896171 -0.487602
```

Select via integer slicing

```
In [59]: df1.iloc[:3]
Out[59]:
          0         2         4         6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [60]: df1.iloc[1:5,2:4]
Out[60]:
          4         6
```

```
2   0.301624 -2.179861
4   1.462696 -1.743161
6   1.314232  0.690579
8   0.014871  3.357427
```

Select via integer list

```
In [61]: df1.iloc[[1,3,5],[1,3]]
Out[61]:
           2         6
2  -0.154951 -2.179861
6  -0.345352  0.690579
10 -1.236269 -0.487602
```

For slicing rows explicitly (equiv to deprecated `df.irow(slice(1,3))`).

```
In [62]: df1.iloc[1:3,:]
Out[62]:
          0         2         4         6
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
```

For slicing columns explicitly (equiv to deprecated `df.icol(slice(1,3))`).

```
In [63]: df1.iloc[:,1:3]
Out[63]:
           2         4
0  -0.732339  0.687738
2  -0.154951  0.301624
4  -0.954208  1.462696
6  -0.345352  1.314232
8   2.396780  0.014871
10 -1.236269  0.896171
```

For getting a scalar via integer position (equiv to deprecated `df.get_value(1,1)`)

```
# this is also equivalent to ``df1.iat[1,1]``
In [64]: df1.iloc[1,1]
Out[64]: -0.15495077442490321
```

For getting a cross section using an integer position (equiv to `df.xs(1)`)

```
In [65]: df1.iloc[1]
Out[65]:
0    0.403310
2   -0.154951
4    0.301624
6   -2.179861
Name: 2, dtype: float64
```

Out of range slice indexes are handled gracefully just as in Python/Numpy.

```
# these are allowed in python/numpy.
# Only works in Pandas starting from v0.14.0.
In [66]: x = list('abcdef')

In [67]: x
Out[67]: ['a', 'b', 'c', 'd', 'e', 'f']

In [68]: x[4:10]
```

```
Out[68]: ['e', 'f']

In [69]: x[8:10]
Out[69]: []

In [70]: s = Series(x)

In [71]: s
Out[71]:
0    a
1    b
2    c
3    d
4    e
5    f
dtype: object

In [72]: s.iloc[4:10]
Out[72]:
4    e
5    f
dtype: object

In [73]: s.iloc[8:10]
Out[73]: Series([], dtype: object)
```

Note: Prior to v0.14.0, `iloc` would not accept out of bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed.

Note that this could result in an empty axis (e.g. an empty DataFrame being returned)

```
In [74]: dfl = DataFrame(np.random.randn(5,2),columns=list('AB'))

In [75]: dfl
Out[75]:
          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 [76]: dfl.iloc[:,2:3]
Out[76]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [77]: dfl.iloc[:,1:3]
Out[77]:
          B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885

In [78]: dfl.iloc[4:6]
```

```
Out[78]:
         A         B
4  0.27423  0.132885
```

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`

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

dfl.iloc[:,4]
IndexError: single positional indexer is out-of-bounds
```

13.8 Selecting Random Samples

A random selection of rows or columns from a Series, DataFrame, or Panel with the `sample()` method. The method will sample rows by default, and accepts a specific number of rows/columns to return, or a fraction of rows.

```
In [79]: s = Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1 row.
In [80]: s.sample()
Out[80]:
5    5
dtype: int64

# One may specify either a number of rows:
In [81]: s.sample(n=3)
Out[81]:
1    1
5    5
2    2
dtype: int64

# Or a fraction of the rows:
In [82]: s.sample(frac=0.5)
Out[82]:
4    4
5    5
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 [83]: s = Series([0,1,2,3,4,5])

 # Without replacement (default):
In [84]: s.sample(n=6, replace=False)
Out[84]:
4    4
1    1
3    3
5    5
0    0
2    2
```

```
dtype: int64

 # With replacement:
In [85]: s.sample(n=6, replace=True)
Out[85]:
2    2
0    0
3    3
2    2
4    4
4    4
dtype: int64
```

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a numpy array, or a Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```
In [86]: s = Series([0,1,2,3,4,5])

In [87]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [88]: s.sample(n=3, weights=example_weights)
Out[88]:
2    2
5    5
4    4
dtype: int64

# Weights will be re-normalized automatically
In [89]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [90]: s.sample(n=1, weights=example_weights2)
Out[90]:
0    0
dtype: int64
```

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```
In [91]: df2 = DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})

In [92]: df2.sample(n = 3, weights = 'weight_column')
Out[92]:
   col1  weight_column
0     9            0.5
1     8            0.4
2     7            0.1
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [93]: df3 = DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

In [94]: df3.sample(n=1, axis=1)
Out[94]:
   col1
0     1
1     2
```

```
2     3
```

Finally, one can also set a seed for `sample`‘s random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a numpy RandomState object.

```
In [95]: df4 = DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

# With a given seed, the sample will always draw the same rows.
In [96]: df4.sample(n=2, random_state=2)
Out[96]:
   col1  col2
2     3     4
1     2     3

In [97]: df4.sample(n=2, random_state=2)
Out[97]:
   col1  col2
2     3     4
1     2     3
```

13.9 Setting With Enlargement

New in version 0.13.

The `.loc/.ix/[]` operations can perform enlargement when setting a non-existant key for that axis.

In the `Series` case this is effectively an appending operation

```
In [98]: se = Series([1,2,3])

In [99]: se
Out[99]:
0    1
1    2
2    3
dtype: int64

In [100]: se[5] = 5.

In [101]: se
Out[101]:
0    1
1    2
2    3
5    5
dtype: float64
```

A `DataFrame` can be enlarged on either axis via `.loc`

```
In [102]: dfi = DataFrame(np.arange(6).reshape(3,2),
   .....:                 columns=['A','B'])
   .....:

In [103]: dfi
Out[103]:
   A  B
0  0  1
```

```
1  2  3
2  4  5

In [104]: dfi.loc[:,'C'] = dfi.loc[:,'A']

In [105]: dfi
Out[105]: 
   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 [106]: dfi.loc[3] = 5

In [107]: dfi
Out[107]: 
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

13.10 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 [108]: s.iat[5]
Out[108]: 5

In [109]: df.at[dates[5], 'A']
Out[109]: 0.11364840968888545

In [110]: df.iat[3, 0]
Out[110]: -0.70677113363008437
```

You can also set using these same indexers.

```
In [111]: df.at[dates[5], 'E'] = 7

In [112]: df.iat[3, 0] = 7
```

`at` may enlarge the object in-place as above if the indexer is missing.

```
In [113]: df.at[dates[-1]+1, 0] = 7

In [114]: df
Out[114]: 
                   A         B         C         D   E   0
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632 NaN NaN
2000-01-02 -0.173215  1.212112  0.119209 -1.044236 NaN NaN
```

```
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804 NaN NaN
2000-01-04  7.000000  0.721555 -1.039575  0.271860 NaN NaN
2000-01-05  0.567020 -0.424972  0.276232 -1.087401 NaN NaN
2000-01-06  0.113648 -0.673690 -1.478427  0.524988   7 NaN
2000-01-07  0.577046  0.404705 -1.715002 -1.039268 NaN NaN
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885 NaN NaN
2000-01-09       NaN       NaN       NaN       NaN NaN   7
```

13.11 Boolean indexing

Another common operation is the use of boolean vectors to filter the data. The operators are: `|` for `or`, `&` for `and`, and `~` for `not`. These **must** be grouped by using parentheses.

Using a boolean vector to index a Series works exactly as in a numpy ndarray:

```
In [115]: s = Series(range(-3, 4))

In [116]: s
Out[116]:
0   -3
1   -2
2   -1
3    0
4    1
5    2
6    3
dtype: int32

In [117]: s[s > 0]
Out[117]:
4    1
5    2
6    3
dtype: int32

In [118]: s[(s < -1) | (s > 0.5)]
Out[118]:
0   -3
1   -2
4    1
5    2
6    3
dtype: int32

In [119]: s[~(s < 0)]
Out[119]:
3    0
4    1
5    2
6    3
dtype: int32
```

You may select rows from a DataFrame using a boolean vector the same length as the DataFrame's index (for example, something derived from one of the columns of the DataFrame):

```
In [120]: df[df['A'] > 0]
Out[120]:
                   A         B         C         D    E    0
2000-01-04  7.000000  0.721555 -1.039575  0.271860 NaN NaN
2000-01-05  0.567020 -0.424972  0.276232 -1.087401 NaN NaN
2000-01-06  0.113648 -0.673690 -1.478427  0.524988   7 NaN
2000-01-07  0.577046  0.404705 -1.715002 -1.039268 NaN NaN
```

List comprehensions and `map` method of Series can also be used to produce more complex criteria:

```
In [121]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
   .....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                  'c' : randn(7)})
   .....:

# only want 'two' or 'three'
In [122]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [123]: df2[criterion]
Out[123]:
       a  b         c
2    two  y  1.450520
3  three  x  0.206053
4    two  y -0.251905

# equivalent but slower
In [124]: df2[[x.startswith('t') for x in df2['a']]]
Out[124]:
       a  b         c
2    two  y  1.450520
3  three  x  0.206053
4    two  y -0.251905

# Multiple criteria
In [125]: df2[criterion & (df2['b'] == 'x')]
Out[125]:
       a  b         c
3  three  x  0.206053
```

Note, with the choice methods *Selection by Label*, *Selection by Position*, and *Advanced Indexing* you may select along more than one axis using boolean vectors combined with other indexing expressions.

```
In [126]: df2.loc[criterion & (df2['b'] == 'x'),'b':'c']
Out[126]:
   b         c
3  x  0.206053
```

13.12 Indexing with isin

Consider the `isin` method of Series, which returns a boolean vector that is true wherever the Series elements exist in the passed list. This allows you to select rows where one or more columns have values you want:

```
In [127]: s = Series(np.arange(5),index=np.arange(5)[::-1],dtype='int64')

In [128]: s
Out[128]:
4    0
```

```
3    1
2    2
1    3
0    4
dtype: int64

In [129]: s.isin([2, 4, 6])
Out[129]:
4    False
3    False
2     True
1    False
0     True
dtype: bool

In [130]: s[s.isin([2, 4, 6])]
Out[130]:
2    2
0    4
dtype: int64
```

The same method is available for `Index` objects and is useful for the cases when you don't know which of the sought labels are in fact present:

```
In [131]: s[s.index.isin([2, 4, 6])]
Out[131]:
4    0
2    2
dtype: int64

# compare it to the following
In [132]: s[[2, 4, 6]]
Out[132]:
2     2
4     0
6   NaN
dtype: float64
```

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

```
In [133]: s_mi = Series(np.arange(6),
   .....:               index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']]))
   .....:

In [134]: s_mi
Out[134]:
0  a    0
   b    1
   c    2
1  a    3
   b    4
   c    5
dtype: int32

In [135]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[135]:
0  c    2
1  a    3
dtype: int32
```

```
In [136]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[136]:
0  a    0
   c    2
1  a    3
   c    5
dtype: int32
```

DataFrame also has an `isin` method. When calling `isin`, pass a set of values as either an array or dict. If values is an array, `isin` returns a DataFrame of booleans that is the same shape as the original DataFrame, with True wherever the element is in the sequence of values.

```
In [137]: df = DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
   .....:                 'ids2': ['a', 'n', 'c', 'n']})
   .....:

In [138]: values = ['a', 'b', 1, 3]

In [139]: df.isin(values)
Out[139]:
     ids   ids2   vals
0   True   True   True
1   True  False  False
2  False  False   True
3  False  False  False
```

Oftentimes you'll want to match certain values with certain columns. Just make values a `dict` where the key is the column, and the value is a list of items you want to check for.

```
In [140]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}

In [141]: df.isin(values)
Out[141]:
     ids   ids2   vals
0   True  False   True
1   True  False  False
2  False  False   True
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 [142]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}

In [143]: row_mask = df.isin(values).all(1)

In [144]: df[row_mask]
Out[144]:
  ids ids2  vals
0   a    a     1
```

13.13 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in `Series` and `DataFrame`.

To return only the selected rows

```
In [145]: s[s > 0]
Out[145]:
3    1
2    2
1    3
0    4
dtype: int64
```

To return a Series of the same shape as the original

```
In [146]: s.where(s > 0)
Out[146]:
4   NaN
3     1
2     2
1     3
0     4
dtype: float64
```

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. Equivalent is `df.where(df < 0)`

```
In [147]: df[df < 0]
Out[147]:
                   A         B         C         D
2000-01-01       NaN       NaN -0.863838       NaN
2000-01-02 -1.048089 -0.025747 -0.988387       NaN
2000-01-03       NaN       NaN       NaN -0.055758
2000-01-04       NaN -0.489682       NaN -0.034571
2000-01-05 -2.484478 -0.281461       NaN       NaN
2000-01-06       NaN -0.977349       NaN -0.064034
2000-01-07 -1.282782       NaN -1.071357       NaN
2000-01-08       NaN       NaN       NaN -0.744471
```

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [148]: df.where(df < 0, -df)
Out[148]:
                   A         B         C         D
2000-01-01 -1.266143 -0.299368 -0.863838 -0.408204
2000-01-02 -1.048089 -0.025747 -0.988387 -0.094055
2000-01-03 -1.262731 -1.289997 -0.082423 -0.055758
2000-01-04 -0.536580 -0.489682 -0.369374 -0.034571
2000-01-05 -2.484478 -0.281461 -0.030711 -0.109121
2000-01-06 -1.126203 -0.977349 -1.474071 -0.064034
2000-01-07 -1.282782 -0.781836 -1.071357 -0.441153
2000-01-08 -2.353925 -0.583787 -0.221471 -0.744471
```

You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```
In [149]: s2 = s.copy()

In [150]: s2[s2 < 0] = 0

In [151]: s2
Out[151]:
4    0
3    1
```

```
2    2
1    3
0    4
dtype: int64

In [152]: df2 = df.copy()

In [153]: df2[df2 < 0] = 0

In [154]: df2
Out[154]:
                   A         B         C         D
2000-01-01  1.266143  0.299368  0.000000  0.408204
2000-01-02  0.000000  0.000000  0.000000  0.094055
2000-01-03  1.262731  1.289997  0.082423  0.000000
2000-01-04  0.536580  0.000000  0.369374  0.000000
2000-01-05  0.000000  0.000000  0.030711  0.109121
2000-01-06  1.126203  0.000000  1.474071  0.000000
2000-01-07  0.000000  0.781836  0.000000  0.441153
2000-01-08  2.353925  0.583787  0.221471  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:

```
In [155]: df_orig = df.copy()

In [156]: df_orig.where(df > 0, -df, inplace=True);

In [157]: df_orig
Out[157]:
                   A         B         C         D
2000-01-01  1.266143  0.299368  0.863838  0.408204
2000-01-02  1.048089  0.025747  0.988387  0.094055
2000-01-03  1.262731  1.289997  0.082423  0.055758
2000-01-04  0.536580  0.489682  0.369374  0.034571
2000-01-05  2.484478  0.281461  0.030711  0.109121
2000-01-06  1.126203  0.977349  1.474071  0.064034
2000-01-07  1.282782  0.781836  1.071357  0.441153
2000-01-08  2.353925  0.583787  0.221471  0.744471
```

alignment

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.ix` (but on the contents rather than the axis labels)

```
In [158]: df2 = df.copy()

In [159]: df2[ df2[1:4] > 0 ] = 3

In [160]: df2
Out[160]:
                   A         B         C         D
2000-01-01  1.266143  0.299368 -0.863838  0.408204
2000-01-02 -1.048089 -0.025747 -0.988387  3.000000
2000-01-03  3.000000  3.000000  3.000000 -0.055758
2000-01-04  3.000000 -0.489682  3.000000 -0.034571
2000-01-05 -2.484478 -0.281461  0.030711  0.109121
2000-01-06  1.126203 -0.977349  1.474071 -0.064034
2000-01-07 -1.282782  0.781836 -1.071357  0.441153
```

```
2000-01-08  2.353925  0.583787  0.221471 -0.744471
```

New in version 0.13.

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

```
In [161]: df2 = df.copy()

In [162]: df2.where(df2>0,df2['A'],axis='index')
Out[162]: 
                   A         B         C         D
2000-01-01  1.266143  0.299368  1.266143  0.408204
2000-01-02 -1.048089 -1.048089 -1.048089  0.094055
2000-01-03  1.262731  1.289997  0.082423  1.262731
2000-01-04  0.536580  0.536580  0.369374  0.536580
2000-01-05 -2.484478 -2.484478  0.030711  0.109121
2000-01-06  1.126203  1.126203  1.474071  1.126203
2000-01-07 -1.282782  0.781836 -1.282782  0.441153
2000-01-08  2.353925  0.583787  0.221471  2.353925
```

This is equivalent (but faster than) the following.

```
In [163]: df2 = df.copy()

In [164]: df.apply(lambda x, y: x.where(x>0,y), y=df['A'])
Out[164]: 
                   A         B         C         D
2000-01-01  1.266143  0.299368  1.266143  0.408204
2000-01-02 -1.048089 -1.048089 -1.048089  0.094055
2000-01-03  1.262731  1.289997  0.082423  1.262731
2000-01-04  0.536580  0.536580  0.369374  0.536580
2000-01-05 -2.484478 -2.484478  0.030711  0.109121
2000-01-06  1.126203  1.126203  1.474071  1.126203
2000-01-07 -1.282782  0.781836 -1.282782  0.441153
2000-01-08  2.353925  0.583787  0.221471  2.353925
```

mask

`mask` is the inverse boolean operation of `where`.

```
In [165]: s.mask(s >= 0)
Out[165]: 
4   NaN
3   NaN
2   NaN
1   NaN
0   NaN
dtype: float64

In [166]: df.mask(df >= 0)
Out[166]: 
                   A         B         C         D
2000-01-01       NaN       NaN -0.863838       NaN
2000-01-02 -1.048089 -0.025747 -0.988387       NaN
2000-01-03       NaN       NaN       NaN -0.055758
2000-01-04       NaN -0.489682       NaN -0.034571
2000-01-05 -2.484478 -0.281461       NaN       NaN
2000-01-06       NaN -0.977349       NaN -0.064034
2000-01-07 -1.282782       NaN -1.071357       NaN
2000-01-08       NaN       NaN       NaN -0.744471
```

13.14 The query() Method (Experimental)

New in version 0.13.

DataFrame objects have a query() method that allows selection using an expression.

You can get the value of the frame where column b has values between the values of columns a and c. For example:

```
In [167]: n = 10

In [168]: df = DataFrame(rand(n, 3), columns=list('abc'))

In [169]: df
Out[169]:
          a         b         c
0  0.191519  0.622109  0.437728
1  0.785359  0.779976  0.272593
2  0.276464  0.801872  0.958139
3  0.875933  0.357817  0.500995
4  0.683463  0.712702  0.370251
5  0.561196  0.503083  0.013768
6  0.772827  0.882641  0.364886
7  0.615396  0.075381  0.368824
8  0.933140  0.651378  0.397203
9  0.788730  0.316836  0.568099

# pure python
In [170]: df[(df.a < df.b) & (df.b < df.c)]
Out[170]:
          a         b         c
2  0.276464  0.801872  0.958139

# query
In [171]: df.query('(a < b) & (b < c)')
Out[171]:
          a         b         c
2  0.276464  0.801872  0.958139
```

Do the same thing but fall back on a named index if there is no column with the name a.

```
In [172]: df = DataFrame(randint(n / 2, size=(n, 2)), columns=list('bc'))

In [173]: df.index.name = 'a'

In [174]: df
Out[174]:
   b  c
a
0  2  3
1  4  1
2  4  0
3  4  1
4  1  4
5  1  4
6  0  1
7  0  0
8  4  0
9  4  2
```

```
In [175]: df.query('a < b and b < c')
Out[175]:
   b  c
a
0  2  3
```

If instead you don't want to or cannot name your index, you can use the name `index` in your query expression:

```
In [176]: df = DataFrame(randint(n, size=(n, 2)), columns=list('bc'))

In [177]: df
Out[177]:
   b  c
0  3  1
1  2  5
2  2  5
3  6  7
4  4  3
5  5  6
6  4  6
7  2  4
8  2  7
9  9  7

In [178]: df.query('index < b < c')
Out[178]:
   b  c
1  2  5
3  6  7
```

Note: If the name of your index overlaps with a column name, the column name is given precedence. For example,

```
In [179]: df = DataFrame({'a': randint(5, size=5)})

In [180]: df.index.name = 'a'

In [181]: df.query('a > 2') # uses the column 'a', not the index
Out[181]:
   a
a
0  3
3  4
```

You can still use the index in a query expression by using the special identifier 'index':

```
In [182]: df.query('index > 2')
Out[182]:
   a
a
3  4
4  1
```

If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

13.14.1 MultiIndex query() Syntax

You can also use the levels of a DataFrame with a MultiIndex as if they were columns in the frame:

```
In [183]: import pandas.util.testing as tm

In [184]: n = 10

In [185]: colors = tm.choice(['red', 'green'], size=n)

In [186]: foods = tm.choice(['eggs', 'ham'], size=n)

In [187]: colors
Out[187]:
array(['red', 'green', 'red', 'green', 'red', 'green', 'red', 'green',
       'green', 'green'],
      dtype='|S5')

In [188]: foods
Out[188]:
array(['ham', 'eggs', 'ham', 'ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham',
       'eggs'],
      dtype='|S4')

In [189]: index = MultiIndex.from_arrays([colors, foods], names=['color', 'food'])

In [190]: df = DataFrame(randn(n, 2), index=index)

In [191]: df
Out[191]:
                   0         1
color food
red   ham   0.157622 -0.293555
green eggs  0.111560  0.597679
red   ham  -1.270093  0.120949
green ham  -0.193898  1.804172
red   ham  -0.234694  0.939908
green eggs -0.171520 -0.153055
red   eggs -0.363095 -0.067318
green eggs  1.444721  0.325771
      ham  -0.855732 -0.697595
      eggs -0.276134 -1.258759

In [192]: df.query('color == "red"')
Out[192]:
                   0         1
color food
red   ham   0.157622 -0.293555
      ham  -1.270093  0.120949
      ham  -0.234694  0.939908
      eggs -0.363095 -0.067318
```

If the levels of the MultiIndex are unnamed, you can refer to them using special names:

```
In [193]: df.index.names = [None, None]

In [194]: df
Out[194]:
                   0         1
```

```
red   ham   0.157622 -0.293555
green eggs  0.111560  0.597679
red   ham  -1.270093  0.120949
green ham  -0.193898  1.804172
red   ham  -0.234694  0.939908
green eggs -0.171520 -0.153055
red   eggs -0.363095 -0.067318
green eggs  1.444721  0.325771
      ham  -0.855732 -0.697595
      eggs -0.276134 -1.258759

In [195]: df.query('ilevel_0 == "red"')
Out[195]:
                 0         1
red ham   0.157622 -0.293555
    ham  -1.270093  0.120949
    ham  -0.234694  0.939908
    eggs -0.363095 -0.067318
```

The convention is `ilevel_0`, which means "index level 0" for the 0th level of the `index`.

13.14.2 `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 [196]: df = DataFrame(rand(n, 3), columns=list('abc'))

In [197]: df
Out[197]:
          a         b         c
0  0.972113  0.046532  0.917354
1  0.158930  0.943383  0.763162
2  0.053878  0.254082  0.927973
3  0.838312  0.156925  0.690776
4  0.366946  0.937473  0.613365
5  0.699350  0.502946  0.711111
6  0.134386  0.828932  0.742846
7  0.457034  0.079103  0.373047
8  0.933636  0.418725  0.234212
9  0.572485  0.572111  0.416893

In [198]: df2 = DataFrame(rand(n + 2, 3), columns=df.columns)

In [199]: df2
Out[199]:
           a         b         c
0   0.625883  0.220362  0.622059
1   0.477672  0.974342  0.772985
2   0.027139  0.221022  0.120328
3   0.175274  0.429462  0.657769
4   0.565899  0.569035  0.654196
5   0.368558  0.952385  0.196770
6   0.849930  0.960458  0.381118
7   0.330936  0.260923  0.665491
8   0.181795  0.376800  0.014259
```

```
9   0.339135  0.401351  0.467574
10  0.652106  0.997192  0.517462
11  0.403612  0.058447  0.045196

In [200]: expr = '0.0 <= a <= c <= 0.5'

In [201]: map(lambda frame: frame.query(expr), [df, df2])
Out[201]:
[Empty DataFrame
 Columns: [a, b, c]
 Index: [],           a         b         c
 2  0.027139  0.221022  0.120328
 9  0.339135  0.401351  0.467574]
```

13.14.3 `query()` Python versus pandas Syntax Comparison

Full numpy-like syntax

```
In [202]: df = DataFrame(randint(n, size=(n, 3)), columns=list('abc'))

In [203]: df
Out[203]:
   a  b  c
0  5  3  8
1  8  8  1
2  3  6  8
3  9  1  5
4  8  4  1
5  1  1  2
6  3  4  2
7  1  9  4
8  0  0  2
9  1  2  5

In [204]: df.query('(a < b) & (b < c)')
Out[204]:
   a  b  c
2  3  6  8
9  1  2  5

In [205]: df[(df.a < df.b) & (df.b < df.c)]
Out[205]:
   a  b  c
2  3  6  8
9  1  2  5
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&`/`|`)

```
In [206]: df.query('a < b & b < c')
Out[206]:
   a  b  c
2  3  6  8
9  1  2  5
```

Use English instead of symbols

```
In [207]: df.query('a < b and b < c')
Out[207]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

Pretty close to how you might write it on paper

```
In [208]: df.query('a < b < c')
Out[208]:
   a  b  c
2  3  6  8
9  1  2  5
```

13.14.4 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 [209]: df = DataFrame({'a': list('aabbccddeeff'), 'b': list('aaaabbbbcccc'),
   .....:                 'c': randint(5, size=12), 'd': randint(9, size=12)})
   .....:

In [210]: df
Out[210]:
    a  b  c  d
0   a  a  1  7
1   a  a  0  0
2   b  a  0  2
3   b  a  2  8
4   c  b  0  4
5   c  b  0  8
6   d  b  1  3
7   d  b  1  2
8   e  c  4  4
9   e  c  3  7
10  f  c  2  7
11  f  c  0  0

In [211]: df.query('a in b')
Out[211]:
   a  b  c  d
0  a  a  1  7
1  a  a  0  0
2  b  a  0  2
3  b  a  2  8
4  c  b  0  4
5  c  b  0  8

# How you'd do it in pure Python
In [212]: df[df.a.isin(df.b)]
Out[212]:
   a  b  c  d
0  a  a  1  7
1  a  a  0  0
2  b  a  0  2
3  b  a  2  8
4  c  b  0  4
```

```
5   c  b  0  8

In [213]: df.query('a not in b')
Out[213]:
    a  b  c  d
6   d  b  1  3
7   d  b  1  2
8   e  c  4  4
9   e  c  3  7
10  f  c  2  7
11  f  c  0  0

# pure Python
In [214]: df[~df.a.isin(df.b)]
Out[214]:
    a  b  c  d
6   d  b  1  3
7   d  b  1  2
8   e  c  4  4
9   e  c  3  7
10  f  c  2  7
11  f  c  0  0
```

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 [215]: df.query('a in b and c < d')
Out[215]:
   a  b  c  d
0  a  a  1  7
2  b  a  0  2
3  b  a  2  8
4  c  b  0  4
5  c  b  0  8

# pure Python
In [216]: df[df.b.isin(df.a) & (df.c < df.d)]
Out[216]:
    a  b  c  d
0   a  a  1  7
2   b  a  0  2
3   b  a  2  8
4   c  b  0  4
5   c  b  0  8
6   d  b  1  3
7   d  b  1  2
9   e  c  3  7
10  f  c  2  7
```

Note: Note that `in` and `not in` are evaluated in Python, since `numexpr` has no equivalent of this operation. However, **only the** `in`/`not in` **expression itself** is evaluated in vanilla Python. For example, in the expression

```
df.query('a in b + c + d')
```

`(b + c + d)` is evaluated by `numexpr` and *then* the `in` operation is evaluated in plain Python. In general, any operations that can be evaluated using `numexpr` will be.

13.14.5 Special use of the == operator with `list` objects

Comparing a `list` of values to a column using ==/!= works similarly to `in`/`not in`

```
In [217]: df.query('b == ["a", "b", "c"]')
Out[217]:
    a  b  c  d
0   a  a  1  7
1   a  a  0  0
2   b  a  0  2
3   b  a  2  8
4   c  b  0  4
5   c  b  0  8
6   d  b  1  3
7   d  b  1  2
8   e  c  4  4
9   e  c  3  7
10  f  c  2  7
11  f  c  0  0

# pure Python
In [218]: df[df.b.isin(["a", "b", "c"])]
Out[218]:
    a  b  c  d
0   a  a  1  7
1   a  a  0  0
2   b  a  0  2
3   b  a  2  8
4   c  b  0  4
5   c  b  0  8
6   d  b  1  3
7   d  b  1  2
8   e  c  4  4
9   e  c  3  7
10  f  c  2  7
11  f  c  0  0

In [219]: df.query('c == [1, 2]')
Out[219]:
    a  b  c  d
0   a  a  1  7
3   b  a  2  8
6   d  b  1  3
7   d  b  1  2
10  f  c  2  7

In [220]: df.query('c != [1, 2]')
Out[220]:
    a  b  c  d
1   a  a  0  0
2   b  a  0  2
4   c  b  0  4
5   c  b  0  8
8   e  c  4  4
9   e  c  3  7
11  f  c  0  0

# using in/not in
In [221]: df.query('[1, 2] in c')
```

```
Out[221]:
    a  b  c  d
0   a  a  1  7
3   b  a  2  8
6   d  b  1  3
7   d  b  1  2
10  f  c  2  7

In [222]: df.query('[1, 2] not in c')
Out[222]:
    a  b  c  d
1   a  a  0  0
2   b  a  0  2
4   c  b  0  4
5   c  b  0  8
8   e  c  4  4
9   e  c  3  7
11  f  c  0  0

# pure Python
In [223]: df[df.c.isin([1, 2])]
Out[223]:
    a  b  c  d
0   a  a  1  7
3   b  a  2  8
6   d  b  1  3
7   d  b  1  2
10  f  c  2  7
```

13.14.6 Boolean Operators

You can negate boolean expressions with the word `not` or the ~ operator.

```
In [224]: df = DataFrame(rand(n, 3), columns=list('abc'))

In [225]: df['bools'] = rand(len(df)) > 0.5

In [226]: df.query('~bools')
Out[226]:
          a         b         c  bools
0  0.395827  0.035597  0.171689  False
2  0.582329  0.898831  0.435002  False
3  0.078368  0.224708  0.697626  False
5  0.877177  0.221076  0.287379  False
6  0.993264  0.861585  0.108845  False

In [227]: df.query('not bools')
Out[227]:
          a         b         c  bools
0  0.395827  0.035597  0.171689  False
2  0.582329  0.898831  0.435002  False
3  0.078368  0.224708  0.697626  False
5  0.877177  0.221076  0.287379  False
6  0.993264  0.861585  0.108845  False

In [228]: df.query('not bools') == df[~df.bools]
Out[228]:
```

```
      a     b     c bools
0  True  True  True  True
2  True  True  True  True
3  True  True  True  True
5  True  True  True  True
6  True  True  True  True
```

Of course, expressions can be arbitrarily complex too

```
# short query syntax
In [229]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [230]: longer = df[(df.a < df.b) & (df.b < df.c) & (~df.bools) | (df.bools > 2)]

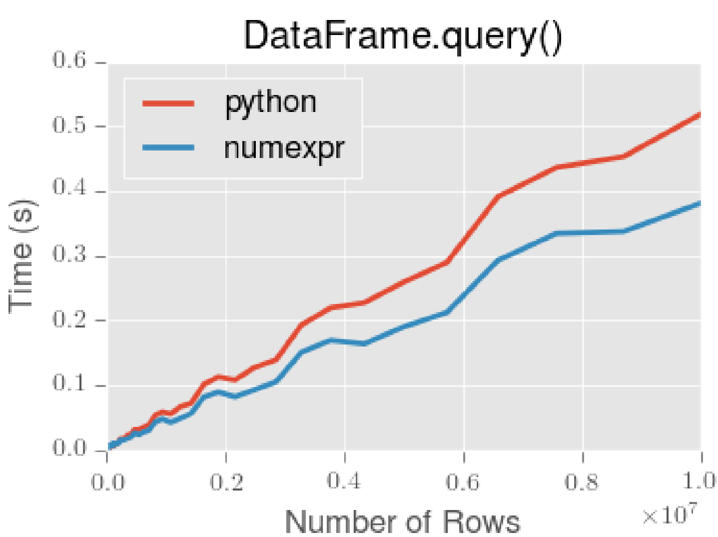
In [231]: shorter
Out[231]:
          a         b         c  bools
3  0.078368  0.224708  0.697626  False

In [232]: longer
Out[232]:
          a         b         c  bools
3  0.078368  0.224708  0.697626  False

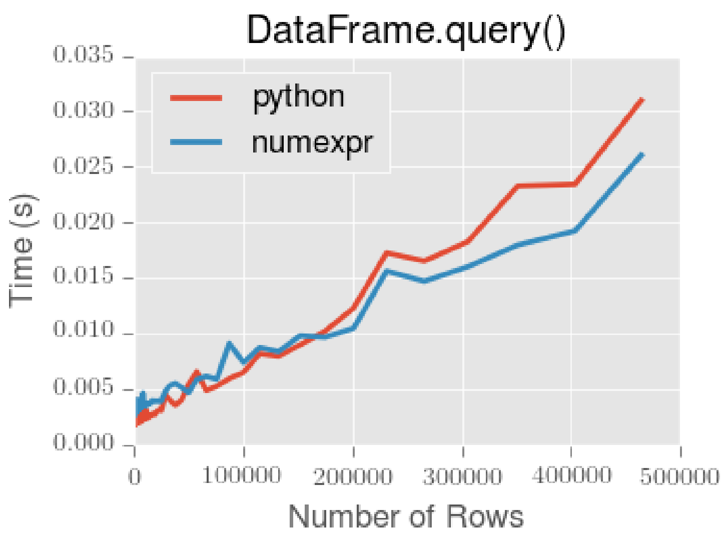
In [233]: shorter == longer
Out[233]:
      a     b     c bools
3  True  True  True  True
```

13.14.7 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()`.

13.15 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 `take_last` parameter that indicates the last observed row should be taken instead.

```
In [234]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
   .....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                  'c' : np.random.randn(7)})
   .....:

In [235]: df2.duplicated(['a','b'])
Out[235]:
0    False
1    False
2    False
3    False
4     True
5     True
6    False
dtype: bool

In [236]: df2.drop_duplicates(['a','b'])
Out[236]:
       a  b         c
0    one  x  0.932713
```

```
1    one  y -0.393510
2    two  y -0.548454
3  three  x  1.130736
6    six  x -1.233298

In [237]: df2.drop_duplicates(['a','b'], take_last=True)
Out[237]:
       a  b         c
1    one  y -0.393510
3  three  x  1.130736
4    two  y -0.447217
5    one  x  1.043921
6    six  x -1.233298
```

An alternative way to drop duplicates on the index is `.groupby(level=0)` combined with `first()` or `last()`.

```
In [238]: df3 = df2.set_index('b')

In [239]: df3
Out[239]:
       a         c
b
x    one  0.932713
y    one -0.393510
y    two -0.548454
x  three  1.130736
y    two -0.447217
x    one  1.043921
x    six -1.233298

In [240]: df3.groupby(level=0).first()
Out[240]:
     a         c
b
x  one  0.932713
y  one -0.393510

# a bit more verbose
In [241]: df3.reset_index().drop_duplicates(subset='b', take_last=False).set_index('b')
Out[241]:
     a         c
b
x  one  0.932713
y  one -0.393510
```

13.16 Dictionary-like `get()` method

Each of Series, DataFrame, and Panel have a `get` method which can return a default value.

```
In [242]: s = Series([1,2,3], index=['a','b','c'])

In [243]: s.get('a')               # equivalent to s['a']
Out[243]: 1

In [244]: s.get('x', default=-1)
Out[244]: -1
```

13.17 The `select()` Method

Another way to extract slices from an object is with the `select` method of Series, DataFrame, and Panel. This method should be used only when there is no more direct way. `select` takes a function which operates on labels along `axis` and returns a boolean. For instance:

```
In [245]: df.select(lambda x: x == 'A', axis=1)
Out[245]:
                   A
2000-01-01  0.454389
2000-01-02  0.036249
2000-01-03  0.378125
2000-01-04  0.075871
2000-01-05 -0.677097
2000-01-06  1.482845
2000-01-07  0.272681
2000-01-08 -0.459059
```

13.18 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 [246]: dflookup = DataFrame(np.random.rand(20,4), columns = ['A','B','C','D'])

In [247]: dflookup.lookup(list(range(0,10,2)), ['B','C','A','B','D'])
Out[247]: array([ 0.012 ,  0.3551,  0.3261,  0.4702,  0.3107])
```

13.19 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 [248]: index = Index(['e', 'd', 'a', 'b'])

In [249]: index
Out[249]: Index([u'e', u'd', u'a', u'b'], dtype='object')

In [250]: 'd' in index
Out[250]: True
```

You can also pass a `name` to be stored in the index:

```
In [251]: index = Index(['e', 'd', 'a', 'b'], name='something')

In [252]: index.name
Out[252]: 'something'
```

The name, if set, will be shown in the console display:

```
In [253]: index = Index(list(range(5)), name='rows')

In [254]: columns = Index(['A', 'B', 'C'], name='cols')

In [255]: df = DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [256]: df
Out[256]:
cols         A         B         C
rows
0     0.603791  0.388713  0.544331
1    -0.152978  1.929541  0.202138
2     0.024972  0.117533 -0.184740
3     1.054144 -0.736061 -0.785352
4    -1.362549 -0.063514  0.487562

In [257]: df['A']
Out[257]:
rows
0    0.603791
1   -0.152978
2    0.024972
3    1.054144
4   -1.362549
Name: A, dtype: float64
```

13.19.1 Setting metadata

New in version 0.13.0. Indexes are "mostly immutable", but it is possible to set and change their metadata, like the index `name` (or, for `MultiIndex`, `levels` and `labels`).

You can use the `rename`, `set_names`, `set_levels`, and `set_labels` to set these attributes directly. They default to returning a copy; however, you can specify `inplace=True` to have the data change in place.

See *Advanced Indexing* for usage of MultiIndexes.

```
In [258]: ind = Index([1, 2, 3])

In [259]: ind.rename("apple")
Out[259]: Int64Index([1, 2, 3], dtype='int64', name=u'apple')

In [260]: ind
Out[260]: Int64Index([1, 2, 3], dtype='int64')

In [261]: ind.set_names(["apple"], inplace=True)

In [262]: ind.name = "bob"

In [263]: ind
Out[263]: Int64Index([1, 2, 3], dtype='int64', name=u'bob')
```

New in version 0.15.0.

`set_names`, `set_levels`, and `set_labels` also take an optional *level*' argument

```
In [264]: index = MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])

In [265]: index
```

```
Out[265]:
MultiIndex(levels=[[0, 1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=[u'first', u'second'])

In [266]: index.levels[1]
Out[266]: Index([u'one', u'two'], dtype='object', name=u'second')

In [267]: index.set_levels(["a", "b"], level=1)
Out[267]:
MultiIndex(levels=[[0, 1, 2], [u'a', u'b']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=[u'first', u'second'])
```

13.19.2 Set operations on Index objects

Warning: In 0.15.0. the set operations + and - were deprecated in order to provide these for numeric type operations on certain index types. + can be replace by `.union()` or `|`, and - by `.difference()`.

The two main operations are `union (|)`, `intersection (&)` These can be directly called as instance methods or used via overloaded operators. Difference is provided via the `.difference()` method.

```
In [268]: a = Index(['c', 'b', 'a'])

In [269]: b = Index(['c', 'e', 'd'])

In [270]: a | b
Out[270]: Index([u'a', u'b', u'c', u'd', u'e'], dtype='object')

In [271]: a & b
Out[271]: Index([u'c'], dtype='object')

In [272]: a.difference(b)
Out[272]: Index([u'a', u'b'], dtype='object')
```

Also available is the `sym_diff (^)` operation, which returns elements that appear in either `idx1` or `idx2` but not both. This is equivalent to the Index created by `idx1.difference(idx2).union(idx2.difference(idx1))`, with duplicates dropped.

```
In [273]: idx1 = Index([1, 2, 3, 4])

In [274]: idx2 = Index([2, 3, 4, 5])

In [275]: idx1.sym_diff(idx2)
Out[275]: Int64Index([1, 5], dtype='int64')

In [276]: idx1 ^ idx2
Out[276]: Int64Index([1, 5], dtype='int64')
```

13.20 Set / Reset Index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you've already done so. There are a couple of different ways.

13.20.1 Set an index

DataFrame has a `set_index` method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`), to create a new, indexed DataFrame:

```
In [277]: data
Out[277]:
     a    b  c  d
0  bar  one  z  1
1  bar  two  y  2
2  foo  one  x  3
3  foo  two  w  4

In [278]: indexed1 = data.set_index('c')

In [279]: indexed1
Out[279]:
     a    b  d
c
z  bar  one  1
y  bar  two  2
x  foo  one  3
w  foo  two  4

In [280]: indexed2 = data.set_index(['a', 'b'])

In [281]: indexed2
Out[281]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4
```

The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [282]: frame = data.set_index('c', drop=False)

In [283]: frame = frame.set_index(['a', 'b'], append=True)

In [284]: frame
Out[284]:
           c  d
c a   b
z bar one  z  1
y bar two  y  2
x foo one  x  3
w foo two  w  4
```

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 [285]: data.set_index('c', drop=False)
Out[285]:
     a    b  c  d
c
z  bar  one  z  1
y  bar  two  y  2
```

```
x  foo  one  x  3
w  foo  two  w  4

In [286]: data.set_index(['a', 'b'], inplace=True)

In [287]: data
Out[287]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4
```

13.20.2 Reset the index

As a convenience, there is a new function on DataFrame called `reset_index` which transfers the index values into the DataFrame's columns and sets a simple integer index. This is the inverse operation to `set_index`

```
In [288]: data
Out[288]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4

In [289]: data.reset_index()
Out[289]:
     a    b  c  d
0  bar  one  z  1
1  bar  two  y  2
2  foo  one  x  3
3  foo  two  w  4
```

The output is more similar to a SQL table or a record array. The names for the columns derived from the index are the ones stored in the `names` attribute.

You can use the `level` keyword to remove only a portion of the index:

```
In [290]: frame
Out[290]:
           c  d
c a   b
z bar one  z  1
y bar two  y  2
x foo one  x  3
w foo two  w  4

In [291]: frame.reset_index(level=1)
Out[291]:
         a  c  d
c b
z one  bar  z  1
y two  bar  y  2
x one  foo  x  3
w two  foo  w  4
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

Note: The `reset_index` method used to be called `delevel` which is now deprecated.

13.20.3 Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

13.21 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 [292]: dfmi = DataFrame([list('abcd'),
   .....:                   list('efgh'),
   .....:                   list('ijkl'),
   .....:                   list('mnop')],
   .....:                  columns=MultiIndex.from_product([['one','two'],
   .....:                                                   ['first','second']]))
   .....:

In [293]: dfmi
Out[293]:
    one          two
  first second first second
0     a      b     c      d
1     e      f     g      h
2     i      j     k      l
3     m      n     o      p
```

Compare these two access methods:

```
In [294]: dfmi['one']['second']
Out[294]:
0    b
1    f
2    j
3    n
Name: second, dtype: object

In [295]: dfmi.loc[:,('one','second')]
Out[295]:
0    b
1    f
2    j
3    n
Name: (one, second), dtype: object
```

These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (`.loc`) is much preferred over method 1 (chained `[]`)

`dfmi['one']` selects the first level of the columns and returns a data frame that is singly-indexed. Then another python operation `dfmi_with_one['second']` selects the series indexed by `'second'` happens. This is indicated by the variable `dfmi_with_one` because pandas sees these operations as separate events. e.g. separate calls to `__getitem__`, so it has to treat them as linear operations, they happen one after another.

Contrast this to `df.loc[:,('one','second')]` which passes a nested tuple of `(slice(None),('one','second'))` to a single call to `__getitem__`. This allows pandas to deal with this as a single entity. Furthermore this order of operations *can* be significantly faster, and allows one to index *both* axes if so desired.

13.21.1 Why does the assignment when using chained indexing fail!

So, why does this show the `SettingWithCopy` warning / and possibly not work when you do chained indexing and assignment:

```
dfmi['one']['second'] = value
```

Since the chained indexing is 2 calls, it is possible that either call may return a **copy** of the data because of the way it is sliced. Thus when setting, you are actually setting a **copy**, and not the original frame data. It is impossible for pandas to figure this out because their are 2 separate python operations that are not connected.

The `SettingWithCopy` warning is a 'heuristic' to detect this (meaning it tends to catch most cases but is simply a lightweight check). Figuring this out for real is way complicated.

The `.loc` operation is a single python operation, and thus can select a slice (which still may be a copy), but allows pandas to assign that slice back into the frame after it is modified, thus setting the values as you would think.

The reason for having the `SettingWithCopy` warning is this. Sometimes when you slice an array you will simply get a view back, which means you can set it no problem. However, even a single dtyped array can generate a copy if it is sliced in a particular way. A multi-dtyped DataFrame (meaning it has say `float` and `object` data), will almost always yield a copy. Whether a view is created is dependent on the memory layout of the array.

13.21.2 Evaluation order matters

Furthermore, in chained expressions, the order may determine whether a copy is returned or not. If an expression will set values on a copy of a slice, then a `SettingWithCopy` exception will be raised (this raise/warn behavior is new starting in 0.13.0)

You can control the action of a chained assignment via the option `mode.chained_assignment`, which can take the values `['raise','warn',None]`, where showing a warning is the default.

```
In [296]: dfb = 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 [297]: dfb['c'][dfb.a.str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```
>>> pd.set_option('mode.chained_assignment','warn')
>>> dfb[dfb.a.str.startswith('o')]['c'] = 42
Traceback (most recent call last)
     ...
SettingWithCopyWarning:
```

```
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_index,col_indexer] = value instead
```

A chained assignment can also crop up in setting in a mixed dtype frame.

Note: These setting rules apply to all of `.loc/.iloc/.ix`

This is the correct access method

```
In [298]: dfc = DataFrame({'A':['aaa','bbb','ccc'],'B':[1,2,3]})

In [299]: dfc.loc[0,'A'] = 11

In [300]: dfc
Out[300]:
     A  B
0   11  1
1  bbb  2
2  ccc  3
```

This *can* work at times, but is not guaranteed, and so should be avoided

```
In [301]: dfc = dfc.copy()

In [302]: dfc['A'][0] = 111

In [303]: dfc
Out[303]:
     A  B
0  111  1
1  bbb  2
2  ccc  3
```

This will **not** work at all, and so should be avoided

```
>>> pd.set_option('mode.chained_assignment','raise')
>>> dfc.loc[0]['A'] = 1111
Traceback (most recent call last)
     ...
SettingWithCopyException:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_index,col_indexer] = value instead
```

Warning: The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertantly reported.

CHAPTER

FOURTEEN

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*

> **Warning:** In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

See the *cookbook* for some advanced strategies

14.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like Series (1d) and DataFrame (2d).

In this section, we will show what exactly we mean by "hierarchical" indexing and how it integrates with the all of the pandas indexing functionality described above and in prior sections. Later, when discussing *group by* and *pivoting and reshaping data*, we'll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the *cookbook* for some advanced strategies

14.1.1 Creating a MultiIndex (hierarchical index) object

The `MultiIndex` object is the hierarchical analogue of the standard `Index` object which typically stores the axis labels in pandas objects. You can think of `MultiIndex` an array of tuples where each tuple is unique. A `MultiIndex` can be created from a list of arrays (using `MultiIndex.from_arrays`), an array of tuples (using `MultiIndex.from_tuples`), or a crossed set of iterables (using `MultiIndex.from_product`). The `Index` constructor will attempt to return a `MultiIndex` when it is passed a list of tuples. The following examples demo different ways to initialize MultiIndexes.

```
In [1]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
   ...:           ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
   ...:

In [2]: tuples = list(zip(*arrays))
```

```
In [3]: tuples
Out[3]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [4]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [5]: index
Out[5]:
MultiIndex(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
           labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
           names=[u'first', u'second'])

In [6]: s = pd.Series(np.random.randn(8), index=index)

In [7]: s
Out[7]:
first  second
bar    one       0.469112
       two      -0.282863
baz    one      -1.509059
       two      -1.135632
foo    one       1.212112
       two      -0.173215
qux    one       0.119209
       two      -1.044236
dtype: float64
```

When you want every pairing of the elements in two iterables, it can be easier to use the `MultiIndex.from_product` function:

```
In [8]: iterables = [['bar', 'baz', 'foo', 'qux'], ['one', 'two']]

In [9]: pd.MultiIndex.from_product(iterables, names=['first', 'second'])
Out[9]:
MultiIndex(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
           labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
           names=[u'first', u'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)

In [12]: s
Out[12]:
bar  one   -0.861849
     two   -2.104569
baz  one   -0.494929
```

```
     two    1.071804
foo  one    0.721555
     two   -0.706771
qux  one   -1.039575
     two    0.271860
dtype: float64

In [13]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)

In [14]: df
Out[14]: 
                0         1         2         3
bar one -0.424972  0.567020  0.276232 -1.087401
    two -0.673690  0.113648 -1.478427  0.524988
baz one  0.404705  0.577046 -1.715002 -1.039268
    two -0.370647 -1.157892 -1.344312  0.844885
foo one  1.075770 -0.109050  1.643563 -1.469388
    two  0.357021 -0.674600 -1.776904 -0.968914
qux one -1.294524  0.413738  0.276662 -0.472035
    two -0.013960 -0.362543 -0.006154 -0.923061
```

All of the `MultiIndex` constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, `None` will be assigned:

```
In [15]: df.index.names
Out[15]: FrozenList([None, None])
```

This index can back any axis of a pandas object, and the number of **levels** of the index is up to you:

```
In [16]: df = pd.DataFrame(np.random.randn(3, 8), index=['A', 'B', 'C'], columns=index)

In [17]: df
Out[17]: 
first        bar                 baz                 foo                 qux  \
second       one       two       one       two       one       two       one   
A       0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299   
B       0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127   
C      -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466   

first             
second       two  
A      -0.226169  
B      -1.436737  
C      -2.006747  

In [18]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
Out[18]: 
first              bar                 baz                 foo          
second             one       two       one       two       one       two
first second                                                            
bar   one    -0.410001 -0.078638  0.545952 -1.219217 -1.226825  0.769804
      two    -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734
baz   one     0.959726 -1.110336 -0.619976  0.149748 -0.732339  0.687738
      two     0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849
foo   one    -0.954208  1.462696 -1.743161 -0.826591 -0.345352  1.314232
      two     0.690579  0.995761  2.396780  0.014871  3.357427 -0.317441
```

We've "sparsified" the higher levels of the indexes to make the console output a bit easier on the eyes.

It's worth keeping in mind that there's nothing preventing you from using tuples as atomic labels on an axis:

```
In [19]: pd.Series(np.random.randn(8), index=tuples)
Out[19]:
(bar, one)   -1.236269
(bar, two)    0.896171
(baz, one)   -0.487602
(baz, two)   -0.082240
(foo, one)   -2.182937
(foo, two)    0.380396
(qux, one)    0.084844
(qux, two)    0.432390
dtype: float64
```

The reason that the `MultiIndex` matters is that it can allow you to do grouping, selection, and reshaping operations as we will describe below and in subsequent areas of the documentation. As you will see in later sections, you can find yourself working with hierarchically-indexed data without creating a `MultiIndex` explicitly yourself. However, when loading data from a file, you may wish to generate your own `MultiIndex` when preparing the data set.

Note that how the index is displayed by be controlled using the `multi_sparse` option in `pandas.set_printoptions`:

```
In [20]: pd.set_option('display.multi_sparse', False)

In [21]: df
Out[21]:
first        bar       bar       baz       baz       foo       foo       qux  \
second       one       two       one       two       one       two       one
A       0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299
B       0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127
C      -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466

first        qux
second       two
A      -0.226169
B      -1.436737
C      -2.006747

In [22]: pd.set_option('display.multi_sparse', True)
```

14.1.2 Reconstructing the level labels

The method `get_level_values` will return a vector of the labels for each location at a particular level:

```
In [23]: index.get_level_values(0)
Out[23]: Index([u'bar', u'bar', u'baz', u'baz', u'foo', u'foo', u'qux', u'qux'], dtype='object', name

In [24]: index.get_level_values('second')
Out[24]: Index([u'one', u'two', u'one', u'two', u'one', u'two', u'one', u'two'], dtype='object', name
```

14.1.3 Basic indexing on axis with MultiIndex

One of the important features of hierarchical indexing is that you can select data by a "partial" label identifying a subgroup in the data. **Partial** selection "drops" levels of the hierarchical index in the result in a completely analogous way to selecting a column in a regular DataFrame:

```
In [25]: df['bar']
Out[25]:
second        one       two
A        0.895717  0.805244
B        0.410835  0.813850
C       -1.413681  1.607920

In [26]: df['bar', 'one']
Out[26]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64

In [27]: df['bar']['one']
Out[27]:
A    0.895717
B    0.410835
C   -1.413681
Name: one, dtype: float64

In [28]: s['qux']
Out[28]:
one   -1.039575
two    0.271860
dtype: float64
```

See *Cross-section with hierarchical index* for how to select on a deeper level.

14.1.4 Data alignment and using `reindex`

Operations between differently-indexed objects having `MultiIndex` on the axes will work as you expect; data alignment will work the same as an Index of tuples:

```
In [29]: s + s[:-2]
Out[29]:
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 [30]: s + s[::2]
Out[30]:
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 [31]: s.reindex(index[:3])
Out[31]:
first  second
bar    one      -0.861849
       two      -2.104569
baz    one      -0.494929
dtype: float64

In [32]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
Out[32]:
foo  two   -0.706771
bar  one   -0.861849
qux  one   -1.039575
baz  one   -0.494929
dtype: float64
```

14.2 Advanced indexing with hierarchical index

Syntactically integrating `MultiIndex` in advanced indexing with `.loc/.ix` is a bit challenging, but we've made every effort to do so. for example the following works as you would expect:

```
In [33]: df = df.T

In [34]: df
Out[34]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
      two     0.805244  0.813850  1.607920
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466
      two    -0.226169 -1.436737 -2.006747

In [35]: df.loc['bar']
Out[35]:
               A         B         C
second
one     0.895717  0.410835 -1.413681
two     0.805244  0.813850  1.607920

In [36]: df.loc['bar', 'two']
Out[36]:
A    0.805244
B    0.813850
C    1.607920
Name: (bar, two), dtype: float64
```

"Partial" slicing also works quite nicely.

```
In [37]: df.loc['baz':'foo']
Out[37]:
                     A         B         C
```

```
first second
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
```

You can slice with a 'range' of values, by providing a slice of tuples.

```
In [38]: df.loc[('baz', 'two'):('qux', 'one')]
Out[38]:
                     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 [39]: df.loc[('baz', 'two'):'foo']
Out[39]:
                     A         B         C
first second
baz   two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
```

Passing a list of labels or tuples works similar to reindexing:

```
In [40]: df.ix[[('bar', 'two'), ('qux', 'one')]]
Out[40]:
                     A         B         C
first second
bar   two     0.805244  0.813850  1.607920
qux   one    -1.170299  1.130127  0.974466
```

14.2.1 Using slicers

New in version 0.14.0.

In 0.14.0 we added a new way to slice multi-indexed objects. You can slice a multi-index by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see *Selection by Label*, including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

Warning: You should specify all axes in the `.loc` specifier, meaning the indexer for the **index** and for the **columns**. Their are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MuliIndex for the rows.

You should do this:

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

rather than this:

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

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

```
In [41]: def mklbl(prefix,n):
   ....:     return ["%s%s" % (prefix,i)  for i in range(n)]
   ....:

In [42]: miindex = pd.MultiIndex.from_product([mklbl('A',4),
   ....:                                       mklbl('B',2),
   ....:                                       mklbl('C',4),
   ....:                                       mklbl('D',2)])
   ....:

In [43]: micolumns = pd.MultiIndex.from_tuples([('a','foo'),('a','bar'),
   ....:                                         ('b','foo'),('b','bah')],
   ....:                                       names=['lvl0', 'lvl1'])
   ....:

In [44]: dfmi = pd.DataFrame(np.arange(len(miindex)*len(micolumns)).reshape((len(miindex),len(micolur
   ....:                     index=miindex,
   ....:                     columns=micolumns).sortlevel().sortlevel(axis=1)
   ....:

In [45]: dfmi
Out[45]:
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 [46]: dfmi.loc[(slice('A1','A3'),slice(None), ['C1','C3']),:]
Out[46]:
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 a `pd.IndexSlice` to have a more natural syntax using `:` rather than using `slice(None)`

```
In [47]: idx = pd.IndexSlice

In [48]: dfmi.loc[idx[:,:,['C1','C3']],idx[:,'foo']]
Out[48]:
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]
```

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

```
In [49]: dfmi.loc['A1',(slice(None),'foo')]
Out[49]:
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

[16 rows x 2 columns]
```

```
In [50]: dfmi.loc[idx[:,:,['C1','C3']],idx[:,'foo']]
Out[50]:
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 [51]: mask = dfmi[('a','foo')]>200

In [52]: dfmi.loc[idx[mask,:,['C1','C3']],idx[:,'foo']]
Out[52]:
lvl0           a    b
lvl1         foo  foo
A3 B0 C1 D1  204  206
      C3 D0  216  218
         D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254
```

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

```
In [53]: dfmi.loc(axis=0)[:,:,['C1','C3']]
Out[53]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C1 D0    9    8   11   10
         D1   13   12   15   14
```

```
      C3 D0   25   24   27   26
         D1   29   28   31   30
   B1 C1 D0   41   40   43   42
         D1   45   44   47   46
      C3 D0   57   56   59   58
...          ...  ...  ...  ...
A3 B0 C1 D1  205  204  207  206
      C3 D0  217  216  219  218
         D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
      C3 D0  249  248  251  250
         D1  253  252  255  254

[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

```
In [54]: df2 = dfmi.copy()

In [55]: df2.loc(axis=0)[:,:,['C1','C3']] = -10

In [56]: df2
Out[56]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
         D1    5    4    7    6
      C1 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10
      C2 D0   17   16   19   18
         D1   21   20   23   22
      C3 D0  -10  -10  -10  -10
...          ...  ...  ...  ...
A3 B1 C0 D1  229  228  231  230
      C1 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10
      C2 D0  241  240  243  242
         D1  245  244  247  246
      C3 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10

[64 rows x 4 columns]
```

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

```
In [57]: df2 = dfmi.copy()

In [58]: df2.loc[idx[:,:,['C1','C3']],:] = df2*1000

In [59]: df2
Out[59]:
lvl0              a               b
lvl1            bar     foo     bah     foo
A0 B0 C0 D0       1       0       3       2
         D1       5       4       7       6
      C1 D0    9000    8000   11000   10000
         D1   13000   12000   15000   14000
      C2 D0      17      16      19      18
```

```
          D1      21      20      23      22
       C3 D0   25000   24000   27000   26000
...              ...     ...     ...     ...
A3 B1  C0 D1     229     228     231     230
       C1 D0  233000  232000  235000  234000
          D1  237000  236000  239000  238000
       C2 D0     241     240     243     242
          D1     245     244     247     246
       C3 D0  249000  248000  251000  250000
          D1  253000  252000  255000  254000

[64 rows x 4 columns]
```

14.2.2 Cross-section

The `xs` method of `DataFrame` additionally takes a level argument to make selecting data at a particular level of a MultiIndex easier.

```
In [60]: df
Out[60]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
      two     0.805244  0.813850  1.607920
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466
      two    -0.226169 -1.436737 -2.006747

In [61]: df.xs('one', level='second')
Out[61]:
              A         B         C
first
bar    0.895717  0.410835 -1.413681
baz   -1.206412  0.132003  1.024180
foo    1.431256 -0.076467  0.875906
qux   -1.170299  1.130127  0.974466

# using the slicers (new in 0.14.0)
In [62]: df.loc[(slice(None),'one'),:]
Out[62]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
baz   one    -1.206412  0.132003  1.024180
foo   one     1.431256 -0.076467  0.875906
qux   one    -1.170299  1.130127  0.974466
```

You can also select on the columns with `xs()`, by providing the axis argument

```
In [63]: df = df.T

In [64]: df.xs('one', level='second', axis=1)
Out[64]:
first       bar       baz       foo       qux
```

```
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466

# using the slicers (new in 0.14.0)
In [65]: df.loc[:,(slice(None),'one')]
Out[65]:
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
```

`xs()` also allows selection with multiple keys

```
In [66]: df.xs(('one', 'bar'), level=('second', 'first'), axis=1)
Out[66]:
first        bar
second       one
A       0.895717
B       0.410835
C      -1.413681

# using the slicers (new in 0.14.0)
In [67]: df.loc[:,('bar','one')]
Out[67]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64
```

New in version 0.13.0.

You can pass `drop_level=False` to `xs()` to retain the level that was selected

```
In [68]: df.xs('one', level='second', axis=1, drop_level=False)
Out[68]:
first        bar       baz       foo       qux
second       one       one       one       one
A       0.895717 -1.206412  1.431256 -1.170299
B       0.410835  0.132003 -0.076467  1.130127
C      -1.413681  1.024180  0.875906  0.974466
```

versus the result with `drop_level=True` (the default value)

```
In [69]: df.xs('one', level='second', axis=1, drop_level=True)
Out[69]:
first       bar       baz       foo       qux
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

14.2.3 Advanced reindexing and alignment

The parameter `level` has been added to the `reindex` and `align` methods of pandas objects. This is useful to broadcast values across a level. For instance:

```
In [70]: midx = pd.MultiIndex(levels=[['zero', 'one'], ['x','y']],
   ....:                      labels=[[1,1,0,0],[1,0,1,0]])
   ....:

In [71]: df = pd.DataFrame(np.random.randn(4,2), index=midx)

In [72]: df
Out[72]:
               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 [73]: df2 = df.mean(level=0)

In [74]: df2
Out[74]:
             0         1
zero  1.271532  0.713416
one   1.060074 -0.109716

In [75]: df2.reindex(df.index, level=0)
Out[75]:
               0         1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416

# aligning
In [76]: df_aligned, df2_aligned = df.align(df2, level=0)

In [77]: df_aligned
Out[77]:
               0         1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [78]: df2_aligned
Out[78]:
               0         1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416
```

14.2.4 Swapping levels with `swaplevel()`

The `swaplevel` function can switch the order of two levels:

```
In [79]: df[:5]
Out[79]:
               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 [80]: df[:5].swaplevel(0, 1, axis=0)
Out[80]: 
               0         1
y one   1.519970 -0.493662
x one   0.600178  0.274230
y zero  0.132885 -0.023688
x zero  2.410179  1.450520
```

14.2.5 Reordering levels with `reorder_levels()`

The `reorder_levels` function generalizes the `swaplevel` function, allowing you to permute the hierarchical index levels in one step:

```
In [81]: df[:5].reorder_levels([1,0], axis=0)
Out[81]: 
               0         1
y one   1.519970 -0.493662
x one   0.600178  0.274230
y zero  0.132885 -0.023688
x zero  2.410179  1.450520
```

14.3 The need for sortedness with `MultiIndex`

Caveat emptor: the present implementation of `MultiIndex` requires that the labels be sorted for some of the slicing / indexing routines to work correctly. You can think about breaking the axis into unique groups, where at the hierarchical level of interest, each distinct group shares a label, but no two have the same label. However, the `MultiIndex` does not enforce this: **you are responsible for ensuring that things are properly sorted**. There is an important new method `sortlevel` to sort an axis within a `MultiIndex` so that its labels are grouped and sorted by the original ordering of the associated factor at that level. Note that this does not necessarily mean the labels will be sorted lexicographically!

```
In [82]: import random; random.shuffle(tuples)

In [83]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))

In [84]: s
Out[84]: 
foo  two    0.206053
bar  one   -0.251905
baz  two   -2.213588
foo  one    1.063327
baz  one    1.266143
qux  two    0.299368
bar  two   -0.863838
qux  one    0.408204
dtype: float64

In [85]: s.sortlevel(0)
Out[85]: 
bar  one   -0.251905
```

```
     two   -0.863838
baz  one    1.266143
     two   -2.213588
foo  one    1.063327
     two    0.206053
qux  one    0.408204
     two    0.299368
dtype: float64

In [86]: s.sortlevel(1)
Out[86]:
bar  one   -0.251905
baz  one    1.266143
foo  one    1.063327
qux  one    0.408204
bar  two   -0.863838
baz  two   -2.213588
foo  two    0.206053
qux  two    0.299368
dtype: float64
```

Note, you may also pass a level name to `sortlevel` if the MultiIndex levels are named.

```
In [87]: s.index.set_names(['L1', 'L2'], inplace=True)

In [88]: s.sortlevel(level='L1')
Out[88]:
L1   L2
bar  one   -0.251905
     two   -0.863838
baz  one    1.266143
     two   -2.213588
foo  one    1.063327
     two    0.206053
qux  one    0.408204
     two    0.299368
dtype: float64

In [89]: s.sortlevel(level='L2')
Out[89]:
L1   L2
bar  one   -0.251905
baz  one    1.266143
foo  one    1.063327
qux  one    0.408204
bar  two   -0.863838
baz  two   -2.213588
foo  two    0.206053
qux  two    0.299368
dtype: float64
```

Some indexing will work even if the data are not sorted, but will be rather inefficient and will also return a copy of the data rather than a view:

```
In [90]: s['qux']
Out[90]:
L2
two    0.299368
one    0.408204
```

```
dtype: float64

In [91]: s.sortlevel(1)['qux']
Out[91]:
L2
one    0.408204
two    0.299368
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a MultiIndex:

```
In [92]: df.T.sortlevel(1, axis=1)
Out[92]:
       zero       one      zero       one
          x         x         y         y
0  2.410179  0.600178  0.132885  1.519970
1  1.450520  0.274230 -0.023688 -0.493662
```

The `MultiIndex` object has code to **explicity check the sort depth**. Thus, if you try to index at a depth at which the index is not sorted, it will raise an exception. Here is a concrete example to illustrate this:

```
In [93]: tuples = [('a', 'a'), ('a', 'b'), ('b', 'a'), ('b', 'b')]

In [94]: idx = pd.MultiIndex.from_tuples(tuples)

In [95]: idx.lexsort_depth
Out[95]: 2

In [96]: reordered = idx[[1, 0, 3, 2]]

In [97]: reordered.lexsort_depth
Out[97]: 1

In [98]: s = pd.Series(np.random.randn(4), index=reordered)

In [99]: s.ix['a':'a']
Out[99]:
a  b   -1.048089
   a   -0.025747
dtype: float64
```

However:

```
>>> s.ix[('a', 'b'):('b', 'a')]
Traceback (most recent call last)
     ...
KeyError: Key length (3) was greater than MultiIndex lexsort depth (2)
```

14.4 Take Methods

Similar to numpy ndarrays, pandas Index, Series, and DataFrame also provides the `take` method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [100]: index = pd.Index(np.random.randint(0, 1000, 10))

In [101]: index
```

```
Out[101]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64')

In [102]: positions = [0, 9, 3]

In [103]: index[positions]
Out[103]: Int64Index([214, 329, 567], dtype='int64')

In [104]: index.take(positions)
Out[104]: Int64Index([214, 329, 567], dtype='int64')

In [105]: ser = pd.Series(np.random.randn(10))

In [106]: ser.iloc[positions]
Out[106]:
0   -0.179666
9    1.824375
3    0.392149
dtype: float64

In [107]: ser.take(positions)
Out[107]:
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 [108]: frm = pd.DataFrame(np.random.randn(5, 3))

In [109]: frm.take([1, 4, 3])
Out[109]:
          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 [110]: frm.take([0, 2], axis=1)
Out[110]:
          0         2
0  0.595974  0.601544
1 -1.237881 -1.276829
2 -0.767101  1.499591
3  0.979542  0.615855
4  0.629675  1.857704
```

It is important to note that the `take` method on pandas objects are not intended to work on boolean indices and may return unexpected results.

```
In [111]: arr = np.random.randn(10)

In [112]: arr.take([False, False, True, True])
Out[112]: array([-1.1935, -1.1935,  0.6775,  0.6775])

In [113]: arr[[0, 1]]
Out[113]: array([-1.1935,  0.6775])

In [114]: ser = pd.Series(np.random.randn(10))
```

```
In [115]: ser.take([False, False, True, True])
Out[115]:
0    0.233141
0    0.233141
1   -0.223540
1   -0.223540
dtype: float64

In [116]: ser.ix[[0, 1]]
Out[116]:
0    0.233141
1   -0.223540
dtype: float64
```

Finally, as a small note on performance, because the `take` method handles a narrower range of inputs, it can offer performance that is a good deal faster than fancy indexing.

14.5 CategoricalIndex

New in version 0.16.1.

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame/Series` with a `category` dtype would convert this to regular object-based `Index`.

```
In [117]: df = pd.DataFrame({'A': np.arange(6),
   .....:                    'B': list('aabbca')})
   .....:

In [118]: df['B'] = df['B'].astype('category', categories=list('cab'))

In [119]: df
Out[119]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a

In [120]: df.dtypes
Out[120]:
A       int32
B    category
dtype: object

In [121]: df.B.cat.categories
Out[121]: Index([u'c', u'a', u'b'], dtype='object')
```

Setting the index, will create create a `CategoricalIndex`

```
In [122]: df2 = df.set_index('B')

In [123]: df2.index
Out[123]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'c', u'a', u'b'], order
```

Indexing with `__getitem__/.iloc/.loc/.ix` works similarly to an `Index` with duplicates. The indexers MUST be in the category or the operation will raise.

```
In [124]: df2.loc['a']
Out[124]:
   A
B
a  0
a  1
a  5
```

These PRESERVE the `CategoricalIndex`

```
In [125]: df2.loc['a'].index
Out[125]: CategoricalIndex([u'a', u'a', u'a'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B
```

Sorting will order by the order of the categories

```
In [126]: df2.sort_index()
Out[126]:
   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

```
In [127]: df2.groupby(level=0).sum()
Out[127]:
   A
B
c  4
a  6
b  5

In [128]: df2.groupby(level=0).sum().index
Out[128]: CategoricalIndex([u'c', u'a', u'b'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B
```

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 arbitrarly index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```
In [129]: df2.reindex(['a','e'])
Out[129]:
    A
B
a   0
a   1
a   5
e NaN

In [130]: df2.reindex(['a','e']).index
Out[130]: Index([u'a', u'a', u'a', u'e'], dtype='object', name=u'B')

In [131]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde')))
```

```
Out[131]:
    A
B
a   0
a   1
a   5
e NaN

In [132]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde'))).index
Out[132]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'b', u'c', u'd', u'e'], orde
```

Warning: Reshaping and Comparision operations on a `CategoricalIndex` must have the same categories or a `TypeError` will be raised.

```
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'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'a', u'b', u'c'], orde

In [12]: pd.concat([df2, df3]
TypeError: categories must match existing categories when appending
```

14.6 Float64Index

Note: As of 0.14.0, `Float64Index` is backed by a native `float64` dtype array. Prior to 0.14.0, `Float64Index` was backed by an `object` dtype array. Using a `float64` dtype in the backend speeds up arithmetic operations by about 30x and boolean indexing operations on the `Float64Index` itself are about 2x as fast.

New in version 0.13.0.

By default a `Float64Index` will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes `[],ix,loc` for scalar indexing and slicing work exactly the same.

```
In [133]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])

In [134]: indexf
Out[134]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

In [135]: sf = pd.Series(range(5), index=indexf)

In [136]: sf
Out[136]:
1.5    0
2.0    1
3.0    2
4.5    3
5.0    4
dtype: int64
```

Scalar selection for `[],.ix,.loc` will always be label based. An integer will match an equal float index (e.g. `3` is equivalent to 3.0)

```
In [137]: sf[3]
Out[137]: 2

In [138]: sf[3.0]
Out[138]: 2

In [139]: sf.ix[3]
Out[139]: 2

In [140]: sf.ix[3.0]
Out[140]: 2

In [141]: sf.loc[3]
Out[141]: 2

In [142]: sf.loc[3.0]
Out[142]: 2
```

The only positional indexing is via `iloc`

```
In [143]: sf.iloc[3]
Out[143]: 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 [144]: sf[2:4]
Out[144]:
2    1
3    2
dtype: int64

In [145]: sf.ix[2:4]
Out[145]:
2    1
3    2
dtype: int64

In [146]: sf.loc[2:4]
Out[146]:
2    1
3    2
dtype: int64

In [147]: sf.iloc[2:4]
Out[147]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats is allowed

```
In [148]: sf[2.1:4.6]
Out[148]:
3.0    2
4.5    3
dtype: int64
```

```
In [149]: sf.loc[2.1:4.6]
Out[149]:
3.0    2
4.5    3
dtype: int64
```

In non-float indexes, slicing using floats will raise a `TypeError`

```
In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type (Int64Index)
```

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

```
In [3]: pd.Series(range(5))[3.0]
Out[3]: 3
```

Here is a typical use-case for using this type of indexing. Imagine that you have a somewhat irregular timedelta-like indexing scheme, but the data is recorded as floats. This could for example be millisecond offsets.

```
In [150]: 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 [151]: dfir
Out[151]:
               A         B
0.0     0.997289 -1.693316
250.0  -0.179129 -1.598062
500.0   0.936914  0.912560
750.0  -1.003401  1.632781
1000.0 -0.724626  0.178219
1000.4  0.310610 -0.108002
1250.5 -0.974226 -1.147708
1500.6 -2.281374  0.760010
1750.7 -0.742532  1.533318
2000.8  2.495362 -0.432771
2250.9 -0.068954  0.043520
```

Selection operations then will always work on a value basis, for all selection operators.

```
In [152]: dfir[0:1000.4]
Out[152]:
               A         B
0.0     0.997289 -1.693316
250.0  -0.179129 -1.598062
500.0   0.936914  0.912560
750.0  -1.003401  1.632781
1000.0 -0.724626  0.178219
1000.4  0.310610 -0.108002

In [153]: dfir.loc[0:1001,'A']
Out[153]:
```

```
0.0       0.997289
250.0    -0.179129
500.0     0.936914
750.0    -1.003401
1000.0   -0.724626
1000.4    0.310610
Name: A, dtype: float64

In [154]: dfir.loc[1000.4]
Out[154]:
A    0.310610
B   -0.108002
Name: 1000.4, dtype: float64
```

You could then easily pick out the first 1 second (1000 ms) of data then.

```
In [155]: dfir[0:1000]
Out[155]:
             A         B
0     0.997289 -1.693316
250  -0.179129 -1.598062
500   0.936914  0.912560
750  -1.003401  1.632781
1000 -0.724626  0.178219
```

Of course if you need integer based selection, then use `iloc`

```
In [156]: dfir.iloc[0:5]
Out[156]:
             A         B
0     0.997289 -1.693316
250  -0.179129 -1.598062
500   0.936914  0.912560
750  -1.003401  1.632781
1000 -0.724626  0.178219
```

CHAPTER

FIFTEEN

COMPUTATIONAL TOOLS

15.1 Statistical functions

15.1.1 Percent Change

`Series`, `DataFrame`, and `Panel` all have a method `pct_change` to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values *before* computing the percent change).

```
In [1]: ser = pd.Series(np.random.randn(8))

In [2]: ser.pct_change()
Out[2]:
0          NaN
1    -1.602976
2     4.334938
3    -0.247456
4    -2.067345
5    -1.142903
6    -1.688214
7    -9.759729
dtype: float64

In [3]: df = pd.DataFrame(np.random.randn(10, 4))

In [4]: df.pct_change(periods=3)
Out[4]:
          0         1         2         3
0       NaN       NaN       NaN       NaN
1       NaN       NaN       NaN       NaN
2       NaN       NaN       NaN       NaN
3 -0.218320 -1.054001  1.987147 -0.510183
4 -0.439121 -1.816454  0.649715 -4.822809
5 -0.127833 -3.042065 -5.866604 -1.776977
6 -2.596833 -1.959538 -2.111697 -3.798900
7 -0.117826 -2.169058  0.036094 -0.067696
8  2.492606 -1.357320 -1.205802 -1.558697
9 -1.012977  2.324558 -1.003744 -0.371806
```

15.1.2 Covariance

The `Series` object has a method `cov` to compute covariance between series (excluding NA/null values).

```
In [5]: s1 = pd.Series(np.random.randn(1000))

In [6]: s2 = pd.Series(np.random.randn(1000))

In [7]: s1.cov(s2)
Out[7]: 0.00068010881743109993
```

Analogously, `DataFrame` has a method `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.

```
In [8]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [9]: frame.cov()
Out[9]: 
          a         b         c         d         e
a  1.000882 -0.003177 -0.002698 -0.006889  0.031912
b -0.003177  1.024721  0.000191  0.009212  0.000857
c -0.002698  0.000191  0.950735 -0.031743 -0.005087
d -0.006889  0.009212 -0.031743  1.002983 -0.047952
e  0.031912  0.000857 -0.005087 -0.047952  1.042487
```

`DataFrame.cov` also supports an optional `min_periods` keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

```
In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])

In [11]: frame.ix[:5, 'a'] = np.nan

In [12]: frame.ix[5:10, 'b'] = np.nan

In [13]: frame.cov()
Out[13]: 
          a         b         c
a  1.210090 -0.430629  0.018002
b -0.430629  1.240960  0.347188
c  0.018002  0.347188  1.301149

In [14]: frame.cov(min_periods=12)
Out[14]: 
          a         b         c
a  1.210090       NaN  0.018002
b       NaN  1.240960  0.347188
c  0.018002  0.347188  1.301149
```

15.1.3 Correlation

Several methods for computing correlations are provided:

Method name	Description
`pearson (default)`	Standard correlation coefficient
`kendall`	Kendall Tau correlation coefficient
`spearman`	Spearman rank correlation coefficient

All of these are currently computed using pairwise complete observations.

Note: Please see the *caveats* associated with this method of calculating correlation matrices in the *covariance section*.

```
In [15]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [16]: frame.ix[::2] = np.nan

# Series with Series
In [17]: frame['a'].corr(frame['b'])
Out[17]: 0.013479040400098794

In [18]: frame['a'].corr(frame['b'], method='spearman')
Out[18]: -0.0072898851595406388

# Pairwise correlation of DataFrame columns
In [19]: frame.corr()
Out[19]: 
          a         b         c         d         e
a  1.000000  0.013479 -0.049269 -0.042239 -0.028525
b  0.013479  1.000000 -0.020433 -0.011139  0.005654
c -0.049269 -0.020433  1.000000  0.018587 -0.054269
d -0.042239 -0.011139  0.018587  1.000000 -0.017060
e -0.028525  0.005654 -0.054269 -0.017060  1.000000
```

Note that non-numeric columns will be automatically excluded from the correlation calculation.

Like `cov`, `corr` also supports the optional `min_periods` keyword:

```
In [20]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])

In [21]: frame.ix[:5, 'a'] = np.nan

In [22]: frame.ix[5:10, 'b'] = np.nan

In [23]: frame.corr()
Out[23]: 
          a         b         c
a  1.000000 -0.076520  0.160092
b -0.076520  1.000000  0.135967
c  0.160092  0.135967  1.000000

In [24]: frame.corr(min_periods=12)
Out[24]: 
          a         b         c
a  1.000000       NaN  0.160092
b       NaN  1.000000  0.135967
c  0.160092  0.135967  1.000000
```

A related method `corrwith` is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

```
In [25]: index = ['a', 'b', 'c', 'd', 'e']
```

```
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     -0.125501
two     -0.493244
three    0.344056
four     0.004183
dtype: float64

In [30]: df2.corrwith(df1, axis=1)
Out[30]:
a   -0.675817
b    0.458296
c    0.190809
d   -0.186275
e         NaN
dtype: float64
```

15.1.4 Data ranking

The `rank` method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```
In [31]: s = pd.Series(np.random.np.random.randn(5), index=list('abcde'))

In [32]: s['d'] = s['b'] # so there's a tie

In [33]: s.rank()
Out[33]:
a    5.0
b    2.5
c    1.0
d    2.5
e    4.0
dtype: float64
```

`rank` is also a DataFrame method and can rank either the rows (`axis=0`) or the columns (`axis=1`). `NaN` values are excluded from the ranking.

```
In [34]: df = pd.DataFrame(np.random.np.random.randn(10, 6))

In [35]: df[4] = df[2][:5] # some ties

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

In [37]: df.rank(1)
Out[37]:
   0  1    2  3    4  5
0  4  3  1.5  5  1.5  6
1  2  6  4.5  1  4.5  3
2  1  6  3.5  5  3.5  2
3  4  5  1.5  3  1.5  6
4  5  3  1.5  4  1.5  6
5  1  2  5.0  3  NaN  4
6  4  5  3.0  1  NaN  2
7  2  5  3.0  4  NaN  1
8  2  5  3.0  4  NaN  1
9  2  3  1.0  4  NaN  5
```

`rank` optionally takes a parameter `ascending` which by default is true; when false, data is reverse-ranked, with larger values assigned a smaller rank.

`rank` supports different tie-breaking methods, specified with the `method` parameter:

- `average` : average rank of tied group
- `min` : lowest rank in the group
- `max` : highest rank in the group
- `first` : ranks assigned in the order they appear in the array

15.2 Moving (rolling) statistics / moments

For working with time series data, a number of functions are provided for computing common *moving* or *rolling* statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis. All of these methods are in the `pandas` namespace, but otherwise they can be found in `pandas.stats.moments`.

Function	Description
`rolling_count`	Number of non-null observations
`rolling_sum`	Sum of values
`rolling_mean`	Mean of values
`rolling_median`	Arithmetic median of values
`rolling_min`	Minimum
`rolling_max`	Maximum
`rolling_std`	Unbiased standard deviation
`rolling_var`	Unbiased variance
`rolling_skew`	Unbiased skewness (3rd moment)
`rolling_kurt`	Unbiased kurtosis (4th moment)
`rolling_quantile`	Sample quantile (value at %)
`rolling_apply`	Generic apply
`rolling_cov`	Unbiased covariance (binary)
`rolling_corr`	Correlation (binary)
`rolling_window`	Moving window function

Generally these methods all have the same interface. The binary operators (e.g. `rolling_corr`) take two Series or DataFrames. Otherwise, they all accept the following arguments:

- `window`: size of moving window
- `min_periods`: threshold of non-null data points to require (otherwise result is NA)
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants
- `how`: optionally specify method for down or re-sampling. Default is is min for `rolling_min`, max for `rolling_max`, median for `rolling_median`, and mean for all other rolling functions. See `DataFrame.resample()`'s how argument for more information.

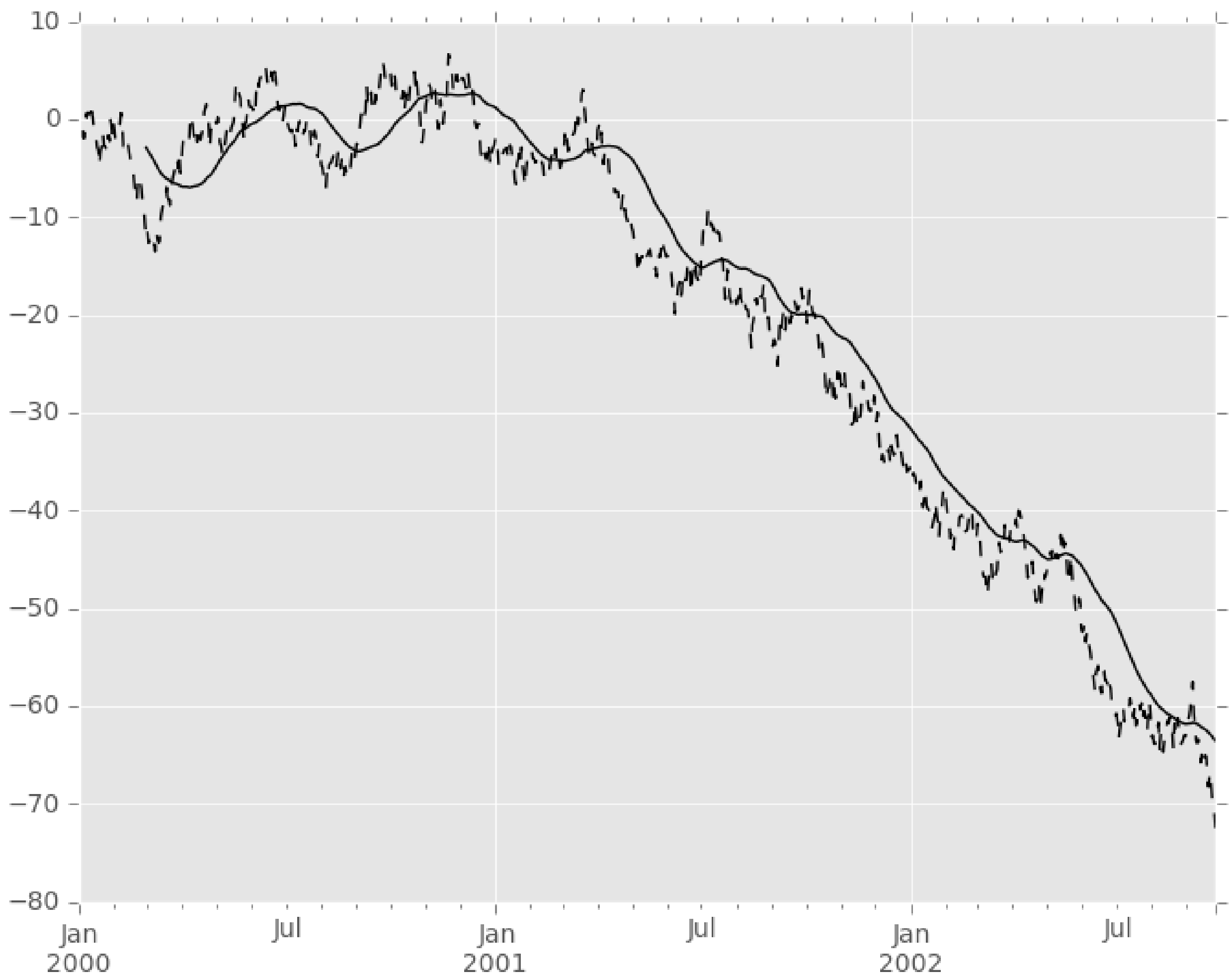
These functions can be applied to ndarrays or Series objects:

```
In [38]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [39]: ts = ts.cumsum()

In [40]: ts.plot(style='k--')
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0xa95eda2c>

In [41]: pd.rolling_mean(ts, 60).plot(style='k')
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0xa95eda2c>
```

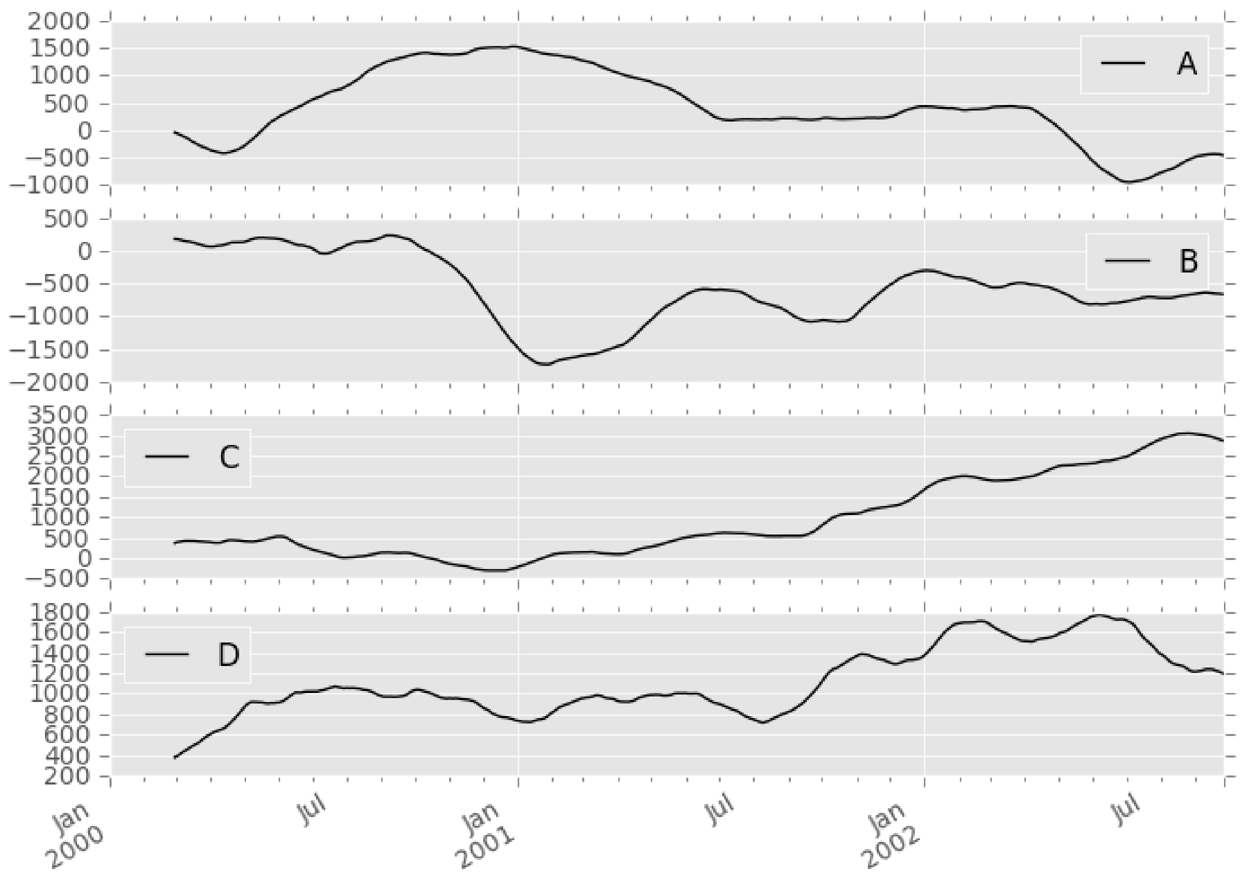


They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window operator to all of the DataFrame's columns:

```
In [42]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
   ....:                   columns=['A', 'B', 'C', 'D'])
   ....:

In [43]: df = df.cumsum()

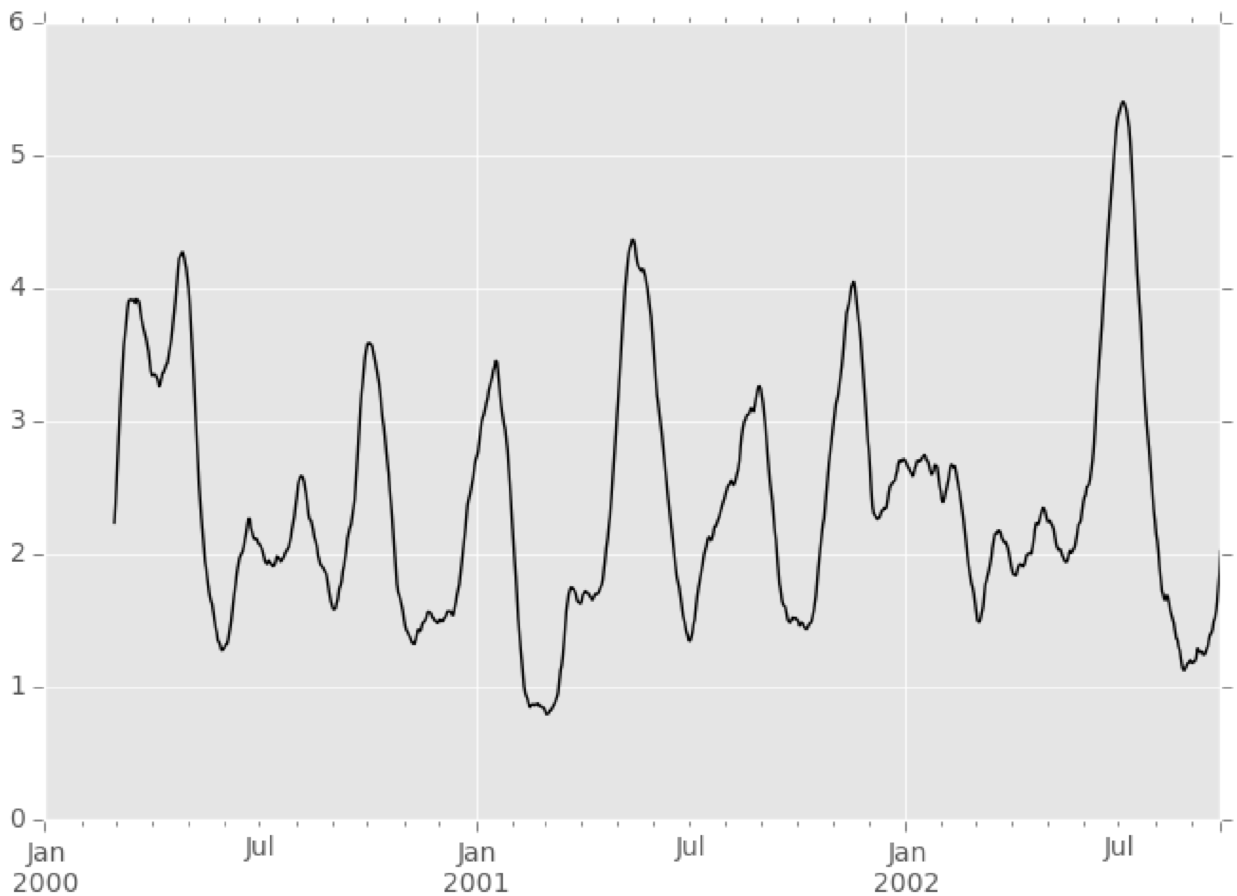
In [44]: pd.rolling_sum(df, 60).plot(subplots=True)
Out[44]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0xaa23020c>,
       <matplotlib.axes._subplots.AxesSubplot object at 0xaa0c410c>,
       <matplotlib.axes._subplots.AxesSubplot object at 0xaa0a592c>,
       <matplotlib.axes._subplots.AxesSubplot object at 0xaa159e4c>], dtype=object)
```



The `rolling_apply` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an ndarray input. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```
In [45]: mad = lambda x: np.fabs(x - x.mean()).mean()

In [46]: pd.rolling_apply(ts, 60, mad).plot(style='k')
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0xa9b4b84c>
```



The rolling_window function performs a generic rolling window computation on the input data. The weights used in the window are specified by the win_type keyword. The list of recognized types are:

- boxcar
- triang
- blackman
- hamming
- bartlett
- parzen
- bohman
- blackmanharris
- nuttall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general_gaussian (needs power, width)
- slepian (needs width).

```
In [47]: ser = pd.Series(np.random.randn(10), index=pd.date_range('1/1/2000', periods=10))

In [48]: pd.rolling_window(ser, 5, 'triang')
Out[48]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -1.037870
2000-01-06   -0.767705
2000-01-07   -0.383197
2000-01-08   -0.395513
2000-01-09   -0.558440
2000-01-10   -0.672416
Freq: D, dtype: float64
```

Note that the `boxcar` window is equivalent to `rolling_mean`.

```
In [49]: pd.rolling_window(ser, 5, 'boxcar')
Out[49]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64

In [50]: pd.rolling_mean(ser, 5)
Out[50]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64
```

For some windowing functions, additional parameters must be specified:

```
In [51]: pd.rolling_window(ser, 5, 'gaussian', std=0.1)
Out[51]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -1.309989
2000-01-06   -1.153000
2000-01-07    0.606382
2000-01-08   -0.681101
2000-01-09   -0.289724
```

```
2000-01-10   -0.996632
Freq: D, dtype: float64
```

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center. This keyword is available in other rolling functions as well.

```
In [52]: pd.rolling_window(ser, 5, 'boxcar')
Out[52]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64

In [53]: pd.rolling_window(ser, 5, 'boxcar', center=True)
Out[53]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03   -0.841164
2000-01-04   -0.779948
2000-01-05   -0.565487
2000-01-06   -0.502815
2000-01-07   -0.553755
2000-01-08   -0.472211
2000-01-09         NaN
2000-01-10         NaN
Freq: D, dtype: float64

In [54]: pd.rolling_mean(ser, 5, center=True)
Out[54]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03   -0.841164
2000-01-04   -0.779948
2000-01-05   -0.565487
2000-01-06   -0.502815
2000-01-07   -0.553755
2000-01-08   -0.472211
2000-01-09         NaN
2000-01-10         NaN
Freq: D, dtype: float64
```

Note: In rolling sum mode (`mean=False`) there is no normalization done to the weights. Passing custom weights of `[1, 1, 1]` will yield a different result than passing weights of `[2, 2, 2]`, for example. When passing a `win_type` instead of explicitly specifying the weights, the weights are already normalized so that the largest weight is 1.

In contrast, the nature of the rolling mean calculation (`mean=True`)is such that the weights are normalized with respect to each other. Weights of `[1, 1, 1]` and `[2, 2, 2]` yield the same result.

15.2.1 Binary rolling moments

`rolling_cov` and `rolling_corr` can compute moving window statistics about two `Series` or any combination of `DataFrame/Series` or `DataFrame/DataFrame`. Here is the behavior in each case:

- two `Series`: compute the statistic for the pairing.
- `DataFrame/Series`: compute the statistics for each column of the DataFrame with the passed Series, thus returning a DataFrame.
- `DataFrame/DataFrame`: by default compute the statistic for matching column names, returning a DataFrame. If the keyword argument `pairwise=True` is passed then computes the statistic for each pair of columns, returning a `Panel` whose `items` are the dates in question (see *the next section*).

For example:

```
In [55]: df2 = df[:20]

In [56]: pd.rolling_corr(df2, df2['B'], window=5)
Out[56]:
                   A    B         C         D
2000-01-01       NaN  NaN       NaN       NaN
2000-01-02       NaN  NaN       NaN       NaN
2000-01-03       NaN  NaN       NaN       NaN
2000-01-04       NaN  NaN       NaN       NaN
2000-01-05 -0.262853    1  0.334449  0.193380
2000-01-06 -0.083745    1 -0.521587 -0.556126
2000-01-07 -0.292940    1 -0.658532 -0.458128
...              ...   ..       ...       ...
2000-01-14  0.519499    1 -0.687277  0.192822
2000-01-15  0.048982    1  0.167669 -0.061463
2000-01-16  0.217190    1  0.167564 -0.326034
2000-01-17  0.641180    1 -0.164780 -0.111487
2000-01-18  0.130422    1  0.322833  0.632383
2000-01-19  0.317278    1  0.384528  0.813656
2000-01-20  0.293598    1  0.159538  0.742381

[20 rows x 4 columns]
```

15.2.2 Computing rolling pairwise covariances and correlations

In financial data analysis and other fields it's common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of `DataFrame` inputs will yield a `Panel` whose `items` are the dates in question. In the case of a single DataFrame argument the `pairwise` argument can even be omitted:

Note: Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the *covariance section* for *caveats* associated with this method of calculating covariance and correlation matrices.

```
In [57]: covs = pd.rolling_cov(df[['B','C','D']], df[['A','B','C']], 50, pairwise=True)

In [58]: covs[df.index[-50]]
Out[58]:
          A         B         C
B  2.667506  1.671711  1.938634
```

```
C  8.513843  1.938634  10.556436
D -7.714737 -1.434529  -7.082653

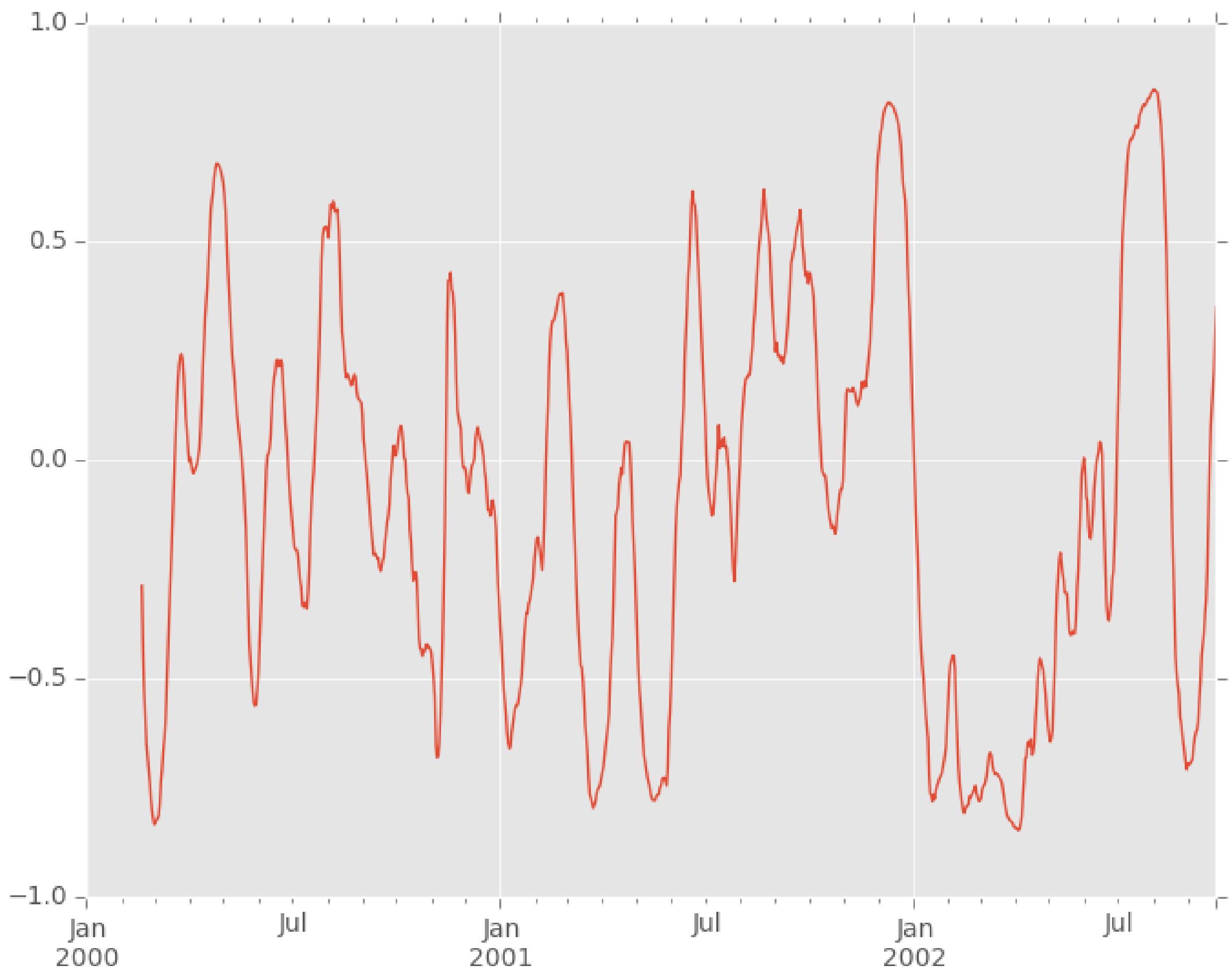
In [59]: correls = pd.rolling_corr(df, 50)

In [60]: correls[df.index[-50]]
Out[60]:
          A         B         C         D
A  1.000000  0.604221  0.767429 -0.776170
B  0.604221  1.000000  0.461484 -0.381148
C  0.767429  0.461484  1.000000 -0.748863
D -0.776170 -0.381148 -0.748863  1.000000
```

Note: Prior to version 0.14 this was available through `rolling_corr_pairwise` which is now simply syntactic sugar for calling `rolling_corr(..., pairwise=True)` and deprecated. This is likely to be removed in a future release.

You can efficiently retrieve the time series of correlations between two columns using `ix` indexing:

```
In [61]: correls.ix[:, 'A', 'C'].plot()
Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0xa63e68ac>
```



15.3 Expanding window moment functions

A common alternative to rolling statistics is to use an *expanding* window, which yields the value of the statistic with all the data available up to that point in time. As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [62]: pd.rolling_mean(df, window=len(df), min_periods=1)[:5]
Out[62]:
                   A         B         C         D
2000-01-01 -1.388345  3.317290  0.344542 -0.036968
2000-01-02 -1.123132  3.622300  1.675867  0.595300
2000-01-03 -0.628502  3.626503  2.455240  1.060158
2000-01-04 -0.768740  3.888917  2.451354  1.281874
2000-01-05 -0.824034  4.108035  2.556112  1.140723

In [63]: pd.expanding_mean(df)[:5]
Out[63]:
                   A         B         C         D
2000-01-01 -1.388345  3.317290  0.344542 -0.036968
2000-01-02 -1.123132  3.622300  1.675867  0.595300
2000-01-03 -0.628502  3.626503  2.455240  1.060158
2000-01-04 -0.768740  3.888917  2.451354  1.281874
2000-01-05 -0.824034  4.108035  2.556112  1.140723
```

Like the `rolling_` functions, the following methods are included in the `pandas` namespace or can be located in `pandas.stats.moments`.

Function	Description
`expanding_count`	Number of non-null observations
`expanding_sum`	Sum of values
`expanding_mean`	Mean of values
`expanding_median`	Arithmetic median of values
`expanding_min`	Minimum
`expanding_max`	Maximum
`expanding_std`	Unbiased standard deviation
`expanding_var`	Unbiased variance
`expanding_skew`	Unbiased skewness (3rd moment)
`expanding_kurt`	Unbiased kurtosis (4th moment)
`expanding_quantile`	Sample quantile (value at %)
`expanding_apply`	Generic apply
`expanding_cov`	Unbiased covariance (binary)
`expanding_corr`	Correlation (binary)

Aside from not having a `window` parameter, these functions have the same interfaces as their `rolling_` counterpart. Like above, the parameters they all accept are:

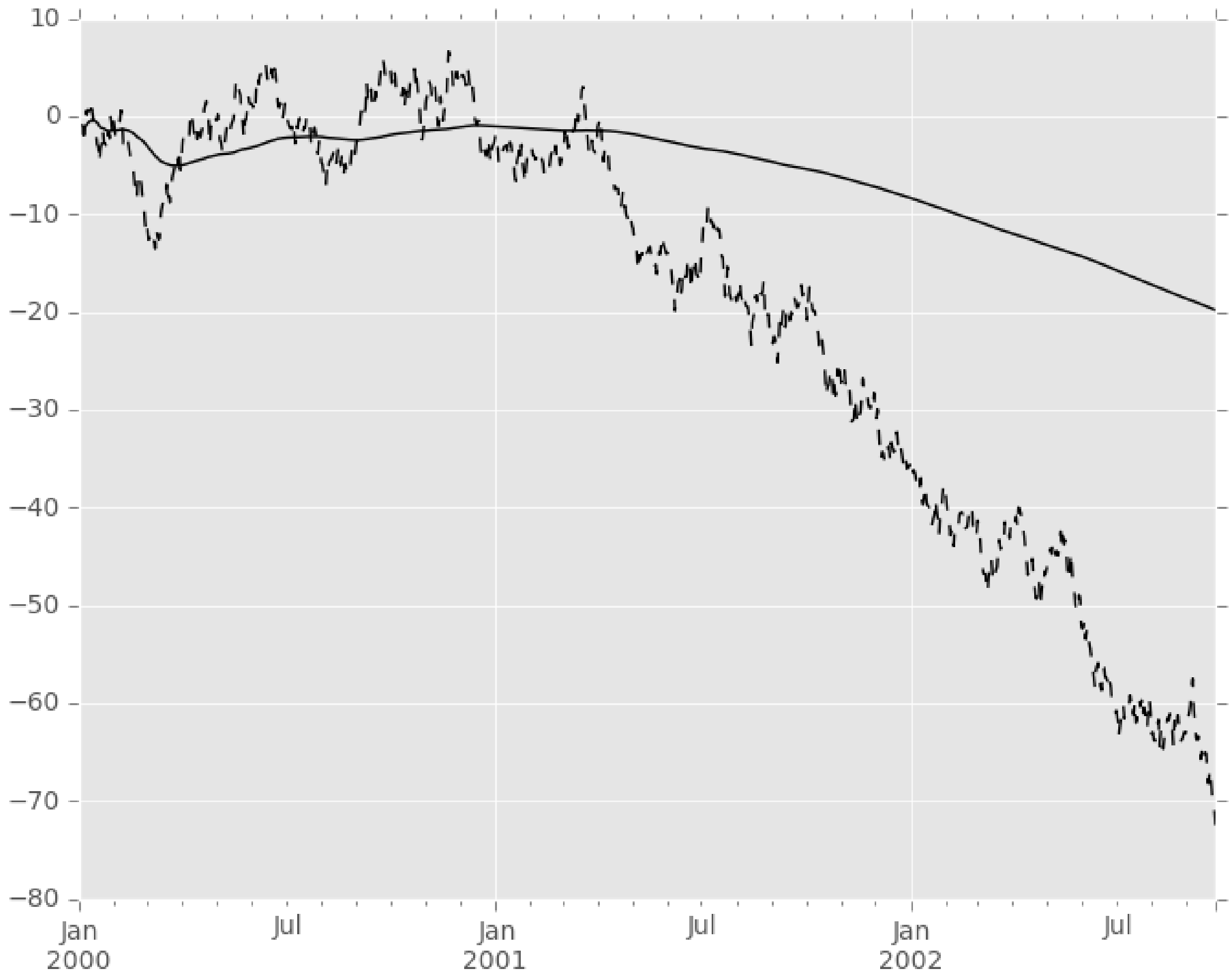
- `min_periods`: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No `NaNs` will be output once `min_periods` non-null data points have been seen.
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants

Note: The output of the `rolling_` and `expanding_` functions do not return a `NaN` if there are at least `min_periods` non-null values in the current window. This differs from `cumsum`, `cumprod`, `cummax`, and `cummin`, which return `NaN` in the output wherever a `NaN` is encountered in the input.

An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the expanding_mean output for the previous time series dataset:

```
In [64]: ts.plot(style='k--')
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ba130c>

In [65]: pd.expanding_mean(ts).plot(style='k')
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ba130c>
```



15.4 Exponentially weighted moment functions

A related set of functions are exponentially weighted versions of several of the above statistics. A number of expanding EW (exponentially weighted) functions are provided:

Function	Description
ewma	EW moving average
ewmvar	EW moving variance
ewmstd	EW moving standard deviation
ewmcorr	EW moving correlation
ewmcov	EW moving covariance

In general, a weighted moving average is calculated as

$$y_t = \frac{\sum_{i=0}^t w_i x_{t-i}}{\sum_{i=0}^t w_i},$$

where x_t is the input at y_t is the result.

The EW functions support two variants of exponential weights: The default, `adjust=True`, uses the weights $w_i = (1-\alpha)^i$. When `adjust=False` is specified, moving averages are calculated as

$$\begin{aligned} y_0 &= x_0 \\ y_t &= (1-\alpha)y_{t-1} + \alpha x_t, \end{aligned}$$

which is equivalent to using weights

$$w_i = \begin{cases} \alpha(1-\alpha)^i & \text{if } i < t \\ (1-\alpha)^i & \text{if } i = t. \end{cases}$$

Note: These equations are sometimes written in terms of $\alpha' = 1 - \alpha$, e.g.

$$y_t = \alpha' y_{t-1} + (1-\alpha')x_t.$$

One must have $0 < \alpha \leq 1$, but rather than pass α directly, it's easier to think about either the **span**, **center of mass (com)** or **halflife** of an EW moment:

$$\alpha = \begin{cases} \frac{2}{s+1}, & s = \text{span} \\ \frac{1}{1+c}, & c = \text{center of mass} \\ 1 - \exp^{\frac{\log 0.5}{h}}, & h = \text{half life} \end{cases}$$

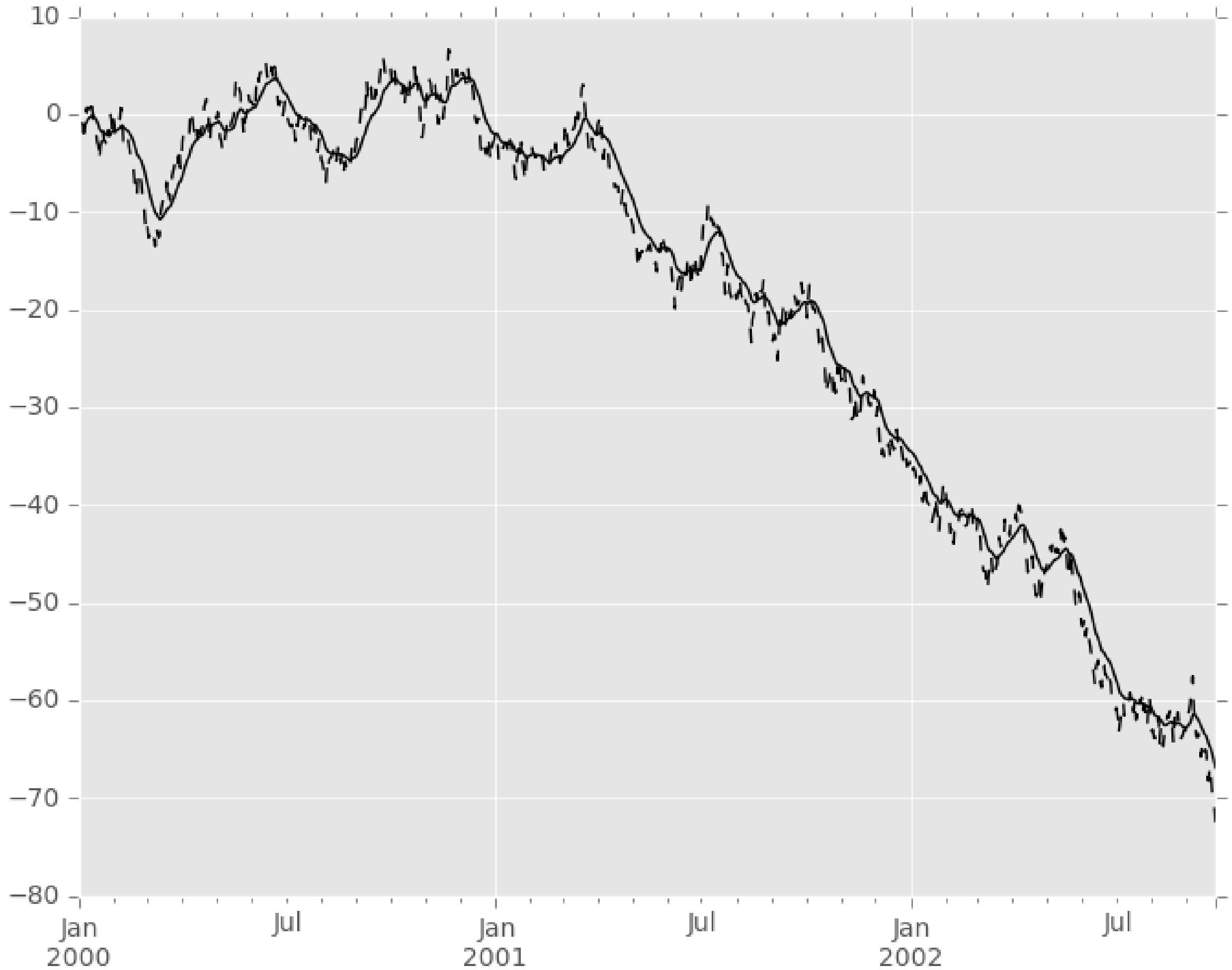
One must specify precisely one of the three to the EW functions. **Span** corresponds to what is commonly called a "20-day EW moving average" for example. **Center of mass** has a more physical interpretation. For example, **span** = 20 corresponds to **com** = 9.5. **Halflife** is the period of time for the exponential weight to reduce to one half.

Here is an example for a univariate time series:

```
In [66]: plt.close('all')

In [67]: ts.plot(style='k--')
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0xa9b1732c>

In [68]: pd.ewma(ts, span=20).plot(style='k')
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0xa9b1732c>
```



All the EW functions have a `min_periods` argument, which has the same meaning it does for all the `expanding_` and `rolling_` functions: no output values will be set until at least `min_periods` non-null values are encountered in the (expanding) window. (This is a change from versions prior to 0.15.0, in which the `min_periods` argument affected only the `min_periods` consecutive entries starting at the first non-null value.)

All the EW functions also have an `ignore_na` argument, which deterines 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` (which reproduces the behavior in versions prior to 0.15.0), weights are calculated by ignoring intermediate null values. For example, assuming `adjust=True`, if `ignore_na=False`, the weighted average of `3, NaN, 5` would be calculated as

$$\frac{(1-\alpha)^2 \cdot 3 + 1 \cdot 5}{(1-\alpha)^2 + 1}$$

Whereas if `ignore_na=True`, the weighted average would be calculated as

$$\frac{(1-\alpha) \cdot 3 + 1 \cdot 5}{(1-\alpha) + 1}.$$

The `ewmvar`, `ewmstd`, and `ewmcov` functions have a `bias` argument, specifying whether the result should 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 http://en.wikipedia.org/wiki/Weighted_arithmetic_mean#Weighted_sample_variance for further details.

CHAPTER

SIXTEEN

WORKING WITH MISSING DATA

In this section, we will discuss missing (also referred to as NA) values in pandas.

Note: The choice of using `NaN` internally to denote missing data was largely for simplicity and performance reasons. It differs from the MaskedArray approach of, for example, `scikits.timeseries`. We are hopeful that NumPy will soon be able to provide a native NA type solution (similar to R) performant enough to be used in pandas.

See the *cookbook* for some advanced strategies

16.1 Missing data basics

16.1.1 When / why does data become missing?

Some might quibble over our usage of *missing*. By "missing" we simply mean **null** or "not present for whatever reason". Many data sets simply arrive with missing data, either because it exists and was not collected or it never existed. For example, in a collection of financial time series, some of the time series might start on different dates. Thus, values prior to the start date would generally be marked as missing.

In pandas, one of the most common ways that missing data is **introduced** into a data set is by reindexing. For example

```
In [1]: df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f', 'h'],
   ...:                   columns=['one', 'two', 'three'])
   ...:

In [2]: df['four'] = 'bar'

In [3]: df['five'] = df['one'] > 0

In [4]: df
Out[4]:
        one       two     three four   five
a  0.469112 -0.282863 -1.509059  bar   True
c -1.135632  1.212112 -0.173215  bar  False
e  0.119209 -1.044236 -0.861849  bar   True
f -2.104569 -0.494929  1.071804  bar  False
h  0.721555 -0.706771 -1.039575  bar   True

In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

In [6]: df2
Out[6]:
        one       two     three four   five
```

```
a  0.469112 -0.282863 -1.509059  bar   True
b       NaN       NaN       NaN  NaN    NaN
c -1.135632  1.212112 -0.173215  bar  False
d       NaN       NaN       NaN  NaN    NaN
e  0.119209 -1.044236 -0.861849  bar   True
f -2.104569 -0.494929  1.071804  bar  False
g       NaN       NaN       NaN  NaN    NaN
h  0.721555 -0.706771 -1.039575  bar   True
```

16.1.2 Values considered "missing"

As data comes in many shapes and forms, pandas aims to be flexible with regard to handling missing data. While `NaN` is the default missing value marker for reasons of computational speed and convenience, we need to be able to easily detect this value with data of different types: floating point, integer, boolean, and general object. In many cases, however, the Python `None` will arise and we wish to also consider that "missing" or "null".

Prior to version v0.10.0 `inf` and `-inf` were also considered to be "null" in computations. This is no longer the case by default; use the `mode.use_inf_as_null` option to recover it. To make detecting missing values easier (and across different array dtypes), pandas provides the `isnull()` and `notnull()` functions, which are also methods on `Series` objects:

```
In [7]: df2['one']
Out[7]:
a    0.469112
b         NaN
c   -1.135632
d         NaN
e    0.119209
f   -2.104569
g         NaN
h    0.721555
Name: one, dtype: float64

In [8]: isnull(df2['one'])
Out[8]:
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool

In [9]: df2['four'].notnull()
Out[9]:
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
Name: four, dtype: bool
```

Summary: `NaN` and `None` (in object arrays) are considered missing by the `isnull` and `notnull` functions. `inf` and `-inf` are no longer considered missing by default.

16.2 Datetimes

For datetime64[ns] types, `NaT` represents missing values. This is a pseudo-native sentinel value that can be represented by numpy in a singular dtype (datetime64[ns]). pandas objects provide intercompatibility between `NaT` and `NaN`.

```
In [10]: df2 = df.copy()

In [11]: df2['timestamp'] = Timestamp('20120101')

In [12]: df2
Out[12]:
        one       two     three four   five  timestamp
a  0.469112 -0.282863 -1.509059  bar   True 2012-01-01
c -1.135632  1.212112 -0.173215  bar  False 2012-01-01
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h  0.721555 -0.706771 -1.039575  bar   True 2012-01-01

In [13]: df2.ix[['a','c','h'],['one','timestamp']] = np.nan

In [14]: df2
Out[14]:
        one       two     three four   five  timestamp
a       NaN -0.282863 -1.509059  bar   True        NaT
c       NaN  1.212112 -0.173215  bar  False        NaT
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h       NaN -0.706771 -1.039575  bar   True        NaT

In [15]: df2.get_dtype_counts()
Out[15]:
bool              1
datetime64[ns]    1
float64           3
object            1
dtype: int64
```

16.3 Inserting missing data

You can insert missing values by simply assigning to containers. The actual missing value used will be chosen based on the dtype.

For example, numeric containers will always use `NaN` regardless of the missing value type chosen:

```
In [16]: s = pd.Series([1, 2, 3])

In [17]: s.loc[0] = None

In [18]: s
Out[18]:
0   NaN
```

```
1    2
2    3
dtype: float64
```

Likewise, datetime containers will always use `NaT`.

For object containers, pandas will use the value given:

```
In [19]: s = pd.Series(["a", "b", "c"])

In [20]: s.loc[0] = None

In [21]: s.loc[1] = np.nan

In [22]: s
Out[22]:
0    None
1     NaN
2       c
dtype: object
```

16.4 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [23]: a
Out[23]:
        one       two
a       NaN -0.282863
c       NaN  1.212112
e  0.119209 -1.044236
f -2.104569 -0.494929
h -2.104569 -0.706771

In [24]: b
Out[24]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [25]: a + b
Out[25]:
        one  three       two
a       NaN    NaN -0.565727
c       NaN    NaN  2.424224
e  0.238417    NaN -2.088472
f -4.209138    NaN -0.989859
h       NaN    NaN -1.413542
```

The descriptive statistics and computational methods discussed in the *data structure overview* (and listed *here* and *here*) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero
- If the data are all NA, the result will be NA

- Methods like **cumsum** and **cumprod** ignore NA values, but preserve them in the resulting arrays

```
In [26]: df
Out[26]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [27]: df['one'].sum()
Out[27]: -1.9853605075978744

In [28]: df.mean(1)
Out[28]:
a   -0.895961
c    0.519449
e   -0.595625
f   -0.509232
h   -0.873173
dtype: float64

In [29]: df.cumsum()
Out[29]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  0.929249 -1.682273
e  0.119209 -0.114987 -2.544122
f -1.985361 -0.609917 -1.472318
h       NaN -1.316688 -2.511893
```

16.4.1 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example.

16.5 Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

16.5.1 Filling missing values: fillna

The **fillna** function can "fill in" NA values with non-null data in a couple of ways, which we illustrate:

Replace NA with a scalar value

```
In [30]: df2
Out[30]:
        one       two     three four   five  timestamp
a       NaN -0.282863 -1.509059  bar   True        NaT
c       NaN  1.212112 -0.173215  bar  False        NaT
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h       NaN -0.706771 -1.039575  bar   True        NaT
```

```
In [31]: df2.fillna(0)
Out[31]:
        one       two     three four   five  timestamp
a  0.000000 -0.282863 -1.509059  bar   True 1970-01-01
c  0.000000  1.212112 -0.173215  bar  False 1970-01-01
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h  0.000000 -0.706771 -1.039575  bar   True 1970-01-01

In [32]: df2['four'].fillna('missing')
Out[32]:
a    bar
c    bar
e    bar
f    bar
h    bar
Name: four, dtype: object
```

Fill gaps forward or backward

Using the same filling arguments as *reindexing*, we can propagate non-null values forward or backward:

```
In [33]: df
Out[33]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [34]: df.fillna(method='pad')
Out[34]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h -2.104569 -0.706771 -1.039575
```

Limit the amount of filling

If we only want consecutive gaps filled up to a certain number of data points, we can use the *limit* keyword:

```
In [35]: df
Out[35]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN       NaN       NaN
f  NaN       NaN       NaN
h  NaN -0.706771 -1.039575

In [36]: df.fillna(method='pad', limit=1)
Out[36]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  1.212112 -0.173215
```

```
f  NaN       NaN       NaN
h  NaN -0.706771 -1.039575
```

To remind you, these are the available filling methods:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward

With time series data, using pad/ffill is extremely common so that the "last known value" is available at every time point.

The `ffill()` function is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

16.5.2 Filling with a PandasObject

New in version 0.12.

You can 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.

```
In [37]: dff = pd.DataFrame(np.random.randn(10,3),columns=list('ABC'))

In [38]: dff.iloc[3:5,0] = np.nan

In [39]: dff.iloc[4:6,1] = np.nan

In [40]: dff.iloc[5:8,2] = np.nan

In [41]: dff
Out[41]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3       NaN  0.577046 -1.715002
4       NaN       NaN -1.157892
5 -1.344312       NaN       NaN
6 -0.109050  1.643563       NaN
7  0.357021 -0.674600       NaN
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960

In [42]: dff.fillna(dff.mean())
Out[42]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3 -0.140857  0.577046 -1.715002
4 -0.140857 -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

```
In [43]: dff.fillna(dff.mean()['B':'C'])
Out[43]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3       NaN  0.577046 -1.715002
4       NaN -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

New in version 0.13.

Same result as above, but is aligning the 'fill' value which is a Series in this case.

```
In [44]: dff.where(notnull(dff),dff.mean(),axis='columns')
Out[44]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3 -0.140857  0.577046 -1.715002
4 -0.140857 -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

16.5.3 Dropping axis labels with missing data: dropna

You may wish to simply exclude labels from a data set which refer to missing data. To do this, use the **dropna** method:

```
In [45]: df
Out[45]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  0.000000  0.000000
f  NaN  0.000000  0.000000
h  NaN -0.706771 -1.039575

In [46]: df.dropna(axis=0)
Out[46]:
Empty DataFrame
Columns: [one, two, three]
Index: []

In [47]: df.dropna(axis=1)
Out[47]:
        two     three
a -0.282863 -1.509059
c  1.212112 -0.173215
e  0.000000  0.000000
f  0.000000  0.000000
```

```
h -0.706771 -1.039575

In [48]: df['one'].dropna()
Out[48]: Series([], Name: one, dtype: float64)
```

Series.dropna is a simpler method as it only has one axis to consider. DataFrame.dropna has considerably more options than Series.dropna, which can be examined *in the API*.

16.5.4 Interpolation

New in version 0.13.0: `interpolate()`, and `interpolate()` have revamped interpolation methods and functionality.

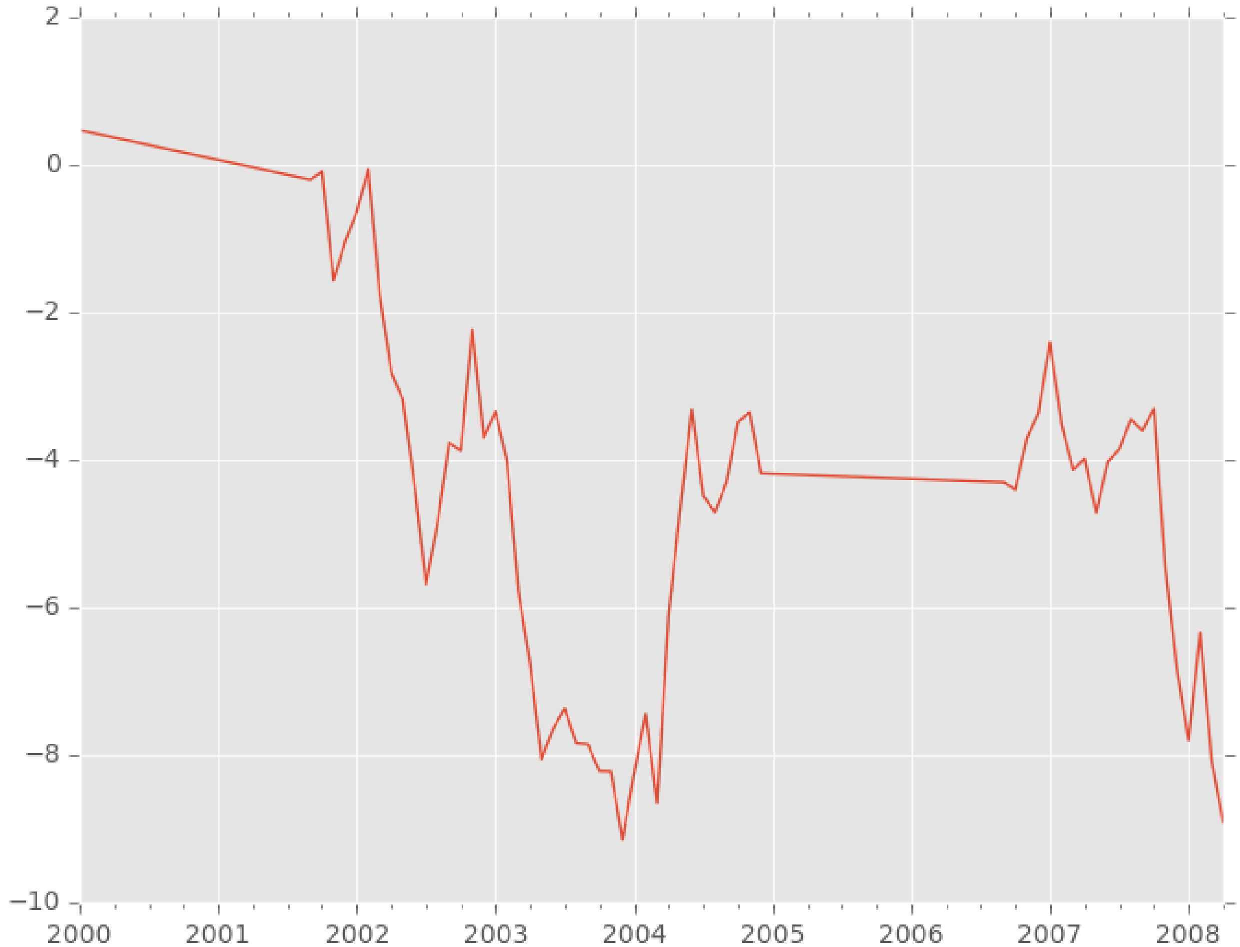
Both Series and Dataframe objects have an `interpolate` method that, by default, performs linear interpolation at missing datapoints.

```
In [49]: ts
Out[49]:
2000-01-31    0.469112
2000-02-29         NaN
2000-03-31         NaN
2000-04-28         NaN
2000-05-31         NaN
2000-06-30         NaN
2000-07-31         NaN
                ...
2007-10-31   -3.305259
2007-11-30   -5.485119
2007-12-31   -6.854968
2008-01-31   -7.809176
2008-02-29   -6.346480
2008-03-31   -8.089641
2008-04-30   -8.916232
Freq: BM, dtype: float64

In [50]: ts.count()
Out[50]: 61

In [51]: ts.interpolate().count()
Out[51]: 100

In [52]: ts.interpolate().plot()
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x9b28fc8c>
```



Index aware interpolation is available via the `method` keyword:

```
In [53]: ts2
Out[53]:
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 [54]: ts2.interpolate()
Out[54]:
2000-01-31    0.469112
2000-02-29   -2.610313
2002-07-31   -5.689738
2005-01-31   -7.302985
2008-04-30   -8.916232
dtype: float64

In [55]: ts2.interpolate(method='time')
Out[55]:
2000-01-31    0.469112
2000-02-29    0.273272
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'`:

```
In [56]: ser
Out[56]: 
0      0
1    NaN
10    10
dtype: float64

In [57]: ser.interpolate()
Out[57]: 
0      0
1      5
10    10
dtype: float64

In [58]: ser.interpolate(method='values')
Out[58]: 
0      0
1      1
10    10
dtype: float64
```

You can also interpolate with a DataFrame:

```
In [59]: 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 [60]: df
Out[60]: 
     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 [61]: df.interpolate()
Out[61]: 
     A      B
0  1.0   0.25
1  2.1   1.50
2  3.4   2.75
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40
```

The `method` argument gives access to fancier interpolation methods. If you have scipy installed, you can set pass the name of a 1-d interpolation routine to `method`. You'll want to consult the full scipy interpolation documentation and reference guide for details. The appropriate interpolation method will depend on the type of data you are working with. For example, if you are dealing with a time series that is growing at an increasing rate, `method='quadratic'` may be appropriate. If you have values approximating a cumulative distribution function, then `method='pchip'` should work well.

Warning: These methods require `scipy`.

```
In [62]: df.interpolate(method='barycentric')
Out[62]:
      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 [63]: df.interpolate(method='pchip')
Out[63]:
          A          B
0  1.000000   0.250000
1  2.100000   1.130135
2  3.429309   2.337586
3  4.700000   4.000000
4  5.600000  12.200000
5  6.800000  14.400000
```

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```
In [64]: df.interpolate(method='spline', order=2)
Out[64]:
          A          B
0  1.000000   0.250000
1  2.100000  -0.428598
2  3.404545   1.206900
3  4.700000   4.000000
4  5.600000  12.200000
5  6.800000  14.400000

In [65]: df.interpolate(method='polynomial', order=2)
Out[65]:
          A          B
0  1.000000   0.250000
1  2.100000  -4.161538
2  3.547059  -2.911538
3  4.700000   4.000000
4  5.600000  12.200000
5  6.800000  14.400000
```

Compare several methods:

```
In [66]: np.random.seed(2)

In [67]: ser = pd.Series(np.arange(1, 10.1, .25)**2 + np.random.randn(37))

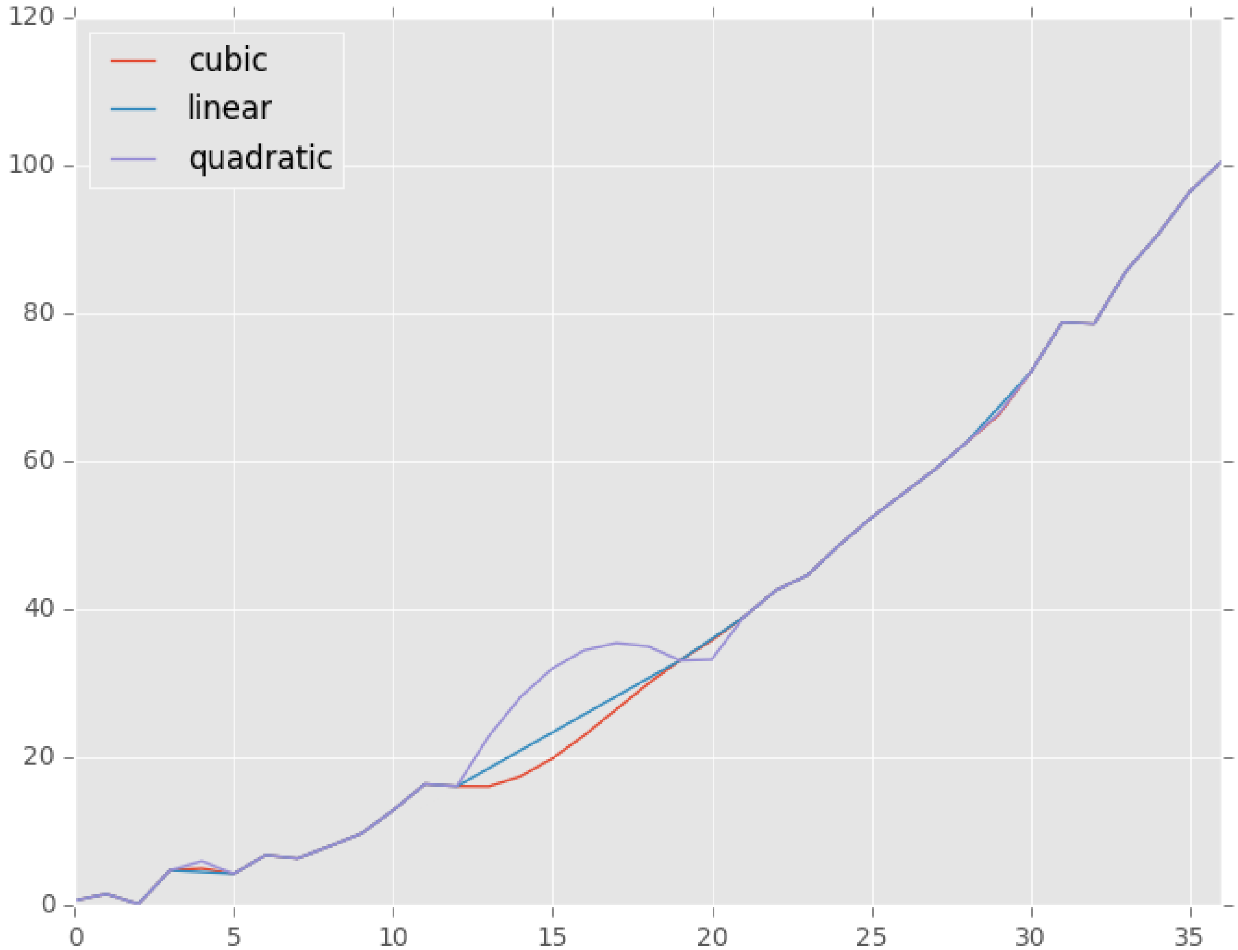
In [68]: bad = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])

In [69]: ser[bad] = np.nan

In [70]: methods = ['linear', 'quadratic', 'cubic']

In [71]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})
```

```
In [72]: df.plot()
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x9b28c8cc>
```



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 [73]: ser = pd.Series(np.sort(np.random.uniform(size=100)))

# interpolate at new_index
In [74]: new_index = ser.index | Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])

In [75]: interp_s = ser.reindex(new_index).interpolate(method='pchip')

In [76]: interp_s[49:51]
Out[76]:
49.00    0.471410
49.25    0.476841
49.50    0.481780
49.75    0.485998
50.00    0.489266
50.25    0.491814
50.50    0.493995
50.75    0.495763
```

```
51.00    0.497074
dtype: float64
```

Like other pandas fill methods, `interpolate` accepts a `limit` keyword argument. Use this to limit the number of consecutive interpolations, keeping `NaN` values for interpolations that are too far from the last valid observation:

```
In [77]: ser = pd.Series([1, 3, np.nan, np.nan, np.nan, 11])

In [78]: ser.interpolate(limit=2)
Out[78]:
0      1
1      3
2      5
3      7
4    NaN
5     11
dtype: float64
```

16.5.5 Replacing Generic Values

Often times we want to replace arbitrary values with other values. New in v0.8 is the `replace` method in Series/DataFrame that provides an efficient yet flexible way to perform such replacements.

For a Series, you can replace a single value or a list of values by another value:

```
In [79]: ser = pd.Series([0., 1., 2., 3., 4.])

In [80]: ser.replace(0, 5)
Out[80]:
0    5
1    1
2    2
3    3
4    4
dtype: float64
```

You can replace a list of values by a list of other values:

```
In [81]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[81]:
0    4
1    3
2    2
3    1
4    0
dtype: float64
```

You can also specify a mapping dict:

```
In [82]: ser.replace({0: 10, 1: 100})
Out[82]:
0     10
1    100
2      2
3      3
4      4
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```
In [83]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})

In [84]: df.replace({'a': 0, 'b': 5}, 100)
Out[84]:
     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 [85]: ser.replace([1, 2, 3], method='pad')
Out[85]:
0    0
1    0
2    0
3    0
4    4
dtype: float64
```

16.5.6 String/Regular Expression Replacement

Note: Python strings prefixed with the `r` character such as `r'hello world'` are so-called "raw" strings. They have different semantics regarding backslashes than strings without this prefix. Backslashes in raw strings will be interpreted as an escaped backslash, e.g., `r'\' == '\\'`. You should read about them if this is unclear.

Replace the '.' with `nan` (str -> str)

```
In [86]: d = {'a': list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}

In [87]: df = pd.DataFrame(d)

In [88]: df.replace('.', np.nan)
Out[88]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Now do it with a regular expression that removes surrounding whitespace (regex -> regex)

```
In [89]: df.replace(r'\s*\.\s*', np.nan, regex=True)
Out[89]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Replace a few different values (list -> list)

```
In [90]: df.replace(['a', '.'], ['b', np.nan])
Out[90]:
   a    b    c
0  0    b    b
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

list of regex -> list of regex

```
In [91]: df.replace([r'\.', r'(a)'], ['dot', '\1stuff'], regex=True)
Out[91]:
   a       b       c
0  0  {stuff  {stuff
1  1       b       b
2  2     dot     NaN
3  3     dot       d
```

Only search in column 'b' (dict -> dict)

```
In [92]: df.replace({'b': '.'}, {'b': np.nan})
Out[92]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict)

```
In [93]: df.replace({'b': r'\s*\.\s*'}, {'b': np.nan}, regex=True)
Out[93]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

You can pass nested dictionaries of regular expressions that use `regex=True`

```
In [94]: df.replace({'b': {'b': r''}}, regex=True)
Out[94]:
   a  b    c
0  0  a    a
1  1       b
2  2  .  NaN
3  3  .    d
```

or you can pass the nested dictionary like so

```
In [95]: df.replace(regex={'b': {r'\s*\.\s*': np.nan}})
Out[95]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well

```
In [96]: df.replace({'b': r'\s*(\.)\s*'}, {'b': r'\1ty'}, regex=True)
Out[96]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  .ty  NaN
3  3  .ty    d
```

You can pass a list of regular expressions, of which those that match will be replaced with a scalar (list of regex -> regex)

```
In [97]: df.replace([r'\s*\.\s*', r'a|b'], np.nan, regex=True)
Out[97]:
   a   b    c
0  0 NaN  NaN
1  1 NaN  NaN
2  2 NaN  NaN
3  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 [98]: df.replace(regex=[r'\s*\.\s*', r'a|b'], value=np.nan)
Out[98]:
   a   b    c
0  0 NaN  NaN
1  1 NaN  NaN
2  2 NaN  NaN
3  3 NaN    d
```

This can be convenient if you do not want to pass `regex=True` every time you want to use a regular expression.

Note: Anywhere in the above `replace` examples that you see a regular expression a compiled regular expression is valid as well.

16.5.7 Numeric Replacement

Similar to `DataFrame.fillna`

```
In [99]: df = pd.DataFrame(np.random.randn(10, 2))

In [100]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5

In [101]: df.replace(1.5, np.nan)
Out[101]:
          0         1
0 -0.844214 -1.021415
1  0.432396 -0.323580
2  0.423825  0.799180
3  1.262614  0.751965
4       NaN       NaN
5       NaN       NaN
6 -0.498174 -1.060799
7  0.591667 -0.183257
8  1.019855 -1.482465
9       NaN       NaN
```

Replacing more than one value via lists works as well

```
In [102]: df00 = df.values[0, 0]

In [103]: df.replace([1.5, df00], [np.nan, 'a'])
Out[103]:
           0         1
0          a -1.021415
1  0.4323957 -0.323580
2  0.4238247  0.799180
3   1.262614  0.751965
4        NaN       NaN
5        NaN       NaN
6 -0.4981742 -1.060799
7  0.5916665 -0.183257
8   1.019855 -1.482465
9        NaN       NaN

In [104]: df[1].dtype
Out[104]: dtype('float64')
```

You can also operate on the DataFrame in place

```
In [105]: df.replace(1.5, np.nan, inplace=True)
```

Warning: When replacing multiple `bool` or `datetime64` objects, the first argument to `replace` (`to_replace`) must match the type of the value being replaced type. For example,

```
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,

```
In [106]: s = pd.Series([True, False, True])

In [107]: s.replace('a string', 'another string')
Out[107]:
0     True
1    False
2     True
dtype: bool
```

the original `NDFrame` object will be returned untouched. We're working on unifying this API, but for backwards compatibility reasons we cannot break the latter behavior. See GH6354 for more details.

16.6 Missing data casting rules and indexing

While pandas supports storing arrays of integer and boolean type, these types are not capable of storing missing data. Until we can switch to using a native NA type in NumPy, we've established some "casting rules" when reindexing will cause missing data to be introduced into, say, a Series or DataFrame. Here they are:

data type	Cast to
integer	float
boolean	object
float	no cast
object	no cast

For example:

```
In [108]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])

In [109]: s > 0
Out[109]:
0    True
2    True
4    True
6    True
7    True
dtype: bool

In [110]: (s > 0).dtype
Out[110]: dtype('bool')

In [111]: crit = (s > 0).reindex(list(range(8)))

In [112]: crit
Out[112]:
0    True
1     NaN
2    True
3     NaN
4    True
5     NaN
6    True
7    True
dtype: object

In [113]: crit.dtype
Out[113]: dtype('O')
```

Ordinarily NumPy will complain if you try to use an object array (even if it contains boolean values) instead of a boolean array to get or set values from an ndarray (e.g. selecting values based on some criteria). If a boolean vector contains NAs, an exception will be generated:

```
In [114]: reindexed = s.reindex(list(range(8))).fillna(0)

In [115]: reindexed[crit]
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-115-2da204ed1ac7> in <module>()
----> 1 reindexed[crit]

/home/joris/scipy/pandas/pandas/core/series.pyc in __getitem__(self, key)
    556                 key = list(key)
    557
--> 558         if is_bool_indexer(key):
    559             key = check_bool_indexer(self.index, key)
    560

/home/joris/scipy/pandas/pandas/core/common.pyc in is_bool_indexer(key)
```

```
   2126             if not lib.is_bool_array(key):
   2127                 if isnull(key).any():
-> 2128                     raise ValueError('cannot index with vector containing '
   2129                                      'NA / NaN values')
   2130                 return False

ValueError: cannot index with vector containing NA / NaN values
```

However, these can be filled in using **fillna** and it will work fine:

```
In [116]: reindexed[crit.fillna(False)]
Out[116]:
0    0.126504
2    0.696198
4    0.697416
6    0.601516
7    0.003659
dtype: float64

In [117]: reindexed[crit.fillna(True)]
Out[117]:
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
```

CHAPTER

SEVENTEEN

GROUP BY: SPLIT-APPLY-COMBINE

By "group by" we are referring to a process involving one or more of the following steps

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

Of these, the split step is the most straightforward. In fact, in many situations you may wish to split the data set into groups and do something with those groups yourself. In the apply step, we might wish to one of the following:

- **Aggregation**: computing a summary statistic (or statistics) about each group. Some examples:
  - Compute group sums or means
  - Compute group sizes / counts
- **Transformation**: perform some group-specific computations and return a like-indexed. Some examples:
  - Standardizing data (zscore) within group
  - Filling NAs within groups with a value derived from each group
- **Filtration**: discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
  - Discarding data that belongs to groups with only a few members
  - Filtering out data based on the group sum or mean
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn't fit into either of the above two categories

Since the set of object instance method on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or `itertools`), in which you can write code like:

```
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We'll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the *cookbook* for some advanced strategies

17.1 Splitting an object into groups

pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you do the following:

```
>>> grouped = obj.groupby(key)
>>> grouped = obj.groupby(key, axis=1)
>>> grouped = obj.groupby([key1, key2])
```

The mapping can be specified many different ways:

- A Python function, to be called on each of the axis labels
- A list or NumPy array of the same length as the selected axis
- A dict or Series, providing a `label -> group name` mapping
- For DataFrame objects, a string indicating a column to be used to group. Of course `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`, but it makes life simpler
- A list of any of the above things

Collectively we refer to the grouping objects as the **keys**. For example, consider the following DataFrame:

```
In [1]: df = DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
   ...:                        'foo', 'bar', 'foo', 'foo'],
   ...:                 'B' : ['one', 'one', 'two', 'three',
   ...:                        'two', 'two', 'one', 'three'],
   ...:                 'C' : randn(8), 'D' : randn(8)})
   ...:

In [2]: df
Out[2]:
     A      B         C         D
0  foo    one  0.469112 -0.861849
1  bar    one -0.282863 -2.104569
2  foo    two -1.509059 -0.494929
3  bar  three -1.135632  1.071804
4  foo    two  1.212112  0.721555
5  bar    two -0.173215 -0.706771
6  foo    one  0.119209 -1.039575
7  foo  three -1.044236  0.271860
```

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)
```

Starting with 0.8, pandas Index objects now supports duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

```
In [7]: lst = [1, 2, 3, 1, 2, 3]

In [8]: s = Series([1, 2, 3, 10, 20, 30], lst)

In [9]: grouped = s.groupby(level=0)

In [10]: grouped.first()
Out[10]:
1    1
2    2
3    3
dtype: int64

In [11]: grouped.last()
Out[11]:
1    10
2    20
3    30
dtype: int64

In [12]: grouped.sum()
Out[12]:
1    11
2    22
3    33
dtype: int64
```

Note that **no splitting occurs** until it's needed. Creating the GroupBy object only verifies that you've passed a valid mapping.

Note: Many kinds of complicated data manipulations can be expressed in terms of GroupBy operations (though can't be guaranteed to be the most efficient). You can get quite creative with the label mapping functions.

17.1.1 GroupBy 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:

```
In [13]: df.groupby('A').groups
Out[13]: {'bar': [1L, 3L, 5L], 'foo': [0L, 2L, 4L, 6L, 7L]}

In [14]: df.groupby(get_letter_type, axis=1).groups
Out[14]: {'consonant': ['B', 'C', 'D'], 'vowel': ['A']}
```

Calling the standard Python `len` function on the GroupBy object just returns the length of the `groups` dict, so it is largely just a convenience:

```
In [15]: grouped = df.groupby(['A', 'B'])

In [16]: grouped.groups
Out[16]:
{('bar', 'one'): [1L],
 ('bar', 'three'): [3L],
```

```
 ('bar', 'two'): [5L],
 ('foo', 'one'): [0L, 6L],
 ('foo', 'three'): [7L],
 ('foo', 'two'): [2L, 4L]}

In [17]: len(grouped)
Out[17]: 6
```

By default the group keys are sorted during the groupby operation. You may however pass `sort=False` for potential speedups:

```
In [18]: df2 = DataFrame({'X' : ['B', 'B', 'A', 'A'], 'Y' : [1, 2, 3, 4]})

In [19]: df2.groupby(['X'], sort=True).sum()
Out[19]: 
   Y
X   
A  7
B  3

In [20]: df2.groupby(['X'], sort=False).sum()
Out[20]: 
   Y
X   
B  3
A  7
```

`GroupBy` will tab complete column names (and other attributes)

```
In [21]: df
Out[21]: 
            gender     height      weight
2000-01-01    male  42.849980  157.500553
2000-01-02    male  49.607315  177.340407
2000-01-03    male  56.293531  171.524640
2000-01-04  female  48.421077  144.251986
2000-01-05    male  46.556882  152.526206
2000-01-06  female  68.448851  168.272968
2000-01-07    male  70.757698  136.431469
2000-01-08  female  58.909500  176.499753
2000-01-09  female  76.435631  174.094104
2000-01-10    male  45.306120  177.540920

In [22]: gb = df.groupby('gender')

In [23]: gb.<TAB>
gb.agg        gb.boxplot    gb.cummin     gb.describe   gb.filter     gb.get_group  gb.height     gb
gb.aggregate  gb.count      gb.cumprod    gb.dtype      gb.first      gb.groups     gb.hist       gb
gb.apply      gb.cummax     gb.cumsum     gb.fillna     gb.gender     gb.head       gb.indices    gb
```

17.1.2 GroupBy with MultiIndex

With *hierarchically-indexed data*, it's quite natural to group by one of the levels of the hierarchy.

```
In [24]: s
Out[24]: 
first  second
```

```
bar    one      -0.575247
       two       0.254161
baz    one      -1.143704
       two       0.215897
foo    one       1.193555
       two      -0.077118
qux    one      -0.408530
       two      -0.862495
dtype: float64

In [25]: grouped = s.groupby(level=0)

In [26]: grouped.sum()
Out[26]:
first
bar   -0.321085
baz   -0.927807
foo    1.116437
qux   -1.271025
dtype: float64
```

If the MultiIndex has names specified, these can be passed instead of the level number:

```
In [27]: s.groupby(level='second').sum()
Out[27]:
second
one   -0.933926
two   -0.469555
dtype: float64
```

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

```
In [28]: s.sum(level='second')
Out[28]:
second
one   -0.933926
two   -0.469555
dtype: float64
```

Also as of v0.6, grouping with multiple levels is supported.

```
In [29]: s
Out[29]:
first  second  third
bar    doo     one       1.346061
               two       1.511763
baz    bee     one       1.627081
               two      -0.990582
foo    bop     one      -0.441652
               two       1.211526
qux    bop     one       0.268520
               two       0.024580
dtype: float64

In [30]: s.groupby(level=['first','second']).sum()
Out[30]:
first  second
bar    doo       2.857824
```

```
baz    bee       0.636499
foo    bop       0.769873
qux    bop       0.293100
dtype: float64
```

More on the `sum` function and aggregation later.

17.1.3 DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, for example, you might want to do something different for each of the columns. Thus, using `[]` similar to getting a column from a DataFrame, you can do:

```
In [31]: grouped = df.groupby(['A'])

In [32]: grouped_C = grouped['C']

In [33]: grouped_D = grouped['D']
```

This is mainly syntactic sugar for the alternative and much more verbose:

```
In [34]: df['C'].groupby(df['A'])
Out[34]: <pandas.core.groupby.SeriesGroupBy object at 0xa0c4de8c>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

17.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby`:

```
In [35]: grouped = df.groupby('A')

In [36]: for name, group in grouped:
   ....:        print(name)
   ....:        print(group)
   ....:
bar
     A      B         C         D
1  bar    one -0.042379 -0.089329
3  bar  three -0.009920 -0.945867
5  bar    two  0.495767  1.956030
foo
     A      B         C         D
0  foo    one -0.919854 -1.131345
2  foo    two  1.247642  0.337863
4  foo    two  0.290213 -0.932132
6  foo    one  0.362949  0.017587
7  foo  three  1.548106 -0.016692
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [37]: for name, group in df.groupby(['A', 'B']):
   ....:        print(name)
   ....:        print(group)
   ....:
('bar', 'one')
```

```
     A    B         C         D
1  bar  one -0.042379 -0.089329
('bar', 'three')
     A      B        C         D
3  bar  three -0.00992 -0.945867
('bar', 'two')
     A    B         C        D
5  bar  two  0.495767  1.95603
('foo', 'one')
     A    B         C         D
0  foo  one -0.919854 -1.131345
6  foo  one  0.362949  0.017587
('foo', 'three')
     A      B         C         D
7  foo  three  1.548106 -0.016692
('foo', 'two')
     A    B         C         D
2  foo  two  1.247642  0.337863
4  foo  two  0.290213 -0.932132
```

It's standard Python-fu but remember you can unpack the tuple in the for loop statement if you wish: `for (k1, k2), group in grouped:`.

17.3 Selecting a group

A single group can be selected using `GroupBy.get_group()`:

```
In [38]: grouped.get_group('bar')
Out[38]:
     A      B         C         D
1  bar    one -0.042379 -0.089329
3  bar  three -0.009920 -0.945867
5  bar    two  0.495767  1.956030
```

Or for an object grouped on multiple columns:

```
In [39]: df.groupby(['A', 'B']).get_group(('bar', 'one'))
Out[39]:
     A    B         C         D
1  bar  one -0.042379 -0.089329
```

17.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data.

An obvious one is aggregation via the `aggregate` or equivalently `agg` method:

```
In [40]: grouped = df.groupby('A')

In [41]: grouped.aggregate(np.sum)
Out[41]:
            C         D
A
bar  0.443469  0.920834
```

```
foo  2.529056 -1.724719

In [42]: grouped = df.groupby(['A', 'B'])

In [43]: grouped.aggregate(np.sum)
Out[43]: 
                  C         D
A   B                        
bar one   -0.042379 -0.089329
    three -0.009920 -0.945867
    two    0.495767  1.956030
foo one   -0.556905 -1.113758
    three  1.548106 -0.016692
    two    1.537855 -0.594269
```

As you can see, the result of the aggregation will have the group names as the new index along the grouped axis. In the case of multiple keys, the result is a *MultiIndex* by default, though this can be changed by using the `as_index` option:

```
In [44]: grouped = df.groupby(['A', 'B'], as_index=False)

In [45]: grouped.aggregate(np.sum)
Out[45]: 
     A      B         C         D
0  bar    one -0.042379 -0.089329
1  bar  three -0.009920 -0.945867
2  bar    two  0.495767  1.956030
3  foo    one -0.556905 -1.113758
4  foo  three  1.548106 -0.016692
5  foo    two  1.537855 -0.594269

In [46]: df.groupby('A', as_index=False).sum()
Out[46]: 
     A         C         D
0  bar  0.443469  0.920834
1  foo  2.529056 -1.724719
```

Note that you could use the `reset_index` DataFrame function to achieve the same result as the column names are stored in the resulting `MultiIndex`:

```
In [47]: df.groupby(['A', 'B']).sum().reset_index()
Out[47]: 
     A      B         C         D
0  bar    one -0.042379 -0.089329
1  bar  three -0.009920 -0.945867
2  bar    two  0.495767  1.956030
3  foo    one -0.556905 -1.113758
4  foo  three  1.548106 -0.016692
5  foo    two  1.537855 -0.594269
```

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 [48]: grouped.size()
Out[48]: 
A    B    
bar  one      1
     three    1
     two      1
```

```
foo  one      2
     three    1
     two      2
dtype: int64

In [49]: grouped.describe()
Out[49]:
                C         D
0 count  1.000000  1.000000
  mean  -0.042379 -0.089329
  std         NaN       NaN
  min   -0.042379 -0.089329
  25%   -0.042379 -0.089329
  50%   -0.042379 -0.089329
  75%   -0.042379 -0.089329
...           ...       ...
5 mean   0.768928 -0.297134
  std    0.677005  0.898022
  min    0.290213 -0.932132
  25%    0.529570 -0.614633
  50%    0.768928 -0.297134
  75%    1.008285  0.020364
  max    1.247642  0.337863

[48 rows x 2 columns]
```

Note: Aggregation functions **will not** return the groups that you are aggregating over if they are named *columns*, when `as_index=True`, the default. The grouped columns will be the **indices** of the returned object.

Passing `as_index=False` **will** return the groups that you are aggregating over, if they are named *columns*.

Aggregating functions are ones that reduce the dimension of the returned objects, for example: `mean, sum, size, count, std, var, sem, describe, first, last, nth, min, max`. This is what happens when you do for example `DataFrame.sum()` and get back a `Series`.

`nth` can act as a reducer *or* a filter, see *here*

17.4.1 Applying multiple functions at once

With grouped Series you can also pass a list or dict of functions to do aggregation with, outputting a DataFrame:

```
In [50]: grouped = df.groupby('A')

In [51]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[51]:
          sum      mean       std
A
bar  0.443469  0.147823  0.301765
foo  2.529056  0.505811  0.966450
```

If a dict is passed, the keys will be used to name the columns. Otherwise the function's name (stored in the function object) will be used.

```
In [52]: grouped['D'].agg({'result1' : np.sum,
   ....:                   'result2' : np.mean})
   ....:
Out[52]:
```

```
      result2   result1
A
bar  0.306945  0.920834
foo -0.344944 -1.724719
```

On a grouped DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [53]: grouped.agg([np.sum, np.mean, np.std])
Out[53]:
            C                             D
          sum      mean       std       sum      mean       std
A
bar  0.443469  0.147823  0.301765  0.920834  0.306945  1.490982
foo  2.529056  0.505811  0.966450 -1.724719 -0.344944  0.645875
```

Passing a dict of functions has different behavior by default, see the next section.

17.4.2 Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```
In [54]: grouped.agg({'C' : np.sum,
   ....:              'D' : lambda x: np.std(x, ddof=1)})
   ....:
Out[54]:
            C         D
A
bar  0.443469  1.490982
foo  2.529056  0.645875
```

The function names can also be strings. In order for a string to be valid it must be either implemented on GroupBy or available via *dispatching*:

```
In [55]: grouped.agg({'C' : 'sum', 'D' : 'std'})
Out[55]:
            C         D
A
bar  0.443469  1.490982
foo  2.529056  0.645875
```

17.4.3 Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, `std`, and `sem`, have optimized Cython implementations:

```
In [56]: df.groupby('A').sum()
Out[56]:
            C         D
A
bar  0.443469  0.920834
foo  2.529056 -1.724719

In [57]: df.groupby(['A', 'B']).mean()
Out[57]:
                  C         D
A   B
bar one   -0.042379 -0.089329
```

```
    three -0.009920 -0.945867
    two    0.495767  1.956030
foo one   -0.278452 -0.556879
    three  1.548106 -0.016692
    two    0.768928 -0.297134
```

Of course `sum` and `mean` are implemented on pandas objects, so the above code would work even without the special versions via dispatching (see below).

17.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. Thus, the passed transform function should return a result that is the same size as the group chunk. For example, suppose we wished to standardize the data within each group:

```
In [58]: index = date_range('10/1/1999', periods=1100)

In [59]: ts = Series(np.random.normal(0.5, 2, 1100), index)

In [60]: ts = rolling_mean(ts, 100, 100).dropna()

In [61]: ts.head()
Out[61]: 
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 [62]: ts.tail()
Out[62]: 
2002-09-30    0.660294
2002-10-01    0.631095
2002-10-02    0.673601
2002-10-03    0.709213
2002-10-04    0.719369
Freq: D, dtype: float64

In [63]: key = lambda x: x.year

In [64]: zscore = lambda x: (x - x.mean()) / x.std()

In [65]: 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 [66]: grouped = ts.groupby(key)

In [67]: grouped.mean()
Out[67]: 
2000    0.442441
2001    0.526246
2002    0.459365
```

```
dtype: float64

In [68]: grouped.std()
Out[68]:
2000    0.131752
2001    0.210945
2002    0.128753
dtype: float64

# Transformed Data
In [69]: grouped_trans = transformed.groupby(key)

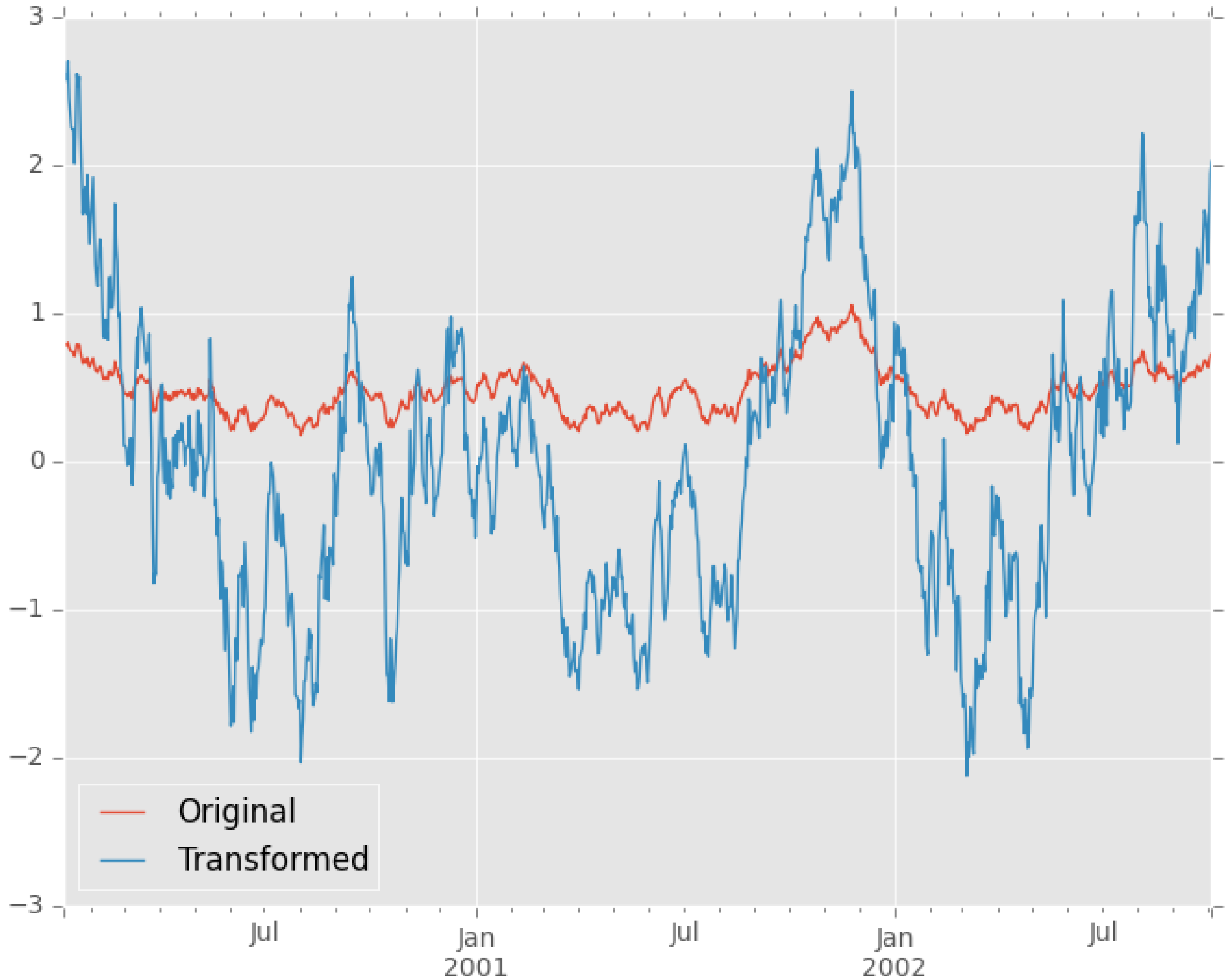
In [70]: grouped_trans.mean()
Out[70]:
2000   -1.250934e-16
2001   -4.291848e-16
2002    2.404815e-17
dtype: float64

In [71]: grouped_trans.std()
Out[71]:
2000    1
2001    1
2002    1
dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [72]: compare = DataFrame({'Original': ts, 'Transformed': transformed})

In [73]: compare.plot()
Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0xa46880ec>
```



Another common data transform is to replace missing data with the group mean.

```
In [74]: data_df
Out[74]:
            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 [75]: countries = np.array(['US', 'UK', 'GR', 'JP'])

In [76]: key = countries[np.random.randint(0, 4, 1000)]

In [77]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [78]: grouped.count()
Out[78]:
      A    B    C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217

In [79]: f = lambda x: x.fillna(x.mean())

In [80]: 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 [81]: grouped_trans = transformed.groupby(key)

In [82]: grouped.mean() # original group means
Out[82]:
           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 [83]: grouped_trans.mean() # transformation did not change group means
Out[83]:
           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 [84]: grouped.count() # original has some missing data points
Out[84]:
      A    B    C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217

In [85]: grouped_trans.count() # counts after transformation
Out[85]:
      A    B    C
GR  228  228  228
JP  267  267  267
UK  247  247  247
US  258  258  258

In [86]: grouped_trans.size() # Verify non-NA count equals group size
Out[86]:
```

```
GR    228
JP    267
UK    247
US    258
dtype: int64
```

Note: Some functions when applied to a groupby object will automatically transform the input, 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 [87]: grouped.ffill()
Out[87]: 
            A         B         C
0    1.539708 -1.166480  0.533026
1    1.302092 -0.505754  0.533026
2   -0.371983  1.104803 -0.651520
3   -1.309622  1.118697 -1.161657
4   -1.924296  0.396437  0.812436
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 -0.774753
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148 -0.774753
999  0.234564  0.517098  0.393534

[1000 rows x 3 columns]
```

17.6 Filtration

New in version 0.12.

The `filter` method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [88]: sf = Series([1, 1, 2, 3, 3, 3])

In [89]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[89]: 
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must be a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [90]: dff = DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

In [91]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[91]: 
```

```
   A  B
2  2  b
3  3  b
4  4  b
5  5  b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [92]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[92]:
     A    B
0  NaN  NaN
1  NaN  NaN
2    2    b
3    3    b
4    4    b
5    5    b
6  NaN  NaN
7  NaN  NaN
```

For dataframes with multiple columns, filters should explicitly specify a column as the filter criterion.

```
In [93]: dff['C'] = np.arange(8)

In [94]: dff.groupby('B').filter(lambda x: len(x['C']) > 2)
Out[94]:
   A  B  C
2  2  b  2
3  3  b  3
4  4  b  4
5  5  b  5
```

Note: Some functions when applied to a groupby object will act as a **filter** on the input, returning a reduced shape of the original (and potentitally eliminating groups), but with the index unchanged. Passing `as_index=False` will not affect these transformation methods.

For example: `head, tail`.

```
In [95]: dff.groupby('B').head(2)
Out[95]:
   A  B  C
0  0  a  0
1  1  a  1
2  2  b  2
3  3  b  3
6  6  c  6
7  7  c  7
```

17.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```
In [96]: grouped = df.groupby('A')
```

```
In [97]: grouped.agg(lambda x: x.std())
Out[97]:
            C         D
A
bar  0.301765  1.490982
foo  0.966450  0.645875
```

But, it's rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, GroupBy now has the ability to "dispatch" method calls to the groups:

```
In [98]: grouped.std()
Out[98]:
            C         D
A
bar  0.301765  1.490982
foo  0.966450  0.645875
```

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the gluing, documented next). This enables some operations to be carried out rather succinctly:

```
In [99]: tsdf = DataFrame(randn(1000, 3),
   ....:                  index=date_range('1/1/2000', periods=1000),
   ....:                  columns=['A', 'B', 'C'])
   ....:

In [100]: tsdf.ix[::2] = np.nan

In [101]: grouped = tsdf.groupby(lambda x: x.year)

In [102]: grouped.fillna(method='pad')
Out[102]:
                   A         B         C
2000-01-01       NaN       NaN       NaN
2000-01-02 -0.353501 -0.080957 -0.876864
2000-01-03 -0.353501 -0.080957 -0.876864
2000-01-04  0.050976  0.044273 -0.559849
2000-01-05  0.050976  0.044273 -0.559849
2000-01-06  0.030091  0.186460 -0.680149
2000-01-07  0.030091  0.186460 -0.680149
...              ...       ...       ...
2002-09-20  2.310215  0.157482 -0.064476
2002-09-21  2.310215  0.157482 -0.064476
2002-09-22  0.005011  0.053897 -1.026922
2002-09-23  0.005011  0.053897 -1.026922
2002-09-24 -0.456542 -1.849051  1.559856
2002-09-25 -0.456542 -1.849051  1.559856
2002-09-26  1.123162  0.354660  1.128135

[1000 rows x 3 columns]
```

In this example, we chopped the collection of time series into yearly chunks then independently called *fillna* on the groups.

New in version 0.14.1.

The `nlargest` and `nsmallest` methods work on `Series` style groupbys:

```
In [103]: s = Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])

In [104]: g = Series(list('abababab'))

In [105]: gb = s.groupby(g)

In [106]: gb.nlargest(3)
Out[106]:
a  4    19.0
   0     9.0
   2     7.0
b  1     8.0
   3     5.0
   7     3.3
dtype: float64

In [107]: gb.nsmallest(3)
Out[107]:
a  6    4.2
   2    7.0
   0    9.0
b  5    1.0
   7    3.3
   3    5.0
dtype: float64
```

17.8 Flexible apply

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want GroupBy to infer how to combine the results. For these, use the `apply` function, which can be substituted for both `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```
In [108]: df
Out[108]:
     A      B         C         D
0  foo    one -0.919854 -1.131345
1  bar    one -0.042379 -0.089329
2  foo    two  1.247642  0.337863
3  bar  three -0.009920 -0.945867
4  foo    two  0.290213 -0.932132
5  bar    two  0.495767  1.956030
6  foo    one  0.362949  0.017587
7  foo  three  1.548106 -0.016692

In [109]: grouped = df.groupby('A')

# could also just call .describe()
In [110]: grouped['C'].apply(lambda x: x.describe())
Out[110]:
A
bar  count    3.000000
     mean     0.147823
     std      0.301765
     min     -0.042379
     25%     -0.026149
```

```
     50%     -0.009920
     75%      0.242924
                ...
foo  mean     0.505811
     std      0.966450
     min     -0.919854
     25%      0.290213
     50%      0.362949
     75%      1.247642
     max      1.548106
dtype: float64
```

The dimension of the returned result can also change:

```
In [111]: grouped = df.groupby('A')['C']

In [112]: def f(group):
   .....:     return DataFrame({'original' : group,
   .....:                       'demeaned' : group - group.mean()})
   .....:

In [113]: grouped.apply(f)
Out[113]:
   demeaned  original
0 -1.425665 -0.919854
1 -0.190202 -0.042379
2  0.741831  1.247642
3 -0.157743 -0.009920
4 -0.215598  0.290213
5  0.347944  0.495767
6 -0.142862  0.362949
7  1.042295  1.548106
```

`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 [114]: def f(x):
   .....:   return Series([ x, x**2 ], index = ['x', 'x^s'])
   .....:

In [115]: s
Out[115]:
0     9.0
1     8.0
2     7.0
3     5.0
4    19.0
5     1.0
6     4.2
7     3.3
dtype: float64

In [116]: s.apply(f)
Out[116]:
      x     x^s
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 apply. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

Warning: In the current implementation apply calls func twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first group.

```
In [117]: d = DataFrame({"a":["x", "y"], "b":[1,2]})

In [118]: def identity(df):
   .....:     print df
   .....:     return df
   .....:

In [119]: d.groupby("a").apply(identity)
   a  b
0  x  1
   a  b
0  x  1
   a  b
1  y  2
Out[119]:
   a  b
0  x  1
1  y  2
```

17.9 Other useful features

17.9.1 Automatic exclusion of "nuisance" columns

Again consider the example DataFrame we've been looking at:

```
In [120]: df
Out[120]:
     A      B         C         D
0  foo    one -0.919854 -1.131345
1  bar    one -0.042379 -0.089329
2  foo    two  1.247642  0.337863
3  bar  three -0.009920 -0.945867
4  foo    two  0.290213 -0.932132
5  bar    two  0.495767  1.956030
6  foo    one  0.362949  0.017587
7  foo  three  1.548106 -0.016692
```

Supposed we wished to compute the standard deviation grouped by the `A` column. There is a slight problem, namely that we don't care about the data in column `B`. We refer to this as a "nuisance" column. If the passed aggregation function can't be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

```
In [121]: df.groupby('A').std()
Out[121]:
            C         D
A
bar  0.301765  1.490982
foo  0.966450  0.645875
```

17.9.2 NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. So there will never be an "NA group" or "NaT group". This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

17.9.3 Grouping with ordered factors

Categorical variables represented as instance of pandas's `Categorical` class can be used as group keys. If so, the order of the levels will be preserved:

```
In [122]: data = Series(np.random.randn(100))

In [123]: factor = qcut(data, [0, .25, .5, .75, 1.])

In [124]: data.groupby(factor).mean()
Out[124]:
[-2.617, -0.684]    -1.331461
(-0.684, -0.0232]   -0.272816
(-0.0232, 0.541]     0.263607
(0.541, 2.369]       1.166038
dtype: float64
```

17.9.4 Grouping with a Grouper specification

Your may need to specify a bit more data to properly group. You can use the `pd.Grouper` to provide this local control.

```
In [125]: import datetime as DT

In [126]: df = 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' : [
   .....:             DT.datetime(2013,1,1,13,0),
   .....:             DT.datetime(2013,1,1,13,5),
   .....:             DT.datetime(2013,10,1,20,0),
   .....:             DT.datetime(2013,10,2,10,0),
   .....:             DT.datetime(2013,10,1,20,0),
   .....:             DT.datetime(2013,10,2,10,0),
   .....:             DT.datetime(2013,12,2,12,0),
   .....:             DT.datetime(2013,12,2,14,0),
   .....:             ]})
```

```
   .....:

In [127]: df
Out[127]:
  Branch Buyer                Date  Quantity
0      A  Carl 2013-01-01 13:00:00         1
1      A  Mark 2013-01-01 13:05:00         3
2      A  Carl 2013-10-01 20:00:00         5
3      A  Carl 2013-10-02 10:00:00         1
4      A   Joe 2013-10-01 20:00:00         8
5      A   Joe 2013-10-02 10:00:00         1
6      A   Joe 2013-12-02 12:00:00         9
7      B  Carl 2013-12-02 14:00:00         3
```

Groupby a specific column with the desired frequency. This is like resampling.

```
In [128]: df.groupby([pd.Grouper(freq='1M',key='Date'),'Buyer']).sum()
Out[128]:
                  Quantity
Date       Buyer
2013-01-31 Carl          1
           Mark          3
2013-10-31 Carl          6
           Joe           9
2013-12-31 Carl          3
           Joe           9
```

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.

```
In [129]: df = df.set_index('Date')

In [130]: df['Date'] = df.index + pd.offsets.MonthEnd(2)

In [131]: df.groupby([pd.Grouper(freq='6M',key='Date'),'Buyer']).sum()
Out[131]:
                  Quantity
Date       Buyer
2013-02-28 Carl          1
           Mark          3
2014-02-28 Carl          9
           Joe          18

In [132]: df.groupby([pd.Grouper(freq='6M',level='Date'),'Buyer']).sum()
Out[132]:
                  Quantity
Date       Buyer
2013-01-31 Carl          1
           Mark          3
2014-01-31 Carl          9
           Joe          18
```

17.9.5 Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

```
In [133]: df = DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [134]: df
```

```
Out[134]:
   A  B
0  1  2
1  1  4
2  5  6

In [135]: g = df.groupby('A')

In [136]: g.head(1)
Out[136]:
   A  B
0  1  2
2  5  6

In [137]: g.tail(1)
Out[137]:
   A  B
1  1  4
2  5  6
```

This shows the first or last n rows from each group.

Warning: Before 0.14.0 this was implemented with a fall-through apply, so the result would incorrectly respect the as_index flag:

```
>>> g.head(1):   # was equivalent to g.apply(lambda x: x.head(1))
      A  B
 A
 1 0  1  2
 5 2  5  6
```

17.9.6 Taking the nth row of each group

To select from a DataFrame or Series the nth item, use the nth method. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [138]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [139]: g = df.groupby('A')

In [140]: g.nth(0)
Out[140]:
    B
A
1 NaN
5   6

In [141]: g.nth(-1)
Out[141]:
   B
A
1  4
5  6

In [142]: g.nth(1)
Out[142]:
```

```
   B
A
1  4
```

If you want to select the nth not-null item, use the `dropna` kwarg. For a DataFrame this should be either `'any'` or `'all'` just like you would pass to dropna, for a Series this just needs to be truthy.

```
# nth(0) is the same as g.first()
In [143]: g.nth(0, dropna='any')
Out[143]:
   B
A
1  4
5  6

In [144]: g.first()
Out[144]:
   B
A
1  4
5  6

# nth(-1) is the same as g.last()
In [145]: g.nth(-1, dropna='any')  # NaNs denote group exhausted when using dropna
Out[145]:
   B
A
1  4
5  6

In [146]: g.last()
Out[146]:
   B
A
1  4
5  6

In [147]: g.B.nth(0, dropna=True)
Out[147]:
A
1    4
5    6
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```
In [148]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [149]: g = df.groupby('A',as_index=False)

In [150]: g.nth(0)
Out[150]:
   A   B
0  1 NaN
2  5   6

In [151]: g.nth(-1)
Out[151]:
   A  B
```

```
1  1  4
2  5  6
```

You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

```
In [152]: business_dates = date_range(start='4/1/2014', end='6/30/2014', freq='B')

In [153]: df = DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [154]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
Out[154]:
            a  b
2014-04-01  1  1
2014-04-04  1  1
2014-04-30  1  1
2014-05-01  1  1
2014-05-06  1  1
2014-05-30  1  1
2014-06-02  1  1
2014-06-05  1  1
2014-06-30  1  1
```

17.9.7 Enumerate group items

New in version 0.13.0.

To see the order in which each row appears within its group, use the `cumcount` method:

```
In [155]: df = pd.DataFrame(list('aaabba'), columns=['A'])

In [156]: df
Out[156]:
   A
0  a
1  a
2  a
3  b
4  b
5  a

In [157]: df.groupby('A').cumcount()
Out[157]:
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64

In [158]: df.groupby('A').cumcount(ascending=False)  # kwarg only
Out[158]:
0    3
1    2
2    1
3    1
4    0
```

```
5    0
dtype: int64
```

17.9.8 Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame my differ by group, in this case, the values in column 1 where the group is "B" are 3 higher on average.

```
In [159]: np.random.seed(1234)

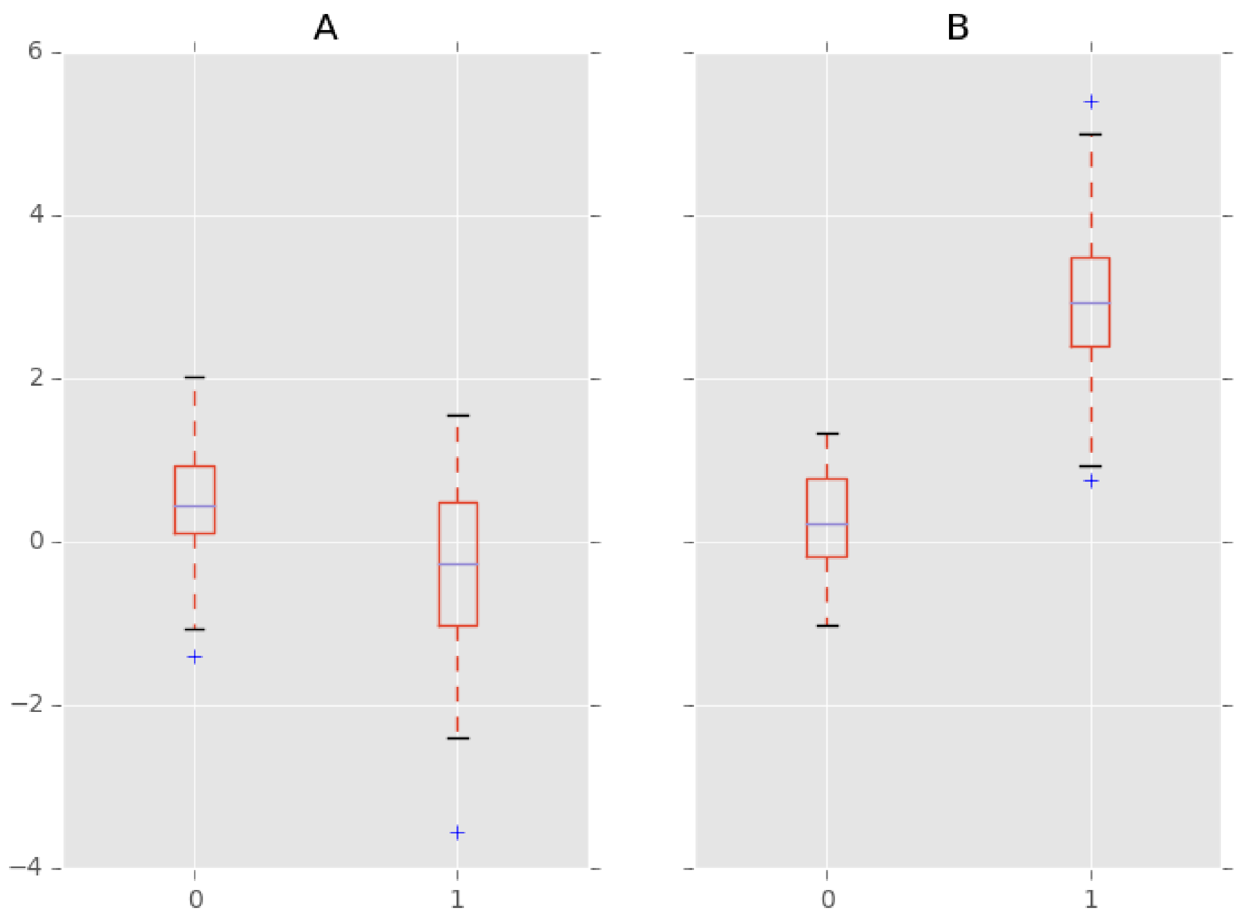
In [160]: df = DataFrame(np.random.randn(50, 2))

In [161]: df['g'] = np.random.choice(['A', 'B'], size=50)

In [162]: df.loc[df['g'] == 'B', 1] += 3
```

We can easily visualize this with a boxplot:

```
In [163]: df.groupby('g').boxplot()
Out[163]: OrderedDict([('A', {'boxes': [<matplotlib.lines.Line2D object at 0xa0f5b04c>, <matplotlib.l
```



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.

17.10 Examples

17.10.1 Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

```
In [164]: df = pd.DataFrame({'a':[1,0,0], 'b':[0,1,0], 'c':[1,0,0], 'd':[2,3,4]})

In [165]: df
Out[165]:
   a  b  c  d
0  1  0  1  2
1  0  1  0  3
2  0  0  0  4

In [166]: df.groupby(df.sum(), axis=1).sum()
Out[166]:
   1  9
0  2  2
1  1  3
2  0  4
```

17.10.2 Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the column index name will be used as the name of the inserted column:

```
In [167]: df = pd.DataFrame({
   .....:        'a':  [0, 0, 0, 0, 1, 1, 1, 1, 2, 2, 2, 2],
   .....:        'b':  [0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
   .....:        'c':  [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
   .....:        'd':  [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
   .....:        })
   .....:

In [168]: def compute_metrics(x):
   .....:     result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
   .....:     return pd.Series(result, name='metrics')
   .....:

In [169]: result = df.groupby('a').apply(compute_metrics)

In [170]: result
Out[170]:
metrics  b_sum  c_mean
a
0            2     0.5
1            2     0.5
2            2     0.5
```

```
In [171]: result.stack()
Out[171]:
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
```

CHAPTER

EIGHTEEN

MERGE, JOIN, AND CONCATENATE

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

18.1 Concatenating objects

The `concat` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say "if any" because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

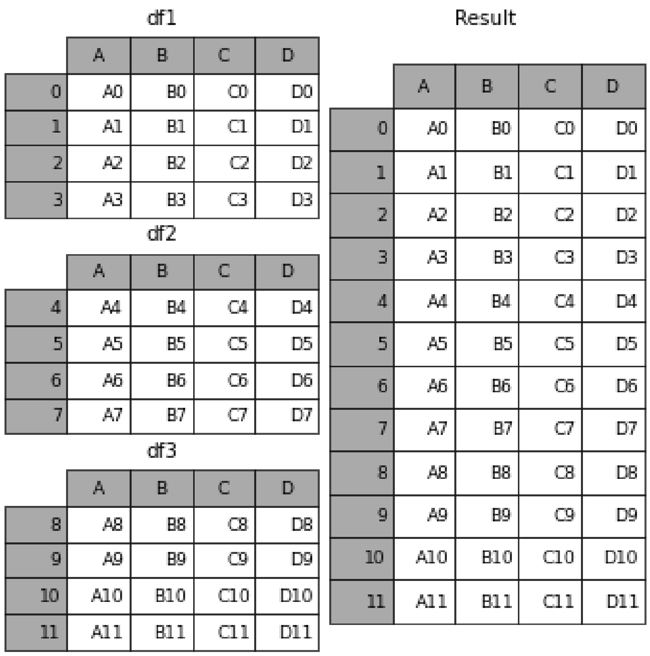
```
In [1]: df1 = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ...:                  'B': ['B0', 'B1', 'B2', 'B3'],
   ...:                  'C': ['C0', 'C1', 'C2', 'C3'],
   ...:                  'D': ['D0', 'D1', 'D2', 'D3']},
   ...:                 index=[0, 1, 2, 3])
   ...:

In [2]: df2 = 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 = 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 = concat(frames)
```



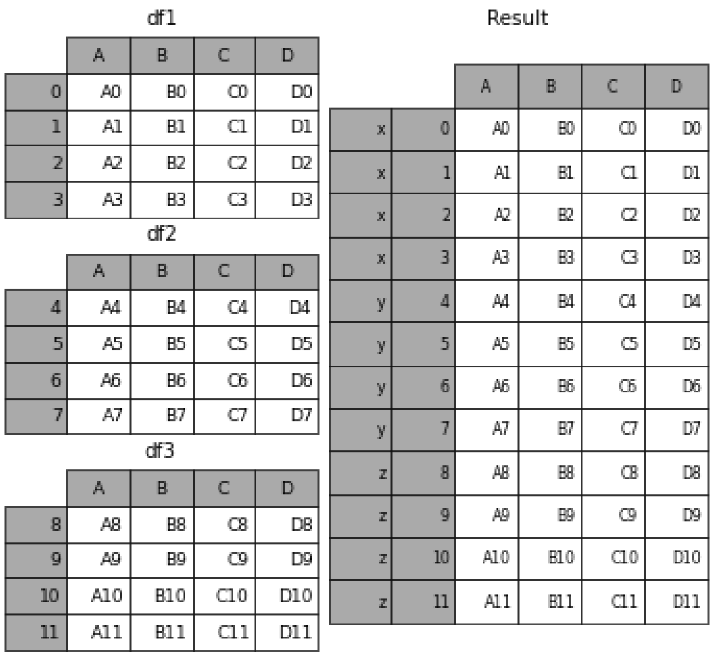
Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of "what to do with the other axes":

```
concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
       keys=None, levels=None, names=None, verify_integrity=False)
```

- `objs`: list or dict of Series, DataFrame, or Panel objects. If a dict is passed, the sorted keys will be used as the *keys* argument, unless it is passed, in which case the values will be selected (see below)
- `axis`: {0, 1, ...}, default 0. The axis to concatenate along
- `join`: {'inner', 'outer'}, default 'outer'. How to handle indexes on other axis(es). Outer for union and inner for intersection
- `join_axes`: list of Index objects. Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic
- `keys`: sequence, default None. Construct hierarchical index using the passed keys as the outermost level If multiple levels passed, should contain tuples.
- `levels` : list of sequences, default None. If keys passed, specific levels to use for the resulting MultiIndex. Otherwise they will be inferred from the keys
- `names`: list, default None. Names for the levels in the resulting hierarchical index
- `verify_integrity`: boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation
- `ignore_index` : boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information.

Without a little bit of context and example many of these arguments don't make much sense. Let's take the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```
In [6]: result = concat(frames, keys=['x', 'y', 'z'])
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

		A	B	C	D
x	0	A0	B0	C0	D0
x	1	A1	B1	C1	D1
x	2	A2	B2	C2	D2
x	3	A3	B3	C3	D3
y	4	A4	B4	C4	D4
y	5	A5	B5	C5	D5
y	6	A6	B6	C6	D6
y	7	A7	B7	C7	D7
z	8	A8	B8	C8	D8
z	9	A9	B9	C9	D9
z	10	A10	B10	C10	D10
z	11	A11	B11	C11	D11

As you can see (if you've read the rest of the documentation), the resulting object's index has a *hierarchical index*. This means that we can now do stuff like select out each chunk by key:

```
In [7]: result.ix['y']
Out[7]:
    A   B   C   D
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 however, that `concat` (and therefore `append`) makes a full copy of the data, and that constantly reusing this function can create a signifcant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```

18.1.1 Set logic on the other axes

When gluing together multiple DataFrames (or Panels or...), for example, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in three ways:

- Take the (sorted) union of them all, `join='outer'`. This is the default option as it results in zero information loss.

- Take the intersection, `join='inner'`.
- Use a specific index (in the case of DataFrame) or indexes (in the case of Panel or future higher dimensional objects), i.e. the `join_axes` argument

Here is a example of each of these methods. First, the default `join='outer'` behavior:

```
In [8]: df4 = DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
   ...:                  'D': ['D2', 'D3', 'D6', 'D7'],
   ...:                  'F': ['F2', 'F3', 'F6', 'F7']},
   ...:                 index=[2, 3, 6, 7])
   ...:

In [9]: result = concat([df1, df4], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3
6	NaN	NaN	NaN	NaN	B6	D6	F6
7	NaN	NaN	NaN	NaN	B7	D7	F7

Note that the row indexes have been unioned and sorted. Here is the same thing with `join='inner'`:

```
In [10]: result = concat([df1, df4], axis=1, join='inner')
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:

```
In [11]: result = concat([df1, df4], axis=1, join_axes=[df1.index])
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

18.1.2 Concatenating using `append`

A useful shortcut to `concat` are the `append` instance methods on Series and DataFrame. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

```
In [12]: result = df1.append(df2)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

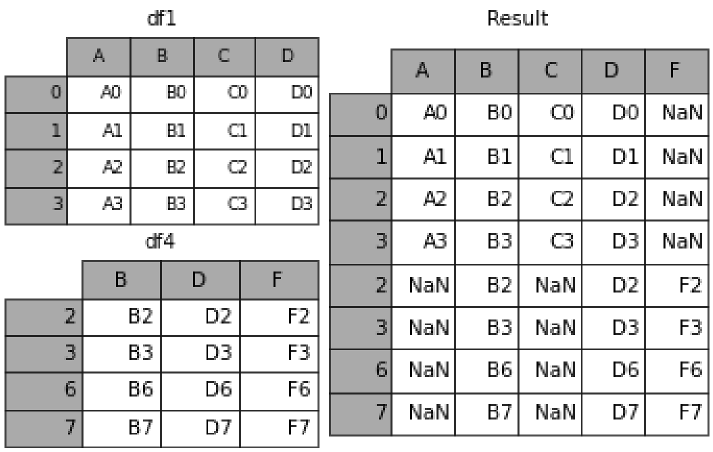
	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

Result

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

In the case of DataFrame, the indexes must be disjoint but the columns do not need to be:

```
In [13]: result = df1.append(df4)
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

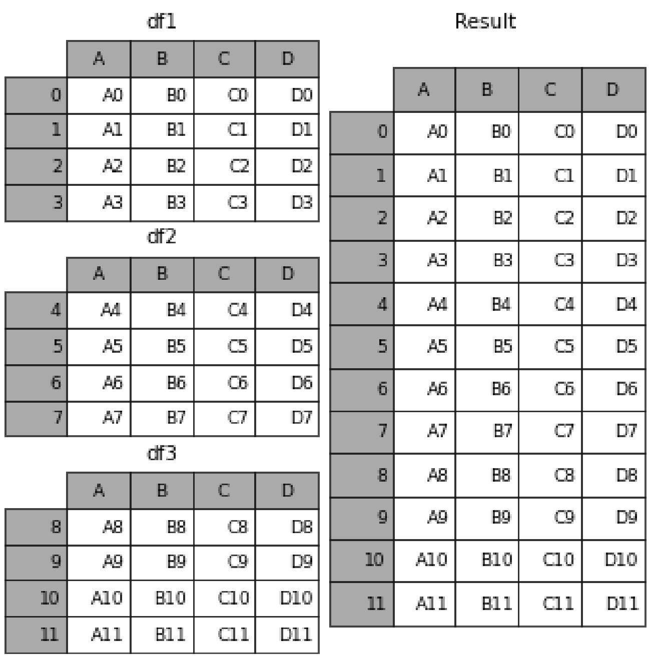
	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	F
0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	NaN
2	NaN	B2	NaN	D2	F2
3	NaN	B3	NaN	D3	F3
6	NaN	B6	NaN	D6	F6
7	NaN	B7	NaN	D7	F7

`append` may take multiple objects to concatenate:

```
In [14]: result = df1.append([df2, df3])
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

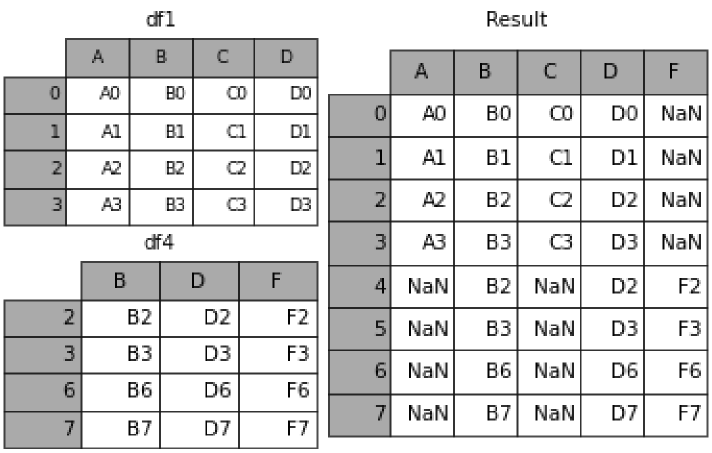
Note: Unlike *list.append* method, which appends to the original list and returns nothing, `append` here **does not** modify `df1` and returns its copy with `df2` appended.

18.1.3 Ignoring indexes on the concatenation axis

For DataFrames which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes:

To do this, use the `ignore_index` argument:

```
In [15]: result = concat([df1, df4], ignore_index=True)
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

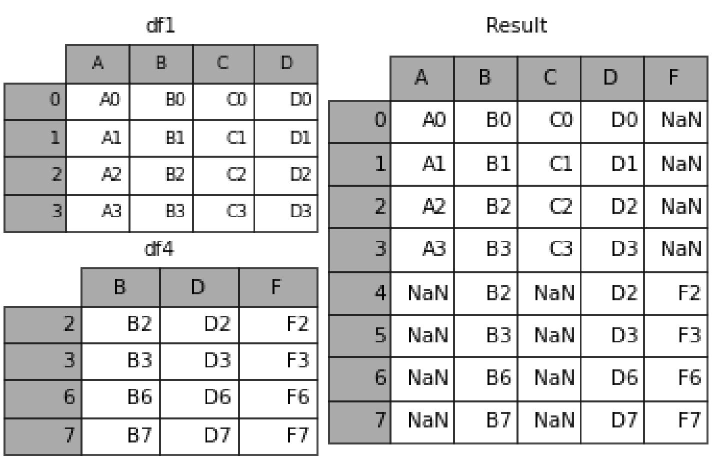
	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	F
0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	NaN
4	NaN	B2	NaN	D2	F2
5	NaN	B3	NaN	D3	F3
6	NaN	B6	NaN	D6	F6
7	NaN	B7	NaN	D7	F7

This is also a valid argument to `DataFrame.append`:

```
In [16]: result = df1.append(df4, ignore_index=True)
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	F
0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	NaN
4	NaN	B2	NaN	D2	F2
5	NaN	B3	NaN	D3	F3
6	NaN	B6	NaN	D6	F6
7	NaN	B7	NaN	D7	F7

18.1.4 Concatenating with mixed ndims

You can concatenate a mix of Series and DataFrames. The Series will be transformed to DataFrames with the column name as the name of the Series.

```
In [17]: s1 = Series(['X0', 'X1', 'X2', 'X3'], name='X')

In [18]: result = concat([df1, s1], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

	A	B	C	D	X
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

If unnamed Series are passed they will be numbered consecutively.

```
In [19]: s2 = Series(['_0', '_1', '_2', '_3'])

In [20]: result = concat([df1, s2, s2, s2], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s2

0	_0
1	_1
2	_2
3	_3

Result

	A	B	C	D	0	1	2
0	A0	B0	C0	D0	_0	_0	_0
1	A1	B1	C1	D1	_1	_1	_1
2	A2	B2	C2	D2	_2	_2	_2
3	A3	B3	C3	D3	_3	_3	_3

Passing `ignore_index=True` will drop all name references.

```
In [21]: result = concat([df1, s1], axis=1, ignore_index=True)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

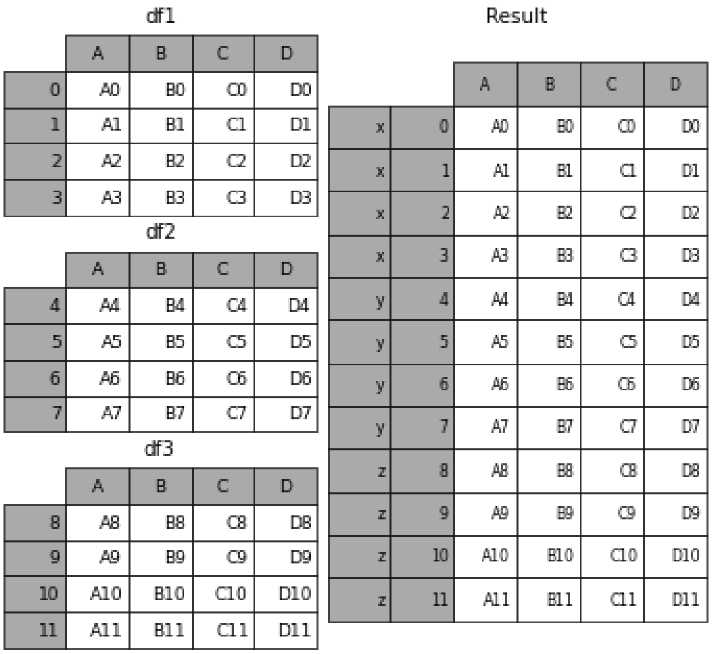
Result

	0	1	2	3	4
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

18.1.5 More concatenating with group keys

Let's consider a variation on the first example presented:

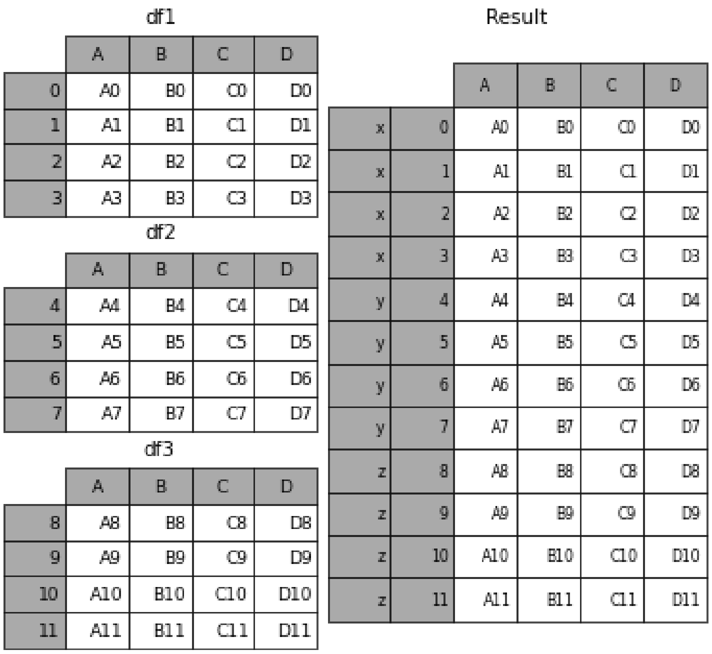
```
In [22]: result = concat(frames, keys=['x', 'y', 'z'])
```



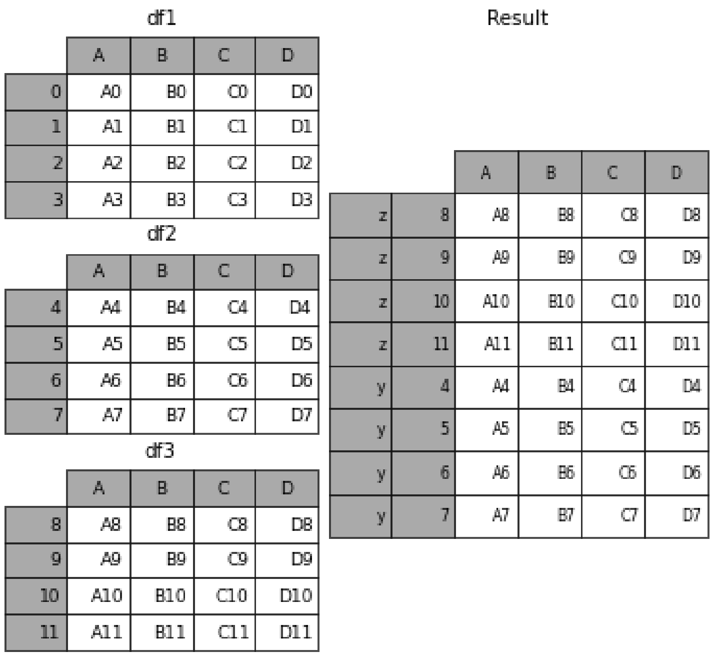
You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```
In [23]: pieces = {'x': df1, 'y': df2, 'z': df3}

In [24]: result = concat(pieces)
```



```
In [25]: result = concat(pieces, keys=['z', 'y'])
```



df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

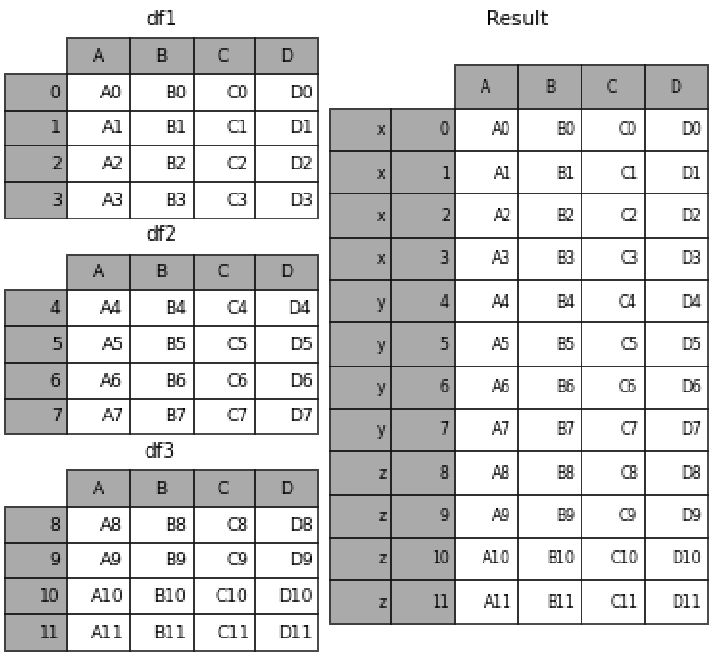
		A	B	C	D
z	8	A8	B8	C8	D8
z	9	A9	B9	C9	D9
z	10	A10	B10	C10	D10
z	11	A11	B11	C11	D11
y	4	A4	B4	C4	D4
y	5	A5	B5	C5	D5
y	6	A6	B6	C6	D6
y	7	A7	B7	C7	D7

The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame pieces:

```
In [26]: result.index.levels
Out[26]: FrozenList([[u'z', u'y'], [4, 5, 6, 7, 8, 9, 10, 11]])
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [27]: result = concat(pieces, keys=['x', 'y', 'z'],
   ....:                 levels=[['z', 'y', 'x', 'w']],
   ....:                 names=['group_key'])
   ....:
```




```
In [28]: result.index.levels
Out[28]: FrozenList([[u'z', u'y', u'x', u'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

Yes, this is fairly esoteric, but is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

18.1.6 Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a DataFrame by passing a Series or dict to `append`, which returns a new DataFrame as above.

```
In [29]: s2 = Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])

In [30]: result = df1.append(s2, ignore_index=True)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s2

A	X0
B	X1
C	X2
D	X3

Result

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	X0	X1	X2	X3

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 [31]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4},
   ....:          {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
   ....:

In [32]: result = df1.append(dicts, ignore_index=True)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

dicts

	A	B	C	X	Y
0	1	2	3	4.0	NaN
1	5	6	7	NaN	8.0

Result

	A	B	C	D	X	Y
0	A0	B0	C0	D0	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN
2	A2	B2	C2	D2	NaN	NaN
3	A3	B3	C3	D3	NaN	NaN
4	1	2	3	NaN	4.0	NaN
5	5	6	7	NaN	NaN	8.0

18.2 Database-style DataFrame joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and internal layout of the data in DataFrame.

See the *cookbook* for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a *comparison with SQL*.

pandas provides a single function, merge, as the entry point for all standard database join operations between DataFrame objects:

```
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)
```

Here's a description of what each argument is for:

- left: A DataFrame object
- right: Another DataFrame object
- on: Columns (names) to join on. Must be found in both the left and right DataFrame objects. If not passed and left_index and right_index are False, the intersection of the columns in the DataFrames will be inferred to be the join keys
- left_on: Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- right_on: Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- left_index: If True, use the index (row labels) from the left DataFrame as its join key(s). In the case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame
- right_index: Same usage as left_index for the right DataFrame
- how: One of 'left', 'right', 'outer', 'inner'. Defaults to inner. See below for more detailed description of each method
- sort: Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve performance substantially in many cases
- suffixes: A tuple of string suffixes to apply to overlapping columns. Defaults to ('_x', '_y').
- copy: Always copy data (default True) from the passed DataFrame objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.

The return type will be the same as left. If left is a DataFrame and right is a subclass of DataFrame, the return type will still be DataFrame.

merge is a function in the pandas namespace, and it is also available as a DataFrame instance method, with the calling DataFrame being implicitly considered the left object in the join.

The related DataFrame.join method, uses merge internally for the index-on-index and index-on-column(s) joins, but *joins on indexes* by default rather than trying to join on common columns (the default behavior for merge). If you are joining on index, you may wish to use DataFrame.join to save yourself some typing.

18.2.1 Brief primer on merge methods (relational algebra)

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (DataFrame objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two DataFrame objects on their indexes (which must contain unique values)
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a DataFrame

- **many-to-many** joins: joining columns on columns.

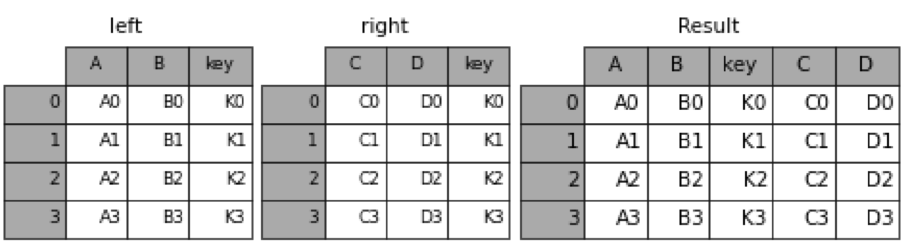
Note: When joining columns on columns (potentially a many-to-many join), any indexes on the passed DataFrame objects **will be discarded**.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```
In [33]: left = DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
   ....:                  'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                  'B': ['B0', 'B1', 'B2', 'B3']})
   ....:

In [34]: right = DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
   ....:                   'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                   'D': ['D0', 'D1', 'D2', 'D3']})
   ....:

In [35]: result = merge(left, right, on='key')
```



left

	A	B	key
0	A0	B0	K0
1	A1	B1	K1
2	A2	B2	K2
3	A3	B3	K3

right

	C	D	key
0	C0	D0	K0
1	C1	D1	K1
2	C2	D2	K2
3	C3	D3	K3

Result

	A	B	key	C	D
0	A0	B0	K0	C0	D0
1	A1	B1	K1	C1	D1
2	A2	B2	K2	C2	D2
3	A3	B3	K3	C3	D3

Here is a more complicated example with multiple join keys:

```
In [36]: left = DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
   ....:                  'key2': ['K0', 'K1', 'K0', 'K1'],
   ....:                  'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                  'B': ['B0', 'B1', 'B2', 'B3']})
   ....:

In [37]: right = DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
   ....:                   'key2': ['K0', 'K0', 'K0', 'K0'],
   ....:                   'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                   'D': ['D0', 'D1', 'D2', 'D3']})
   ....:

In [38]: result = merge(left, right, on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

	C	D	key1	key2
0	C0	D0	K0	K0
1	C1	D1	K1	K0
2	C2	D2	K1	K0
3	C3	D3	K2	K0

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A2	B2	K1	K0	C1	D1
2	A2	B2	K1	K0	C2	D2

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:

Merge method	SQL Join Name	Description
`left`	`LEFT OUTER JOIN`	Use keys from left frame only
`right`	`RIGHT OUTER JOIN`	Use keys from right frame only
`outer`	`FULL OUTER JOIN`	Use union of keys from both frames
`inner`	`INNER JOIN`	Use intersection of keys from both frames

```
In [39]: result = merge(left, right, how='left', on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

	C	D	key1	key2
0	C0	D0	K0	K0
1	C1	D1	K1	K0
2	C2	D2	K1	K0
3	C3	D3	K2	K0

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A1	B1	K0	K1	NaN	NaN
2	A2	B2	K1	K0	C1	D1
3	A2	B2	K1	K0	C2	D2
4	A3	B3	K2	K1	NaN	NaN

```
In [40]: result = merge(left, right, how='right', on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

	C	D	key1	key2
0	C0	D0	K0	K0
1	C1	D1	K1	K0
2	C2	D2	K1	K0
3	C3	D3	K2	K0

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A2	B2	K1	K0	C1	D1
2	A2	B2	K1	K0	C2	D2
3	NaN	NaN	K2	K0	C3	D3

```
In [41]: result = merge(left, right, how='outer', on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

	C	D	key1	key2
0	C0	D0	K0	K0
1	C1	D1	K1	K0
2	C2	D2	K1	K0
3	C3	D3	K2	K0

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A1	B1	K0	K1	NaN	NaN
2	A2	B2	K1	K0	C1	D1
3	A2	B2	K1	K0	C2	D2
4	A3	B3	K2	K1	NaN	NaN
5	NaN	NaN	K2	K0	C3	D3

```
In [42]: result = merge(left, right, how='inner', on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

	C	D	key1	key2
0	C0	D0	K0	K0
1	C1	D1	K1	K0
2	C2	D2	K1	K0
3	C3	D3	K2	K0

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A2	B2	K1	K0	C1	D1
2	A2	B2	K1	K0	C2	D2

18.2.2 Joining on index

`DataFrame.join` is a convenient method for combining the columns of two potentially differently-indexed DataFrames into a single result DataFrame. Here is a very basic example:

```
In [43]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
   ....:                   'B': ['B0', 'B1', 'B2']},
   ....:                   index=['K0', 'K1', 'K2'])
   ....:

In [44]: right = DataFrame({'C': ['C0', 'C2', 'C3'],
   ....:                    'D': ['D0', 'D2', 'D3']},
   ....:                    index=['K0', 'K2', 'K3'])
   ....:

In [45]: result = left.join(right)
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2

```
In [46]: result = left.join(right, how='outer')
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2
K3	NaN	NaN	C3	D3

```
In [47]: result = left.join(right, how='inner')
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K2	A2	B2	C2	D2

The data alignment here is on the indexes (row labels). This same behavior can be achieved using `merge` plus additional arguments instructing it to use the indexes:

```
In [48]: result = merge(left, right, left_index=True, right_index=True, how='outer')
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2
K3	NaN	NaN	C3	D3

```
In [49]: result = merge(left, right, left_index=True, right_index=True, how='inner');
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K2	A2	B2	C2	D2

18.2.3 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:

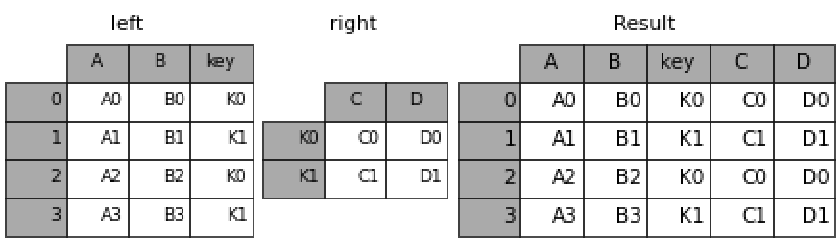
```
left.join(right, on=key_or_keys)
merge(left, right, left_on=key_or_keys, right_index=True,
      how='left', sort=False)
```

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:

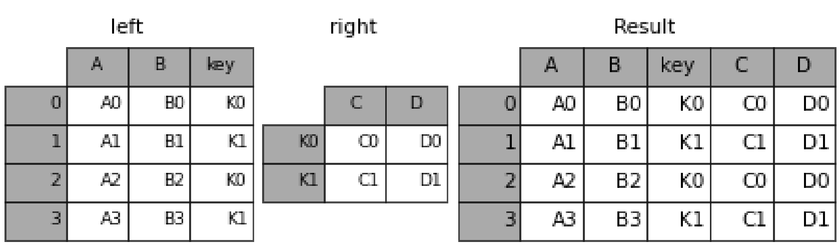
```
In [50]: left = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                   'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                   'key': ['K0', 'K1', 'K0', 'K1']})
   ....:

In [51]: right = DataFrame({'C': ['C0', 'C1'],
   ....:                    'D': ['D0', 'D1']},
   ....:                   index=['K0', 'K1'])
   ....:

In [52]: result = left.join(right, on='key')
```




```
In [53]: result = merge(left, right, left_on='key', right_index=True,
   ....:                how='left', sort=False);
   ....:
```



To join on multiple keys, the passed DataFrame must have a `MultiIndex`:

```
In [54]: left = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                   'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                   'key1': ['K0', 'K0', 'K1', 'K2'],
```

```
   ....:                     'key2': ['K0', 'K1', 'K0', 'K1']})
   ....:

In [55]: index = MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'),
   ....:                                  ('K2', 'K0'), ('K2', 'K1')])
   ....:

In [56]: right = DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                     'D': ['D0', 'D1', 'D2', 'D3']},
   ....:                    index=index)
   ....:
```

Now this can be joined by passing the two key column names:

```
In [57]: result = left.join(right, on=['key1', 'key2'])
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

		C	D
K0	K0	C0	D0
K1	K0	C1	D1
K2	K0	C2	D2
K2	K1	C3	D3

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
1	A1	B1	K0	K1	NaN	NaN
2	A2	B2	K1	K0	C1	D1
3	A3	B3	K2	K1	C3	D3

The default for `DataFrame.join` is to perform a left join (essentially a "VLOOKUP" operation, for Excel users), which uses only the keys found in the calling DataFrame. Other join types, for example inner join, can be just as easily performed:

```
In [58]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

left

	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

right

		C	D
K0	K0	C0	D0
K1	K0	C1	D1
K2	K0	C2	D2
K2	K1	C3	D3

Result

	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
2	A2	B2	K1	K0	C1	D1
3	A3	B3	K2	K1	C3	D3

As you can see, this drops any rows where there was no match.

18.2.4 Joining a single Index to a Multi-index

New in version 0.14.0.

You can join a singly-indexed `DataFrame` with a level of a multi-indexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the multi-indexed frame.

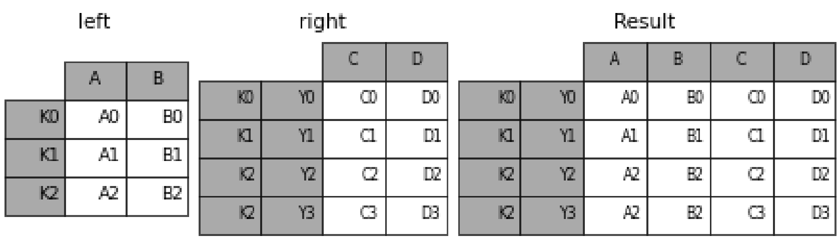
```
In [59]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
   ....:                   'B': ['B0', 'B1', 'B2']},
```

```
   ....:                   index=Index(['K0', 'K1', 'K2'], name='key'))
   ....:

In [60]: index = MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
   ....:                                 ('K2', 'Y2'), ('K2', 'Y3')],
   ....:                                names=['key', 'Y'])
   ....:

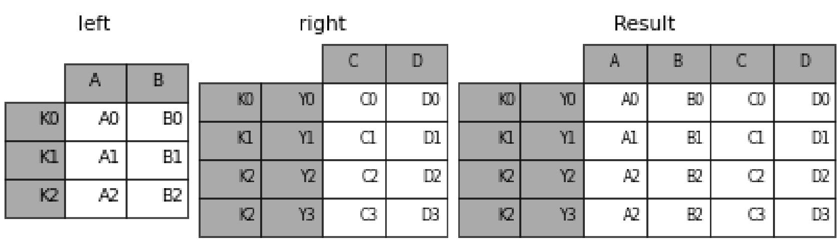
In [61]: right = DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                    'D': ['D0', 'D1', 'D2', 'D3']},
   ....:                   index=index)
   ....:

In [62]: result = left.join(right, how='inner')
```



This is equivalent but less verbose and more memory efficient / faster than this.

```
In [63]: result = merge(left.reset_index(), right.reset_index(),
   ....:       on=['key'], how='inner').set_index(['key','Y'])
   ....:
```



18.2.5 Joining with two multi-indexes

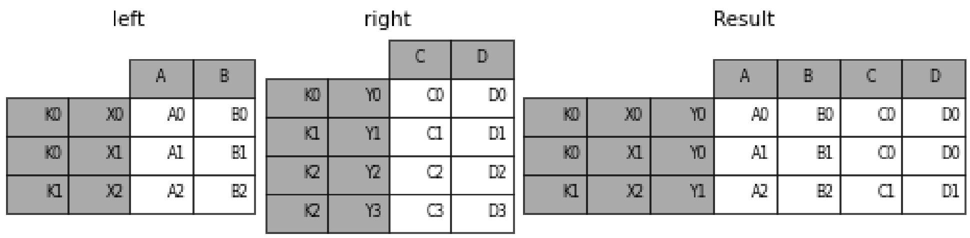
This is not Implemented via `join` at-the-moment, however it can be done using the following.

```
In [64]: index = MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
   ....:                                 ('K1', 'X2')],
   ....:                                names=['key', 'X'])
   ....:

In [65]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
   ....:                   'B': ['B0', 'B1', 'B2']},
```

```
   ....:                  index=index)
   ....:

In [66]: result = merge(left.reset_index(), right.reset_index(),
   ....:                on=['key'], how='inner').set_index(['key','X','Y'])
   ....:
```



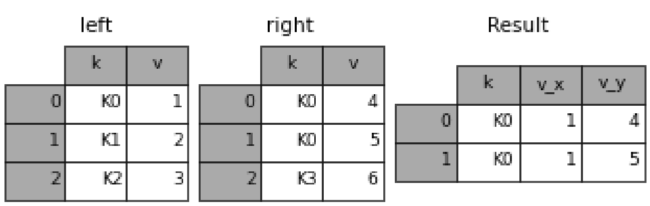
18.2.6 Overlapping value columns

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:

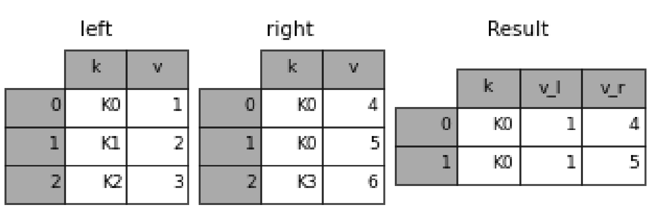
```
In [67]: left = DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [68]: right = DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

In [69]: result = merge(left, right, on='k')
```




```
In [70]: result = merge(left, right, on='k', suffixes=['_l', '_r'])
```

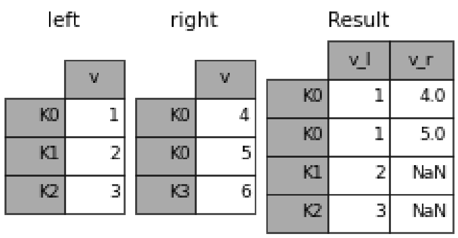


`DataFrame.join` has `lsuffix` and `rsuffix` arguments which behave similarly.

```
In [71]: left = left.set_index('k')

In [72]: right = right.set_index('k')

In [73]: result = left.join(right, lsuffix='_l', rsuffix='_r')
```

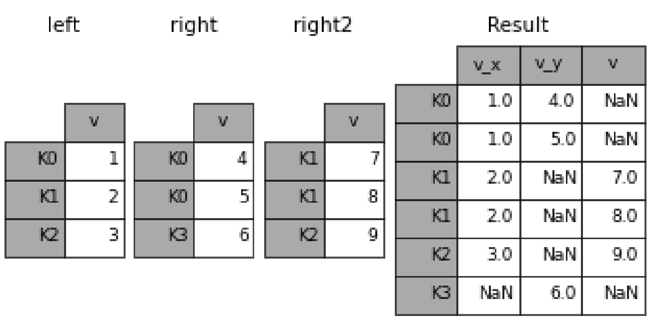


18.2.7 Joining multiple DataFrame or Panel objects

A list or tuple of DataFrames can also be passed to `DataFrame.join` to join them together on their indexes. The same is true for `Panel.join`.

```
In [74]: right2 = DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])

In [75]: result = left.join([right, right2])
```



18.2.8 Merging Ordered Data

New in v0.8.0 is the ordered_merge function for combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [76]: left = DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
   ....:                   'lv': [1, 2, 3, 4],
   ....:                   's': ['a', 'b', 'c', 'd']})
   ....:

In [77]: right = DataFrame({'k': ['K1', 'K2', 'K4'],
   ....:                    'rv': [1, 2, 3]})
```

```
   ....:

In [78]: result = ordered_merge(left, right, fill_method='ffill', left_by='s')
```

left

	k	lv	s
0	K0	1	a
1	K1	2	b
2	K1	3	c
3	K2	4	d

right

	k	rv
0	K1	1
1	K2	2
2	K4	3

Result

	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

18.2.9 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 [79]: df1 = DataFrame([[nan, 3., 5.], [-4.6, np.nan, nan],
   ....:                   [nan, 7., nan]])
   ....:

In [80]: df2 = DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4]],
   ....:                  index=[1, 2])
   ....:
```

For this, use the `combine_first` method:

```
In [81]: result = df1.combine_first(df2)
```

df1

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	NaN
2	NaN	7.0	NaN

df2

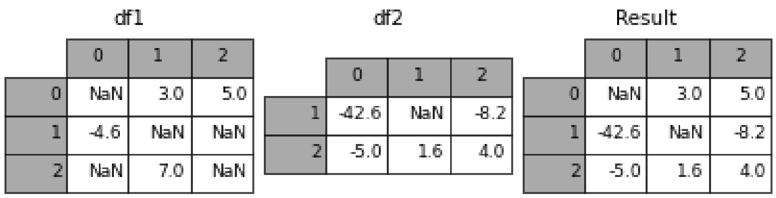
	0	1	2
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

Result

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	-8.2
2	-5.0	7.0	4.0

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 [82]: df1.update(df2)
```



CHAPTER

NINETEEN

RESHAPING AND PIVOT TABLES

19.1 Reshaping by pivoting DataFrame objects

Data is often stored in CSV files or databases in so-called "stacked" or "record" format:

```
In [1]: df
Out[1]:
          date variable     value
0   2000-01-03        A  0.469112
1   2000-01-04        A -0.282863
2   2000-01-05        A -1.509059
3   2000-01-03        B -1.135632
4   2000-01-04        B  1.212112
5   2000-01-05        B -0.173215
6   2000-01-03        C  0.119209
7   2000-01-04        C -1.044236
8   2000-01-05        C -0.861849
9   2000-01-03        D -2.104569
10  2000-01-04        D -0.494929
11  2000-01-05        D  1.071804
```

For the curious here is how the above DataFrame was created:

```
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:

```
In [2]: df[df['variable'] == 'A']
Out[2]:
        date variable     value
0 2000-01-03        A  0.469112
1 2000-01-04        A -0.282863
2 2000-01-05        A -1.509059
```

But suppose we wish to do time series operations with the variables. A better representation would be where the columns are the unique variables and an index of dates identifies individual observations. To reshape the data into this form, use the pivot function:

```
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
variable           A         B         C         D
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804
```

If the values argument is omitted, and the input DataFrame has more than one column of values which are not used as column or index inputs to pivot, then the resulting "pivoted" DataFrame will have *hierarchical columns* whose topmost level indicates the respective value column:

```
In [4]: df['value2'] = df['value'] * 2

In [5]: pivoted = df.pivot('date', 'variable')

In [6]: pivoted
Out[6]:
               value                                  value2                \
variable           A         B         C         D         A         B
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569  0.938225 -2.271265
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429


variable           C         D
date
2000-01-03  0.238417 -4.209138
2000-01-04 -2.088472 -0.989859
2000-01-05 -1.723698  2.143608
```

You of course can then select subsets from the pivoted DataFrame:

```
In [7]: pivoted['value2']
Out[7]:
variable           A         B         C         D
date
2000-01-03  0.938225 -2.271265  0.238417 -4.209138
2000-01-04 -0.565727  2.424224 -2.088472 -0.989859
2000-01-05 -3.018117 -0.346429 -1.723698  2.143608
```

Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

19.2 Reshaping by stacking and unstacking

Closely related to the pivot function are the related stack and unstack functions currently available on Series and DataFrame. These functions are designed to work together with MultiIndex objects (see the section on *hierarchical indexing*). Here are essentially what these functions do:

- stack: "pivot" a level of the (possibly hierarchical) column labels, returning a DataFrame with an index with a new inner-most level of row labels.
- unstack: inverse operation from stack: "pivot" a level of the (possibly hierarchical) row index to the column axis, producing a reshaped DataFrame with a new inner-most level of column labels.

The clearest way to explain is by example. Let's take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
   ...:                      'foo', 'foo', 'qux', 'qux'],
   ...:                     ['one', 'two', 'one', 'two',
   ...:                      'one', 'two', 'one', 'two']]))
   ...:

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [11]: df2 = df[:4]

In [12]: df2
Out[12]:
                     A         B
first second
bar   one     0.721555 -0.706771
      two    -1.039575  0.271860
baz   one    -0.424972  0.567020
      two     0.276232 -1.087401
```

The `stack` function "compresses" a level in the DataFrame's columns to produce either:

- A Series, in the case of a simple column Index
- A DataFrame, in the case of a `MultiIndex` in the columns

If the columns have a `MultiIndex`, you can choose which level to stack. The stacked level becomes the new lowest level in a `MultiIndex` on the columns:

```
In [13]: stacked = df2.stack()

In [14]: stacked
Out[14]:
first  second
bar    one     A    0.721555
               B   -0.706771
       two     A   -1.039575
               B    0.271860
baz    one     A   -0.424972
               B    0.567020
       two     A    0.276232
               B   -1.087401
dtype: float64
```

With a "stacked" DataFrame or Series (having a `MultiIndex` as the `index`), the inverse operation of `stack` is `unstack`, which by default unstacks the **last level**:

```
In [15]: stacked.unstack()
Out[15]:
                     A         B
first second
bar   one     0.721555 -0.706771
      two    -1.039575  0.271860
baz   one    -0.424972  0.567020
      two     0.276232 -1.087401

In [16]: stacked.unstack(1)
Out[16]:
second        one       two
```

```
first
bar    A  0.721555 -1.039575
       B -0.706771  0.271860
baz    A -0.424972  0.276232
       B  0.567020 -1.087401

In [17]: stacked.unstack(0)
Out[17]:
first          bar       baz
second
one     A  0.721555 -0.424972
        B -0.706771  0.567020
two     A -1.039575  0.276232
        B  0.271860 -1.087401
```

If the indexes have names, you can use the level names instead of specifying the level numbers:

```
In [18]: stacked.unstack('second')
Out[18]:
second        one       two
first
bar    A  0.721555 -1.039575
       B -0.706771  0.271860
baz    A -0.424972  0.276232
       B  0.567020 -1.087401
```

Notice that the `stack` and `unstack` methods implicitly sort the index levels involved. Hence a call to `stack` and then `unstack`, or viceversa, 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())
Out[22]: True
```

while the above code will raise a `TypeError` if the call to `sort` is removed.

19.2.1 Multiple Levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.

```
In [23]: columns = pd.MultiIndex.from_tuples([
   ....:         ('A', 'cat', 'long'), ('B', 'cat', 'long'),
   ....:         ('A', 'dog', 'short'), ('B', 'dog', 'short')
   ....:     ],
   ....:     names=['exp', 'animal', 'hair_length']
   ....: )
   ....:
```

```
In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)

In [25]: df
Out[25]:
exp                   A         B         A         B
animal              cat       cat       dog       dog
hair_length        long      long     short     short
0              1.075770 -0.109050  1.643563 -1.469388
1              0.357021 -0.674600 -1.776904 -0.968914
2             -1.294524  0.413738  0.276662 -0.472035
3             -0.013960 -0.362543 -0.006154 -0.923061

In [26]: df.stack(level=['animal', 'hair_length'])
Out[26]:
exp                          A         B
  animal hair_length
0 cat    long         1.075770 -0.109050
  dog    short        1.643563 -1.469388
1 cat    long         0.357021 -0.674600
  dog    short       -1.776904 -0.968914
2 cat    long        -1.294524  0.413738
  dog    short        0.276662 -0.472035
3 cat    long        -0.013960 -0.362543
  dog    short       -0.006154 -0.923061
```

The list of levels can contain either level names or level numbers (but not a mixture of the two).

```
# df.stack(level=['animal', 'hair_length'])
# from above is equivalent to:
In [27]: df.stack(level=[1, 2])
Out[27]:
exp                          A         B
  animal hair_length
0 cat    long         1.075770 -0.109050
  dog    short        1.643563 -1.469388
1 cat    long         0.357021 -0.674600
  dog    short       -1.776904 -0.968914
2 cat    long        -1.294524  0.413738
  dog    short        0.276662 -0.472035
3 cat    long        -0.013960 -0.362543
  dog    short       -0.006154 -0.923061
```

19.2.2 Missing Data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sortlevel`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
   ....:                                      ('B', 'cat'), ('A', 'dog')],
   ....:                                     names=['exp', 'animal'])
   ....:

In [29]: index = pd.MultiIndex.from_product([('bar', 'baz', 'foo', 'qux'),
   ....:                                     ('one', 'two')],
   ....:                                    names=['first', 'second'])
```

```
   ....:

In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.ix[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
exp                   A         B                   A
animal              cat       dog       cat       dog
first second
bar   one     0.895717  0.805244 -1.206412  2.565646
      two     1.431256  1.340309 -1.170299 -0.226169
baz   one     0.410835  0.813850  0.132003 -0.827317
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]:
animal                 cat       dog
first second exp
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]:
exp                         A         B
first second animal
bar   one    cat     0.895717 -1.206412
             dog     2.565646  0.805244
      two    cat     1.431256 -1.170299
             dog    -0.226169  1.340309
baz   one    cat     0.410835  0.132003
             dog    -0.827317  0.813850
foo   one    cat    -1.413681  1.024180
             dog     0.569605  1.607920
      two    cat     0.875906  0.974466
             dog    -2.006747 -2.211372
qux   two    cat    -1.226825 -1.281247
             dog    -0.727707  0.769804
```

19.2.3 With a MultiIndex

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```
In [35]: df[:3].unstack(0)
Out[35]:
exp             A                   B                                     A   \
animal        cat                 dog                cat                dog
first         bar       baz       bar       baz      bar       baz      bar
second
one      0.895717  0.410835  0.805244   0.81385 -1.206412  0.132003  2.565646
two      1.431256       NaN  1.340309       NaN -1.170299       NaN -0.226169

exp
animal
first         baz
second
one     -0.827317
two           NaN

In [36]: df2.unstack(1)
Out[36]:
exp             A                   B                                     A   \
animal        cat                 dog                 cat                dog
second        one       two       one       two       one       two      one
first
bar      0.895717  1.431256  0.805244  1.340309 -1.206412 -1.170299  2.565646
baz      0.410835       NaN  0.813850       NaN  0.132003       NaN -0.827317
foo     -1.413681  0.875906  1.607920 -2.211372  1.024180  0.974466  0.569605
qux           NaN -1.226825       NaN  0.769804       NaN -1.281247       NaN

exp
animal
second        two
first
bar     -0.226169
baz           NaN
foo     -2.006747
qux     -0.727707
```

19.3 Reshaping by Melt

The `melt()` function is useful to massage a DataFrame into a format where one or more columns are identifier variables, while all other columns, considered measured variables, are "unpivoted" to the row axis, leaving just two non-identifier columns, "variable" and "value". The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```
In [37]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
   ....:                        'last' : ['Doe', 'Bo'],
   ....:                        'height' : [5.5, 6.0],
   ....:                        'weight' : [130, 150]})
   ....:

In [38]: cheese
Out[38]:
  first  height last  weight
0  John     5.5  Doe     130
1  Mary     6.0   Bo     150
```

```
In [39]: pd.melt(cheese, id_vars=['first', 'last'])
Out[39]:
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [40]: pd.melt(cheese, id_vars=['first', 'last'], var_name='quantity')
Out[40]:
  first last quantity  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0
```

Another way to transform is to use the `wide_to_long` panel data convenience function.

```
In [41]: dft = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
   ....:                     "A1980" : {0 : "d", 1 : "e", 2 : "f"},
   ....:                     "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
   ....:                     "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
   ....:                     "X"     : dict(zip(range(3), np.random.randn(3)))
   ....:                    })
   ....:

In [42]: dft["id"] = dft.index

In [43]: dft
Out[43]:
  A1970 A1980  B1970  B1980         X  id
0     a     d    2.5    3.2 -0.121306   0
1     b     e    1.2    1.3 -0.097883   1
2     c     f    0.7    0.1  0.695775   2

In [44]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
Out[44]:
                X  A    B
id year
0  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
```

19.4 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 [45]: df
Out[45]:
exp                  A         B                   A
animal             cat       dog       cat       dog
first second
```

```
bar   one     0.895717  0.805244 -1.206412  2.565646
      two     1.431256  1.340309 -1.170299 -0.226169
baz   one     0.410835  0.813850  0.132003 -0.827317
      two    -0.076467 -1.187678  1.130127 -1.436737
foo   one    -1.413681  1.607920  1.024180  0.569605
      two     0.875906 -2.211372  0.974466 -2.006747
qux   one    -0.410001 -0.078638  0.545952 -1.219217
      two    -1.226825  0.769804 -1.281247 -0.727707

In [46]: df.stack().mean(1).unstack()
Out[46]:
animal             cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

# same result, another way
In [47]: df.groupby(level=1, axis=1).mean()
Out[47]:
animal             cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

In [48]: df.stack().groupby(level=1).mean()
Out[48]:
exp            A         B
second
one     0.071448  0.455513
two    -0.424186 -0.204486

In [49]: df.mean().unstack(0)
Out[49]:
exp            A         B
animal
cat     0.060843  0.018596
dog    -0.413580  0.232430
```

19.5 Pivot tables and cross-tabulations

The function `pandas.pivot_table` can be used to create spreadsheet-style pivot tables. See the *cookbook* for some advanced strategies

It takes a number of arguments

- `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 [50]: import datetime

In [51]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 6,
   ....:                    'B': ['A', 'B', 'C'] * 8,
   ....:                    'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 4,
   ....:                    'D': np.random.randn(24),
   ....:                    'E': np.random.randn(24),
   ....:                    'F': [datetime.datetime(2013, i, 1) for i in range(1, 13)] +
   ....:                         [datetime.datetime(2013, i, 15) for i in range(1, 13)]})
   ....:

In [52]: df
Out[52]:
        A  B    C         D         E          F
0     one  A  foo  0.341734 -0.317441 2013-01-01
1     one  B  foo  0.959726 -1.236269 2013-02-01
2     two  C  foo -1.110336  0.896171 2013-03-01
3   three  A  bar -0.619976 -0.487602 2013-04-01
4     one  B  bar  0.149748 -0.082240 2013-05-01
5     one  C  bar -0.732339 -2.182937 2013-06-01
6     two  A  foo  0.687738  0.380396 2013-07-01
..    ... ..  ...       ...       ...        ...
17    one  C  bar -0.345352  0.206053 2013-06-15
18    two  A  foo  1.314232 -0.251905 2013-07-15
19  three  B  foo  0.690579 -2.213588 2013-08-15
20    one  C  foo  0.995761  1.063327 2013-09-15
21    one  A  bar  2.396780  1.266143 2013-10-15
22    two  B  bar  0.014871  0.299368 2013-11-15
23  three  C  bar  3.357427 -0.863838 2013-12-15

[24 rows x 6 columns]
```

We can produce pivot tables from this data very easily:

```
In [53]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[53]:
C             bar       foo
A     B
one   A  1.120915 -0.514058
      B -0.338421  0.002759
      C -0.538846  0.699535
three A -1.181568       NaN
      B       NaN  0.433512
      C  0.588783       NaN
two   A       NaN  1.000985
      B  0.158248       NaN
      C       NaN  0.176180
```

```
In [54]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[54]:
A       one               three                 two
C       bar       foo       bar       foo       bar       foo
B
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360

In [55]: pd.pivot_table(df, values=['D','E'], index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[55]:
          D                                                           E  \
A       one               three                 two                 one
C       bar       foo       bar       foo       bar       foo       bar
B
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971  2.786113
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN  1.368280
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360 -1.976883


A                 three                 two
C       foo       bar       foo       bar       foo
B
A -0.043211  1.922577       NaN       NaN  0.128491
B -1.103384       NaN -2.128743 -0.194294       NaN
C  1.495717 -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:

```
In [56]: pd.pivot_table(df, index=['A', 'B'], columns=['C'])
Out[56]:
                D                   E
C             bar       foo       bar       foo
A     B
one   A  1.120915 -0.514058  1.393057 -0.021605
      B -0.338421  0.002759  0.684140 -0.551692
      C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568       NaN  0.961289       NaN
      B       NaN  0.433512       NaN -1.064372
      C  0.588783       NaN -0.131830       NaN
two   A       NaN  1.000985       NaN  0.064245
      B  0.158248       NaN -0.097147       NaN
      C       NaN  0.176180       NaN  0.436241
```

Also, you can use `Grouper` for `index` and `columns` keywords. For detail of `Grouper`, see *Grouping with a Grouper specification*.

```
In [57]: pd.pivot_table(df, values='D', index=Grouper(freq='M', key='F'), columns='C')
Out[57]:
C                 bar       foo
F
2013-01-31        NaN -0.514058
2013-02-28        NaN  0.002759
2013-03-31        NaN  0.176180
2013-04-30 -1.181568       NaN
2013-05-31 -0.338421       NaN
```

```
2013-06-30 -0.538846       NaN
2013-07-31       NaN  1.000985
2013-08-31       NaN  0.433512
2013-09-30       NaN  0.699535
2013-10-31  1.120915       NaN
2013-11-30  0.158248       NaN
2013-12-31  0.588783       NaN
```

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```
In [58]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])

In [59]: print(table.to_string(na_rep=''))
                D                   E          
C             bar       foo       bar       foo
A     B                                        
one   A  1.120915 -0.514058  1.393057 -0.021605
      B -0.338421  0.002759  0.684140 -0.551692
      C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568            0.961289          
      B            0.433512           -1.064372
      C  0.588783           -0.131830          
two   A            1.000985            0.064245
      B  0.158248           -0.097147          
      C            0.176180            0.436241
```

Note that `pivot_table` is also available as an instance method on DataFrame.

19.5.1 Cross tabulations

Use the `crosstab` function to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index`: array-like, values to group by in the rows
- `columns`: array-like, values to group by in the columns
- `values`: array-like, optional, array of values to aggregate according to the factors
- `aggfunc`: function, optional, If no values array is passed, computes a frequency table
- `rownames`: sequence, default None, must match number of row arrays passed
- `colnames`: sequence, default None, if passed, must match number of column arrays passed
- `margins`: boolean, default False, Add row/column margins (subtotals)

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [60]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'

In [61]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)

In [62]: b = np.array([one, one, two, one, two, one], dtype=object)

In [63]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)
```

```
In [64]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
Out[64]:
b    one        two
c   dull shiny dull shiny
a
bar    1     0    0     1
foo    2     1    1     0
```

19.5.2 Adding margins (partial aggregates)

If you pass `margins=True` to `pivot_table`, special `All` columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [65]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[65]:
                D                             E
C             bar       foo       All       bar       foo       All
A     B
one   A  1.804346  1.210272  1.569879  0.179483  0.418374  0.858005
      B  0.690376  1.353355  0.898998  1.083825  0.968138  1.101401
      C  0.273641  0.418926  0.771139  1.689271  0.446140  1.422136
three A  0.794212       NaN  0.794212  2.049040       NaN  2.049040
      B       NaN  0.363548  0.363548       NaN  1.625237  1.625237
      C  3.915454       NaN  3.915454  1.035215       NaN  1.035215
two   A       NaN  0.442998  0.442998       NaN  0.447104  0.447104
      B  0.202765       NaN  0.202765  0.560757       NaN  0.560757
      C       NaN  1.819408  1.819408       NaN  0.650439  0.650439
All      1.556686  0.952552  1.246608  1.250924  0.899904  1.059389
```

19.6 Tiling

The `cut` function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```
In [66]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [67]: pd.cut(ages, bins=3)
Out[67]:
[(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
Categories (3, object): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60]]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [68]: pd.cut(ages, bins=[0, 18, 35, 70])
Out[68]:
[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]]
Categories (3, object): [(0, 18] < (18, 35] < (35, 70]]
```

19.7 Computing indicator / dummy variables

To convert a categorical variable into a "dummy" or "indicator" DataFrame, for example a column in a DataFrame (a Series) which has `k` distinct values, can derive a DataFrame containing `k` columns of 1s and 0s:

```
In [69]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})

In [70]: pd.get_dummies(df['key'])
Out[70]: 
   a  b  c
0  0  1  0
1  0  1  0
2  1  0  0
3  0  0  1
4  1  0  0
5  0  1  0
```

Sometimes it's useful to prefix the column names, for example when merging the result with the original DataFrame:

```
In [71]: dummies = pd.get_dummies(df['key'], prefix='key')

In [72]: dummies
Out[72]: 
   key_a  key_b  key_c
0      0      1      0
1      0      1      0
2      1      0      0
3      0      0      1
4      1      0      0
5      0      1      0

In [73]: df[['data1']].join(dummies)
Out[73]: 
   data1  key_a  key_b  key_c
0      0      0      1      0
1      1      0      1      0
2      2      1      0      0
3      3      0      0      1
4      4      1      0      0
5      5      0      1      0
```

This function is often used along with discretization functions like `cut`:

```
In [74]: values = np.random.randn(10)

In [75]: values
Out[75]: 
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29  ,
        0.0824, -0.0558,  0.5366])

In [76]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [77]: pd.get_dummies(pd.cut(values, bins))
Out[77]: 
   (0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1]
0         0           0           1           0         0
1         0           0           0           0         0
2         0           0           0           0         0
3         0           0           0           0         0
4         1           0           0           0         0
5         0           0           0           0         0
6         0           0           0           0         0
7         1           0           0           0         0
8         0           0           0           0         0
```

```
9         0           0           1           0         0
```

See also Series.str.get_dummies.

New in version 0.15.0.

get_dummies() also accepts a DataFrame. By default all categorical variables (categorical in the statistical sense, those with *object* or *categorical* dtype) are encoded as dummy variables.

```
In [78]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
   ....:                    'C': [1, 2, 3]})
   ....:

In [79]: pd.get_dummies(df)
Out[79]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0
```

All non-object columns are included untouched in the output.

You can control the columns that are encoded with the `columns` keyword.

```
In [80]: pd.get_dummies(df, columns=['A'])
Out[80]:
   B  C  A_a  A_b
0  c  1    1    0
1  c  2    0    1
2  b  3    1    0
```

Notice that the `B` column is still included in the output, it just hasn't been encoded. You can drop `B` before calling `get_dummies` if you don't want to include it in the output.

As with the Series version, you can pass values for the `prefix` and `prefix_sep`. By default the column name is used as the prefix, and '_' as the prefix separator. You can specify `prefix` and `prefix_sep` in 3 ways

- string: Use the same value for `prefix` or `prefix_sep` for each column to be encoded
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix

```
In [81]: simple = pd.get_dummies(df, prefix='new_prefix')

In [82]: simple
Out[82]:
   C  new_prefix_a  new_prefix_b  new_prefix_b  new_prefix_c
0  1             1             0             0             1
1  2             0             1             0             1
2  3             1             0             1             0

In [83]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])

In [84]: from_list
Out[84]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1         1         0         0         1
1  2         0         1         0         1
2  3         1         0         1         0

In [85]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})
```

```
In [86]: from_dict
Out[86]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1         1         0         0         1
1  2         0         1         0         1
2  3         1         0         1         0
```

19.8 Factorizing values

To encode 1-d values as an enumerated type use `factorize`:

```
In [87]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])

In [88]: x
Out[88]:
0       A
1       A
2     NaN
3       B
4    3.14
5     inf
dtype: object

In [89]: labels, uniques = pd.factorize(x)

In [90]: labels
Out[90]: array([ 0,  0, -1,  1,  2,  3])

In [91]: uniques
Out[91]: Index([u'A', u'B', 3.14, inf], dtype='object')
```

Note that `factorize` is similar to `numpy.unique`, but differs in its handling of NaN:

Note: The following `numpy.unique` will fail under Python 3 with a `TypeError` because of an ordering bug. See also Here

```
In [92]: pd.factorize(x, sort=True)
Out[92]:
(array([ 2,  2, -1,  3,  0,  1]),
 Index([3.14, inf, u'A', u'B'], dtype='object'))

In [93]: np.unique(x, return_inverse=True)[::-1]
Out[93]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

Note: If you just want to handle one column as a categorical variable (like R's factor), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on `Categorical`, see the *Categorical introduction* and the *API documentation*. This feature was introduced in version 0.15.

CHAPTER

TWENTY

TIME SERIES / DATE FUNCTIONALITY

pandas has proven very successful as a tool for working with time series data, especially in the financial data analysis space. With the 0.8 release, we have further improved the time series API in pandas by leaps and bounds. Using the new NumPy `datetime64` dtype, we have consolidated a large number of features from other Python libraries like `scikits.timeseries` as well as created a tremendous amount of new functionality for manipulating time series data.

In working with time series data, we will frequently seek to:

- generate sequences of fixed-frequency dates and time spans
- conform or convert time series to a particular frequency
- compute "relative" dates based on various non-standard time increments (e.g. 5 business days before the last business day of the year), or "roll" dates forward or backward

pandas provides a relatively compact and self-contained set of tools for performing the above tasks.

Create a range of dates:

```
# 72 hours starting with midnight Jan 1st, 2011
In [1]: rng = date_range('1/1/2011', periods=72, freq='H')

In [2]: rng[:5]
Out[2]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 01:00:00',
               '2011-01-01 02:00:00', '2011-01-01 03:00:00',
               '2011-01-01 04:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

Index pandas objects with dates:

```
In [3]: ts = Series(randn(len(rng)), index=rng)

In [4]: ts.head()
Out[4]:
2011-01-01 00:00:00    0.469112
2011-01-01 01:00:00   -0.282863
2011-01-01 02:00:00   -1.509059
2011-01-01 03:00:00   -1.135632
2011-01-01 04:00:00    1.212112
Freq: H, dtype: float64
```

Change frequency and fill gaps:

```
# to 45 minute frequency and forward fill
In [5]: converted = ts.asfreq('45Min', method='pad')
```

```
In [6]: converted.head()
Out[6]:
2011-01-01 00:00:00    0.469112
2011-01-01 00:45:00    0.469112
2011-01-01 01:30:00   -0.282863
2011-01-01 02:15:00   -1.509059
2011-01-01 03:00:00   -1.135632
Freq: 45T, dtype: float64
```

Resample:

```
# Daily means
In [7]: ts.resample('D', how='mean')
Out[7]:
2011-01-01   -0.319569
2011-01-02   -0.337703
2011-01-03    0.117258
Freq: D, dtype: float64
```

20.1 Time Stamps vs. Time Spans

Time-stamped data is the most basic type of timeseries data that associates values with points in time. For pandas objects it means using the points in time to create the index

```
In [8]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]

In [9]: ts = Series(np.random.randn(3), dates)

In [10]: type(ts.index)
Out[10]: pandas.tseries.index.DatetimeIndex

In [11]: ts
Out[11]:
2012-05-01   -0.410001
2012-05-02   -0.078638
2012-05-03    0.545952
dtype: float64
```

However, in many cases it is more natural to associate things like change variables with a time span instead.

For example:

```
In [12]: periods = PeriodIndex([Period('2012-01'), Period('2012-02'),
   ....:                        Period('2012-03')])
   ....:

In [13]: ts = Series(np.random.randn(3), periods)

In [14]: type(ts.index)
Out[14]: pandas.tseries.period.PeriodIndex

In [15]: ts
Out[15]:
2012-01   -1.219217
2012-02   -1.226825
2012-03    0.769804
Freq: M, dtype: float64
```

Starting with 0.8, pandas allows you to capture both representations and convert between them. Under the hood, pandas represents timestamps using instances of `Timestamp` and sequences of timestamps using instances of `DatetimeIndex`. For regular time spans, pandas uses `Period` objects for scalar values and `PeriodIndex` for sequences of spans. Better support for irregular intervals with arbitrary start and end points are forth-coming in future releases.

20.2 Converting to Timestamps

To convert a Series or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the `to_datetime` function. When passed a Series, this returns a Series (with the same index), while a list-like is converted to a DatetimeIndex:

```
In [16]: to_datetime(Series(['Jul 31, 2009', '2010-01-10', None]))
Out[16]:
0   2009-07-31
1   2010-01-10
2          NaT
dtype: datetime64[ns]

In [17]: to_datetime(['2005/11/23', '2010.12.31'])
Out[17]: DatetimeIndex(['2005-11-23', '2010-12-31'], dtype='datetime64[ns]', freq=None, tz=None)
```

If you use dates which start with the day first (i.e. European style), you can pass the `dayfirst` flag:

```
In [18]: to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[18]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None, tz=None)

In [19]: to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[19]: DatetimeIndex(['2012-01-14', '2012-01-14'], dtype='datetime64[ns]', freq=None, tz=None)
```

Warning: You see in the above example that `dayfirst` isn't strict, so if a date can't be parsed with the day being first it will be parsed as if `dayfirst` were False.

Note: Specifying a `format` argument will potentially speed up the conversion considerably and on versions later then 0.13.0 explicitly specifying a format string of '%Y%m%d' takes a faster path still.

20.2.1 Invalid Data

Pass `coerce=True` to convert invalid data to `NaT` (not a time):

```
In [20]: to_datetime(['2009-07-31', 'asd'])
Out[20]: array(['2009-07-31', 'asd'], dtype=object)

In [21]: to_datetime(['2009-07-31', 'asd'], coerce=True)
Out[21]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None, tz=None)
```

Take care, `to_datetime` may not act as you expect on mixed data:

```
In [22]: to_datetime([1, '1'])
Out[22]: array([1, '1'], dtype=object)
```

20.2.2 Epoch Timestamps

It's also possible to convert integer or float epoch times. The default unit for these is nanoseconds (since these are how Timestamps are stored). However, often epochs are stored in another `unit` which can be specified:

Typical epoch stored units

```
In [23]: to_datetime([1349720105, 1349806505, 1349892905,
   ....:              1349979305, 1350065705], unit='s')
   ....:
Out[23]:
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, tz=None)

In [24]: to_datetime([1349720105100, 1349720105200, 1349720105300,
   ....:              1349720105400, 1349720105500 ], unit='ms')
   ....:
Out[24]:
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, tz=None)
```

These *work*, but the results may be unexpected.

```
In [25]: to_datetime([1])
Out[25]: DatetimeIndex(['1970-01-01 00:00:00.000000001'], dtype='datetime64[ns]', freq=None, tz=None)

In [26]: to_datetime([1, 3.14], unit='s')
Out[26]: DatetimeIndex(['1970-01-01 00:00:01', '1970-01-01 00:00:03.140000'], dtype='datetime64[ns]',
```

Note: Epoch times will be rounded to the nearest nanosecond.

20.3 Generating Ranges of Timestamps

To generate an index with time stamps, you can use either the DatetimeIndex or Index constructor and pass in a list of datetime objects:

```
In [27]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]

In [28]: index = DatetimeIndex(dates)

In [29]: index # Note the frequency information
Out[29]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None,

In [30]: index = Index(dates)

In [31]: index # Automatically converted to DatetimeIndex
Out[31]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None,
```

Practically, this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the pandas functions `date_range` and `bdate_range` to create timestamp indexes.

```
In [32]: index = date_range('2000-1-1', periods=1000, freq='M')

In [33]: index
Out[33]:
DatetimeIndex(['2000-01-31', '2000-02-29', '2000-03-31', '2000-04-30',
               '2000-05-31', '2000-06-30', '2000-07-31', '2000-08-31',
               '2000-09-30', '2000-10-31',
               ...
               '2082-07-31', '2082-08-31', '2082-09-30', '2082-10-31',
               '2082-11-30', '2082-12-31', '2083-01-31', '2083-02-28',
               '2083-03-31', '2083-04-30'],
              dtype='datetime64[ns]', length=1000, freq='M', tz=None)

In [34]: index = bdate_range('2012-1-1', periods=250)

In [35]: index
Out[35]:
DatetimeIndex(['2012-01-02', '2012-01-03', '2012-01-04', '2012-01-05',
               '2012-01-06', '2012-01-09', '2012-01-10', '2012-01-11',
               '2012-01-12', '2012-01-13',
               ...
               '2012-12-03', '2012-12-04', '2012-12-05', '2012-12-06',
               '2012-12-07', '2012-12-10', '2012-12-11', '2012-12-12',
               '2012-12-13', '2012-12-14'],
              dtype='datetime64[ns]', length=250, freq='B', tz=None)
```

Convenience functions like `date_range` and `bdate_range` utilize a variety of frequency aliases. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**

```
In [36]: start = datetime(2011, 1, 1)

In [37]: end = datetime(2012, 1, 1)

In [38]: rng = date_range(start, end)

In [39]: rng
Out[39]:
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
               '2011-01-05', '2011-01-06', '2011-01-07', '2011-01-08',
               '2011-01-09', '2011-01-10',
               ...
               '2011-12-23', '2011-12-24', '2011-12-25', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30',
               '2011-12-31', '2012-01-01'],
              dtype='datetime64[ns]', length=366, freq='D', tz=None)

In [40]: rng = bdate_range(start, end)

In [41]: rng
Out[41]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14',
               ...
               '2011-12-19', '2011-12-20', '2011-12-21', '2011-12-22',
               '2011-12-23', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', length=260, freq='B', tz=None)
```

`date_range` and `bdate_range` make it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`:

```
In [42]: date_range(start, end, freq='BM')
Out[42]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM', tz=None)

In [43]: date_range(start, end, freq='W')
Out[43]:
DatetimeIndex(['2011-01-02', '2011-01-09', '2011-01-16', '2011-01-23',
               '2011-01-30', '2011-02-06', '2011-02-13', '2011-02-20',
               '2011-02-27', '2011-03-06', '2011-03-13', '2011-03-20',
               '2011-03-27', '2011-04-03', '2011-04-10', '2011-04-17',
               '2011-04-24', '2011-05-01', '2011-05-08', '2011-05-15',
               '2011-05-22', '2011-05-29', '2011-06-05', '2011-06-12',
               '2011-06-19', '2011-06-26', '2011-07-03', '2011-07-10',
               '2011-07-17', '2011-07-24', '2011-07-31', '2011-08-07',
               '2011-08-14', '2011-08-21', '2011-08-28', '2011-09-04',
               '2011-09-11', '2011-09-18', '2011-09-25', '2011-10-02',
               '2011-10-09', '2011-10-16', '2011-10-23', '2011-10-30',
               '2011-11-06', '2011-11-13', '2011-11-20', '2011-11-27',
               '2011-12-04', '2011-12-11', '2011-12-18', '2011-12-25',
               '2012-01-01'],
              dtype='datetime64[ns]', freq='W-SUN', tz=None)

In [44]: bdate_range(end=end, periods=20)
Out[44]:
DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-12', '2011-12-13', '2011-12-14',
               '2011-12-15', '2011-12-16', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', freq='B', tz=None)

In [45]: bdate_range(start=start, periods=20)
Out[45]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14', '2011-01-17', '2011-01-18',
               '2011-01-19', '2011-01-20', '2011-01-21', '2011-01-24',
               '2011-01-25', '2011-01-26', '2011-01-27', '2011-01-28'],
              dtype='datetime64[ns]', freq='B', tz=None)
```

The start and end dates are strictly inclusive. So it will not generate any dates outside of those dates if specified.

20.4 DatetimeIndex

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many timeseries related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice)
- Fast shifting using the `shift` and `tshift` method on pandas objects

- Unioning of overlapping DatetimeIndex objects with the same frequency is very fast (important for fast data alignment)
- Quick access to date fields via properties such as `year`, `month`, etc.
- Regularization functions like `snap` and very fast `asof` logic

DatetimeIndex objects has all the basic functionality of regular Index objects and a smorgasbord of advanced timeseries-specific methods for easy frequency processing.

See also:

Reindexing methods

Note: While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted. So please be careful.

`DatetimeIndex` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [46]: rng = date_range(start, end, freq='BM')

In [47]: ts = Series(randn(len(rng)), index=rng)

In [48]: ts.index
Out[48]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM', tz=None)

In [49]: ts[:5].index
Out[49]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31'],
              dtype='datetime64[ns]', freq='BM', tz=None)

In [50]: ts[::2].index
Out[50]:
DatetimeIndex(['2011-01-31', '2011-03-31', '2011-05-31', '2011-07-29',
               '2011-09-30', '2011-11-30'],
              dtype='datetime64[ns]', freq='2BM', tz=None)
```

20.4.1 DatetimeIndex Partial String Indexing

You can pass in dates and strings that parse to dates as indexing parameters:

```
In [51]: ts['1/31/2011']
Out[51]: -1.2812473076599529

In [52]: ts[datetime(2011, 12, 25):]
Out[52]:
2011-12-30    0.687738
Freq: BM, dtype: float64

In [53]: ts['10/31/2011':'12/31/2011']
Out[53]:
2011-10-31    0.149748
```

```
2011-11-30   -0.732339
2011-12-30    0.687738
Freq: BM, dtype: float64
```

To provide convenience for accessing longer time series, you can also pass in the year or year and month as strings:

```
In [54]: ts['2011']
Out[54]:
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 [55]: ts['2011-6']
Out[55]:
2011-06-30    0.341734
Freq: BM, dtype: float64
```

This type of slicing will work on a DataFrame with a `DateTimeIndex` as well. Since the partial string selection is a form of label slicing, the endpoints **will be** included. This would include matching times on an included date. Here's an example:

```
In [56]: dft = DataFrame(randn(100000,1),columns=['A'],index=date_range('20130101',periods=100000,fre

In [57]: dft
Out[57]:
                            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 [58]: dft['2013']
Out[58]:
                            A
2013-01-01 00:00:00  0.176444
2013-01-01 00:01:00  0.403310
```

```
2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...                       ...
2013-03-11 10:33:00 -0.293083
2013-03-11 10:34:00 -0.059881
2013-03-11 10:35:00  1.252450
2013-03-11 10:36:00  0.046611
2013-03-11 10:37:00  0.059478
2013-03-11 10:38:00 -0.286539
2013-03-11 10:39:00  0.841669

[100000 rows x 1 columns]
```

This starts on the very first time in the month, and includes the last date & time for the month

```
In [59]: dft['2013-1':'2013-2']
Out[59]:
                            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 a stop time **that includes all of the times on the last day**

```
In [60]: dft['2013-1':'2013-2-28']
Out[60]:
                            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 [61]: dft['2013-1':'2013-2-28 00:00:00']
Out[61]:
                            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 [62]: dft['2013-1-15':'2013-1-15 12:30:00']
Out[62]:
                            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]
```

Warning: The following selection will raise a `KeyError`; otherwise this selection methodology would be inconsistent with other selection methods in pandas (as this is not a *slice*, nor does it resolve to one)

```
dft['2013-1-15 12:30:00']
```

To select a single row, use `.loc`

```
In [63]: dft.loc['2013-1-15 12:30:00']
Out[63]:
A    0.193284
Name: 2013-01-15 12:30:00, dtype: float64
```

20.4.2 Datetime Indexing

Indexing a `DateTimeIndex` with a partial string depends on the "accuracy" of the period, in other words how specific the interval is in relation to the frequency of the index. In contrast, indexing with datetime objects is exact, because the objects have exact meaning. These also follow the semantics of *including both endpoints*.

These `datetime` objects are specific `hours, minutes,` and `seconds` even though they were not explicitly specified (they are `0`).

```
In [64]: dft[datetime(2013, 1, 1):datetime(2013,2,28)]
Out[64]:
                            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 [65]: dft[datetime(2013, 1, 1, 10, 12, 0):datetime(2013, 2, 28, 10, 12, 0)]
Out[65]:
                            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
...                       ...
2013-02-28 10:06:00  0.311249
```

```
2013-02-28 10:07:00  2.366080
2013-02-28 10:08:00 -0.490372
2013-02-28 10:09:00  0.373340
2013-02-28 10:10:00  0.638442
2013-02-28 10:11:00  1.330135
2013-02-28 10:12:00 -0.945450

[83521 rows x 1 columns]
```

20.4.3 Truncating & Fancy Indexing

A `truncate` convenience function is provided that is equivalent to slicing:

```
In [66]: ts.truncate(before='10/31/2011', after='12/31/2011')
Out[66]:
2011-10-31    0.149748
2011-11-30   -0.732339
2011-12-30    0.687738
Freq: BM, dtype: float64
```

Even complicated fancy indexing that breaks the DatetimeIndex's frequency regularity will result in a `DatetimeIndex` (but frequency is lost):

```
In [67]: ts[[0, 2, 6]].index
Out[67]: DatetimeIndex(['2011-01-31', '2011-03-31', '2011-07-29'], dtype='datetime64[ns]', freq=None,
```

20.4.4 Time/Date Components

There are several time/date properties that one can access from `Timestamp` or a collection of timestamps like a `DateTimeIndex`.

Property	Description
year	The year of the datetime
month	The month of the datetime
day	The days of the datetime
hour	The hour of the datetime
minute	The minutes of the datetime
second	The seconds of the datetime
microsecond	The microseconds of the datetime
nanosecond	The nanoseconds of the datetime
date	Returns datetime.date
time	Returns datetime.time
dayofyear	The ordinal day of year
weekofyear	The week ordinal of the year
week	The week ordinal of the year
dayofweek	The day of the week with Monday=0, Sunday=6
weekday	The day of the week with Monday=0, Sunday=6
quarter	Quarter of the date: Jan=Mar = 1, Apr-Jun = 2, etc.
is_month_start	Logical indicating if first day of month (defined by frequency)
is_month_end	Logical indicating if last day of month (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)

Furthermore, if you have a `Series` with datetimelike values, then you can access these properties via the `.dt` accessor, see the *docs*

20.5 DateOffset objects

In the preceding examples, we created DatetimeIndex objects at various frequencies by passing in frequency strings like 'M', 'W', and 'BM to the `freq` keyword. Under the hood, these frequency strings are being translated into an instance of pandas `DateOffset`, which represents a regular frequency increment. Specific offset logic like "month", "business day", or "one hour" is represented in its various subclasses.

Class name	Description
DateOffset	Generic offset class, defaults to 1 calendar day
BDay	business day (weekday)
CDay	custom business day (experimental)
Week	one week, optionally anchored on a day of the week
WeekOfMonth	the x-th day of the y-th week of each month
LastWeekOfMonth	the x-th day of the last week of each month
MonthEnd	calendar month end
MonthBegin	calendar month begin
BMonthEnd	business month end
BMonthBegin	business month begin
CBMonthEnd	custom business month end
CBMonthBegin	custom business month begin
QuarterEnd	calendar quarter end
QuarterBegin	calendar quarter begin
BQuarterEnd	business quarter end
BQuarterBegin	business quarter begin
FY5253Quarter	retail (aka 52-53 week) quarter
YearEnd	calendar year end
YearBegin	calendar year begin
BYearEnd	business year end
BYearBegin	business year begin
FY5253	retail (aka 52-53 week) year
BusinessHour	business hour
Hour	one hour
Minute	one minute
Second	one second
Milli	one millisecond
Micro	one microsecond
Nano	one nanosecond

The basic `DateOffset` takes the same arguments as `dateutil.relativedelta`, which works like:

```
In [68]: d = datetime(2008, 8, 18, 9, 0)

In [69]: d + relativedelta(months=4, days=5)
Out[69]: datetime.datetime(2008, 12, 23, 9, 0)
```

We could have done the same thing with `DateOffset`:

```
In [70]: from pandas.tseries.offsets import *

In [71]: d + DateOffset(months=4, days=5)
Out[71]: Timestamp('2008-12-23 09:00:00')
```

The key features of a `DateOffset` object are:

- it can be added / subtracted to/from a datetime object to obtain a shifted date
- it can be multiplied by an integer (positive or negative) so that the increment will be applied multiple times
- it has `rollforward` and `rollback` methods for moving a date forward or backward to the next or previous "offset date"

Subclasses of `DateOffset` define the `apply` function which dictates custom date increment logic, such as adding business days:

```
class BDay(DateOffset):
    """DateOffset increments between business days"""
    def apply(self, other):
        ...
```

```
In [72]: d - 5 * BDay()
Out[72]: Timestamp('2008-08-11 09:00:00')

In [73]: d + BMonthEnd()
Out[73]: Timestamp('2008-08-29 09:00:00')
```

The `rollforward` and `rollback` methods do exactly what you would expect:

```
In [74]: d
Out[74]: datetime.datetime(2008, 8, 18, 9, 0)

In [75]: offset = BMonthEnd()

In [76]: offset.rollforward(d)
Out[76]: Timestamp('2008-08-29 09:00:00')

In [77]: offset.rollback(d)
Out[77]: Timestamp('2008-07-31 09:00:00')
```

It's definitely worth exploring the `pandas.tseries.offsets` module and the various docstrings for the classes.

These operations (`apply`, `rollforward` and `rollback`) preserves time (hour, minute, etc) information by default. To reset time, use `normalize=True` keyword when creating the offset instance. If `normalize=True`, result is normalized after the function is applied.

```
In [78]: day = Day()

In [79]: day.apply(Timestamp('2014-01-01 09:00'))
Out[79]: Timestamp('2014-01-02 09:00:00')

In [80]: day = Day(normalize=True)

In [81]: day.apply(Timestamp('2014-01-01 09:00'))
Out[81]: Timestamp('2014-01-02 00:00:00')

In [82]: hour = Hour()

In [83]: hour.apply(Timestamp('2014-01-01 22:00'))
Out[83]: Timestamp('2014-01-01 23:00:00')

In [84]: hour = Hour(normalize=True)

In [85]: hour.apply(Timestamp('2014-01-01 22:00'))
Out[85]: Timestamp('2014-01-01 00:00:00')
```

```
In [86]: hour.apply(Timestamp('2014-01-01 23:00'))
Out[86]: Timestamp('2014-01-02 00:00:00')
```

20.5.1 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 [87]: d
Out[87]: datetime.datetime(2008, 8, 18, 9, 0)

In [88]: d + Week()
Out[88]: Timestamp('2008-08-25 09:00:00')

In [89]: d + Week(weekday=4)
Out[89]: Timestamp('2008-08-22 09:00:00')

In [90]: (d + Week(weekday=4)).weekday()
Out[90]: 4

In [91]: d - Week()
Out[91]: Timestamp('2008-08-11 09:00:00')
```

`normalize` option will be effective for addition and subtraction.

```
In [92]: d + Week(normalize=True)
Out[92]: Timestamp('2008-08-25 00:00:00')

In [93]: d - Week(normalize=True)
Out[93]: Timestamp('2008-08-11 00:00:00')
```

Another example is parameterizing `YearEnd` with the specific ending month:

```
In [94]: d + YearEnd()
Out[94]: Timestamp('2008-12-31 09:00:00')

In [95]: d + YearEnd(month=6)
Out[95]: Timestamp('2009-06-30 09:00:00')
```

20.5.2 Custom Business Days (Experimental)

The `CDay` or `CustomBusinessDay` class provides a parametric `BusinessDay` class which can be used to create customized business day calendars which account for local holidays and local weekend conventions.

```
In [96]: from pandas.tseries.offsets import CustomBusinessDay

# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [97]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [98]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]
```

```
In [99]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [100]: dt = datetime(2013, 4, 30)

In [101]: dt + 2 * bday_egypt
Out[101]: Timestamp('2013-05-05 00:00:00')

In [102]: dts = date_range(dt, periods=5, freq=bday_egypt)

In [103]: Series(dts.weekday, dts).map(Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
Out[103]:
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

As of v0.14 holiday calendars can be used to provide the list of holidays. See the *holiday calendar* section for more information.

```
In [104]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [105]: bday_us = CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [106]: dt = datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [107]: dt + bday_us
Out[107]: Timestamp('2014-01-21 00:00:00')
```

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [108]: from pandas.tseries.offsets import CustomBusinessMonthBegin

In [109]: bmth_us = CustomBusinessMonthBegin(calendar=USFederalHolidayCalendar())

# Skip new years
In [110]: dt = datetime(2013, 12, 17)

In [111]: dt + bmth_us
Out[111]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
In [112]: from pandas import DatetimeIndex

In [113]: DatetimeIndex(start='20100101',end='20120101',freq=bmth_us)
Out[113]:
DatetimeIndex(['2010-01-04', '2010-02-01', '2010-03-01', '2010-04-01',
               '2010-05-03', '2010-06-01', '2010-07-01', '2010-08-02',
               '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
               '2011-01-03', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
              dtype='datetime64[ns]', freq='CBMS', tz=None)
```

Note: The frequency string 'C' is used to indicate that a CustomBusinessDay DateOffset is used, it is important to note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is not detectable from the 'C' frequency string. The user therefore needs to ensure that the 'C' frequency string is used consistently within the user's application.

Note: This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

Warning: There are known problems with the timezone handling in Numpy 1.7 and users should therefore use this **experimental(!)** feature with caution and at their own risk.
To the extent that the `datetime64` and `busdaycalendar` APIs in Numpy have to change to fix the timezone issues, the behaviour of the `CustomBusinessDay` class may have to change in future versions.

20.5.3 Business Hour

The `BusinessHour` class provides a business hour representation on `BusinessDay`, allowing to use specific start and end times.

By default, `BusinessHour` uses 9:00 - 17:00 as business hours. Adding `BusinessHour` will increment `Timestamp` by hourly. If target `Timestamp` is out of business hours, move to the next business hour then increment it. If the result exceeds the business hours end, remaining is added to the next business day.

```
In [114]: bh = BusinessHour()

In [115]: bh
Out[115]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [116]: Timestamp('2014-08-01 10:00').weekday()
Out[116]: 4

In [117]: Timestamp('2014-08-01 10:00') + bh
Out[117]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as Timestamp('2014-08-01 09:00') + bh
In [118]: Timestamp('2014-08-01 08:00') + bh
Out[118]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [119]: Timestamp('2014-08-01 16:00') + bh
Out[119]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day
In [120]: Timestamp('2014-08-01 16:30') + bh
Out[120]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [121]: Timestamp('2014-08-01 10:00') + BusinessHour(2)
Out[121]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [122]: Timestamp('2014-08-01 10:00') + BusinessHour(-3)
Out[122]: Timestamp('2014-07-31 15:00:00')
```

Also, you can specify `start` and `end` time by keywords. Argument must be `str` which has `hour:minute` representation or `datetime.time` instance. Specifying seconds, microseconds and nanoseconds as business hour results in `ValueError`.

```
In [123]: bh = BusinessHour(start='11:00', end=time(20, 0))

In [124]: bh
Out[124]: <BusinessHour: BH=11:00-20:00>

In [125]: Timestamp('2014-08-01 13:00') + bh
Out[125]: Timestamp('2014-08-01 14:00:00')

In [126]: Timestamp('2014-08-01 09:00') + bh
Out[126]: Timestamp('2014-08-01 12:00:00')

In [127]: Timestamp('2014-08-01 18:00') + bh
Out[127]: 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 [128]: bh = BusinessHour(start='17:00', end='09:00')

In [129]: bh
Out[129]: <BusinessHour: BH=17:00-09:00>

In [130]: Timestamp('2014-08-01 17:00') + bh
Out[130]: Timestamp('2014-08-01 18:00:00')

In [131]: Timestamp('2014-08-01 23:00') + bh
Out[131]: Timestamp('2014-08-02 00:00:00')

# Although 2014-08-02 is Satuaday,
# it is valid because it starts from 08-01 (Friday).
In [132]: Timestamp('2014-08-02 04:00') + bh
Out[132]: 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 [133]: Timestamp('2014-08-04 04:00') + bh
Out[133]: Timestamp('2014-08-04 18:00:00')
```

Applying `BusinessHour.rollforward` and `rollback` to out of business hours results in the next business hour start or previous day's end. Different from other offsets, `BusinessHour.rollforward` may output different results from `apply` by definition.

This is because one day's business hour end is equal to next day's business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between `2014-08-01 17:00` and `2014-08-04 09:00`.

```
# This adjusts a Timestamp to business hour edge
In [134]: BusinessHour().rollback(Timestamp('2014-08-02 15:00'))
Out[134]: Timestamp('2014-08-01 17:00:00')

In [135]: BusinessHour().rollforward(Timestamp('2014-08-02 15:00'))
Out[135]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessHour().apply(Timestamp('2014-08-01 17:00')).
# And it is the same as BusinessHour().apply(Timestamp('2014-08-04 09:00'))
In [136]: BusinessHour().apply(Timestamp('2014-08-02 15:00'))
Out[136]: Timestamp('2014-08-04 10:00:00')

# BusinessDay results (for reference)
```

```
In [137]: BusinessHour().rollforward(Timestamp('2014-08-02'))
Out[137]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessDay().apply(Timestamp('2014-08-01'))
# The result is the same as rollworward because BusinessDay never overlap.
In [138]: BusinessHour().apply(Timestamp('2014-08-02'))
Out[138]: Timestamp('2014-08-04 10:00:00')
```

20.5.4 Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases* (referred to as *time rules* prior to v0.8.0).

Alias	Description
B	business day frequency
C	custom business day frequency (experimental)
D	calendar day frequency
W	weekly frequency
M	month end frequency
BM	business month end frequency
CBM	custom business month end frequency
MS	month start frequency
BMS	business month start frequency
CBMS	custom business month start frequency
Q	quarter end frequency
BQ	business quarter endfrequency
QS	quarter start frequency
BQS	business quarter start frequency
A	year end frequency
BA	business year end frequency
AS	year start frequency
BAS	business year start frequency
BH	business hour frequency
H	hourly frequency
T	minutely frequency
S	secondly frequency
L	milliseonds
U	microseconds
N	nanoseconds

20.5.5 Combining Aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```
In [139]: date_range(start, periods=5, freq='B')
Out[139]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B', tz=None)

In [140]: date_range(start, periods=5, freq=BDay())
Out[140]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
```

```
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B', tz=None)
```

You can combine together day and intraday offsets:

```
In [141]: date_range(start, periods=10, freq='2h20min')
Out[141]:
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', tz=None)

In [142]: date_range(start, periods=10, freq='1D10U')
Out[142]:
DatetimeIndex([       '2011-01-01 00:00:00', '2011-01-02 00:00:00.000010',
               '2011-01-03 00:00:00.000020', '2011-01-04 00:00:00.000030',
               '2011-01-05 00:00:00.000040', '2011-01-06 00:00:00.000050',
               '2011-01-07 00:00:00.000060', '2011-01-08 00:00:00.000070',
               '2011-01-09 00:00:00.000080', '2011-01-10 00:00:00.000090'],
              dtype='datetime64[ns]', freq='86400000010U', tz=None)
```

20.5.6 Anchored Offsets

For some frequencies you can specify an anchoring suffix:

Alias	Description
W-SUN	weekly frequency (sundays). Same as 'W'
W-MON	weekly frequency (mondays)
W-TUE	weekly frequency (tuesdays)
W-WED	weekly frequency (wednesdays)
W-THU	weekly frequency (thursdays)
W-FRI	weekly frequency (fridays)
W-SAT	weekly frequency (saturdays)
(B)Q(S)-DEC	quarterly frequency, year ends in December. Same as 'Q'
(B)Q(S)-JAN	quarterly frequency, year ends in January
(B)Q(S)-FEB	quarterly frequency, year ends in February
(B)Q(S)-MAR	quarterly frequency, year ends in March
(B)Q(S)-APR	quarterly frequency, year ends in April
(B)Q(S)-MAY	quarterly frequency, year ends in May
(B)Q(S)-JUN	quarterly frequency, year ends in June
(B)Q(S)-JUL	quarterly frequency, year ends in July
(B)Q(S)-AUG	quarterly frequency, year ends in August
(B)Q(S)-SEP	quarterly frequency, year ends in September
(B)Q(S)-OCT	quarterly frequency, year ends in October
(B)Q(S)-NOV	quarterly frequency, year ends in November
(B)A(S)-DEC	annual frequency, anchored end of December. Same as 'A'
(B)A(S)-JAN	annual frequency, anchored end of January
(B)A(S)-FEB	annual frequency, anchored end of February
(B)A(S)-MAR	annual frequency, anchored end of March
(B)A(S)-APR	annual frequency, anchored end of April
(B)A(S)-MAY	annual frequency, anchored end of May
(B)A(S)-JUN	annual frequency, anchored end of June

Continued on next page

Table 20.1 – continued from previous page

Alias	Description
(B)A(S)-JUL	annual frequency, anchored end of July
(B)A(S)-AUG	annual frequency, anchored end of August
(B)A(S)-SEP	annual frequency, anchored end of September
(B)A(S)-OCT	annual frequency, anchored end of October
(B)A(S)-NOV	annual frequency, anchored end of November

These can be used as arguments to `date_range`, `bdate_range`, constructors for `DatetimeIndex`, as well as various other timeseries-related functions in pandas.

20.5.7 Legacy Aliases

Note that prior to v0.8.0, time rules had a slightly different look. pandas will continue to support the legacy time rules for the time being but it is strongly recommended that you switch to using the new offset aliases.

Legacy Time Rule	Offset Alias
WEEKDAY	B
EOM	BM
W@MON	W-MON
W@TUE	W-TUE
W@WED	W-WED
W@THU	W-THU
W@FRI	W-FRI
W@SAT	W-SAT
W@SUN	W-SUN
Q@JAN	BQ-JAN
Q@FEB	BQ-FEB
Q@MAR	BQ-MAR
A@JAN	BA-JAN
A@FEB	BA-FEB
A@MAR	BA-MAR
A@APR	BA-APR
A@MAY	BA-MAY
A@JUN	BA-JUN
A@JUL	BA-JUL
A@AUG	BA-AUG
A@SEP	BA-SEP
A@OCT	BA-OCT
A@NOV	BA-NOV
A@DEC	BA-DEC
min	T
ms	L
us	U

As you can see, legacy quarterly and annual frequencies are business quarters and business year ends. Please also note the legacy time rule for milliseconds `ms` versus the new offset alias for month start `MS`. This means that offset alias parsing is case sensitive.

20.5.8 Holidays / Holiday Calendars

Holidays and calendars provide a simple way to define holiday rules to be used with `CustomBusinessDay` or in other analysis that requires a predefined set of holidays. The `AbstractHolidayCalendar` class provides all the necessary methods to return a list of holidays and only `rules` need to be defined in a specific holiday calendar class. Further, `start_date` and `end_date` class attributes determine over what date range holidays are generated. These should be overwritten on the `AbstractHolidayCalendar` class to have the range apply to all calendar subclasses. `USFederalHolidayCalendar` is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

Rule	Description
nearest_workday	move Saturday to Friday and Sunday to Monday
sunday_to_monday	move Sunday to following Monday
next_monday_or_tuesday	move Saturday to Monday and Sunday/Monday to Tuesday
previous_friday	move Saturday and Sunday to previous Friday”
next_monday	move Saturday and Sunday to following Monday

An example of how holidays and holiday calendars are defined:

```
In [143]: from pandas.tseries.holiday import Holiday, USMemorialDay,\
   .....:     AbstractHolidayCalendar, nearest_workday, MO
   .....:

In [144]: 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 [145]: cal = ExampleCalendar()

In [146]: cal.holidays(datetime(2012, 1, 1), datetime(2012, 12, 31))
Out[146]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None
```

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th).

```
In [147]: DatetimeIndex(start='7/1/2012', end='7/10/2012',
   .....:     freq=CDay(calendar=cal)).to_pydatetime()
   .....:
Out[147]:
array([datetime.datetime(2012, 7, 2, 0, 0),
       datetime.datetime(2012, 7, 3, 0, 0),
       datetime.datetime(2012, 7, 5, 0, 0),
       datetime.datetime(2012, 7, 6, 0, 0),
       datetime.datetime(2012, 7, 9, 0, 0),
       datetime.datetime(2012, 7, 10, 0, 0)], dtype=object)

In [148]: offset = CustomBusinessDay(calendar=cal)

In [149]: datetime(2012, 5, 25) + offset
Out[149]: Timestamp('2012-05-29 00:00:00')

In [150]: datetime(2012, 7, 3) + offset
Out[150]: Timestamp('2012-07-05 00:00:00')

In [151]: datetime(2012, 7, 3) + 2 * offset
```

```
Out[151]: Timestamp('2012-07-06 00:00:00')

In [152]: datetime(2012, 7, 6) + offset
Out[152]: Timestamp('2012-07-09 00:00:00')
```

Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are below.

```
In [153]: AbstractHolidayCalendar.start_date
Out[153]: Timestamp('1970-01-01 00:00:00')

In [154]: AbstractHolidayCalendar.end_date
Out[154]: Timestamp('2030-12-31 00:00:00')
```

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

```
In [155]: AbstractHolidayCalendar.start_date = datetime(2012, 1, 1)

In [156]: AbstractHolidayCalendar.end_date = datetime(2012, 12, 31)

In [157]: cal.holidays()
Out[157]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None
```

Every calendar class is accessible by name using the `get_calendar` function which returns a holiday class instance. Any imported calendar class will automatically be available by this function. Also, `HolidayCalendarFactory` provides an easy interface to create calendars that are combinations of calendars or calendars with additional rules.

```
In [158]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory,\
   .....:     USLaborDay
   .....:

In [159]: cal = get_calendar('ExampleCalendar')

In [160]: cal.rules
Out[160]:
[Holiday: MemorialDay (month=5, day=24, offset=<DateOffset: kwds={'weekday': MO(+1)}>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9c164294>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>)]

In [161]: new_cal = HolidayCalendarFactory('NewExampleCalendar', cal, USLaborDay)

In [162]: new_cal.rules
Out[162]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: kwds={'weekday': MO(+1)}>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9c164294>),
 Holiday: MemorialDay (month=5, day=24, offset=<DateOffset: kwds={'weekday': MO(+1)}>)]
```

20.6 Time series-related instance methods

20.6.1 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 [163]: ts = ts[:5]

In [164]: ts.shift(1)
Out[164]:
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 a *offset alias*:

```
In [165]: ts.shift(5, freq=datetools.bday)
Out[165]:
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 [166]: ts.shift(5, freq='BM')
Out[166]:
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 [167]: ts.tshift(5, freq='D')
Out[167]:
2011-02-05    -1.281247
2011-03-05    -0.727707
2011-04-05    -0.121306
2011-05-04    -0.097883
2011-06-05     0.695775
dtype: float64
```

Note that with `tshift`, the leading entry is no longer NaN because the data is not being realigned.

20.6.2 Frequency conversion

The primary function for changing frequencies is the `asfreq` function. For a `DatetimeIndex`, this is basically just a thin, but convenient wrapper around `reindex` which generates a `date_range` and calls `reindex`.

```
In [168]: dr = date_range('1/1/2010', periods=3, freq=3 * datetools.bday)

In [169]: ts = Series(randn(3), index=dr)

In [170]: ts
Out[170]:
2010-01-01    -0.659574
```

```
2010-01-06    1.494522
2010-01-11   -0.778425
Freq: 3B, dtype: float64

In [171]: ts.asfreq(BDay())
Out[171]:
2010-01-01   -0.659574
2010-01-04         NaN
2010-01-05         NaN
2010-01-06    1.494522
2010-01-07         NaN
2010-01-08         NaN
2010-01-11   -0.778425
Freq: B, dtype: float64
```

`asfreq` provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion

```
In [172]: ts.asfreq(BDay(), method='pad')
Out[172]:
2010-01-01   -0.659574
2010-01-04   -0.659574
2010-01-05   -0.659574
2010-01-06    1.494522
2010-01-07    1.494522
2010-01-08    1.494522
2010-01-11   -0.778425
Freq: B, dtype: float64
```

20.6.3 Filling forward / backward

Related to `asfreq` and `reindex` is the `fillna` function documented in the *missing data section*.

20.6.4 Converting to Python datetimes

`DatetimeIndex` can be converted to an array of Python native datetime.datetime objects using the `to_pydatetime` method.

20.7 Up- and downsampling

With 0.8, pandas introduces 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 some *cookbook examples* for some advanced strategies

```
In [173]: rng = date_range('1/1/2012', periods=100, freq='S')

In [174]: ts = Series(randint(0, 500, len(rng)), index=rng)

In [175]: ts.resample('5Min', how='sum')
Out[175]:
2012-01-01    25103
Freq: 5T, dtype: int32
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

The `how` parameter can be a function name or numpy array function that takes an array and produces aggregated values:

```
In [176]: ts.resample('5Min') # default is mean
Out[176]:
2012-01-01    251.03
Freq: 5T, dtype: float64

In [177]: ts.resample('5Min', how='ohlc')
Out[177]:
            open  high  low  close
2012-01-01   308   460    9    205

In [178]: ts.resample('5Min', how=np.max)
Out[178]:
2012-01-01    460
Freq: 5T, dtype: int32
```

Any function available via *dispatching* can be given to the `how` parameter by name, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`.

For downsampling, `closed` can be set to 'left' or 'right' to specify which end of the interval is closed:

```
In [179]: ts.resample('5Min', closed='right')
Out[179]:
2011-12-31 23:55:00    308.000000
2012-01-01 00:00:00    250.454545
Freq: 5T, dtype: float64

In [180]: ts.resample('5Min', closed='left')
Out[180]:
2012-01-01    251.03
Freq: 5T, dtype: float64
```

For upsampling, the `fill_method` and `limit` parameters can be specified to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds
In [181]: ts[:2].resample('250L')
Out[181]:
2012-01-01 00:00:00.000    308
2012-01-01 00:00:00.250    NaN
2012-01-01 00:00:00.500    NaN
2012-01-01 00:00:00.750    NaN
2012-01-01 00:00:01.000    204
Freq: 250L, dtype: float64

In [182]: ts[:2].resample('250L', fill_method='pad')
Out[182]:
2012-01-01 00:00:00.000    308
2012-01-01 00:00:00.250    308
2012-01-01 00:00:00.500    308
2012-01-01 00:00:00.750    308
2012-01-01 00:00:01.000    204
Freq: 250L, dtype: int32

In [183]: ts[:2].resample('250L', fill_method='pad', limit=2)
```

```
Out[183]:
2012-01-01 00:00:00.000    308
2012-01-01 00:00:00.250    308
2012-01-01 00:00:00.500    308
2012-01-01 00:00:00.750    NaN
2012-01-01 00:00:01.000    204
Freq: 250L, dtype: float64
```

Parameters like `label` and `loffset` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval. `loffset` performs a time adjustment on the output labels.

```
In [184]: ts.resample('5Min') # by default label='right'
Out[184]:
2012-01-01    251.03
Freq: 5T, dtype: float64

In [185]: ts.resample('5Min', label='left')
Out[185]:
2012-01-01    251.03
Freq: 5T, dtype: float64

In [186]: ts.resample('5Min', label='left', loffset='1s')
Out[186]:
2012-01-01 00:00:01    251.03
dtype: float64
```

The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a DataFrame.

`kind` can be set to 'timestamp' or 'period' to convert the resulting index to/from time-stamp and time-span representations. By default `resample` retains the input representation.

`convention` can be set to 'start' or 'end' when resampling period data (detail below). It specifies how low frequency periods are converted to higher frequency periods.

Note that 0.8 marks a watershed in the timeseries functionality in pandas. In previous versions, resampling had to be done using a combination of `date_range`, `groupby` with `asof`, and then calling an aggregation function on the grouped object. This was not nearly as convenient or performant as the new pandas timeseries API.

20.8 Time Span Representation

Regular intervals of time are represented by `Period` objects in pandas while sequences of `Period` objects are collected in a `PeriodIndex`, which can be created with the convenience function `period_range`.

20.8.1 Period

A `Period` represents a span of time (e.g., a day, a month, a quarter, etc). It can be created using a frequency alias:

```
In [187]: Period('2012', freq='A-DEC')
Out[187]: Period('2012', 'A-DEC')

In [188]: Period('2012-1-1', freq='D')
Out[188]: Period('2012-01-01', 'D')

In [189]: Period('2012-1-1 19:00', freq='H')
Out[189]: Period('2012-01-01 19:00', 'H')
```

Unlike time stamped data, pandas does not support frequencies at multiples of DateOffsets (e.g., '3Min') for periods.

Adding and subtracting integers from periods shifts the period by its own frequency.

```
In [190]: p = Period('2012', freq='A-DEC')

In [191]: p + 1
Out[191]: Period('2013', 'A-DEC')

In [192]: p - 3
Out[192]: Period('2009', 'A-DEC')
```

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. Otherise, `ValueError` will be raised.

```
In [193]: p = Period('2014-07-01 09:00', freq='H')

In [194]: p + Hour(2)
Out[194]: Period('2014-07-01 11:00', 'H')

In [195]: p + timedelta(minutes=120)
Out[195]: Period('2014-07-01 11:00', 'H')

In [196]: p + np.timedelta64(7200, 's')
Out[196]: 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 [197]: p = Period('2014-07', freq='M')

In [198]: p + MonthEnd(3)
Out[198]: Period('2014-10', 'M')
```

```
In [1]: p + MonthBegin(3)
Traceback
   ...
ValueError: Input has different freq from Period(freq=M)
```

Taking the difference of `Period` instances with the same frequency will return the number of frequency units between them:

```
In [199]: Period('2012', freq='A-DEC') - Period('2002', freq='A-DEC')
Out[199]: 10L
```

20.8.2 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 [200]: prng = period_range('1/1/2011', '1/1/2012', freq='M')

In [201]: prng
Out[201]:
```

```
PeriodIndex(['2011-01', '2011-02', '2011-03', '2011-04', '2011-05', '2011-06',
             '2011-07', '2011-08', '2011-09', '2011-10', '2011-11', '2011-12',
             '2012-01'],
            dtype='int64', freq='M')
```

The `PeriodIndex` constructor can also be used directly:

```
In [202]: PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[202]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='int64', freq='M')
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```
In [203]: ps = Series(randn(len(prng)), prng)

In [204]: ps
Out[204]:
2011-01   -0.253355
2011-02   -1.426908
2011-03    1.548971
2011-04   -0.088718
2011-05   -1.771348
2011-06   -0.989328
2011-07   -1.584789
2011-08   -0.288786
2011-09   -2.029806
2011-10   -0.761200
2011-11   -1.603608
2011-12    1.756171
2012-01    0.256502
Freq: M, dtype: float64
```

`PeriodIndex` supports addition and subtraction with the same rule as `Period`.

```
In [205]: idx = period_range('2014-07-01 09:00', periods=5, freq='H')

In [206]: idx
Out[206]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='int64', freq='H')

In [207]: idx + Hour(2)
Out[207]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')

In [208]: idx = period_range('2014-07', periods=5, freq='M')

In [209]: idx
Out[209]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'], dtype='int64', freq='M

In [210]: idx + MonthEnd(3)
Out[210]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype='int64', freq='M
```

20.8.3 PeriodIndex Partial String Indexing

You can pass in dates and strings to `Series` and `DataFrame` with `PeriodIndex`, in the same manner as `DatetimeIndex`. For details, refer to *DatetimeIndex Partial String Indexing*.

```
In [211]: ps['2011-01']
Out[211]: -0.25335528290092818

In [212]: ps[datetime(2011, 12, 25):]
Out[212]:
2011-12    1.756171
2012-01    0.256502
Freq: M, dtype: float64

In [213]: ps['10/31/2011':'12/31/2011']
Out[213]:
2011-10   -0.761200
2011-11   -1.603608
2011-12    1.756171
Freq: M, dtype: float64
```

Passing a string representing a lower frequency than `PeriodIndex` returns partial sliced data.

```
In [214]: ps['2011']
Out[214]:
2011-01   -0.253355
2011-02   -1.426908
2011-03    1.548971
2011-04   -0.088718
2011-05   -1.771348
2011-06   -0.989328
2011-07   -1.584789
2011-08   -0.288786
2011-09   -2.029806
2011-10   -0.761200
2011-11   -1.603608
2011-12    1.756171
Freq: M, dtype: float64

In [215]: dfp = DataFrame(randn(600,1), columns=['A'],
   .....:                 index=period_range('2013-01-01 9:00', periods=600, freq='T'))
   .....:

In [216]: dfp
Out[216]:
                         A
2013-01-01 09:00  0.020601
2013-01-01 09:01 -0.411719
2013-01-01 09:02  2.079413
2013-01-01 09:03 -1.077911
2013-01-01 09:04  0.099258
2013-01-01 09:05 -0.089851
2013-01-01 09:06  0.711329
...                    ...
2013-01-01 18:53 -1.340038
2013-01-01 18:54  1.315461
2013-01-01 18:55  2.396188
2013-01-01 18:56 -0.501527
2013-01-01 18:57 -3.171938
```

```
2013-01-01 18:58  0.142019
2013-01-01 18:59  0.606998

[600 rows x 1 columns]
```

```
In [217]: dfp['2013-01-01 10H']
Out[217]:
                         A
2013-01-01 10:00 -0.745396
2013-01-01 10:01  0.141880
2013-01-01 10:02 -1.077754
2013-01-01 10:03 -1.301174
2013-01-01 10:04 -0.269628
2013-01-01 10:05 -0.456347
2013-01-01 10:06  0.157766
...                    ...
2013-01-01 10:53  0.168057
2013-01-01 10:54 -0.214306
2013-01-01 10:55 -0.069739
2013-01-01 10:56 -1.511809
2013-01-01 10:57  0.307021
2013-01-01 10:58  1.449776
2013-01-01 10:59  0.782537

[60 rows x 1 columns]
```

As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```
In [218]: dfp['2013-01-01 10H':'2013-01-01 11H']
Out[218]:
                         A
2013-01-01 10:00 -0.745396
2013-01-01 10:01  0.141880
2013-01-01 10:02 -1.077754
2013-01-01 10:03 -1.301174
2013-01-01 10:04 -0.269628
2013-01-01 10:05 -0.456347
2013-01-01 10:06  0.157766
...                    ...
2013-01-01 11:53 -0.064395
2013-01-01 11:54  0.350193
2013-01-01 11:55  1.336433
2013-01-01 11:56 -0.438701
2013-01-01 11:57 -0.915841
2013-01-01 11:58  0.294215
2013-01-01 11:59  0.040959

[120 rows x 1 columns]
```

20.8.4 Frequency Conversion and Resampling with PeriodIndex

The frequency of `Period` and `PeriodIndex` can be converted via the `asfreq` method. Let's start with the fiscal year 2011, ending in December:

```
In [219]: p = Period('2011', freq='A-DEC')
```

```
In [220]: p
Out[220]: Period('2011', 'A-DEC')
```

We can convert it to a monthly frequency. Using the `how` parameter, we can specify whether to return the starting or ending month:

```
In [221]: p.asfreq('M', how='start')
Out[221]: Period('2011-01', 'M')

In [222]: p.asfreq('M', how='end')
Out[222]: Period('2011-12', 'M')
```

The shorthands 's' and 'e' are provided for convenience:

```
In [223]: p.asfreq('M', 's')
Out[223]: Period('2011-01', 'M')

In [224]: p.asfreq('M', 'e')
Out[224]: Period('2011-12', 'M')
```

Converting to a "super-period" (e.g., annual frequency is a super-period of quarterly frequency) automatically returns the super-period that includes the input period:

```
In [225]: p = Period('2011-12', freq='M')

In [226]: p.asfreq('A-NOV')
Out[226]: Period('2012', 'A-NOV')
```

Note that since we converted to an annual frequency that ends the year in November, the monthly period of December 2011 is actually in the 2012 A-NOV period. Period conversions with anchored frequencies are particularly useful for working with various quarterly data common to economics, business, and other fields. Many organizations define quarters relative to the month in which their fiscal year starts and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works for all quarterly frequencies `Q-JAN` through `Q-DEC`.

`Q-DEC` define regular calendar quarters:

```
In [227]: p = Period('2012Q1', freq='Q-DEC')

In [228]: p.asfreq('D', 's')
Out[228]: Period('2012-01-01', 'D')

In [229]: p.asfreq('D', 'e')
Out[229]: Period('2012-03-31', 'D')
```

`Q-MAR` defines fiscal year end in March:

```
In [230]: p = Period('2011Q4', freq='Q-MAR')

In [231]: p.asfreq('D', 's')
Out[231]: Period('2011-01-01', 'D')

In [232]: p.asfreq('D', 'e')
Out[232]: Period('2011-03-31', 'D')
```

20.9 Converting between Representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [233]: rng = date_range('1/1/2012', periods=5, freq='M')

In [234]: ts = Series(randn(len(rng)), index=rng)

In [235]: ts
Out[235]: 
2012-01-31   -0.016142
2012-02-29    0.865782
2012-03-31    0.246439
2012-04-30   -1.199736
2012-05-31    0.407620
Freq: M, dtype: float64

In [236]: ps = ts.to_period()

In [237]: ps
Out[237]: 
2012-01   -0.016142
2012-02    0.865782
2012-03    0.246439
2012-04   -1.199736
2012-05    0.407620
Freq: M, dtype: float64

In [238]: ps.to_timestamp()
Out[238]: 
2012-01-01   -0.016142
2012-02-01    0.865782
2012-03-01    0.246439
2012-04-01   -1.199736
2012-05-01    0.407620
Freq: MS, dtype: float64
```

Remember that 's' and 'e' can be used to return the timestamps at the start or end of the period:

```
In [239]: ps.to_timestamp('D', how='s')
Out[239]: 
2012-01-01   -0.016142
2012-02-01    0.865782
2012-03-01    0.246439
2012-04-01   -1.199736
2012-05-01    0.407620
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [240]: prng = period_range('1990Q1', '2000Q4', freq='Q-NOV')

In [241]: ts = Series(randn(len(prng)), prng)

In [242]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
```

```
In [243]: ts.head()
Out[243]:
1990-03-01 09:00   -2.470970
1990-06-01 09:00   -0.929915
1990-09-01 09:00    1.385889
1990-12-01 09:00   -1.830966
1991-03-01 09:00   -0.328505
Freq: H, dtype: float64
```

20.10 Representing out-of-bounds spans

If you have data that is outside of the `Timestamp` bounds, see *Timestamp limitations*, then you can use a `PeriodIndex` and/or `Series` of `Periods` to do computations.

```
In [244]: span = period_range('1215-01-01', '1381-01-01', freq='D')

In [245]: span
Out[245]:
PeriodIndex(['1215-01-01', '1215-01-02', '1215-01-03', '1215-01-04',
             '1215-01-05', '1215-01-06', '1215-01-07', '1215-01-08',
             '1215-01-09', '1215-01-10',
             ...
             '1380-12-23', '1380-12-24', '1380-12-25', '1380-12-26',
             '1380-12-27', '1380-12-28', '1380-12-29', '1380-12-30',
             '1380-12-31', '1381-01-01'],
            dtype='int64', length=60632, freq='D')
```

To convert from a `int64` based YYYYMMDD representation.

```
In [246]: s = Series([20121231, 20141130, 99991231])

In [247]: s
Out[247]:
0    20121231
1    20141130
2    99991231
dtype: int64

In [248]: def conv(x):
   .....:     return Period(year = x // 10000, month = x//100 % 100, day = x%100, freq='D')
   .....:

In [249]: s.apply(conv)
Out[249]:
0    2012-12-31
1    2014-11-30
2    9999-12-31
dtype: object

In [250]: s.apply(conv)[2]
Out[250]: Period('9999-12-31', 'D')
```

These can easily be converted to a `PeriodIndex`

```
In [251]: span = PeriodIndex(s.apply(conv))
```

```
In [252]: span
Out[252]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='int64', freq='D')
```

20.11 Time Zone Handling

Pandas provides rich support for working with timestamps in different time zones using `pytz` and `dateutil` libraries. `dateutil` support is new in 0.14.1 and currently only supported for fixed offset and tzfile zones. The default library is `pytz`. Support for `dateutil` is provided for compatibility with other applications e.g. if you use `dateutil` in other python packages.

20.11.1 Working with Time Zones

By default, pandas objects are time zone unaware:

```
In [253]: rng = date_range('3/6/2012 00:00', periods=15, freq='D')

In [254]: rng.tz is None
Out[254]: 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`.

```
# pytz
In [255]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
   .....:                        tz='Europe/London')
   .....:

In [256]: rng_pytz.tz
Out[256]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>

# dateutil
In [257]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
   .....:                            tz='dateutil/Europe/London')
   .....:

In [258]: rng_dateutil.tz
Out[258]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case
In [259]: rng_utc = date_range('3/6/2012 00:00', periods=10, freq='D',
   .....:                       tz=dateutil.tz.tzutc())
   .....:

In [260]: rng_utc.tz
Out[260]: tzutc()
```

Note that the `UTC` timezone is a special case in `dateutil` and should be constructed explicitly as an instance of `dateutil.tz.tzutc`. You can also construct other timezones explicitly first, which gives you more control over which time zone is used:

```
# pytz
In [261]: tz_pytz = pytz.timezone('Europe/London')

In [262]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
   .....:                        tz=tz_pytz)
   .....:

In [263]: rng_pytz.tz == tz_pytz
Out[263]: True

# dateutil
In [264]: tz_dateutil = dateutil.tz.gettz('Europe/London')

In [265]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
   .....:                            tz=tz_dateutil)
   .....:

In [266]: rng_dateutil.tz == tz_dateutil
Out[266]: True
```

Timestamps, like Python's `datetime.datetime` object can be either time zone naive or time zone aware. Naive time series and DatetimeIndex objects can be *localized* using `tz_localize`:

```
In [267]: ts = Series(randn(len(rng)), rng)

In [268]: ts_utc = ts.tz_localize('UTC')

In [269]: ts_utc
Out[269]:
2012-03-06 00:00:00+00:00    0.758606
2012-03-07 00:00:00+00:00    2.190827
2012-03-08 00:00:00+00:00    0.706087
2012-03-09 00:00:00+00:00    1.798831
2012-03-10 00:00:00+00:00    1.228481
2012-03-11 00:00:00+00:00   -0.179494
2012-03-12 00:00:00+00:00    0.634073
2012-03-13 00:00:00+00:00    0.262123
2012-03-14 00:00:00+00:00    1.928233
2012-03-15 00:00:00+00:00    0.322573
2012-03-16 00:00:00+00:00   -0.711113
2012-03-17 00:00:00+00:00    1.444272
2012-03-18 00:00:00+00:00   -0.352268
2012-03-19 00:00:00+00:00    0.213008
2012-03-20 00:00:00+00:00   -0.619340
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 [270]: ts_utc.tz_convert('US/Eastern')
Out[270]:
2012-03-05 19:00:00-05:00    0.758606
2012-03-06 19:00:00-05:00    2.190827
2012-03-07 19:00:00-05:00    0.706087
2012-03-08 19:00:00-05:00    1.798831
2012-03-09 19:00:00-05:00    1.228481
2012-03-10 19:00:00-05:00   -0.179494
2012-03-11 20:00:00-04:00    0.634073
2012-03-12 20:00:00-04:00    0.262123
```

```
2012-03-13 20:00:00-04:00    1.928233
2012-03-14 20:00:00-04:00    0.322573
2012-03-15 20:00:00-04:00   -0.711113
2012-03-16 20:00:00-04:00    1.444272
2012-03-17 20:00:00-04:00   -0.352268
2012-03-18 20:00:00-04:00    0.213008
2012-03-19 20:00:00-04:00   -0.619340
Freq: D, dtype: float64
```

Warning: Be wary of conversions between libraries. For some zones `pytz` and `dateutil` have different definitions of the zone. This is more of a problem for unusual timezones than for 'standard' zones like `US/Eastern`.

Warning: Be aware that a timezone definition across versions of timezone libraries may not be considered equal. This may cause problems when working with stored data that is localized using one version and operated on with a different version. See *here* for how to handle such a situation.

Warning: It is incorrect to pass a timezone directly into the `datetime.datetime` constructor (e.g., `datetime.datetime(2011, 1, 1, tz=timezone('US/Eastern'))`. Instead, the datetime needs to be localized using the the localize method on the timezone.

Under the hood, all timestamps are stored in UTC. Scalar values from a `DatetimeIndex` with a time zone will have their fields (day, hour, minute) localized to the time zone. However, timestamps with the same UTC value are still considered to be equal even if they are in different time zones:

```
In [271]: rng_eastern = rng_utc.tz_convert('US/Eastern')

In [272]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')

In [273]: rng_eastern[5]
Out[273]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [274]: rng_berlin[5]
Out[274]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')

In [275]: rng_eastern[5] == rng_berlin[5]
Out[275]: True
```

Like Series, DataFrame, and DatetimeIndex, Timestamps can be converted to other time zones using `tz_convert`:

```
In [276]: rng_eastern[5]
Out[276]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [277]: rng_berlin[5]
Out[277]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')

In [278]: rng_eastern[5].tz_convert('Europe/Berlin')
Out[278]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin')
```

Localization of Timestamps functions just like DatetimeIndex and Series:

```
In [279]: rng[5]
Out[279]: Timestamp('2012-03-11 00:00:00', offset='D')

In [280]: rng[5].tz_localize('Asia/Shanghai')
Out[280]: Timestamp('2012-03-11 00:00:00+0800', tz='Asia/Shanghai')
```

Operations between Series in different time zones will yield UTC Series, aligning the data on the UTC timestamps:

```
In [281]: eastern = ts_utc.tz_convert('US/Eastern')

In [282]: berlin = ts_utc.tz_convert('Europe/Berlin')

In [283]: result = eastern + berlin

In [284]: result
Out[284]:
2012-03-06 00:00:00+00:00    1.517212
2012-03-07 00:00:00+00:00    4.381654
2012-03-08 00:00:00+00:00    1.412174
2012-03-09 00:00:00+00:00    3.597662
2012-03-10 00:00:00+00:00    2.456962
2012-03-11 00:00:00+00:00   -0.358988
2012-03-12 00:00:00+00:00    1.268146
2012-03-13 00:00:00+00:00    0.524245
2012-03-14 00:00:00+00:00    3.856466
2012-03-15 00:00:00+00:00    0.645146
2012-03-16 00:00:00+00:00   -1.422226
2012-03-17 00:00:00+00:00    2.888544
2012-03-18 00:00:00+00:00   -0.704537
2012-03-19 00:00:00+00:00    0.426017
2012-03-20 00:00:00+00:00   -1.238679
Freq: D, dtype: float64

In [285]: result.index
Out[285]:
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]', freq='D', tz='UTC')
```

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 remove timezone after converting to UTC time.

```
In [286]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [287]: didx
Out[287]:
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]', freq='H', tz='US/Eastern')

In [288]: didx.tz_localize(None)
Out[288]:
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=None)

In [289]: didx.tz_convert(None)
```

```
Out[289]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)
In [290]: didx.tz_convert('UCT').tz_localize(None)
Out[290]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

20.11.2 Ambiguous Times when Localizing

In some cases, localize cannot determine the DST and non-DST hours when there are duplicates. This often happens when reading files or database records that simply duplicate the hours. Passing `ambiguous='infer'` (`infer_dst` argument in prior releases) into `tz_localize` will attempt to determine the right offset. Below the top example will fail as it contains ambiguous times and the bottom will infer the right offset.

```
In [291]: rng_hourly = 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 [292]: rng_hourly.tz_localize('US/Eastern')
---------------------------------------------------------------------------
AmbiguousTimeError                        Traceback (most recent call last)
<ipython-input-292-8c5fa6a37f5b> in <module>()
----> 1 rng_hourly.tz_localize('US/Eastern')

/home/joris/scipy/pandas/pandas/util/decorators.pyc in wrapper(*args, **kwargs)
     86                 else:
     87                     kwargs[new_arg_name] = new_arg_value
---> 88             return func(*args, **kwargs)
     89         return wrapper
     90     return _deprecate_kwarg

/home/joris/scipy/pandas/pandas/tseries/index.pyc in tz_localize(self, tz, ambiguous)
   1619
   1620             new_dates = tslib.tz_localize_to_utc(self.asi8, tz,
-> 1621                                                  ambiguous=ambiguous)
   1622         new_dates = new_dates.view(_NS_DTYPE)
   1623         return self._shallow_copy(new_dates, tz=tz)

/home/joris/scipy/pandas/pandas/tslib.so in pandas.tslib.tz_localize_to_utc (pandas/tslib.c:47148)()

AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try using the 'ambig

In [293]: rng_hourly_eastern = rng_hourly.tz_localize('US/Eastern', ambiguous='infer')
```

```
In [294]: rng_hourly_eastern.tolist()
Out[294]:
[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 [295]: rng_hourly_dst = np.array([1, 1, 0, 0, 0])

In [296]: rng_hourly.tz_localize('US/Eastern', ambiguous=rng_hourly_dst).tolist()
Out[296]:
[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 [297]: rng_hourly.tz_localize('US/Eastern', ambiguous='NaT').tolist()
Out[297]:
[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 [298]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [299]: didx
Out[299]:
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]', freq='H', tz='US/Eastern')

In [300]: didx.tz_localize(None)
Out[300]:
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=None)

In [301]: didx.tz_convert(None)
Out[301]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
```

```
              dtype='datetime64[ns]', freq='H', tz=None)

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)
In [302]: didx.tz_convert('UCT').tz_localize(None)
Out[302]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

CHAPTER

TWENTYONE

TIME DELTAS

Note: Starting in v0.15.0, we introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes.

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

21.1 Parsing

You can construct a `Timedelta` scalar through various arguments:

```
# strings
In [1]: Timedelta('1 days')
Out[1]: Timedelta('1 days 00:00:00')

In [2]: Timedelta('1 days 00:00:00')
Out[2]: Timedelta('1 days 00:00:00')

In [3]: Timedelta('1 days 2 hours')
Out[3]: Timedelta('1 days 02:00:00')

In [4]: Timedelta('-1 days 2 min 3us')
Out[4]: Timedelta('-2 days +23:57:59.999997')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [5]: Timedelta(days=1,seconds=1)
Out[5]: Timedelta('1 days 00:00:01')

# integers with a unit
In [6]: Timedelta(1,unit='d')
Out[6]: Timedelta('1 days 00:00:00')

# from a timedelta/np.timedelta64
In [7]: Timedelta(timedelta(days=1,seconds=1))
Out[7]: Timedelta('1 days 00:00:01')

In [8]: Timedelta(np.timedelta64(1,'ms'))
Out[8]: Timedelta('0 days 00:00:00.001000')

# negative Timedeltas have this string repr
```

```
# to be more consistent with datetime.timedelta conventions
In [9]: Timedelta('-1us')
Out[9]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [10]: Timedelta('nan')
Out[10]: NaT

In [11]: Timedelta('nat')
Out[11]: NaT
```

DateOffsets (`Day, Hour, Minute, Second, Milli, Micro, Nano`) can also be used in construction.

```
In [12]: Timedelta(Second(2))
Out[12]: Timedelta('0 days 00:00:02')
```

Further, operations among the scalars yield another scalar `Timedelta`

```
In [13]: Timedelta(Day(2)) + Timedelta(Second(2)) + Timedelta('00:00:00.000123')
Out[13]: Timedelta('2 days 00:00:02.000123')
```

21.1.1 to_timedelta

Warning: Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for Series input, and `Timedelta` for scalar input.
The arguments to `pd.to_timedelta` are now `(arg,unit='ns',box=True)`, previously were `(arg,box=True,unit='ns')` as these are more logical.

Using the top-level `pd.to_timedelta`, you can convert a scalar, array, list, or Series from a recognized timedelta format / value into a `Timedelta` type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise will output a `TimedeltaIndex`

```
In [14]: to_timedelta('1 days 06:05:01.00003')
Out[14]: Timedelta('1 days 06:05:01.000030')

In [15]: to_timedelta('15.5us')
Out[15]: Timedelta('0 days 00:00:00.000015')

In [16]: to_timedelta(['1 days 06:05:01.00003','15.5us','nan'])
Out[16]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta6

In [17]: to_timedelta(np.arange(5),unit='s')
Out[17]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelt

In [18]: to_timedelta(np.arange(5),unit='d')
Out[18]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]',
```

21.2 Operations

You can operate on Series/DataFrames and construct `timedelta64[ns]` Series through subtraction operations on `datetime64[ns]` Series, or `Timestamps`.

```
In [19]: s = Series(date_range('2012-1-1', periods=3, freq='D'))

In [20]: td = Series([ Timedelta(days=i) for i in range(3) ])

In [21]: df = DataFrame(dict(A = s, B = td))

In [22]: df
Out[22]: 
           A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [23]: df['C'] = df['A'] + df['B']

In [24]: df
Out[24]: 
           A      B          C
0 2012-01-01 0 days 2012-01-01
1 2012-01-02 1 days 2012-01-03
2 2012-01-03 2 days 2012-01-05

In [25]: df.dtypes
Out[25]: 
A     datetime64[ns]
B    timedelta64[ns]
C     datetime64[ns]
dtype: object

In [26]: s - s.max()
Out[26]: 
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [27]: s - datetime(2011,1,1,3,5)
Out[27]: 
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [28]: s + timedelta(minutes=5)
Out[28]: 
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [29]: s + Minute(5)
Out[29]: 
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [30]: s + Minute(5) + Milli(5)
```

```
Out[30]:
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 [31]: y = s - s[0]

In [32]: y
Out[32]:
0   0 days
1   1 days
2   2 days
dtype: timedelta64[ns]
```

Series of timedeltas with `NaT` values are supported

```
In [33]: y = s - s.shift()

In [34]: y
Out[34]:
0      NaT
1   1 days
2   1 days
dtype: timedelta64[ns]
```

Elements can be set to `NaT` using `np.nan` analogously to datetimes

```
In [35]: y[1] = np.nan

In [36]: y
Out[36]:
0      NaT
1      NaT
2   1 days
dtype: timedelta64[ns]
```

Operands can also appear in a reversed order (a singular object operated with a Series)

```
In [37]: s.max() - s
Out[37]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [38]: datetime(2011,1,1,3,5) - s
Out[38]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [39]: timedelta(minutes=5) + s
Out[39]:
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

```
In [40]: A = s - Timestamp('20120101') - Timedelta('00:05:05')

In [41]: B = s - Series(date_range('2012-1-2', periods=3, freq='D'))

In [42]: df = DataFrame(dict(A=A, B=B))

In [43]: df
Out[43]:
                  A       B
0 -1 days +23:54:55 -1 days
1   0 days 23:54:55 -1 days
2   1 days 23:54:55 -1 days

In [44]: df.min()
Out[44]:
A   -1 days +23:54:55
B   -1 days +00:00:00
dtype: timedelta64[ns]

In [45]: df.min(axis=1)
Out[45]:
0   -1 days
1   -1 days
2   -1 days
dtype: timedelta64[ns]

In [46]: df.idxmin()
Out[46]:
A    0
B    0
dtype: int64

In [47]: df.idxmax()
Out[47]:
A    2
B    0
dtype: int64
```

`min, max, idxmin, idxmax` operations are supported on Series as well. A scalar result will be a `Timedelta`.

```
In [48]: df.min().max()
Out[48]: Timedelta('-1 days +23:54:55')

In [49]: df.min(axis=1).min()
Out[49]: Timedelta('-1 days +00:00:00')

In [50]: df.min().idxmax()
Out[50]: 'A'

In [51]: df.min(axis=1).idxmin()
Out[51]: 0
```

You can fillna on timedeltas. Integers will be interpreted as seconds. You can pass a timedelta to get a particular value.

```
In [52]: y.fillna(0)
Out[52]:
0    0 days
1    0 days
2    1 days
dtype: timedelta64[ns]

In [53]: y.fillna(10)
Out[53]:
0    0 days 00:00:10
1    0 days 00:00:10
2    1 days 00:00:00
dtype: timedelta64[ns]

In [54]: y.fillna(Timedelta('-1 days, 00:00:05'))
Out[54]:
0   -1 days +00:00:05
1   -1 days +00:00:05
2     1 days 00:00:00
dtype: timedelta64[ns]
```

You can also negate, multiply and use `abs` on `Timedeltas`

```
In [55]: td1 = Timedelta('-1 days 2 hours 3 seconds')

In [56]: td1
Out[56]: Timedelta('-2 days +21:59:57')

In [57]: -1 * td1
Out[57]: Timedelta('1 days 02:00:03')

In [58]: - td1
Out[58]: Timedelta('1 days 02:00:03')

In [59]: abs(td1)
Out[59]: Timedelta('1 days 02:00:03')
```

21.3 Reductions

Numeric reduction operation for `timedelta64[ns]` will return `Timedelta` objects. As usual `NaT` are skipped during evaluation.

```
In [60]: y2 = Series(to_timedelta(['-1 days +00:00:05','nat','-1 days +00:00:05','1 days']))

In [61]: y2
Out[61]:
0   -1 days +00:00:05
1                 NaT
2   -1 days +00:00:05
3     1 days 00:00:00
dtype: timedelta64[ns]

In [62]: y2.mean()
Out[62]: Timedelta('-1 days +16:00:03.333333')

In [63]: y2.median()
```

```
Out[63]: Timedelta('-1 days +00:00:05')

In [64]: y2.quantile(.1)
Out[64]: Timedelta('-1 days +00:00:05')

In [65]: y2.sum()
Out[65]: Timedelta('-1 days +00:00:10')
```

21.4 Frequency Conversion

New in version 0.13.

Timedelta Series, `TimedeltaIndex`, and `Timedelta` scalars can be converted to other 'frequencies' by dividing by another timedelta, or by astyping to a specific timedelta type. These operations yield Series and propogate `NaT` -> `nan`. Note that division by the numpy scalar is true division, while astyping is equivalent of floor division.

```
In [66]: td = Series(date_range('20130101',periods=4)) - \
   ....:      Series(date_range('20121201',periods=4))
   ....:

In [67]: td[2] += timedelta(minutes=5,seconds=3)

In [68]: td[3] = np.nan

In [69]: td
Out[69]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3                NaT
dtype: timedelta64[ns]

# to days
In [70]: td / np.timedelta64(1,'D')
Out[70]:
0    31.000000
1    31.000000
2    31.003507
3          NaN
dtype: float64

In [71]: td.astype('timedelta64[D]')
Out[71]:
0    31
1    31
2    31
3   NaN
dtype: float64

# to seconds
In [72]: td / np.timedelta64(1,'s')
Out[72]:
0    2678400
1    2678400
2    2678703
3        NaN
```

```
dtype: float64

In [73]: td.astype('timedelta64[s]')
Out[73]:
0    2678400
1    2678400
2    2678703
3        NaN
dtype: float64

# to months (these are constant months)
In [74]: td / np.timedelta64(1,'M')
Out[74]:
0    1.018501
1    1.018501
2    1.018617
3         NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

```
In [75]: td * -1
Out[75]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3                  NaT
dtype: timedelta64[ns]

In [76]: td * Series([1,2,3,4])
Out[76]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3                NaT
dtype: timedelta64[ns]
```

21.5 Attributes

You can access various components of the `Timedelta` or `TimedeltaIndex` directly using the attributes `days,seconds,microseconds,nanoseconds`. These are identical to the values returned by `datetime.timedelta`, in that, for example, the `.seconds` attribute represents the number of seconds >= 0 and < 1 day. These are signed according to whether the `Timedelta` is signed.

These operations can also be directly accessed via the `.dt` property of the `Series` as well.

Note: Note that the attributes are NOT the displayed values of the `Timedelta`. Use `.components` to retrieve the displayed values.

For a `Series`

```
In [77]: td.dt.days
Out[77]:
0    31
1    31
```

```
2     31
3    NaN
dtype: float64

In [78]: td.dt.seconds
Out[78]:
0       0
1       0
2     303
3     NaN
dtype: float64
```

You can access the value of the fields for a scalar `Timedelta` directly.

```
In [79]: tds = Timedelta('31 days 5 min 3 sec')

In [80]: tds.days
Out[80]: 31L

In [81]: tds.seconds
Out[81]: 303L

In [82]: (-tds).seconds
Out[82]: 86097L
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a `DataFrame` indexed similarly to the `Series`. These are the *displayed* values of the `Timedelta`.

```
In [83]: td.dt.components
Out[83]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0    31      0        0        0             0             0            0
1    31      0        0        0             0             0            0
2    31      0        5        3             0             0            0
3   NaN    NaN      NaN      NaN           NaN           NaN          NaN

In [84]: td.dt.components.seconds
Out[84]:
0      0
1      0
2      3
3    NaN
Name: seconds, dtype: float64
```

21.6 TimedeltaIndex

New in version 0.15.0.

To generate an index with time delta, you can use either the `TimedeltaIndex` or the `timedelta_range` constructor.

Using `TimedeltaIndex` you can pass string-like, `Timedelta`, `timedelta`, or `np.timedelta64` objects. Passing `np.nan/pd.NaT/nat` will represent missing values.

```
In [85]: TimedeltaIndex(['1 days','1 days, 00:00:05',
   ....:                 np.timedelta64(2,'D'),timedelta(days=2,seconds=2)])
   ....:
```

```
Out[85]:
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)
```

Similarly to `date_range`, you can construct regular ranges of a `TimedeltaIndex`:

```
In [86]: timedelta_range(start='1 days',periods=5,freq='D')
Out[86]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]',

In [87]: timedelta_range(start='1 days',end='2 days',freq='30T')
Out[87]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')
```

21.6.1 Using the TimedeltaIndex

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```
In [88]: s = Series(np.arange(100),
   ....:            index=timedelta_range('1 days',periods=100,freq='h'))
   ....:

In [89]: s
Out[89]:
1 days 00:00:00     0
1 days 01:00:00     1
1 days 02:00:00     2
1 days 03:00:00     3
1 days 04:00:00     4
1 days 05:00:00     5
1 days 06:00:00     6
                   ..
4 days 21:00:00    93
4 days 22:00:00    94
4 days 23:00:00    95
5 days 00:00:00    96
5 days 01:00:00    97
5 days 02:00:00    98
5 days 03:00:00    99
```

```
Freq: H, dtype: int32
```

Selections work similary, with coercion on string-likes and slices:

```
In [90]: s['1 day':'2 day']
Out[90]:
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, dtype: int32

In [91]: s['1 day 01:00:00']
Out[91]: 1

In [92]: s[Timedelta('1 day 1h')]
Out[92]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```
In [93]: s['1 day':'1 day 5 hours']
Out[93]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
Freq: H, dtype: int32
```

21.6.2 Operations

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are NaT preserving:

```
In [94]: tdi = TimedeltaIndex(['1 days',pd.NaT,'2 days'])

In [95]: tdi.tolist()
Out[95]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [96]: dti = date_range('20130101',periods=3)

In [97]: dti.tolist()
Out[97]:
[Timestamp('2013-01-01 00:00:00', offset='D'),
 Timestamp('2013-01-02 00:00:00', offset='D'),
```

```
 Timestamp('2013-01-03 00:00:00', offset='D')]

In [98]: (dti + tdi).tolist()
Out[98]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [99]: (dti - tdi).tolist()
Out[99]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

21.6.3 Conversions

Similarly to frequency conversion on a `Series` above, you can convert these indices to yield another Index.

```
In [100]: tdi / np.timedelta64(1,'s')
Out[100]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [101]: tdi.astype('timedelta64[s]')
Out[101]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a *different* type of index.

```
# adding or timedelta and date -> datelike
In [102]: tdi + Timestamp('20130101')
Out[102]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]', freq=None, tz=No

# subtraction of a date and a timedelta -> datelike
# note that trying to subtract a date from a Timedelta will raise an exception
In [103]: (Timestamp('20130101') - tdi).tolist()
Out[103]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

# timedelta + timedelta -> timedelta
In [104]: tdi + Timedelta('10 days')
Out[104]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]', freq=None)

# division can result in a Timedelta if the divisor is an integer
In [105]: tdi / 2
Out[105]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype='timedelta64[ns]', freq=N

# or a Float64Index if the divisor is a Timedelta
In [106]: tdi / tdi[0]
Out[106]: Float64Index([1.0, nan, 2.0], dtype='float64')
```

21.7 Resampling

Similar to *timeseries resampling*, we can resample with a `TimedeltaIndex`.

```
In [107]: s.resample('D')
Out[107]:
1 days    11.5
2 days    35.5
3 days    59.5
4 days    83.5
5 days    97.5
Freq: D, dtype: float64
```

CHAPTER

TWENTYTWO

CATEGORICAL DATA

New in version 0.15.

Note: While there was *pandas.Categorical* in earlier versions, the ability to use categorical data in *Series* and *DataFrame* is new.

This is an introduction to pandas categorical data type, including a short comparison with R's `factor`.

Categoricals are a pandas data type, which correspond to categorical variables in statistics: a variable, which can take on only a limited, and usually fixed, number of possible values (*categories*; *levels* in R). Examples are gender, social class, blood types, country affiliations, observation time or ratings via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. 'strongly agree' vs 'agree' or 'first observation' vs. 'second observation'), but numerical operations (additions, divisions, ...) are not possible.

All values of categorical data are either in *categories* or *np.nan*. Order is defined by the order of *categories*, not lexical order of the values. Internally, the data structure consists of a *categories* array and an integer array of *codes* which point to the real value in the *categories* array.

The categorical data type is useful in the following cases:

- 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*.

22.1 Object Creation

Categorical *Series* or columns in a *DataFrame* can be created in several ways:

By specifying `dtype="category"` when constructing a *Series*:

```
In [1]: s = pd.Series(["a","b","c","a"], dtype="category")

In [2]: s
Out[2]:
0    a
1    b
```

```
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]
```

By converting an existing *Series* or column to a `category` dtype:

```
In [3]: df = pd.DataFrame({"A":["a","b","c","a"]})

In [4]: df["B"] = df["A"].astype('category')

In [5]: df
Out[5]:
   A  B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using some special functions:

```
In [6]: df = pd.DataFrame({'value': np.random.randint(0, 100, 20)})

In [7]: labels = [ "{0} - {1}".format(i, i + 9) for i in range(0, 100, 10) ]

In [8]: df['group'] = pd.cut(df.value, range(0, 105, 10), right=False, labels=labels)

In [9]: df.head(10)
Out[9]:
   value    group
0     65  60 - 69
1     49  40 - 49
2     56  50 - 59
3     43  40 - 49
4     43  40 - 49
5     91  90 - 99
6     32  30 - 39
7     87  80 - 89
8     36  30 - 39
9      8    0 - 9
```

See *documentation* for `cut()`.

By passing a `pandas.Categorical` object to a *Series* or assigning it to a *DataFrame*.

```
In [10]: raw_cat = pd.Categorical(["a","b","c","a"], categories=["b","c","d"],
   ....:                          ordered=False)
   ....:

In [11]: s = pd.Series(raw_cat)

In [12]: s
Out[12]:
0    NaN
1      b
2      c
3    NaN
dtype: category
Categories (3, object): [b, c, d]
```

```
In [13]: df = pd.DataFrame({"A":["a","b","c","a"]})

In [14]: df["B"] = raw_cat

In [15]: df
Out[15]:
   A    B
0  a  NaN
1  b    b
2  c    c
3  a  NaN
```

You can also specify differently ordered categories or make the resulting data ordered, by passing these arguments to `astype()`:

```
In [16]: s = pd.Series(["a","b","c","a"])

In [17]: s_cat = s.astype("category", categories=["b","c","d"], ordered=False)

In [18]: s_cat
Out[18]:
0    NaN
1      b
2      c
3    NaN
dtype: category
Categories (3, object): [b, c, d]
```

Categorical data has a specific `category` *dtype*:

```
In [19]: df.dtypes
Out[19]:
A      object
B    category
dtype: object
```

Note: In contrast to R's *factor* function, categorical data is not converting input values to strings and categories will end up the same data type as the original values.

Note: In contrast to R's *factor* function, there is currently no way to assign/change labels at creation time. Use *categories* to change the categories after creation time.

To get back to the original Series or *numpy* array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

```
In [20]: s = pd.Series(["a","b","c","a"])

In [21]: s
Out[21]:
0    a
1    b
2    c
3    a
dtype: object

In [22]: s2 = s.astype('category')
```

```
In [23]: s2
Out[23]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]

In [24]: s3 = s2.astype('string')

In [25]: s3
Out[25]:
0    a
1    b
2    c
3    a
dtype: object

In [26]: np.asarray(s2)
Out[26]: array(['a', 'b', 'c', 'a'], dtype=object)
```

If you have already *codes* and *categories*, you can use the `from_codes()` constructor to save the factorize step during normal constructor mode:

```
In [27]: splitter = np.random.choice([0,1], 5, p=[0.5,0.5])

In [28]: s = pd.Series(pd.Categorical.from_codes(splitter, categories=["train", "test"]))
```

22.2 Description

Using `.describe()` on categorical data will produce similar output to a *Series* or *DataFrame* of type `string`.

```
In [29]: cat = pd.Categorical(["a","c","c",np.nan], categories=["b","a","c",np.nan] )

In [30]: df = pd.DataFrame({"cat":cat, "s":["a","c","c",np.nan]})

In [31]: df.describe()
Out[31]:
       cat  s
count    3  3
unique   2  2
top      c  c
freq     2  2

In [32]: df["cat"].describe()
Out[32]:
count     3
unique    2
top       c
freq      2
Name: cat, dtype: object
```

22.3 Working with categories

Categorical data has a *categories* and a *ordered* property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don't manually specify categories and ordering, they are inferred from the passed in values.

```
In [33]: s = pd.Series(["a","b","c","a"], dtype="category")

In [34]: s.cat.categories
Out[34]: Index([u'a', u'b', u'c'], dtype='object')

In [35]: s.cat.ordered
Out[35]: False
```

It's also possible to pass in the categories in a specific order:

```
In [36]: s = pd.Series(pd.Categorical(["a","b","c","a"], categories=["c","b","a"]))

In [37]: s.cat.categories
Out[37]: Index([u'c', u'b', u'a'], dtype='object')

In [38]: s.cat.ordered
Out[38]: False
```

Note: New categorical data are NOT automatically ordered. You must explicity pass `ordered=True` to indicate an ordered `Categorical`.

22.3.1 Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `Categorical.rename_categories()` method:

```
In [39]: s = pd.Series(["a","b","c","a"], dtype="category")

In [40]: s
Out[40]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]

In [41]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]

In [42]: s
Out[42]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]

In [43]: s.cat.rename_categories([1,2,3])
Out[43]:
```

```
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [1, 2, 3]
```

Note: In contrast to R's *factor*, categorical data can have categories of other types than string.

Note: Be aware that assigning new categories is an inplace operations, while most other operation under `Series.cat` per default return a new Series of dtype *category*.

Categories must be unique or a *ValueError* is raised:

```
In [44]: try:
   ....:     s.cat.categories = [1,1,1]
   ....: except ValueError as e:
   ....:     print("ValueError: " + str(e))
   ....:
ValueError: Categorical categories must be unique
```

22.3.2 Appending new categories

Appending categories can be done by using the `Categorical.add_categories()` method:

```
In [45]: s = s.cat.add_categories([4])

In [46]: s.cat.categories
Out[46]: Index([u'Group a', u'Group b', u'Group c', 4], dtype='object')

In [47]: s
Out[47]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (4, object): [Group a, Group b, Group c, 4]
```

22.3.3 Removing categories

Removing categories can be done by using the `Categorical.remove_categories()` method. Values which are removed are replaced by `np.nan`.:

```
In [48]: s = s.cat.remove_categories([4])

In [49]: s
Out[49]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
```

22.3.4 Removing unused categories

Removing unused categories can also be done:

```
In [50]: s = pd.Series(pd.Categorical(["a","b","a"], categories=["a","b","c","d"]))

In [51]: s
Out[51]:
0    a
1    b
2    a
dtype: category
Categories (4, object): [a, b, c, d]

In [52]: s.cat.remove_unused_categories()
Out[52]:
0    a
1    b
2    a
dtype: category
Categories (2, object): [a, b]
```

22.3.5 Setting categories

If you want to do remove and add new categories in one step (which has some speed advantage), or simply set the categories to a predefined scale, use `Categorical.set_categories()`.

```
In [53]: s = pd.Series(["one","two","four", "-"], dtype="category")

In [54]: s
Out[54]:
0     one
1     two
2    four
3       -
dtype: category
Categories (4, object): [-, four, one, two]

In [55]: s = s.cat.set_categories(["one","two","three","four"])

In [56]: s
Out[56]:
0     one
1     two
2    four
3     NaN
dtype: category
Categories (4, object): [one, two, three, four]
```

Note: Be aware that `Categorical.set_categories()` cannot know whether some category is omitted intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., numpys S1 dtype and python strings). This can result in surprising behaviour!

22.4 Sorting and Order

Warning: The default for construction has changed in v0.16.0 to `ordered=False`, from the prior implicit `ordered=True`

If categorical data is ordered (`s.cat.ordered == True`), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, `.min()/.max()` will raise a *TypeError*.

```
In [57]: s = pd.Series(pd.Categorical(["a","b","c","a"], ordered=False))

In [58]: s.sort()

In [59]: s = pd.Series(["a","b","c","a"]).astype('category', ordered=True)

In [60]: s.sort()

In [61]: s
Out[61]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a < b < c]

In [62]: s.min(), s.max()
Out[62]: ('a', 'c')
```

You can set categorical data to be ordered by using `as_ordered()` or unordered by using `as_unordered()`. These will by default return a *new* object.

```
In [63]: s.cat.as_ordered()
Out[63]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a < b < c]

In [64]: s.cat.as_unordered()
Out[64]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a, b, c]
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [65]: s = pd.Series([1,2,3,1], dtype="category")

In [66]: s = s.cat.set_categories([2,3,1], ordered=True)

In [67]: s
```

```
Out[67]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [68]: s.sort()

In [69]: s
Out[69]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [70]: s.min(), s.max()
Out[70]: (2, 1)
```

22.4.1 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 [71]: s = pd.Series([1,2,3,1], dtype="category")

In [72]: s = s.cat.reorder_categories([2,3,1], ordered=True)

In [73]: s
Out[73]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [74]: s.sort()

In [75]: s
Out[75]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [76]: s.min(), s.max()
Out[76]: (2, 1)
```

Note: Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the *Series*, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the *Series* are changed.

Note: If the *Categorical* is not ordered, `Series.min()` and `Series.max()` will raise *TypeError*. Numeric operations like `+`, `-`, `*`, `/` and operations based on them (e.g.‘‘Series.median()‘‘, which would need to compute the mean between two values if the length of an array is even) do not work and raise a *TypeError*.

22.4.2 Multi Column Sorting

A categorical dtyped column will partcipate 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 [77]: dfs = pd.DataFrame({'A' : pd.Categorical(list('bbeebbaa'), categories=['e','a','b'], ordered
   ....:                     'B' : [1,2,1,2,2,1,2,1] })
   ....:

In [78]: dfs.sort(['A', 'B'])
Out[78]:
   A  B
2  e  1
3  e  2
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
```

Reordering the `categories` changes a future sort.

```
In [79]: dfs['A'] = dfs['A'].cat.reorder_categories(['a','b','e'])

In [80]: dfs.sort(['A','B'])
Out[80]:
   A  B
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
2  e  1
3  e  2
```

22.5 Comparisons

Comparing categorical data with other objects is possible in three cases:

- comparing equality (`==` and `!=`) to a list-like object (list, Series, array, ...) of the same length as the categorical data.

- all comparisons (`==`, `!=`, `>`, `>=`, `<`, and `<=`) of categorical data to another categorical Series, when `ordered==True` and the *categories* are the same.
- all comparisons of a categorical data to a scalar.

All other comparisons, especially "non-equality" comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a TypeError.

Note: Any "non-equality" comparisons of categorical data with a *Series*, *np.array*, *list* or categorical data with different categories or ordering will raise an *TypeError* because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

```
In [81]: cat = pd.Series([1,2,3]).astype("category", categories=[3,2,1], ordered=True)

In [82]: cat_base = pd.Series([2,2,2]).astype("category", categories=[3,2,1], ordered=True)

In [83]: cat_base2 = pd.Series([2,2,2]).astype("category", ordered=True)

In [84]: cat
Out[84]:
0    1
1    2
2    3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [85]: cat_base
Out[85]:
0    2
1    2
2    2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [86]: cat_base2
Out[86]:
0    2
1    2
2    2
dtype: category
Categories (1, int64): [2]
```

Comparing to a categorical with the same categories and ordering or to a scalar works:

```
In [87]: cat > cat_base
Out[87]:
0     True
1    False
2    False
dtype: bool

In [88]: cat > 2
Out[88]:
0     True
1    False
2    False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```
In [89]: cat == cat_base
Out[89]:
0    False
1     True
2    False
dtype: bool

In [90]: cat == np.array([1,2,3])
Out[90]:
0    True
1    True
2    True
dtype: bool

In [91]: cat == 2
Out[91]:
0    False
1     True
2    False
dtype: bool
```

This doesn't work because the categories are not the same:

```
In [92]: try:
   ....:     cat > cat_base2
   ....: except TypeError as e:
   ....:      print("TypeError: " + str(e))
   ....:
TypeError: Categoricals can only be compared if 'categories' are the same
```

If you want to do a "non-equality" comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:

```
In [93]: base = np.array([1,2,3])

In [94]: try:
   ....:     cat > base
   ....: except TypeError as e:
   ....:      print("TypeError: " + str(e))
   ....:
TypeError: Cannot compare a Categorical for op __gt__ with type <type 'numpy.ndarray'>. If you want t
compare values, use 'np.asarray(cat) <op> other'.

In [95]: np.asarray(cat) > base
Out[95]: array([False, False, False], dtype=bool)
```

22.6 Operations

Apart from `Series.min()`, `Series.max()` and `Series.mode()`, the following operations are possible with categorical data:

Series methods like *Series.value_counts()* will use all categories, even if some categories are not present in the data:

```
In [96]: s = pd.Series(pd.Categorical(["a","b","c","c"], categories=["c","a","b","d"]))

In [97]: s.value_counts()
Out[97]:
```

```
c    2
b    1
a    1
d    0
dtype: int64
```

Groupby will also show "unused" categories:

```
In [98]: cats = pd.Categorical(["a","b","b","b","c","c","c"], categories=["a","b","c","d"])

In [99]: df = pd.DataFrame({"cats":cats,"values":[1,2,2,2,3,4,5]})

In [100]: df.groupby("cats").mean()
Out[100]:
      values
cats
a          1
b          2
c          4
d        NaN

In [101]: cats2 = pd.Categorical(["a","a","b","b"], categories=["a","b","c"])

In [102]: df2 = pd.DataFrame({"cats":cats2,"B":["c","d","c","d"], "values":[1,2,3,4]})

In [103]: df2.groupby(["cats","B"]).mean()
Out[103]:
        values
cats B
a    c       1
     d       2
b    c       3
     d       4
c    c     NaN
     d     NaN
```

Pivot tables:

```
In [104]: raw_cat = pd.Categorical(["a","a","b","b"], categories=["a","b","c"])

In [105]: df = pd.DataFrame({"A":raw_cat,"B":["c","d","c","d"], "values":[1,2,3,4]})

In [106]: pd.pivot_table(df, values='values', index=['A', 'B'])
Out[106]:
A  B
a  c      1
   d      2
b  c      3
   d      4
c  c    NaN
   d    NaN
Name: values, dtype: float64
```

22.7 Data munging

The optimized pandas data access methods `.loc`, `.iloc`, `.ix` `.at`, and `.iat`, work as normal. The only difference is the return type (for getting) and that only values already in *categories* can be assigned.

22.7.1 Getting

If the slicing operation returns either a *DataFrame* or a column of type *Series*, the `category` dtype is preserved.

```
In [107]: idx = pd.Index(["h","i","j","k","l","m","n",])

In [108]: cats = pd.Series(["a","b","b","b","c","c","c"], dtype="category", index=idx)

In [109]: values= [1,2,2,2,3,4,5]

In [110]: df = pd.DataFrame({"cats":cats,"values":values}, index=idx)

In [111]: df.iloc[2:4,:]
Out[111]:
  cats  values
j    b       2
k    b       2

In [112]: df.iloc[2:4,:].dtypes
Out[112]:
cats      category
values       int64
dtype: object

In [113]: df.loc["h":"j","cats"]
Out[113]:
h    a
i    b
j    b
Name: cats, dtype: category
Categories (3, object): [a, b, c]

In [114]: df.ix["h":"j",0:1]
Out[114]:
  cats
h    a
i    b
j    b

In [115]: df[df["cats"] == "b"]
Out[115]:
  cats  values
i    b       2
j    b       2
k    b       2
```

An example where the category type is not preserved is if you take one single row: the resulting *Series* is of dtype `object`:

```
# get the complete "h" row as a Series
In [116]: df.loc["h", :]
Out[116]:
cats      a
values    1
Name: h, dtype: object
```

Returning a single item from categorical data will also return the value, not a categorical of length "1".

```
In [117]: df.iat[0,0]
Out[117]: 'a'

In [118]: df["cats"].cat.categories = ["x","y","z"]

In [119]: df.at["h","cats"] # returns a string
Out[119]: 'x'
```

Note: This is a difference to R's *factor* function, where `factor(c(1,2,3))[1]` returns a single value *factor*.

To get a single value *Series* of type `category` pass in a list with a single value:

```
In [120]: df.loc[["h"],"cats"]
Out[120]:
h    x
Name: cats, dtype: category
Categories (3, object): [x, y, z]
```

22.7.2 Setting

Setting values in a categorical column (or *Series*) works as long as the value is included in the *categories*:

```
In [121]: idx = pd.Index(["h","i","j","k","l","m","n"])

In [122]: cats = pd.Categorical(["a","a","a","a","a","a","a"], categories=["a","b"])

In [123]: values = [1,1,1,1,1,1,1]

In [124]: df = pd.DataFrame({"cats":cats,"values":values}, index=idx)

In [125]: df.iloc[2:4,:] = [["b",2],["b",2]]

In [126]: df
Out[126]:
  cats  values
h    a       1
i    a       1
j    b       2
k    b       2
l    a       1
m    a       1
n    a       1

In [127]: try:
   .....:     df.iloc[2:4,:] = [["c",3],["c",3]]
   .....: except ValueError as e:
   .....:     print("ValueError: " + str(e))
   .....:
ValueError: cannot setitem on a Categorical with a new category, set the categories first
```

Setting values by assigning categorical data will also check that the *categories* match:

```
In [128]: df.loc["j":"k","cats"] = pd.Categorical(["a","a"], categories=["a","b"])

In [129]: df
Out[129]:
  cats  values
```

```
h    a       1
i    a       1
j    a       2
k    a       2
l    a       1
m    a       1
n    a       1

In [130]: try:
   .....:     df.loc["j":"k","cats"] = pd.Categorical(["b","b"], categories=["a","b","c"])
   .....: except ValueError as e:
   .....:     print("ValueError: " + str(e))
   .....:
ValueError: Cannot set a Categorical with another, without identical categories
```

Assigning a *Categorical* to parts of a column of other types will use the values:

```
In [131]: df = pd.DataFrame({"a":[1,1,1,1,1], "b":["a","a","a","a","a"]})

In [132]: df.loc[1:2,"a"] = pd.Categorical(["b","b"], categories=["a","b"])

In [133]: df.loc[2:3,"b"] = pd.Categorical(["b","b"], categories=["a","b"])

In [134]: df
Out[134]:
   a  b
0  1  a
1  b  a
2  b  b
3  1  b
4  1  a

In [135]: df.dtypes
Out[135]:
a    object
b    object
dtype: object
```

22.7.3 Merging

You can concat two *DataFrames* containing categorical data together, but the categories of these categoricals need to be the same:

```
In [136]: cat = pd.Series(["a","b"], dtype="category")

In [137]: vals = [1,2]

In [138]: df = pd.DataFrame({"cats":cat, "vals":vals})

In [139]: res = pd.concat([df,df])

In [140]: res
Out[140]:
  cats  vals
0    a     1
1    b     2
0    a     1
```

```
1    b     2

In [141]: res.dtypes
Out[141]: 
cats    category
vals       int64
dtype: object
```

In this case the categories are not the same and so an error is raised:

```
In [142]: df_different = df.copy()

In [143]: df_different["cats"].cat.categories = ["c","d"]

In [144]: try:
   .....:     pd.concat([df,df_different])
   .....: except ValueError as e:
   .....:     print("ValueError: " + str(e))
   .....: 
ValueError: incompatible categories in categorical concat
```

The same applies to `df.append(df_different)`.

22.8 Getting Data In/Out

New in version 0.15.2.

Writing data (*Series*, *Frames*) to a HDF store that contains a `category` dtype was implemented in 0.15.2. See *here* for an example and caveats.

Writing data to and reading data from *Stata* format files was implemented in 0.15.2. See *here* for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to *category* and assign the right categories and categories ordering.

```
In [145]: s = pd.Series(pd.Categorical(['a', 'b', 'b', 'a', 'a', 'd']))

# rename the categories
In [146]: s.cat.categories = ["very good", "good", "bad"]

# reorder the categories and add missing categories
In [147]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [148]: df = pd.DataFrame({"cats":s, "vals":[1,2,3,4,5,6]})

In [149]: csv = StringIO()

In [150]: df.to_csv(csv)

In [151]: df2 = pd.read_csv(StringIO(csv.getvalue()))

In [152]: df2.dtypes
Out[152]: 
Unnamed: 0     int64
cats          object
```

```
vals              int64
dtype: object

In [153]: df2["cats"]
Out[153]:
0    very good
1         good
2         good
3    very good
4    very good
5          bad
Name: cats, dtype: object

# Redo the category
In [154]: df2["cats"] = df2["cats"].astype("category")

In [155]: df2["cats"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"],
   .....:                                inplace=True)
   .....:

In [156]: df2.dtypes
Out[156]:
Unnamed: 0       int64
cats          category
vals             int64
dtype: object

In [157]: df2["cats"]
Out[157]:
0    very good
1         good
2         good
3    very good
4    very good
5          bad
Name: cats, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]
```

The same holds for writing to a SQL database with `to_sql`.

22.9 Missing Data

pandas primarily uses the value *np.nan* to represent missing data. It is by default not included in computations. See the *Missing Data section*

There are two ways a *np.nan* can be represented in categorical data: either the value is not available ("missing value") or *np.nan* is a valid category.

```
In [158]: s = pd.Series(["a","b",np.nan,"a"], dtype="category")

# only two categories
In [159]: s
Out[159]:
0      a
1      b
2    NaN
```

```
3      a
dtype: category
Categories (2, object): [a, b]

In [160]: s2 = pd.Series(["a","b","c","a"], dtype="category")

In [161]: s2.cat.categories = [1,2,np.nan]

# three categories, np.nan included
In [162]: s2
Out[162]:
0      1
1      2
2    NaN
3      1
dtype: category
Categories (3, object): [1, 2, NaN]
```

Note: As integer *Series* can't include NaN, the categories were converted to *object*.

Note: Missing value methods like `isnull` and `fillna` will take both missing values as well as *np.nan* categories into account:

```
In [163]: c = pd.Series(["a","b",np.nan], dtype="category")

In [164]: c.cat.set_categories(["a","b",np.nan], inplace=True)

# will be inserted as a NA category:
In [165]: c[0] = np.nan

In [166]: s = pd.Series(c)

In [167]: s
Out[167]:
0    NaN
1      b
2    NaN
dtype: category
Categories (3, object): [a, b, NaN]

In [168]: pd.isnull(s)
Out[168]:
0     True
1    False
2     True
dtype: bool

In [169]: s.fillna("a")
Out[169]:
0    a
1    b
2    a
dtype: category
Categories (3, object): [a, b, NaN]
```

22.9.1 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!

22.10 Gotchas

22.10.1 Memory Usage

The memory usage of a `Categorical` is proportional to the number of categories times the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [170]: s = pd.Series(['foo','bar']*1000)

# object dtype
In [171]: s.nbytes
Out[171]: 8000

# category dtype
In [172]: s.astype('category').nbytes
Out[172]: 2008
```

Note: If the number of categories approaches the length of the data, the `Categorical` will use nearly the same or more memory than an equivalent `object` dtype representation.

```
In [173]: s = pd.Series(['foo%04d' % i for i in range(2000)])

# object dtype
In [174]: s.nbytes
Out[174]: 8000

# category dtype
In [175]: s.astype('category').nbytes
Out[175]: 12000
```

22.10.2 Old style constructor usage

In earlier versions than pandas 0.15, a *Categorical* could be constructed by passing in precomputed *codes* (called then *labels*) instead of values with categories. The *codes* were interpreted as pointers to the categories with *-1* as *NaN*. This type of constructor useage is replaced by the special constructor `Categorical.from_codes()`.

Unfortunately, in some special cases, using code which assumes the old style constructor usage will work with the current pandas version, resulting in subtle bugs:

```
>>> cat = pd.Categorical([1,2], [1,2,3])
>>> # old version
>>> cat.get_values()
array([2, 3], dtype=int64)
>>> # new version
>>> cat.get_values()
array([1, 2], dtype=int64)
```

Warning: If you used *Categoricals* with older versions of pandas, please audit your code before upgrading and change your code to use the `from_codes()` constructor.

22.10.3 *Categorical* is not a *numpy* array

Currently, categorical data and the underlying *Categorical* is implemented as a python object and not as a low-level *numpy* array dtype. This leads to some problems.

numpy itself doesn't know about the new *dtype*:

```
In [176]: try:
   .....:     np.dtype("category")
   .....: except TypeError as e:
   .....:     print("TypeError: " + str(e))
   .....:
TypeError: data type "category" not understood

In [177]: dtype = pd.Categorical(["a"]).dtype

In [178]: try:
   .....:     np.dtype(dtype)
   .....: except TypeError as e:
   .....:      print("TypeError: " + str(e))
   .....:
TypeError: data type not understood
```

Dtype comparisons work:

```
In [179]: dtype == np.str_
Out[179]: False

In [180]: np.str_ == dtype
Out[180]: False
```

To check if a Series contains Categorical data, with pandas 0.16 or later, use `hasattr(s, 'cat')`:

```
In [181]: hasattr(pd.Series(['a'], dtype='category'), 'cat')
Out[181]: True

In [182]: hasattr(pd.Series(['a']), 'cat')
Out[182]: False
```

Using *numpy* functions on a *Series* of type `category` should not work as *Categoricals* are not numeric data (even in the case that `.categories` is numeric).

```
In [183]: s = pd.Series(pd.Categorical([1,2,3,4]))

In [184]: try:
   .....:     np.sum(s)
```

```
   .....: except TypeError as e:
   .....:     print("TypeError: " + str(e))
   .....:
TypeError: Categorical cannot perform the operation sum
```

Note: If such a function works, please file a bug at https://github.com/pydata/pandas!

22.10.4 dtype in apply

Pandas currently does not preserve the dtype in apply functions: If you apply along rows you get a *Series* of `object` *dtype* (same as getting a row -> getting one element will return a basic type) and applying along columns will also convert to object.

```
In [185]: df = pd.DataFrame({"a":[1,2,3,4],
   .....:                    "b":["a","b","c","d"],
   .....:                    "cats":pd.Categorical([1,2,3,2])})
   .....:

In [186]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[186]:
0    <type 'long'>
1    <type 'long'>
2    <type 'long'>
3    <type 'long'>
dtype: object

In [187]: df.apply(lambda col: col.dtype, axis=0)
Out[187]:
a       object
b       object
cats    object
dtype: object
```

22.10.5 Categorical Index

New in version 0.16.1.

A new `CategoricalIndex` index type is introduced in version 0.16.1. See the *advanced indexing docs* for a more detailed explanation.

Setting the index, will create create a `CategoricalIndex`

```
In [188]: cats = pd.Categorical([1,2,3,4], categories=[4,2,3,1])

In [189]: strings = ["a","b","c","d"]

In [190]: values = [4,2,3,1]

In [191]: df = pd.DataFrame({"strings":strings, "values":values}, index=cats)

In [192]: df.index
Out[192]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False, dtype='category')

# This now sorts by the categories order
In [193]: df.sort_index()
```

```
Out[193]:
  strings  values
4       d       1
2       b       2
3       c       3
1       a       4
```

In previous versions (<0.16.1) there is no index of type `category`, so setting the index to categorical column will convert the categorical data to a "normal" dtype first and therefore remove any custom ordering of the categories.

22.10.6 Side Effects

Constructing a *Series* from a *Categorical* will not copy the input *Categorical*. This means that changes to the *Series* will in most cases change the original *Categorical*:

```
In [194]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [195]: s = pd.Series(cat, name="cat")

In [196]: cat
Out[196]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [197]: s.iloc[0:2] = 10

In [198]: cat
Out[198]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [199]: df = pd.DataFrame(s)

In [200]: df["cat"].cat.categories = [1,2,3,4,5]

In [201]: cat
Out[201]:
[5, 5, 3, 5]
Categories (5, int64): [1, 2, 3, 4, 5]
```

Use `copy=True` to prevent such a behaviour or simply don't reuse *Categoricals*:

```
In [202]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [203]: s = pd.Series(cat, name="cat", copy=True)

In [204]: cat
Out[204]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [205]: s.iloc[0:2] = 10

In [206]: cat
Out[206]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

Note: This also happens in some cases when you supply a *numpy* array instead of a *Categorical*: using an int array (e.g. `np.array([1,2,3,4])`) will exhibit the same behaviour, while using a string array (e.g. `np.array(["a","b","c","a"])`) will not.

CHAPTER

TWENTYTHREE

PLOTTING

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
```

The plots in this document are made using matplotlib's `ggplot` style (new in version 1.4):

```
import matplotlib
matplotlib.style.use('ggplot')
```

If your version of matplotlib is 1.3 or lower, you can set `display.mpl_style` to `'default'` with `pd.options.display.mpl_style = 'default'` to produce more appealing plots. When set, matplotlib's `rcParams` are changed (globally!) to nicer-looking settings.

We provide the basics in pandas to easily create decent looking plots. See the *ecosystem* section for visualization libraries that go beyond the basics documented here.

Note: All calls to `np.random` are seeded with 123456.

23.1 Basic Plotting: `plot`

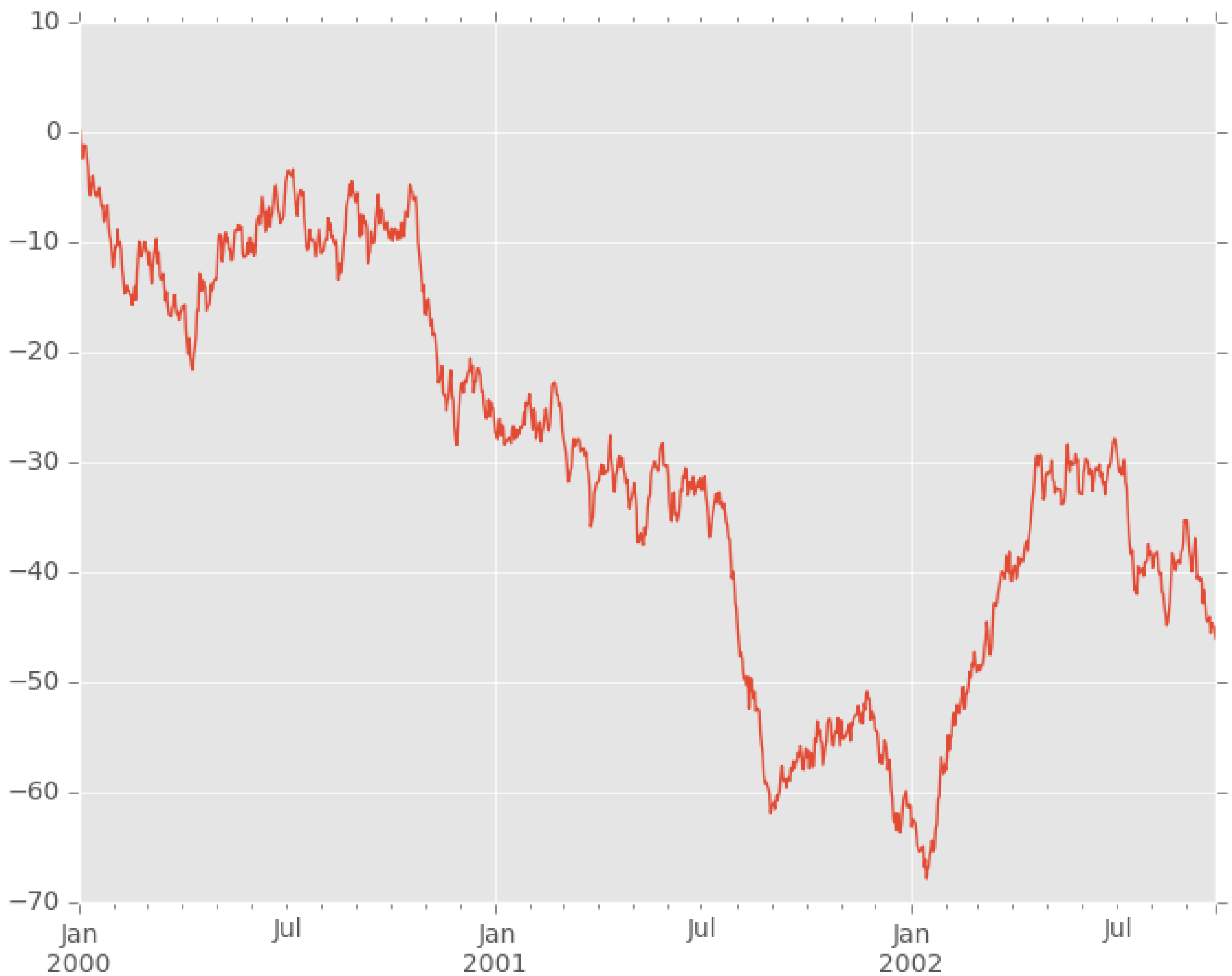
See the *cookbook* for some advanced strategies

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [2]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [3]: ts = ts.cumsum()

In [4]: ts.plot()
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0xaf7a5d6c>
```



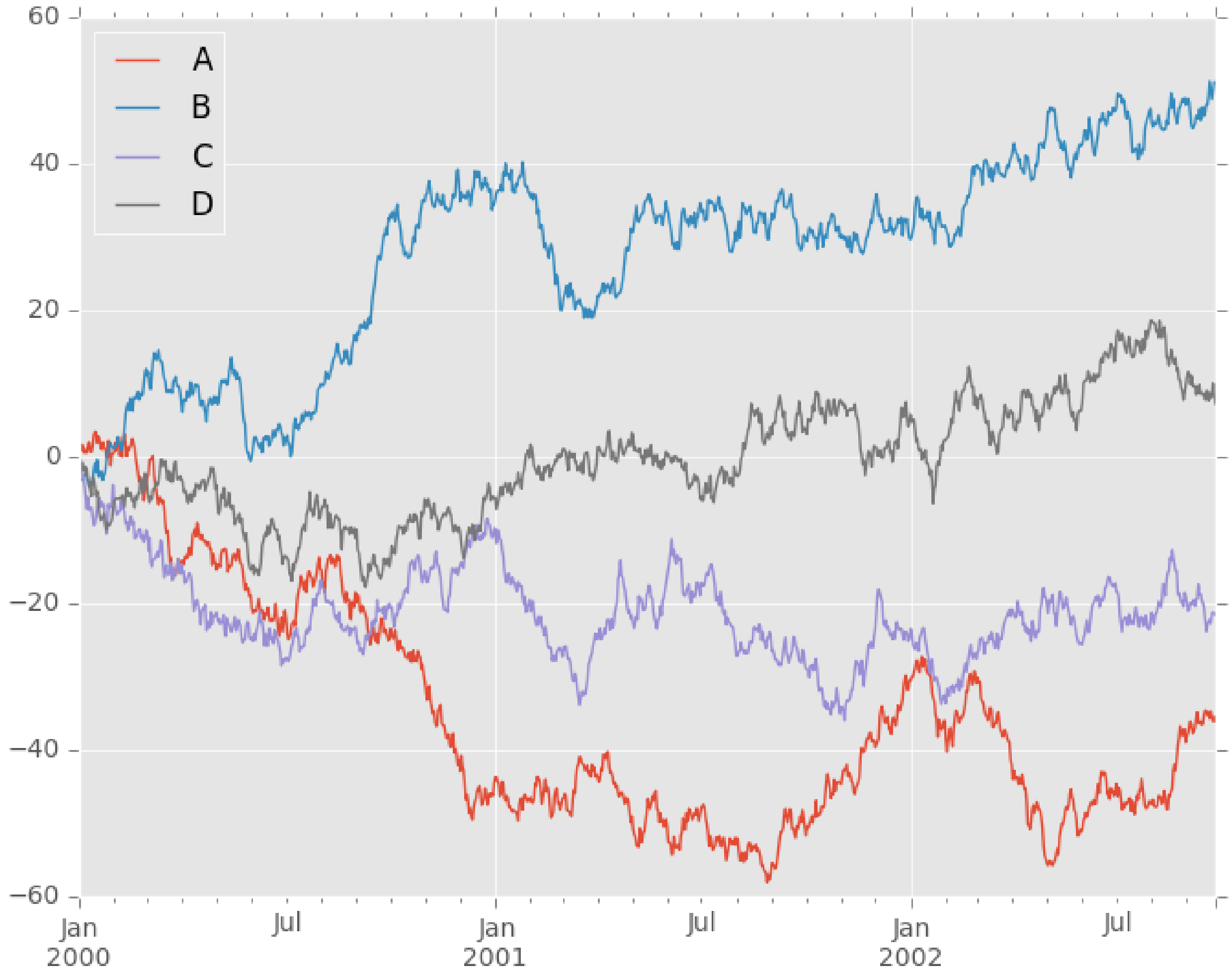
If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [5]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [6]: df = df.cumsum()

In [7]: plt.figure(); df.plot();
```

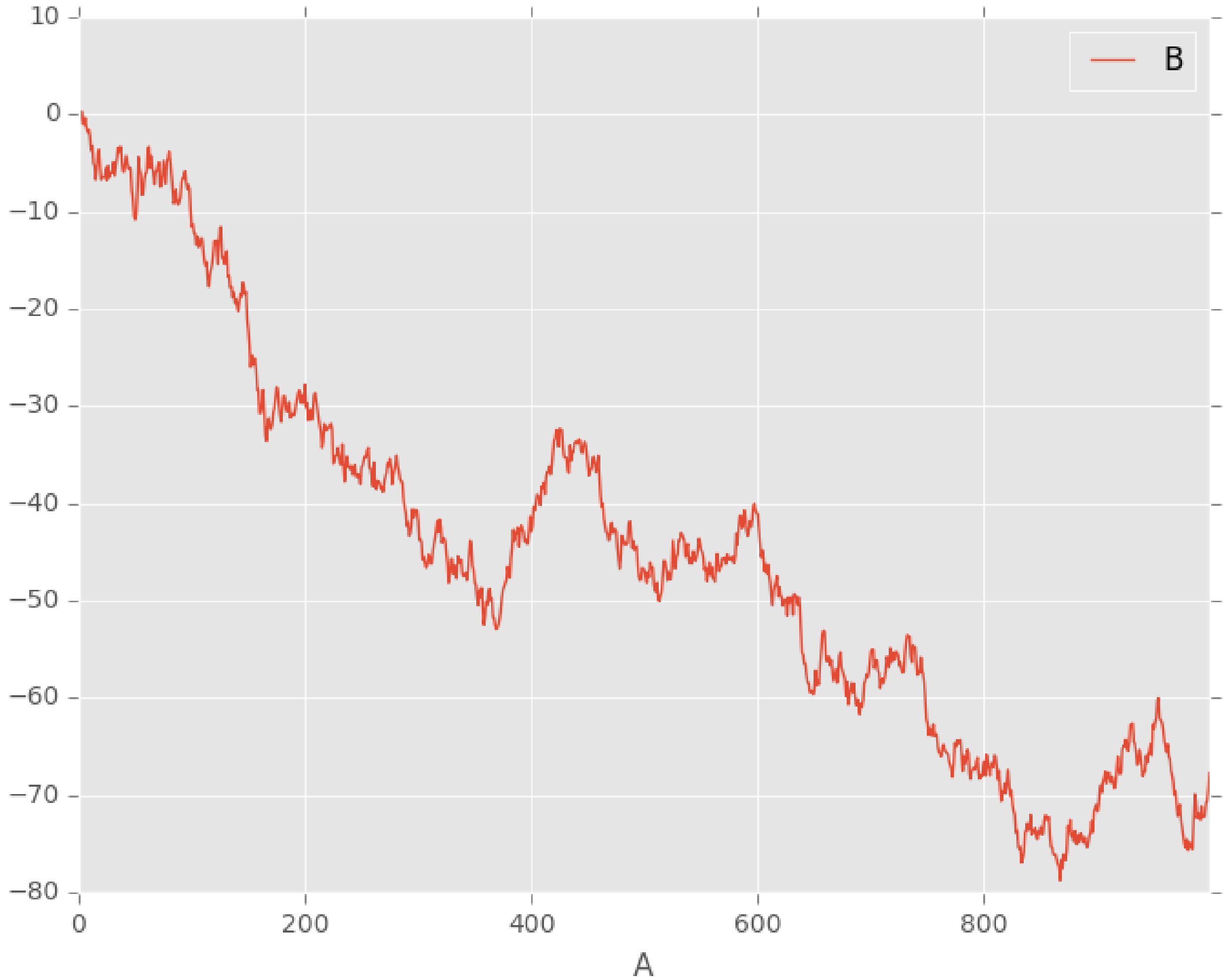


You can plot one column versus another using the *x* and *y* keywords in `plot()`:

```
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 0xaf67144c>
```



Note: For more formatting and sytling options, see *below*.

23.2 Other Plots

The `kind` keyword argument of `plot()` accepts a handful of values for plots other than the default Line plot. These include:

- *'bar'* or *'barh'* for bar plots
- *'hist'* for histogram
- *'box'* for boxplot
- *'kde'* or `'density'` for density plots
- *'area'* for area plots
- *'scatter'* for scatter plots
- *'hexbin'* for hexagonal bin plots
- *'pie'* for pie plots

In addition to these `kind` s, there are the *DataFrame.hist()*, and *DataFrame.boxplot()* methods, which use a separate interface.

Finally, there are several *plotting functions* in `pandas.tools.plotting` that take a `Series` or `DataFrame` as an argument. These include

- *Scatter Matrix*
- *Andrews Curves*
- *Parallel Coordinates*
- *Lag Plot*
- *Autocorrelation Plot*
- *Bootstrap Plot*
- *RadViz*

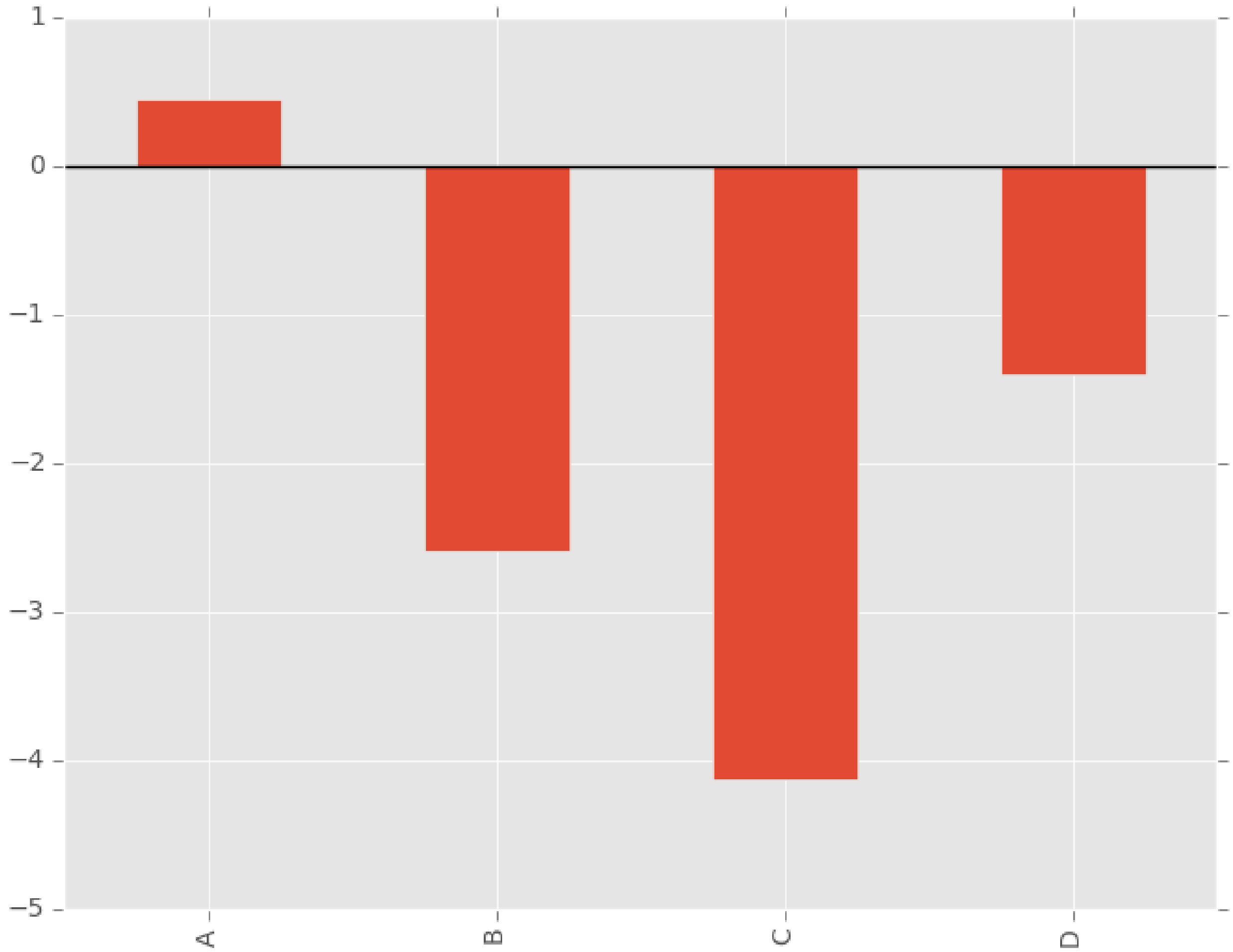
Plots may also be adorned with *errorbars* or *tables*.

23.2.1 Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```
In [11]: plt.figure();

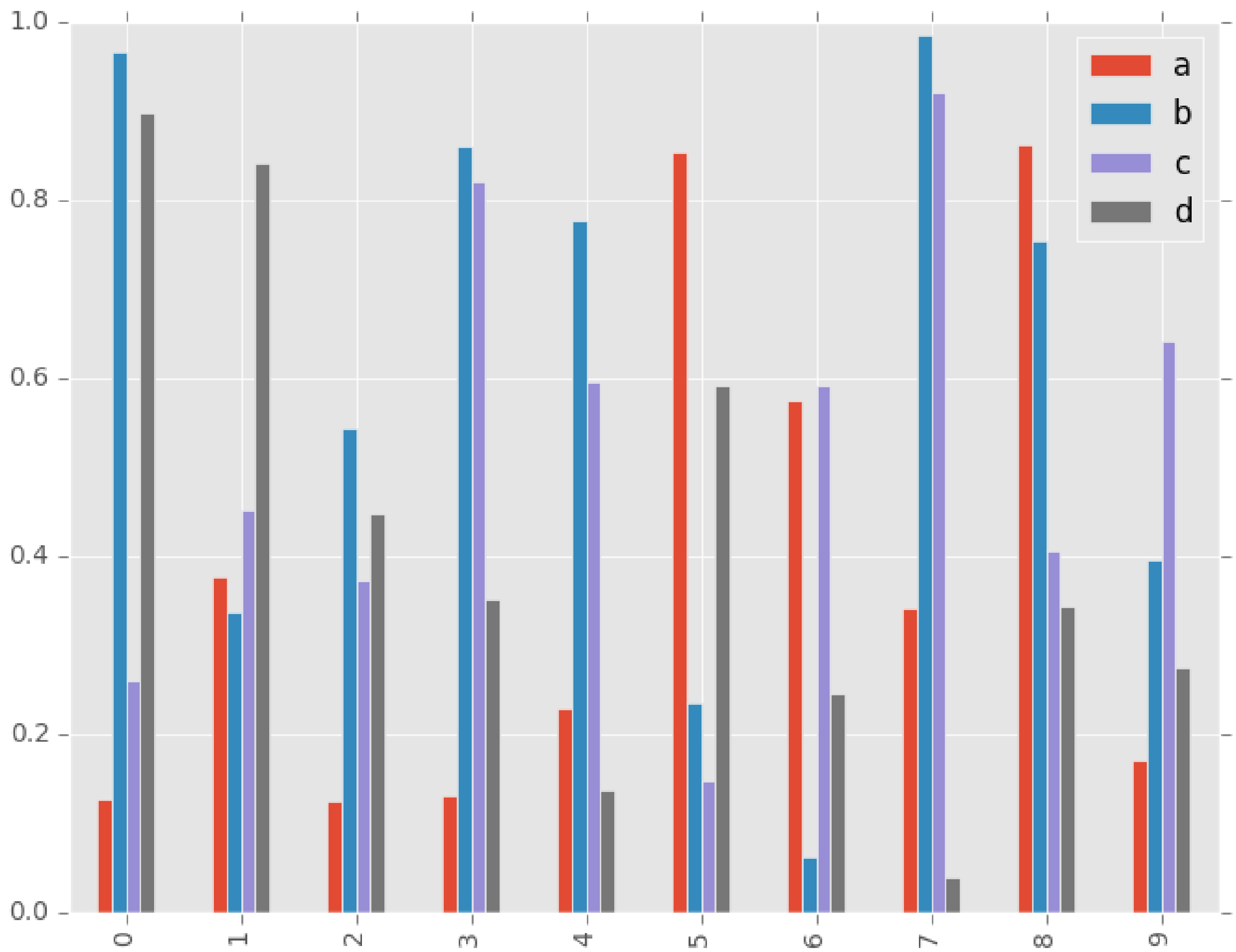
In [12]: df.ix[5].plot(kind='bar'); plt.axhline(0, color='k')
Out[12]: <matplotlib.lines.Line2D at 0xaf5d880c>
```



Calling a DataFrame's `plot()` method with `kind='bar'` produces a multiple bar plot:

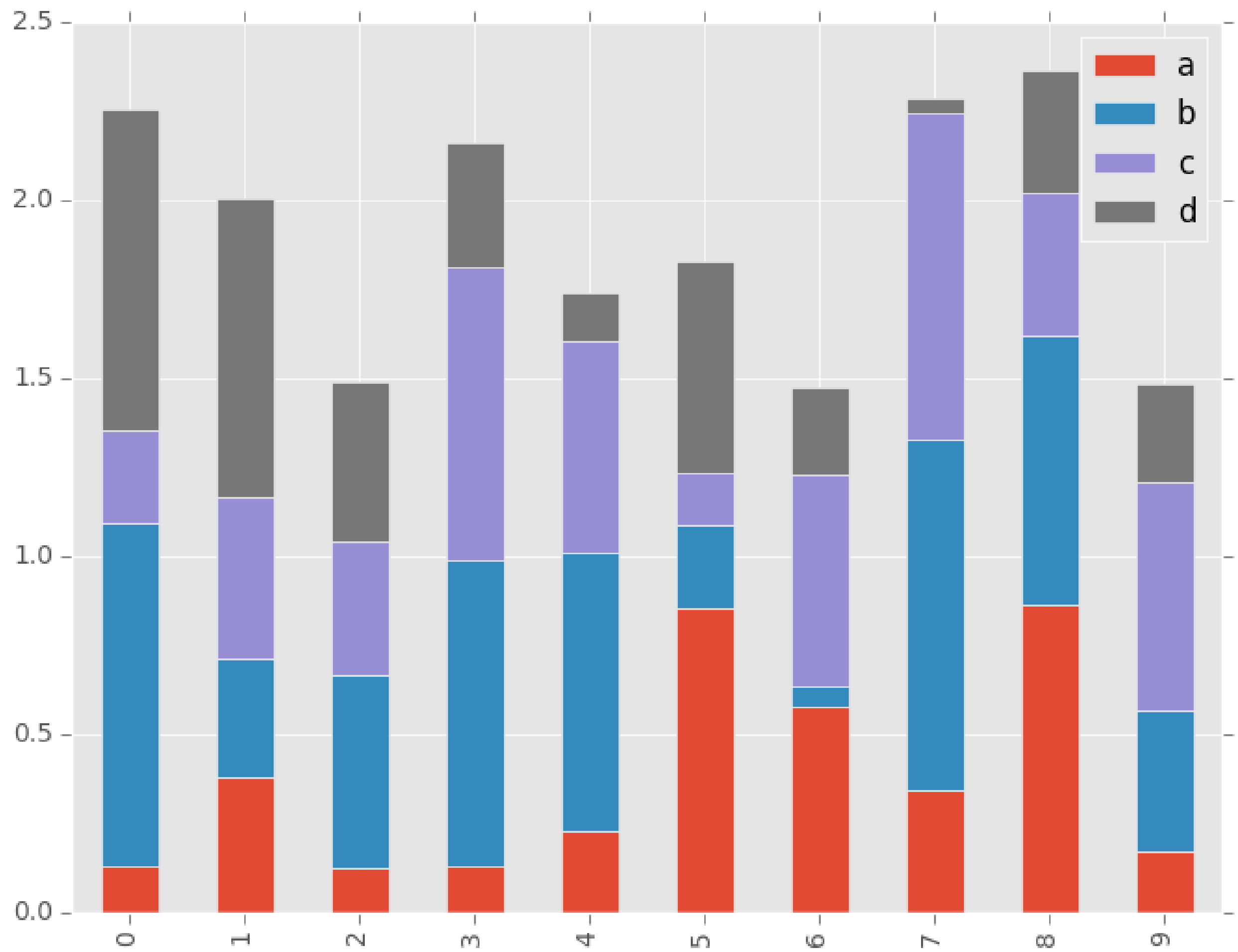
```
In [13]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

In [14]: df2.plot(kind='bar');
```



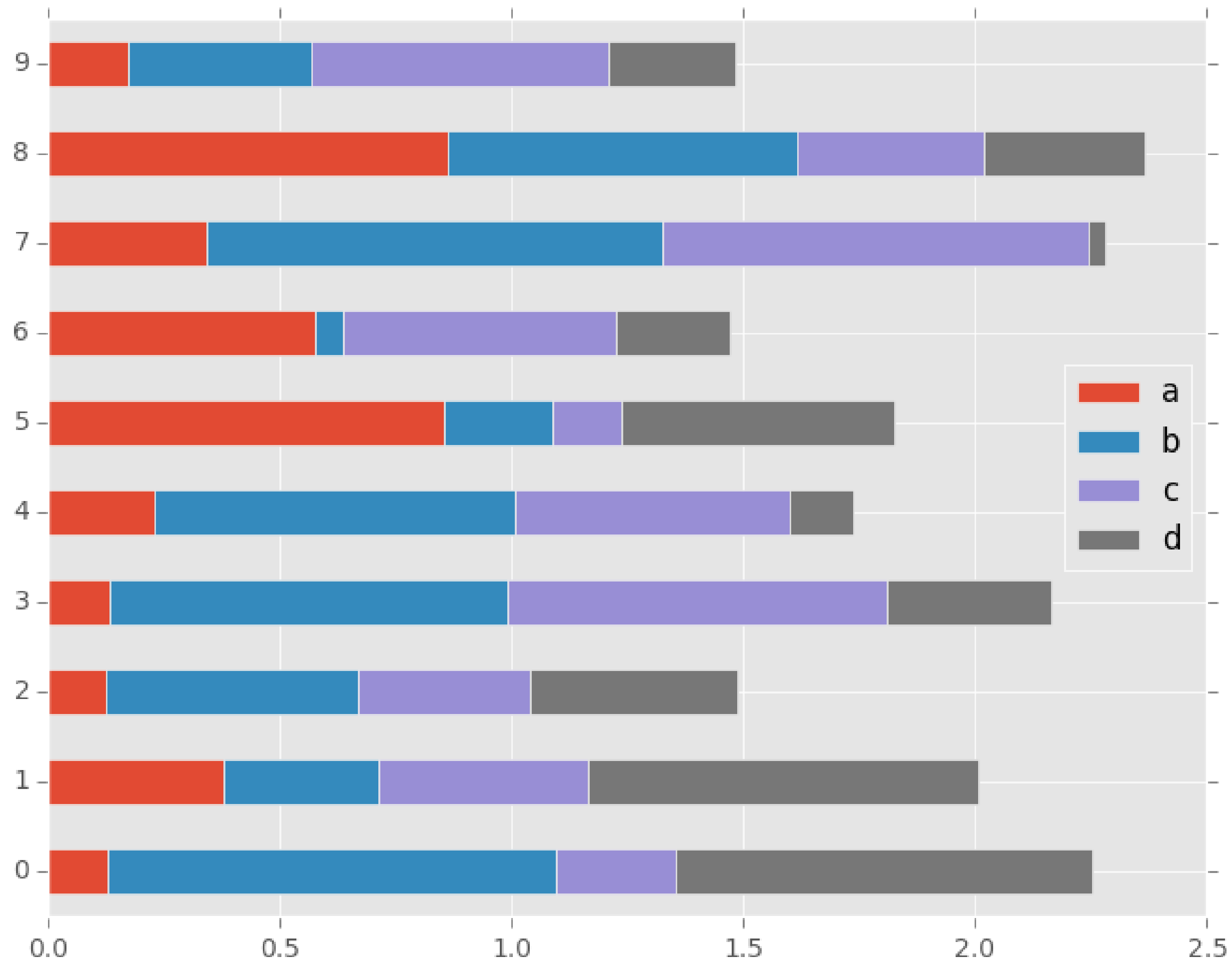
To produce a stacked bar plot, pass `stacked=True`:

```
In [15]: df2.plot(kind='bar', stacked=True);
```



To get horizontal bar plots, pass `kind='barh'`:

```
In [16]: df2.plot(kind='barh', stacked=True);
```



23.2.2 Histograms

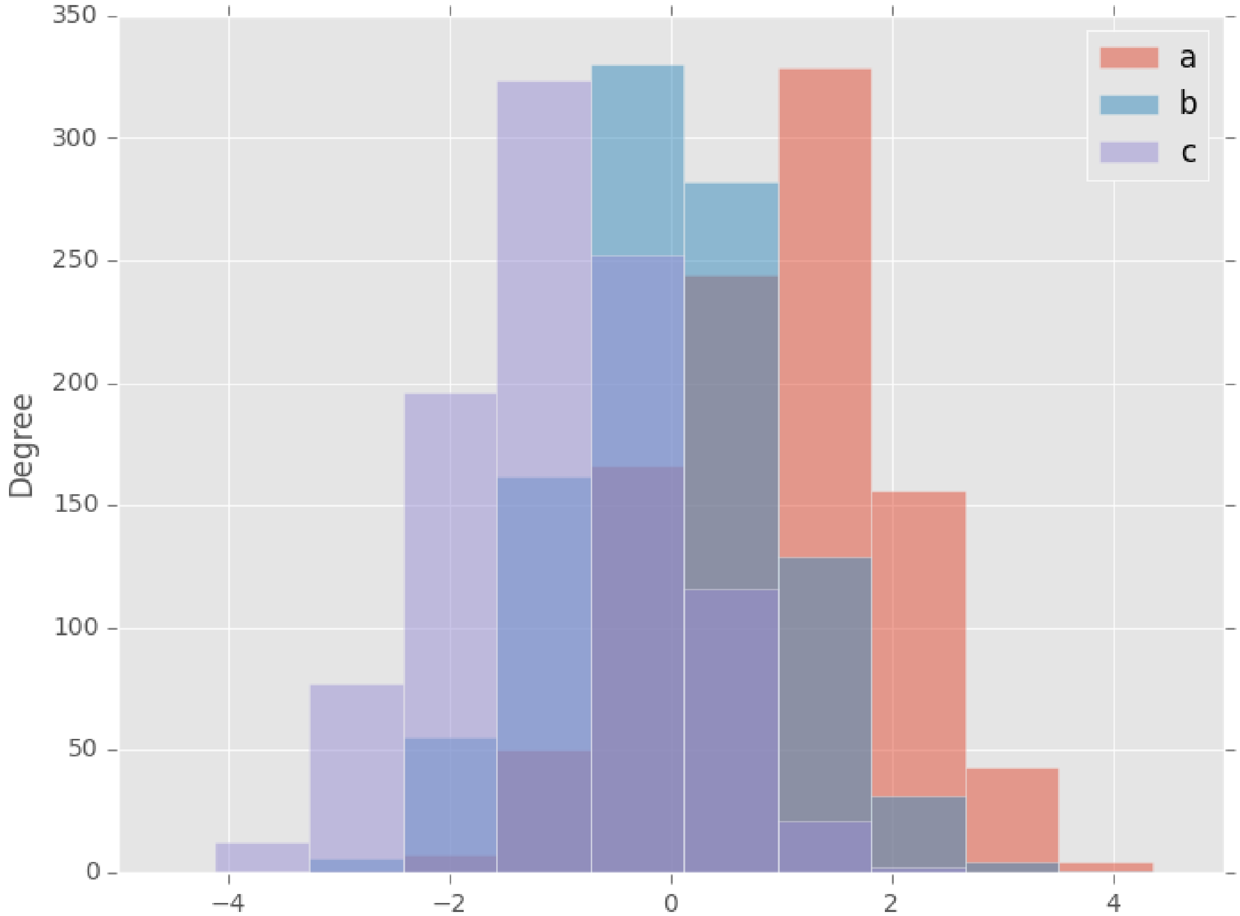
New in version 0.15.0.

Histogram can be drawn specifying kind='hist'.

```
In [17]: 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 [18]: plt.figure();

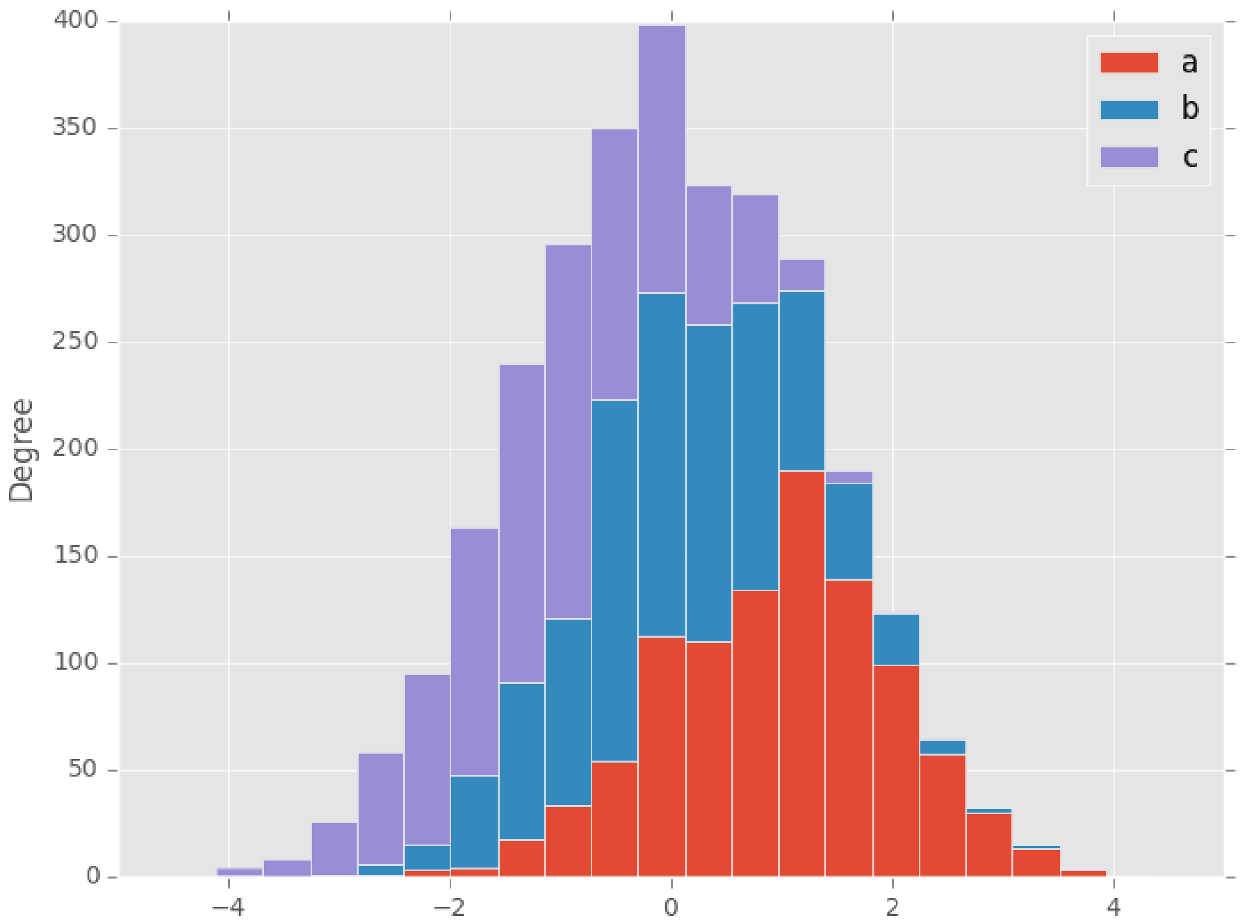
In [19]: df4.plot(kind='hist', alpha=0.5)
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xaf218e4c>
```



Histogram can be stacked by `stacked=True`. Bin size can be changed by `bins` keyword.

```
In [20]: plt.figure();

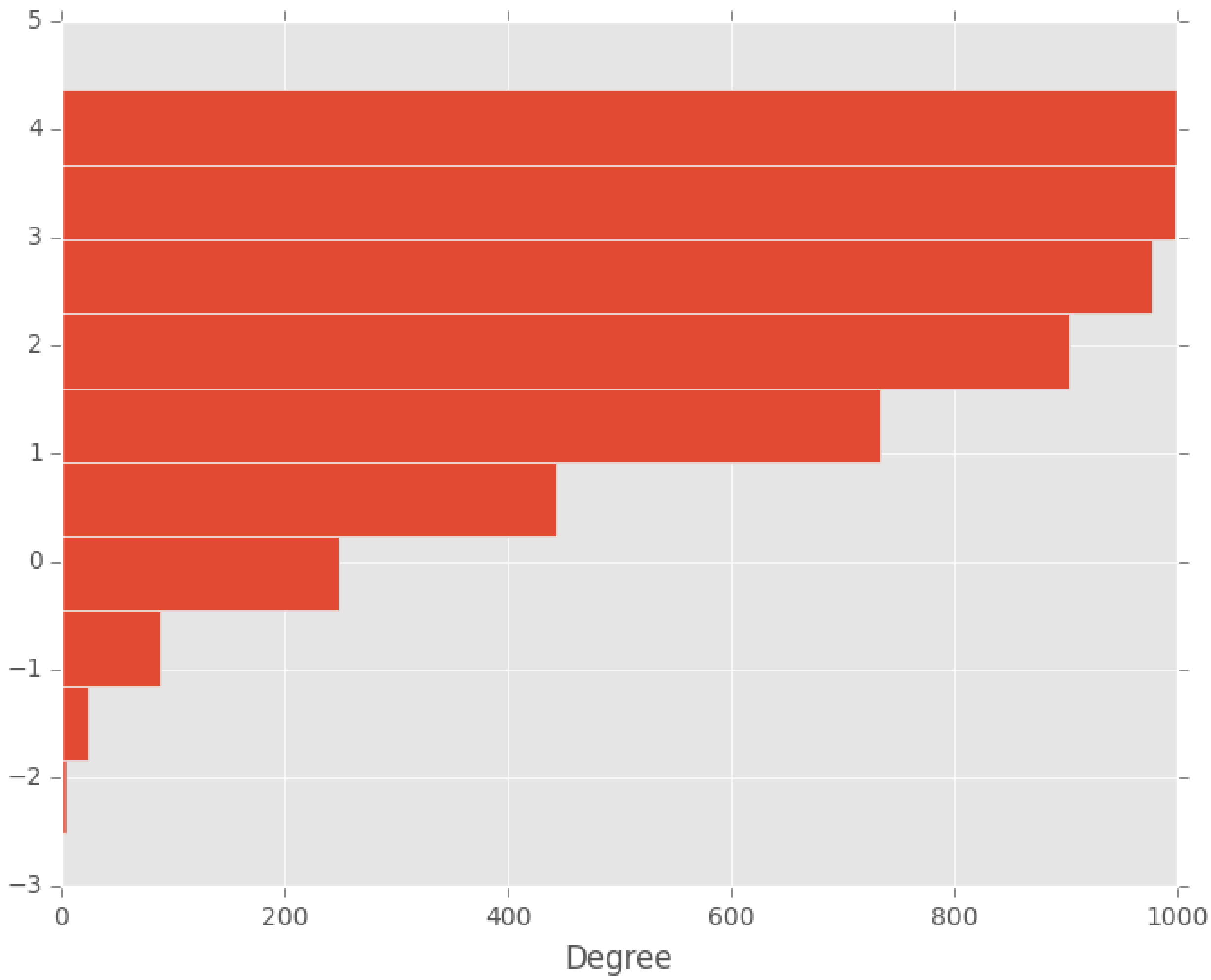
In [21]: df4.plot(kind='hist', stacked=True, bins=20)
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0xaf203dac>
```



You can pass other keywords supported by matplotlib `hist`. For example, horizontal and cumulative histgram can be drawn by `orientation='horizontal'` and `cumulative='True'`.

```
In [22]: plt.figure();

In [23]: df4['a'].plot(kind='hist', orientation='horizontal', cumulative=True)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0xaf4d376c>
```

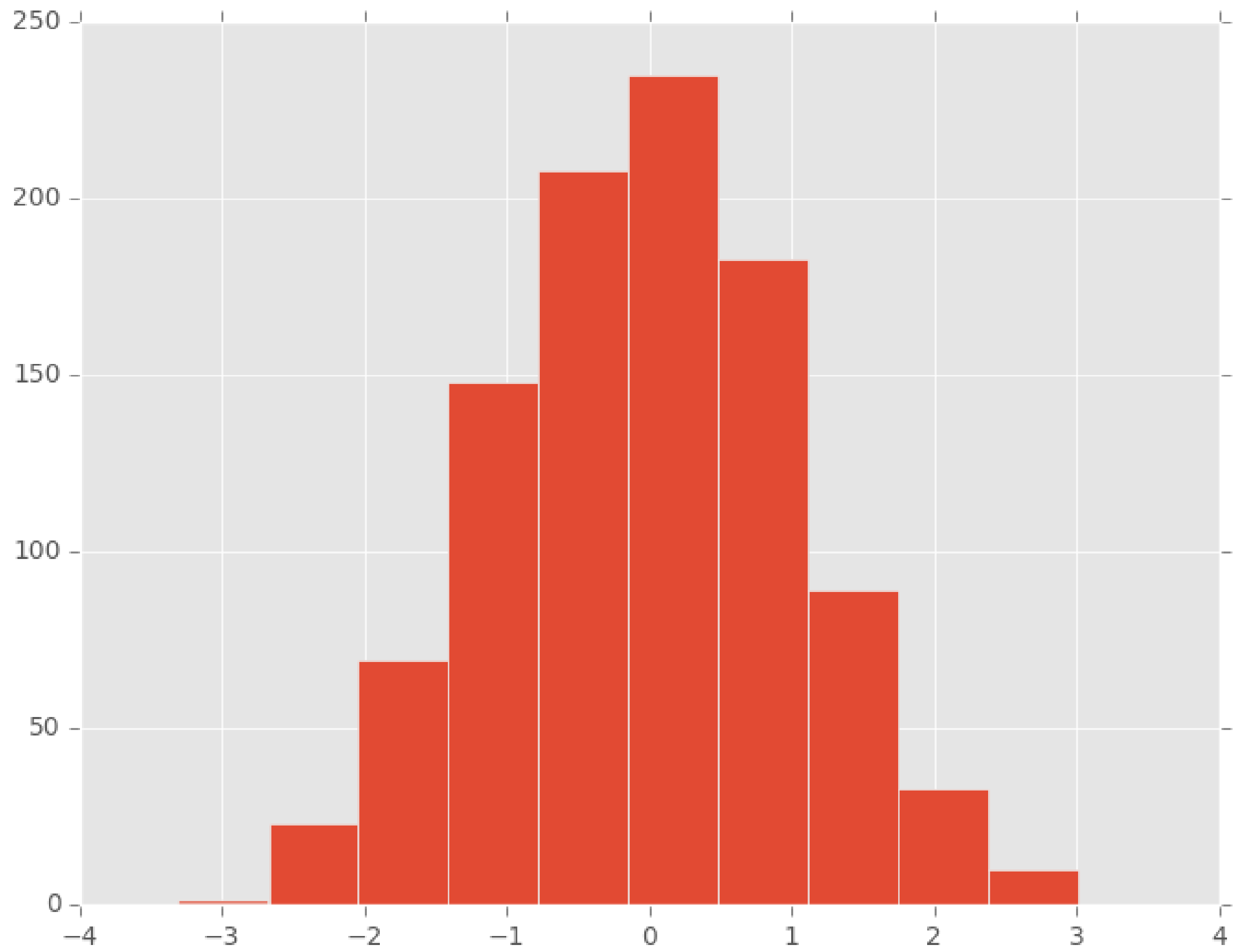


See the hist method and the matplotlib hist documentation for more.

The existing interface DataFrame.hist to plot histogram still can be used.

```
In [24]: plt.figure();

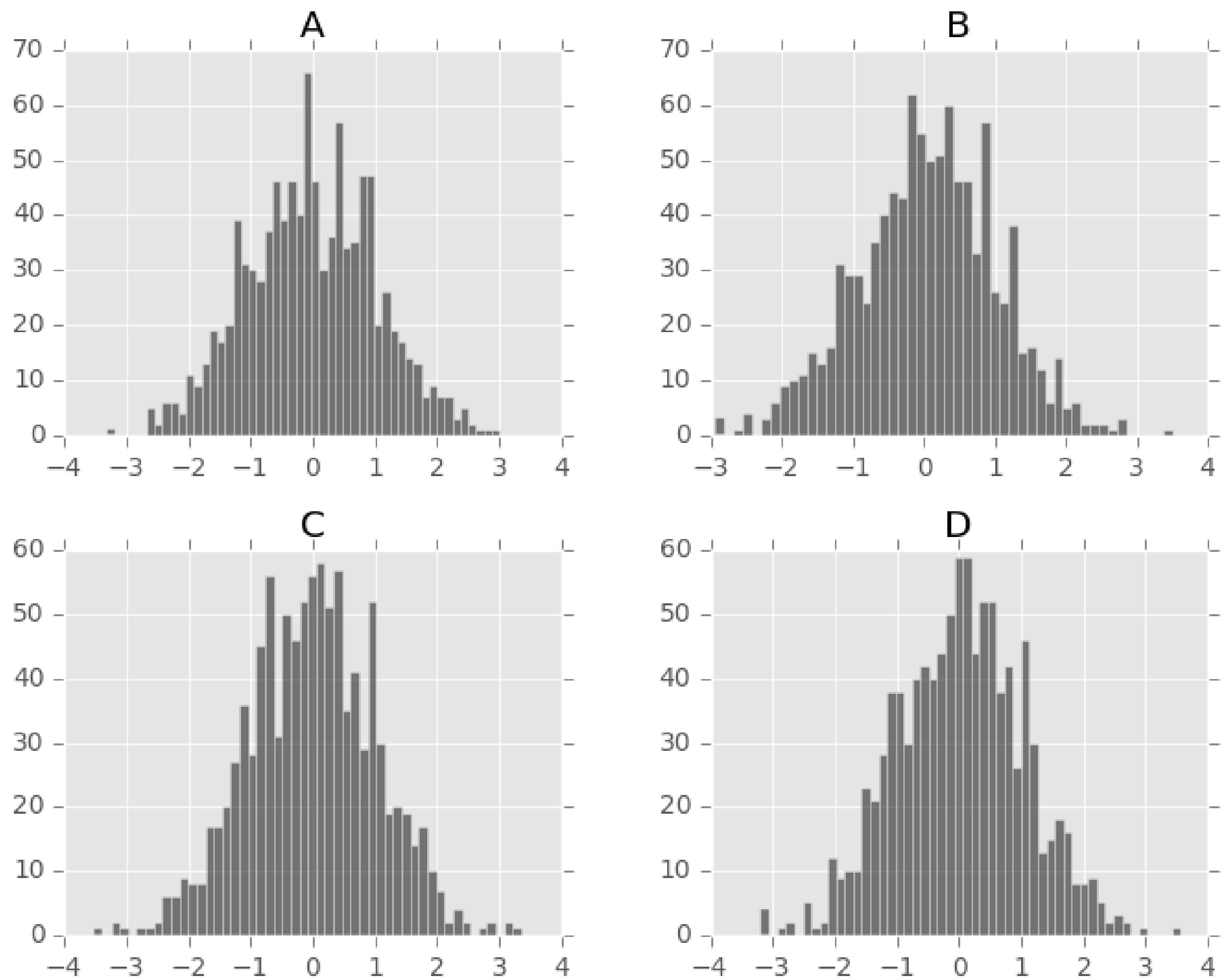
In [25]: df['A'].diff().hist()
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xaf54440c>
```



DataFrame.hist() plots the histograms of the columns on multiple subplots:

```
In [26]: plt.figure()
Out[26]: <matplotlib.figure.Figure at 0xaf22c6ac>

In [27]: df.diff().hist(color='k', alpha=0.5, bins=50)
Out[27]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0xaf5d796c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xaf4c206c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xaeceb1ac>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xaec978ec>]], dtype=object)
```

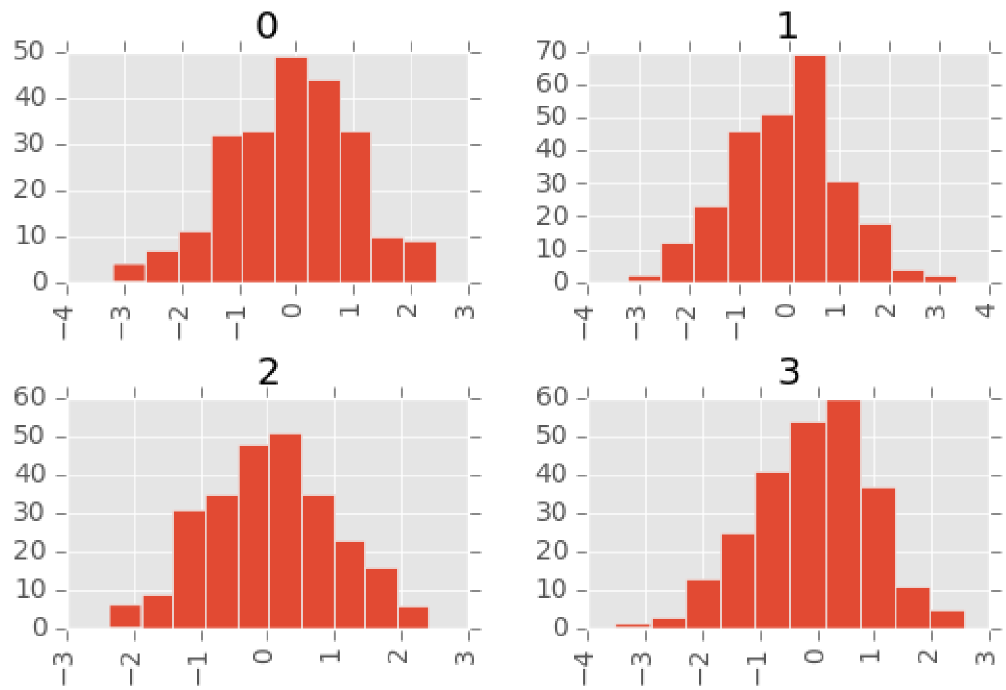


New in version 0.10.0.

The by keyword can be specified to plot grouped histograms:

```
In [28]: data = pd.Series(np.random.randn(1000))

In [29]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
Out[29]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0xaeb9e7ec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xae8208ac>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xae7e092c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xae78ee6c>]], dtype=object)
```



23.2.3 Box Plots

Boxplot can be drawn calling a `Series` and `DataFrame.plot` with `kind='box'`, or `DataFrame.boxplot` to visualize the distribution of values within each column.

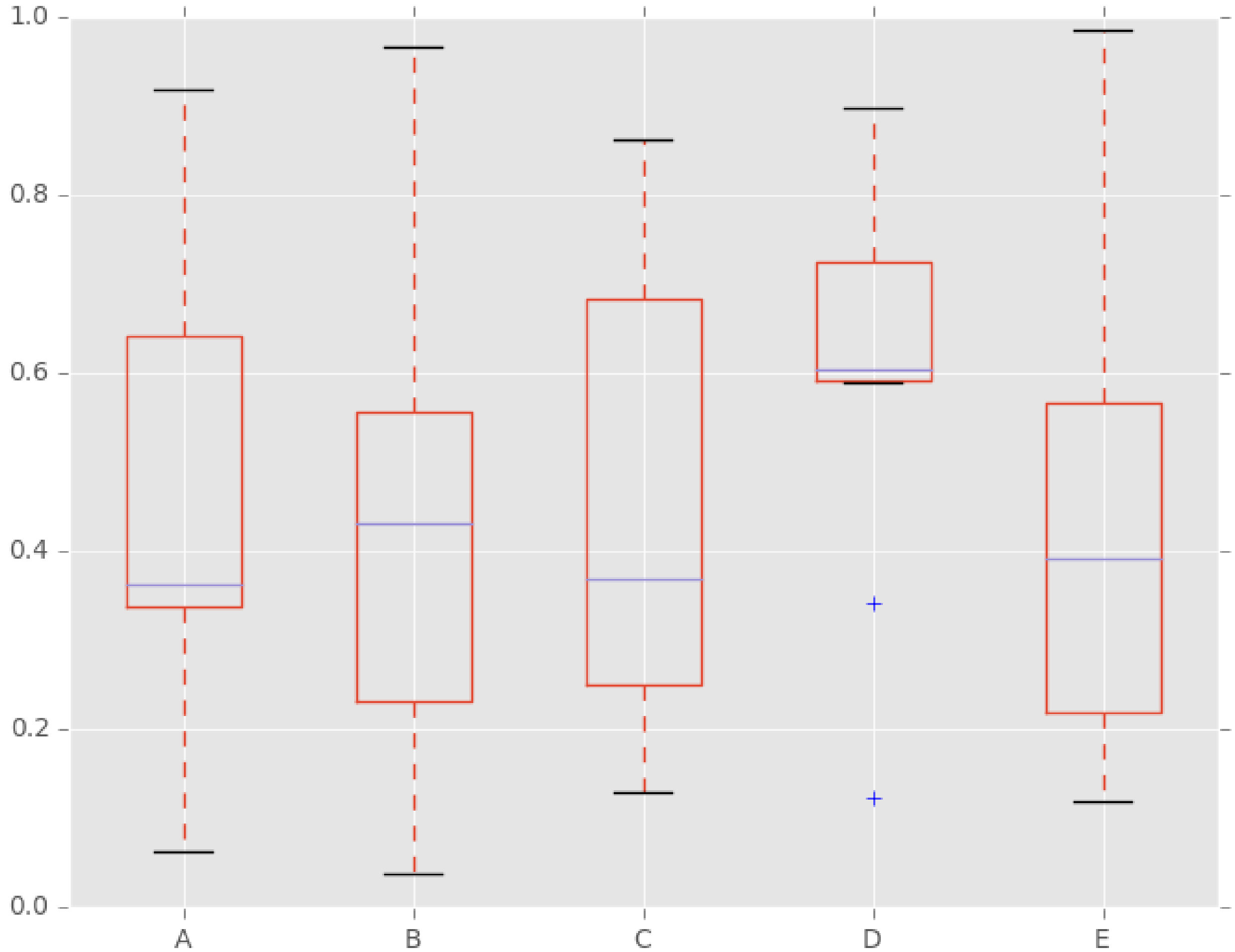
New in version 0.15.0.

`plot` method now supports `kind='box'` to draw boxplot.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```
In [30]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])

In [31]: df.plot(kind='box')
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0xadf5cfcc>
```



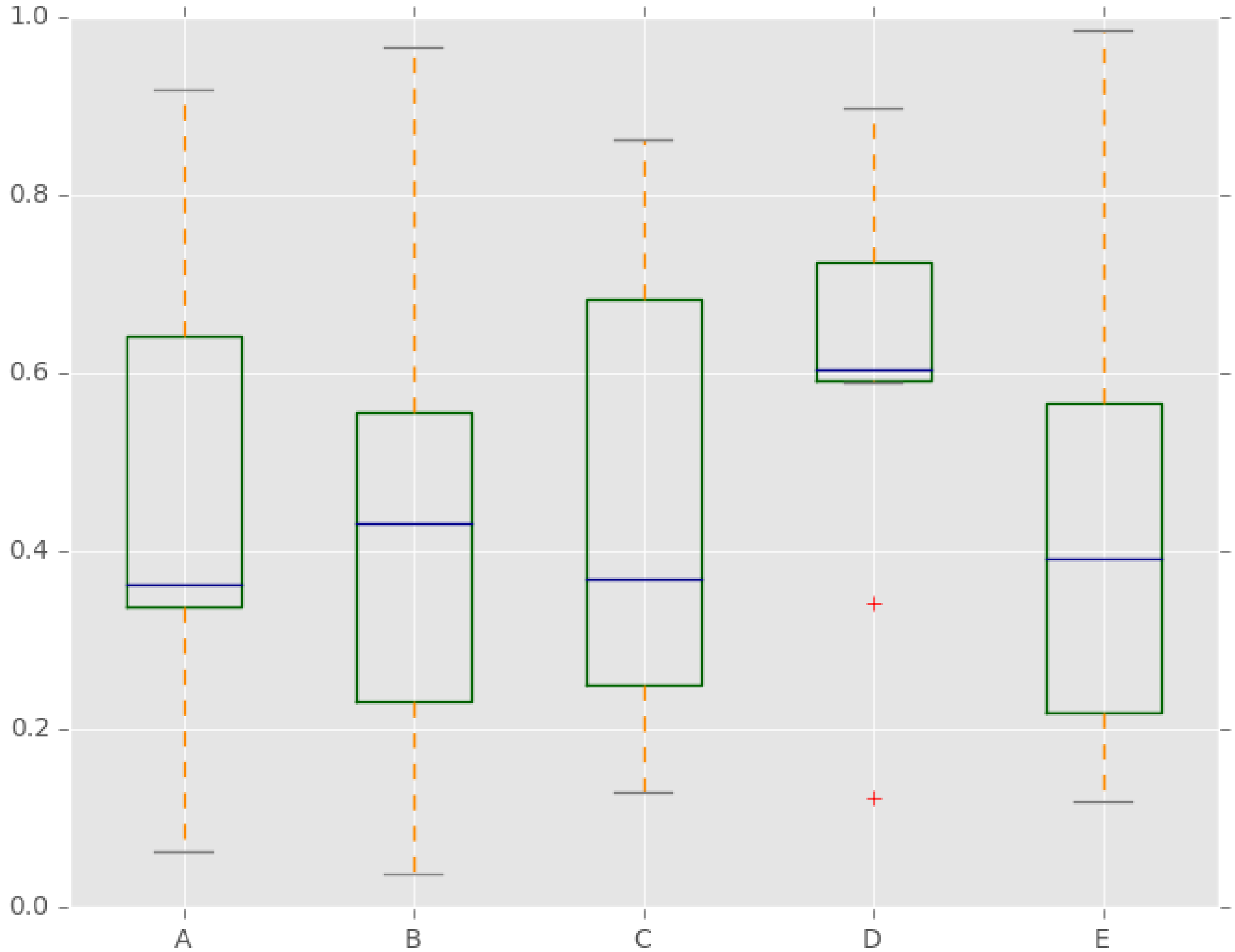
Boxplot can be colorized by passing `color` keyword. You can pass a `dict` whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the `dict`, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

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*.

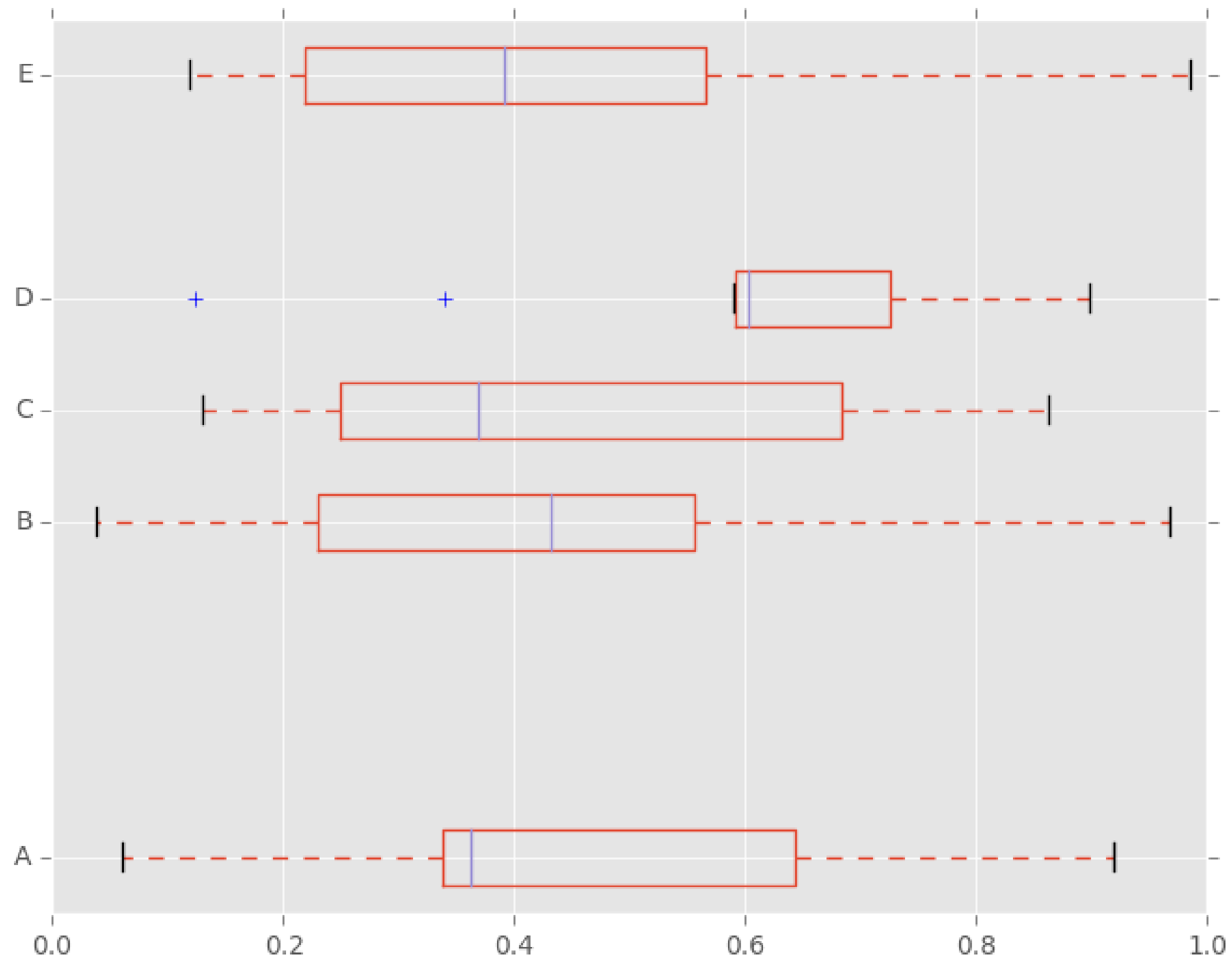
```
In [32]: color = dict(boxes='DarkGreen', whiskers='DarkOrange',
   ....:              medians='DarkBlue', caps='Gray')
   ....:

In [33]: df.plot(kind='box', color=color, sym='r+')
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0xadf84f2c>
```



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 [34]: df.plot(kind='box', vert=False, positions=[1, 4, 5, 6, 8])
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0xade254cc>
```



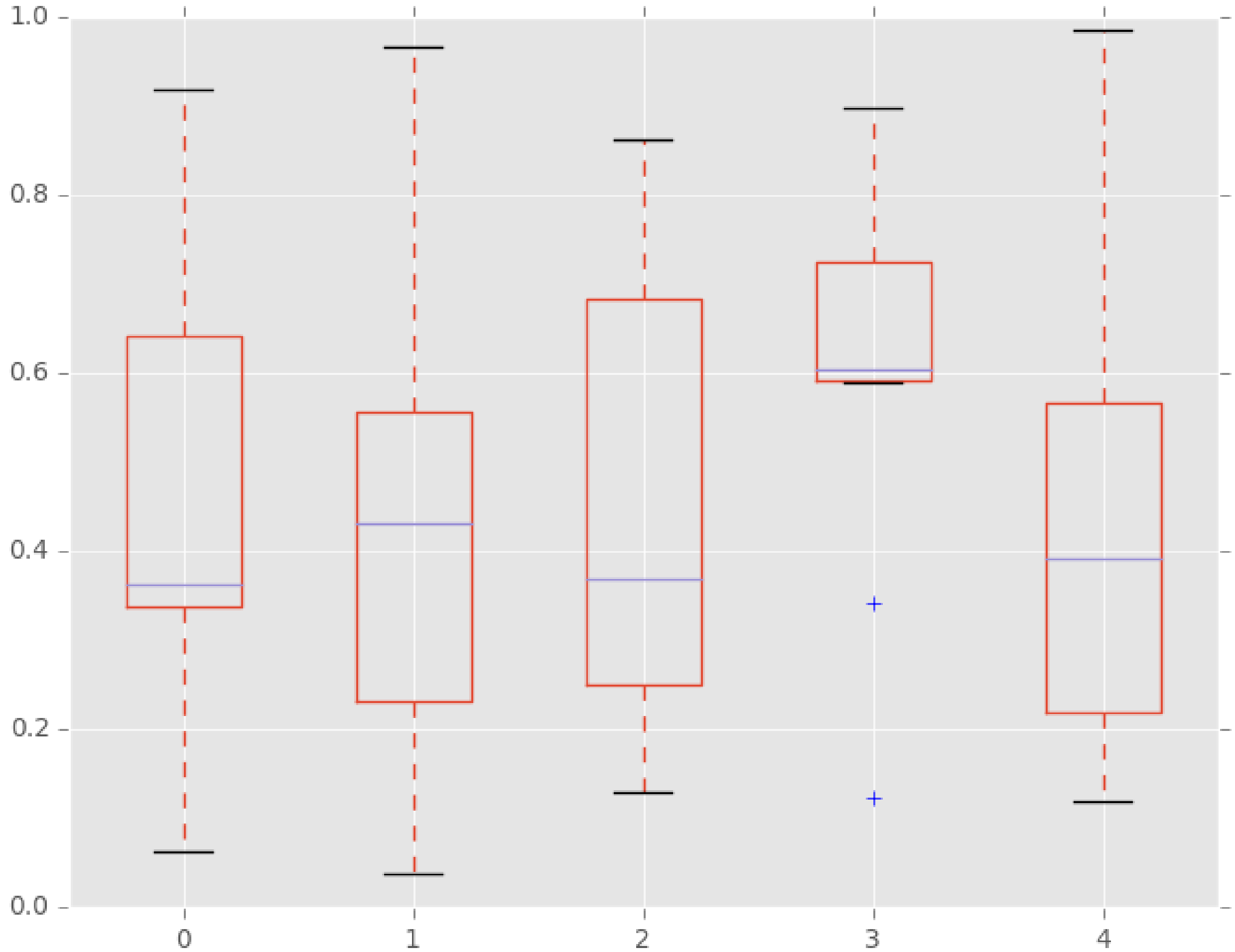
See the boxplot method and the matplotlib boxplot documenation for more.

The existing interface DataFrame.boxplot to plot boxplot still can be used.

```
In [35]: df = pd.DataFrame(np.random.rand(10,5))

In [36]: plt.figure();

In [37]: bp = df.boxplot()
```



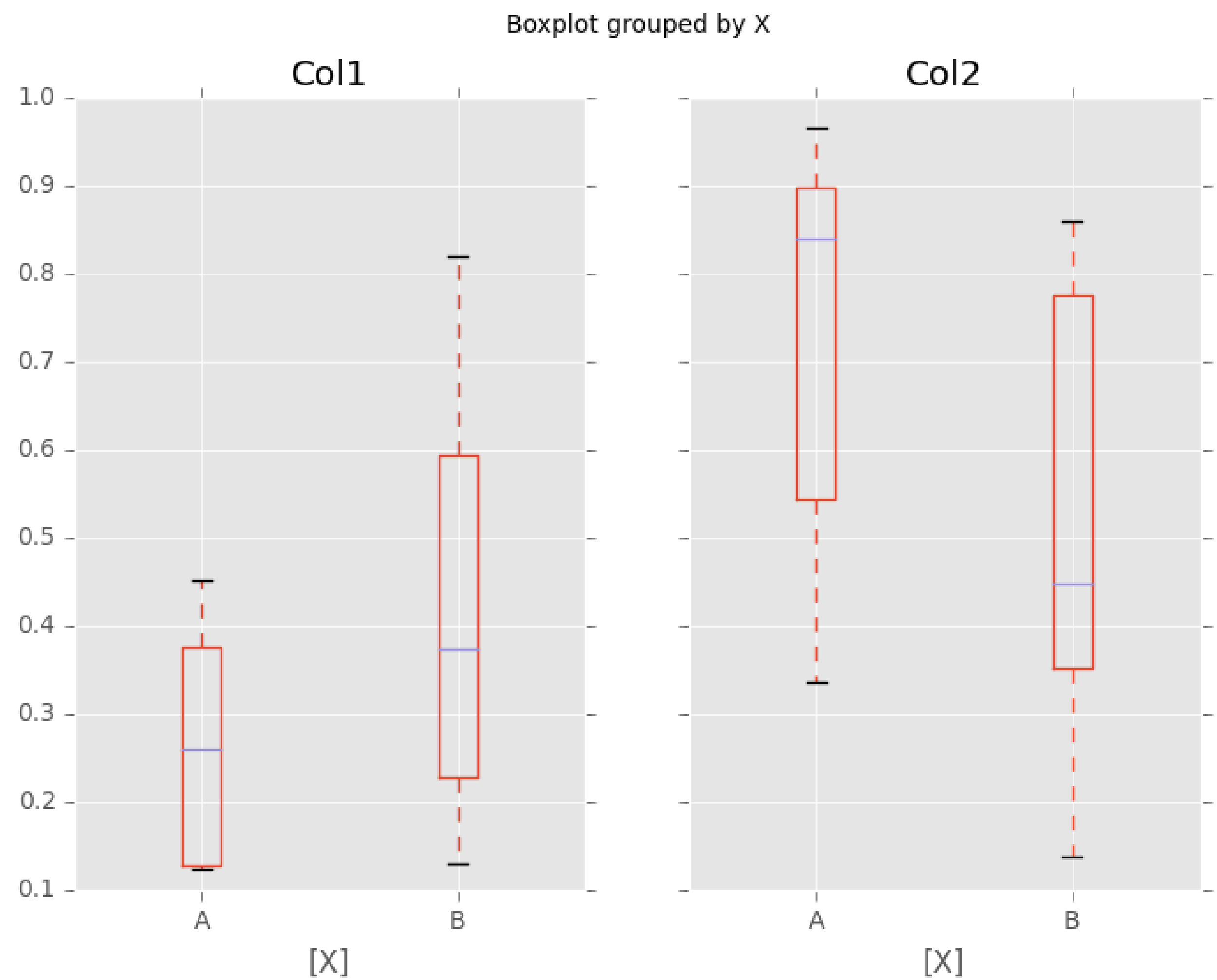
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [38]: df = pd.DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'] )

In [39]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])

In [40]: plt.figure();

In [41]: bp = df.boxplot(by='X')
```



You can also pass a subset of columns to plot, as well as group by multiple columns:

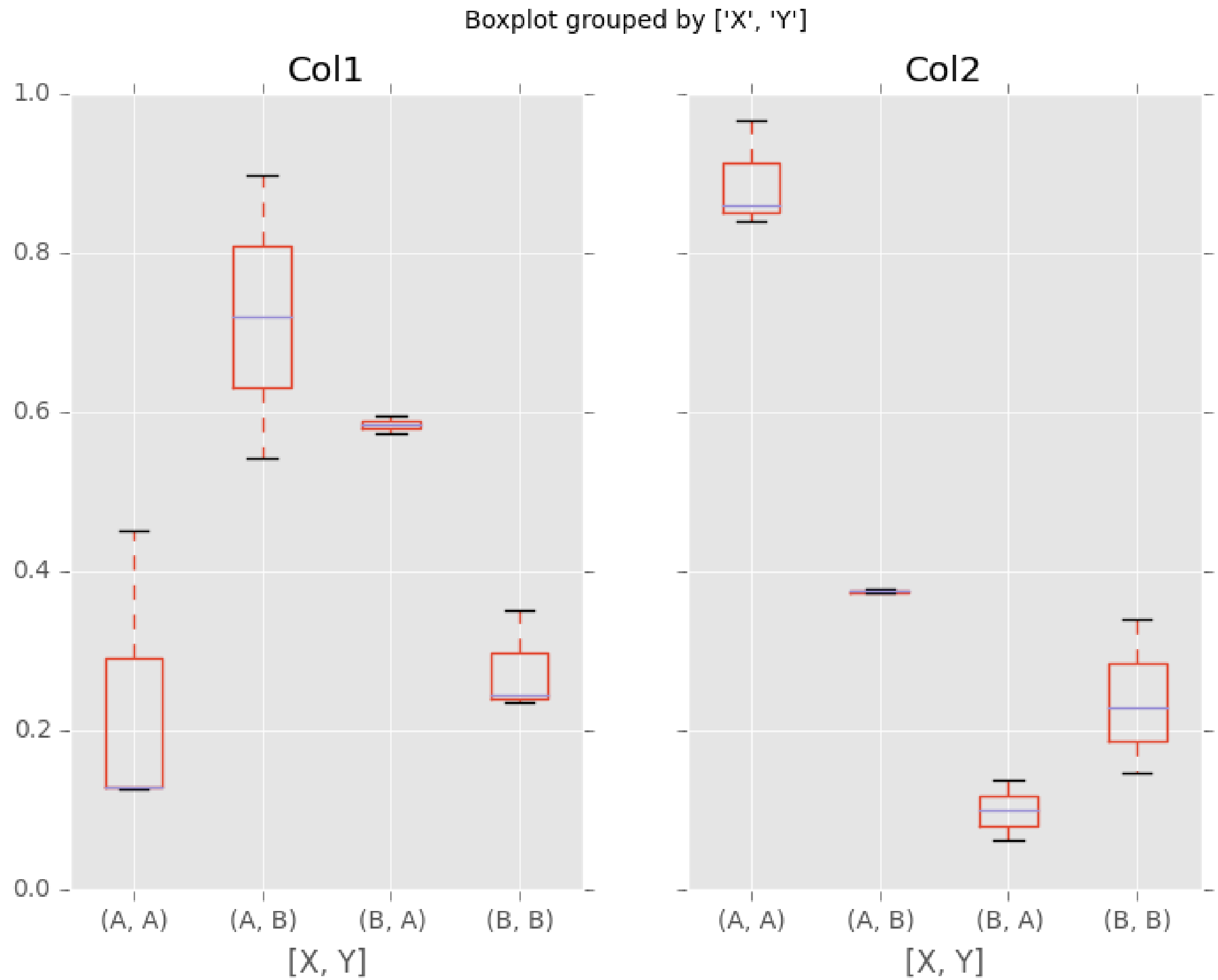
```
In [42]: df = pd.DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])

In [43]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])

In [44]: df['Y'] = pd.Series(['A','B','A','B','A','B','A','B','A','B'])

In [45]: plt.figure();

In [46]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```



Basically, plot functions return `matplotlib Axes` as a return value. In `boxplot`, the return type can be changed by argument `return_type`, and whether the subplots is enabled (`subplots=True` in `plot` or `by` is specified in `boxplot`).

When `subplots=False` / `by` is `None`:

- **if `return_type` is `'dict'`, a dictionary containing the `matplotlib Lines` is returned. The keys are "boxes", "caps"**
  This is the default of `boxplot` in historical reason. Note that `plot(kind='box')` returns `Axes` as default as the same as other plots.
- if `return_type` is `'axes'`, a `matplotlib Axes` containing the boxplot is returned.
- **if `return_type` is `'both'` a namedtuple containging the `matplotlib Axes` and** `matplotlib Lines` is returned

When `subplots=True` / `by` is some column of the DataFrame:

- A dict of `return_type` is returned, where the keys are the columns of the DataFrame. The plot has a facet for each column of the DataFrame, with a separate box for each value of `by`.

Finally, when calling boxplot on a `Groupby` object, a dict of `return_type` is returned, where the keys are the same as the Groupby object. The plot has a facet for each key, with each facet containing a box for each column of the DataFrame.

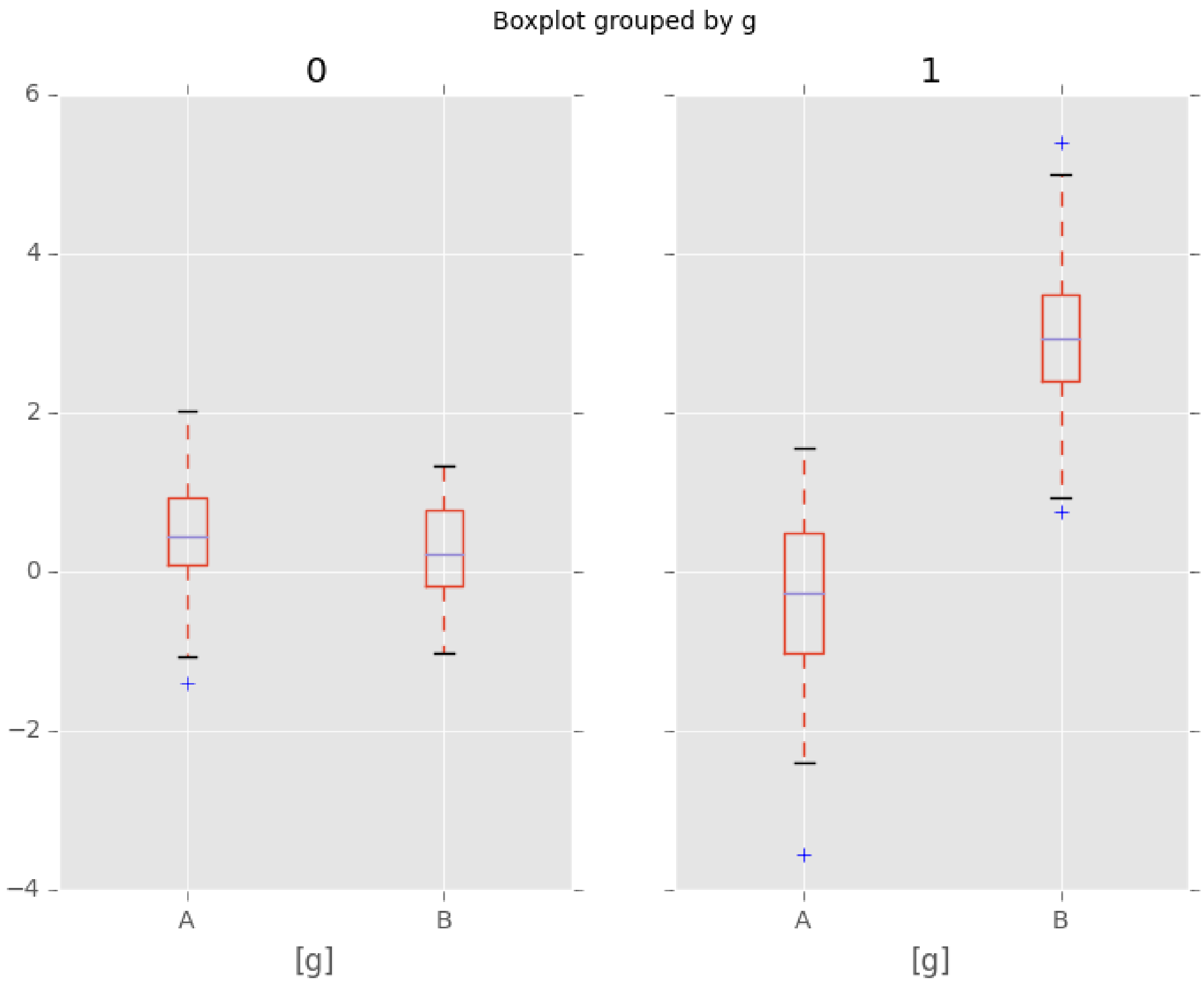
```
In [47]: np.random.seed(1234)

In [48]: df_box = pd.DataFrame(np.random.randn(50, 2))

In [49]: df_box['g'] = np.random.choice(['A', 'B'], size=50)

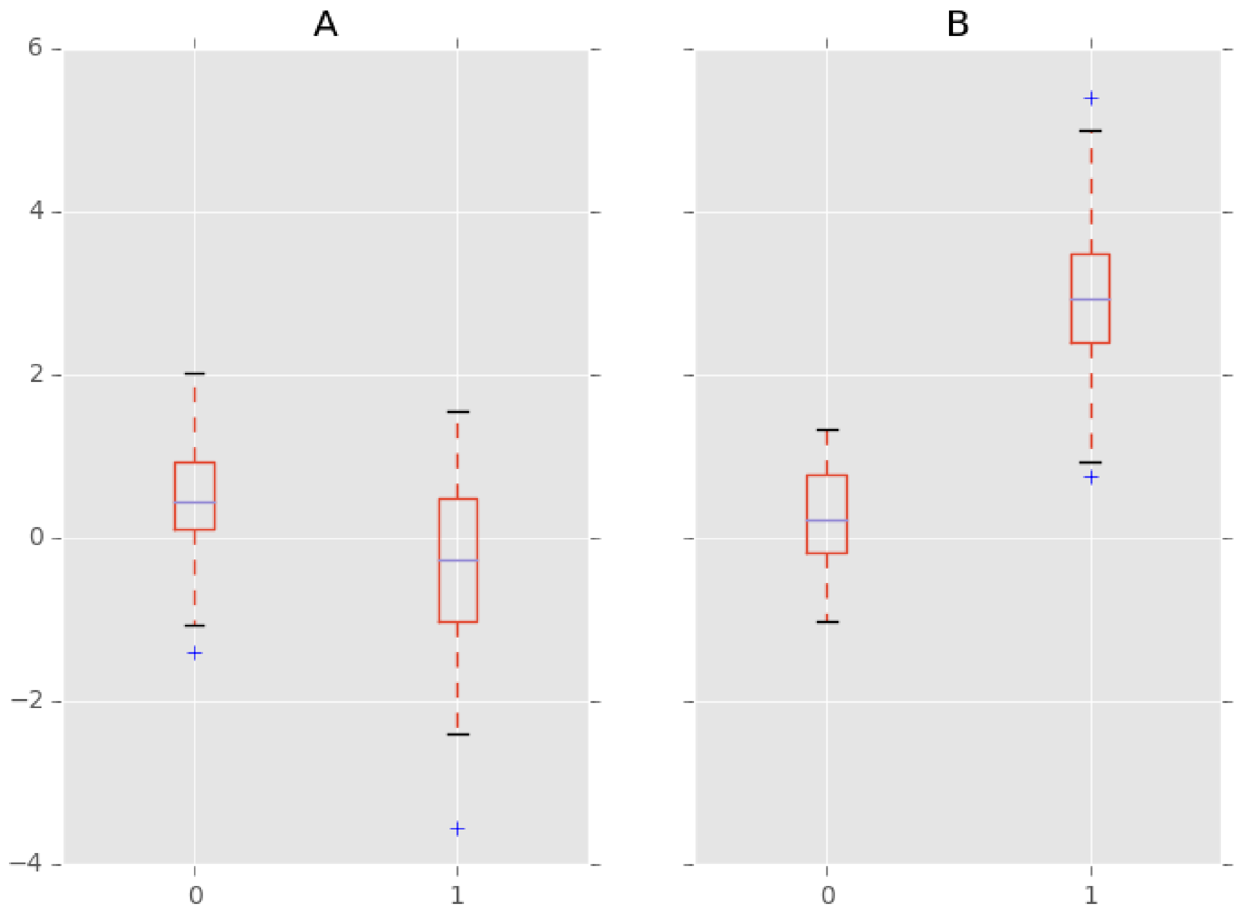
In [50]: df_box.loc[df_box['g'] == 'B', 1] += 3

In [51]: bp = df_box.boxplot(by='g')
```



Compare to:

```
In [52]: bp = df_box.groupby('g').boxplot()
```



23.2.4 Area Plot

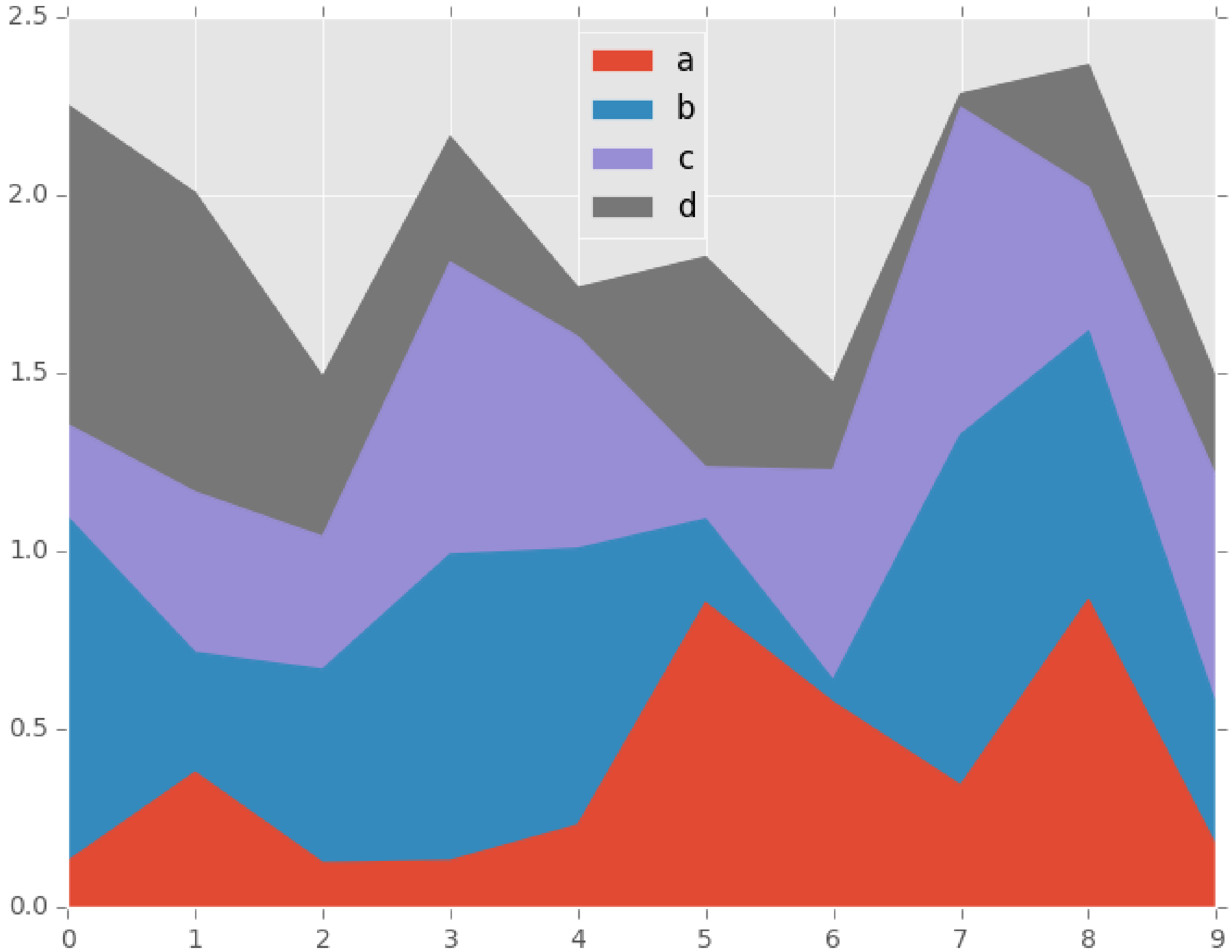
New in version 0.14.

You can create area plots with `Series.plot` and `DataFrame.plot` by passing `kind='area'`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains *NaN*, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling *plot*.

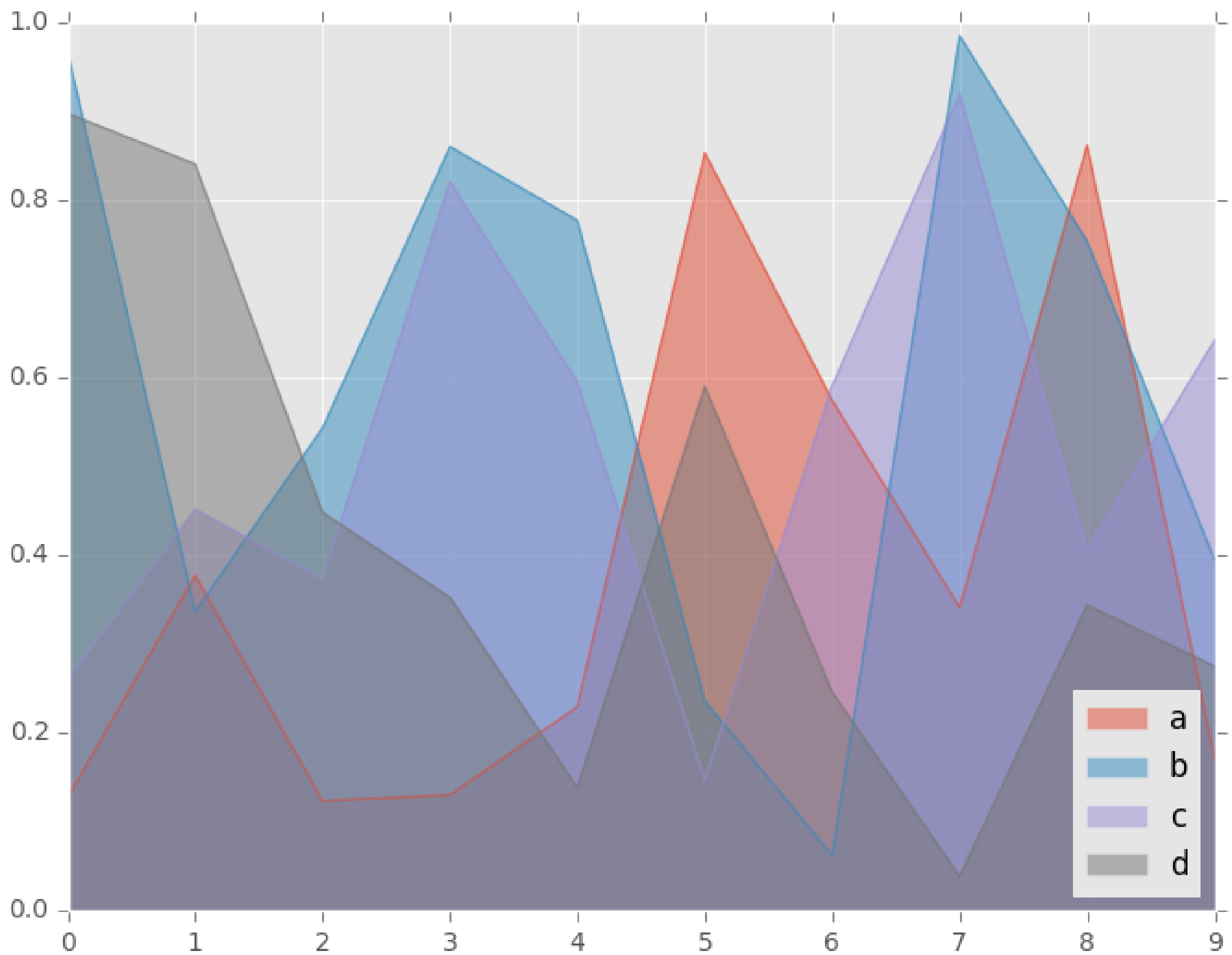
```
In [53]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

In [54]: df.plot(kind='area');
```



To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [55]: df.plot(kind='area', stacked=False);
```



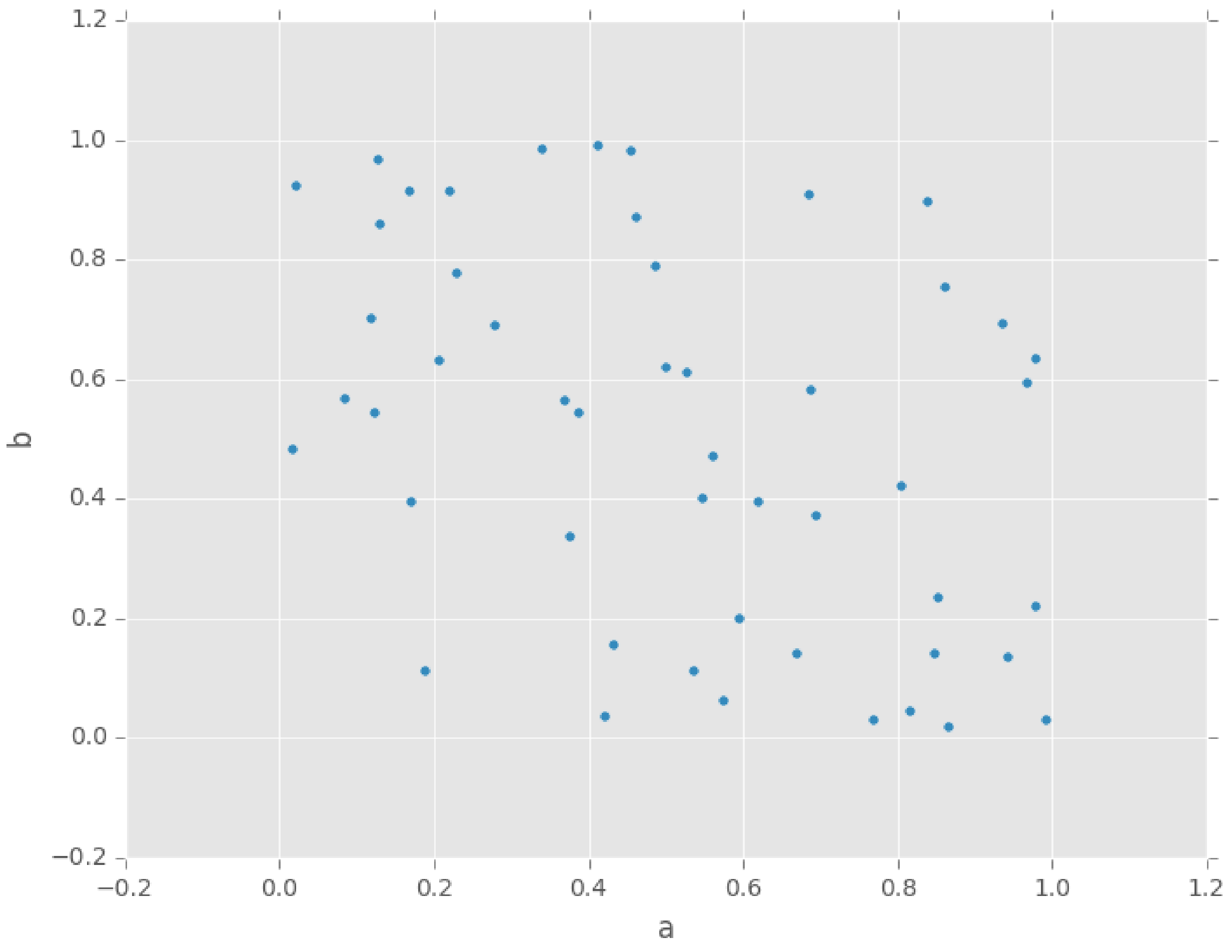
23.2.5 Scatter Plot

New in version 0.13.

You can create scatter plots with `DataFrame.plot` by passing `kind='scatter'`. Scatter plot requires numeric columns for x and y axis. These can be specified by `x` and `y` keywords each.

```
In [56]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])

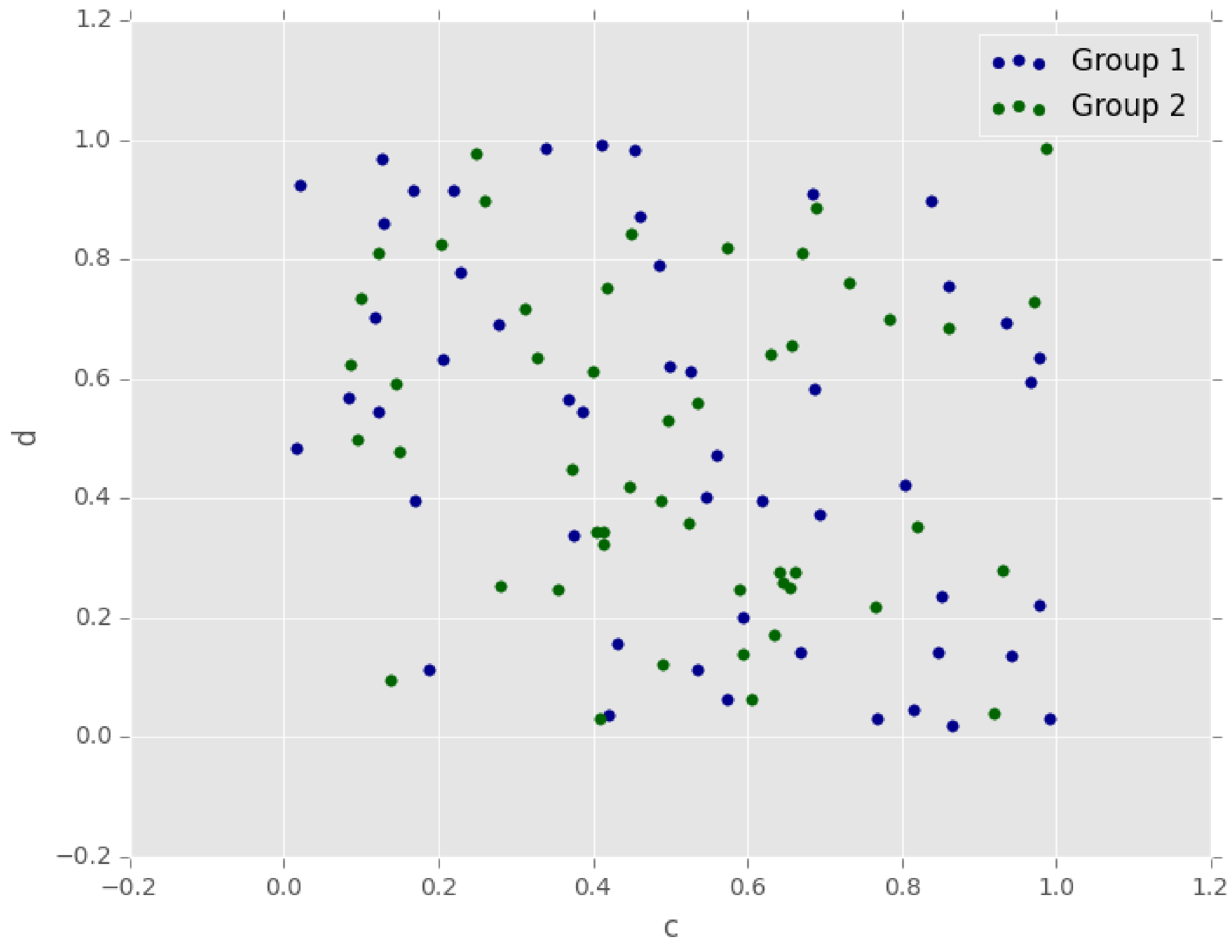
In [57]: df.plot(kind='scatter', x='a', y='b');
```



To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

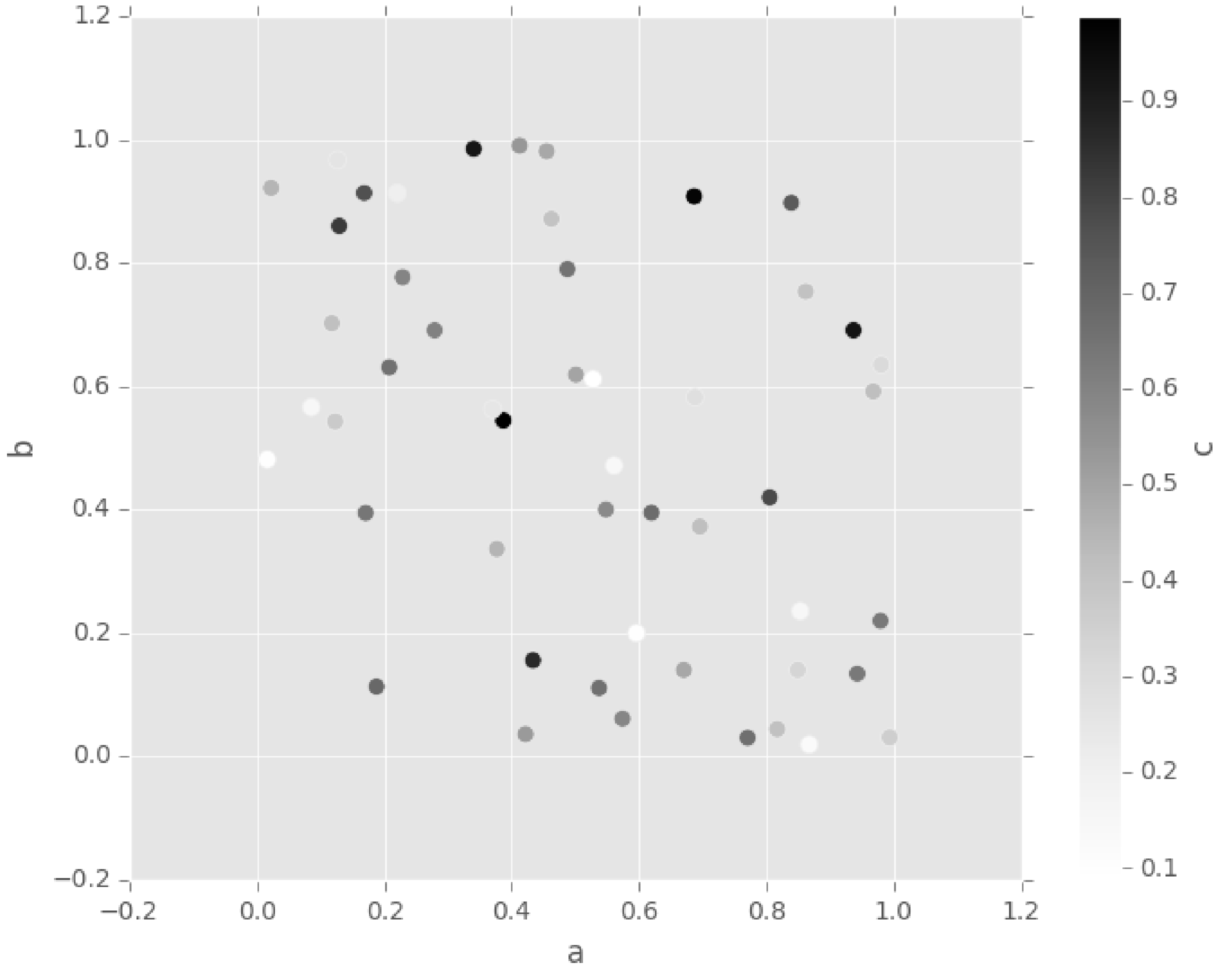
```
In [58]: ax = df.plot(kind='scatter', x='a', y='b',
   ....:              color='DarkBlue', label='Group 1');
   ....:

In [59]: df.plot(kind='scatter', x='c', y='d',
   ....:         color='DarkGreen', label='Group 2', ax=ax);
   ....:
```



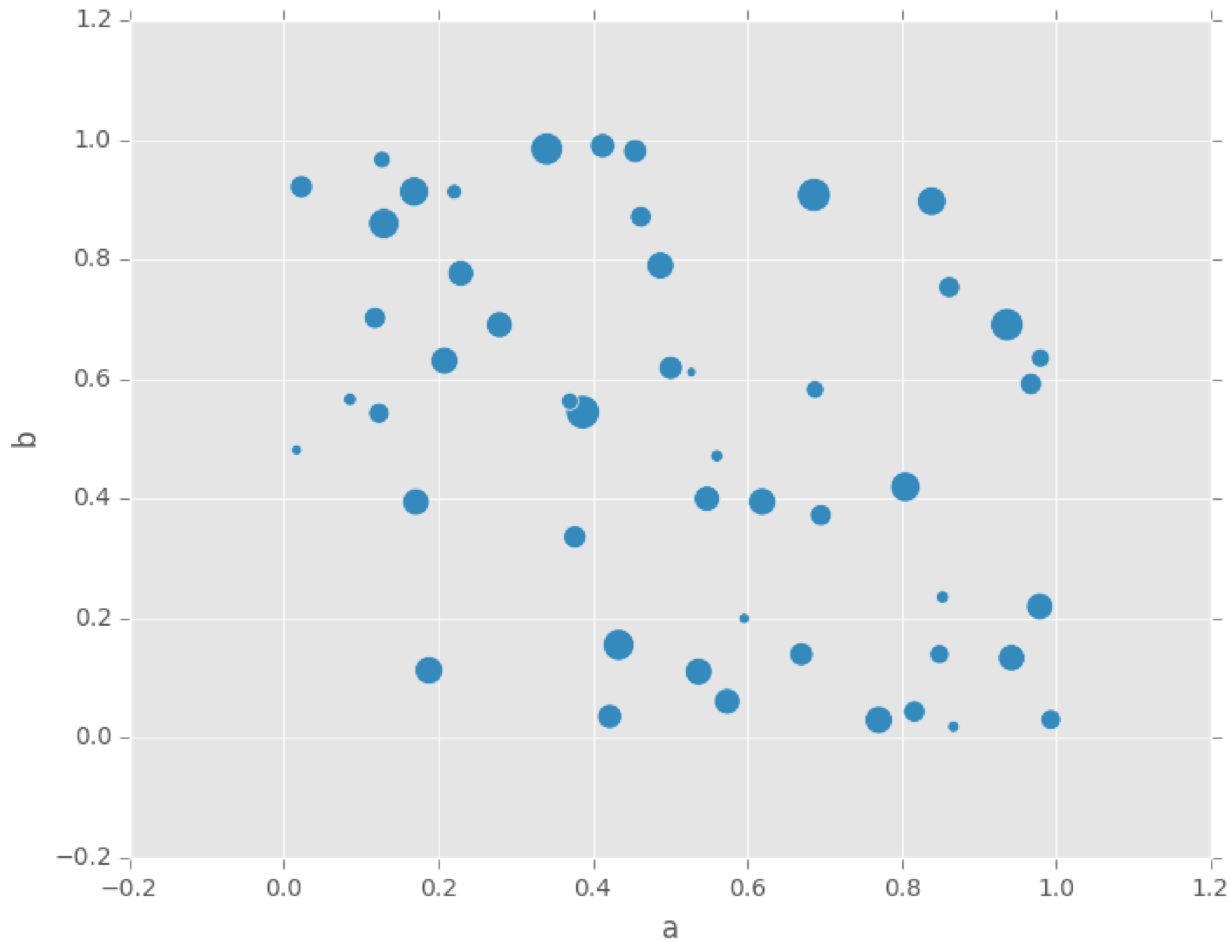
The keyword c may be given as the name of a column to provide colors for each point:

```
In [60]: df.plot(kind='scatter', x='a', y='b', c='c', s=50);
```



You can pass other keywords supported by matplotlib `scatter`. Below example shows a bubble chart using a dataframe column values as bubble size.

```
In [61]: df.plot(kind='scatter', x='a', y='b', s=df['c']*200);
```



See the `scatter` method and the matplotlib scatter documenation for more.

23.2.6 Hexagonal Bin Plot

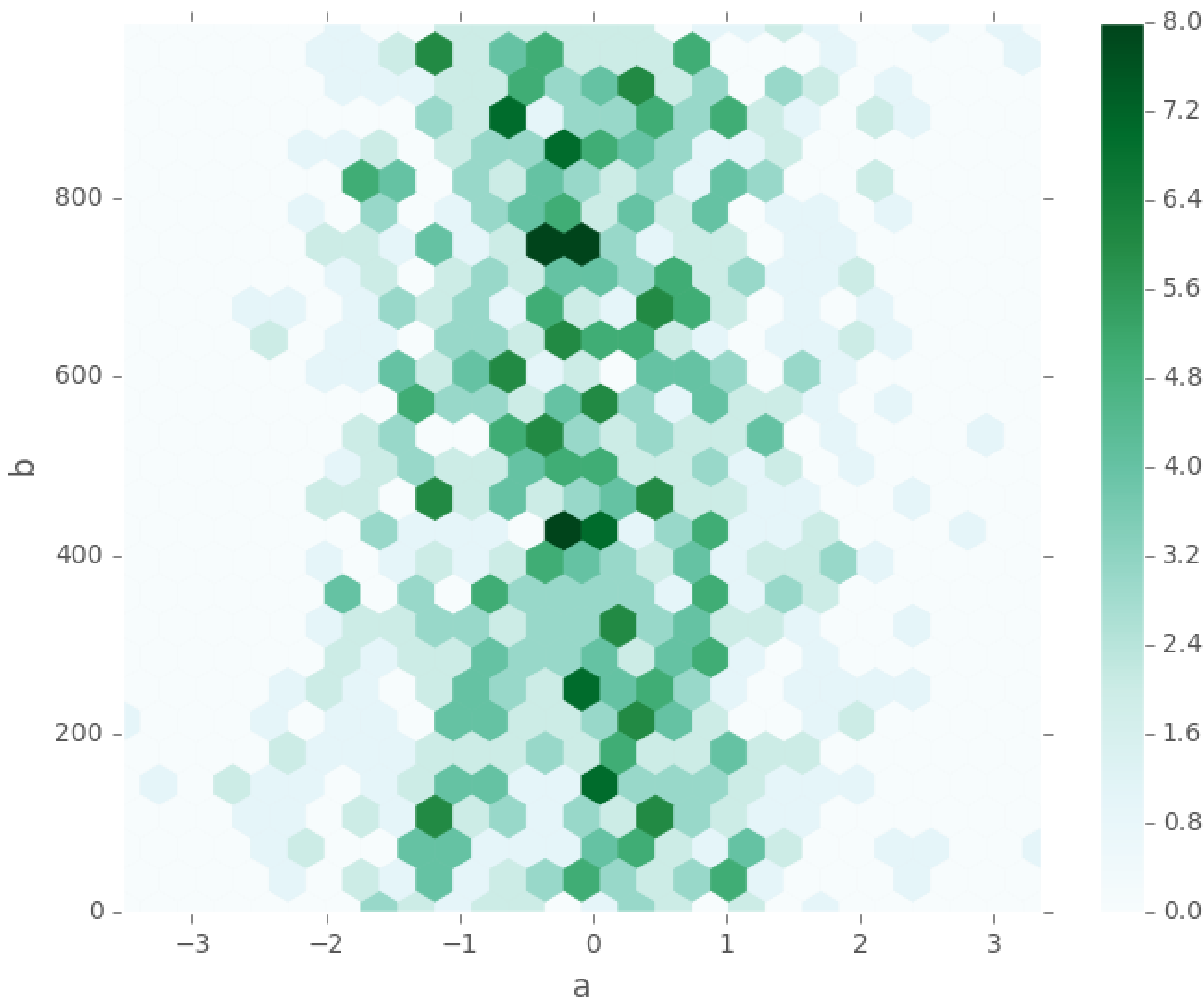
New in version 0.14.

You can create hexagonal bin plots with `DataFrame.plot()` and `kind='hexbin'`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [62]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

In [63]: df['b'] = df['b'] + np.arange(1000)

In [64]: df.plot(kind='hexbin', x='a', y='b', gridsize=25)
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0xad40eccc>
```



A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

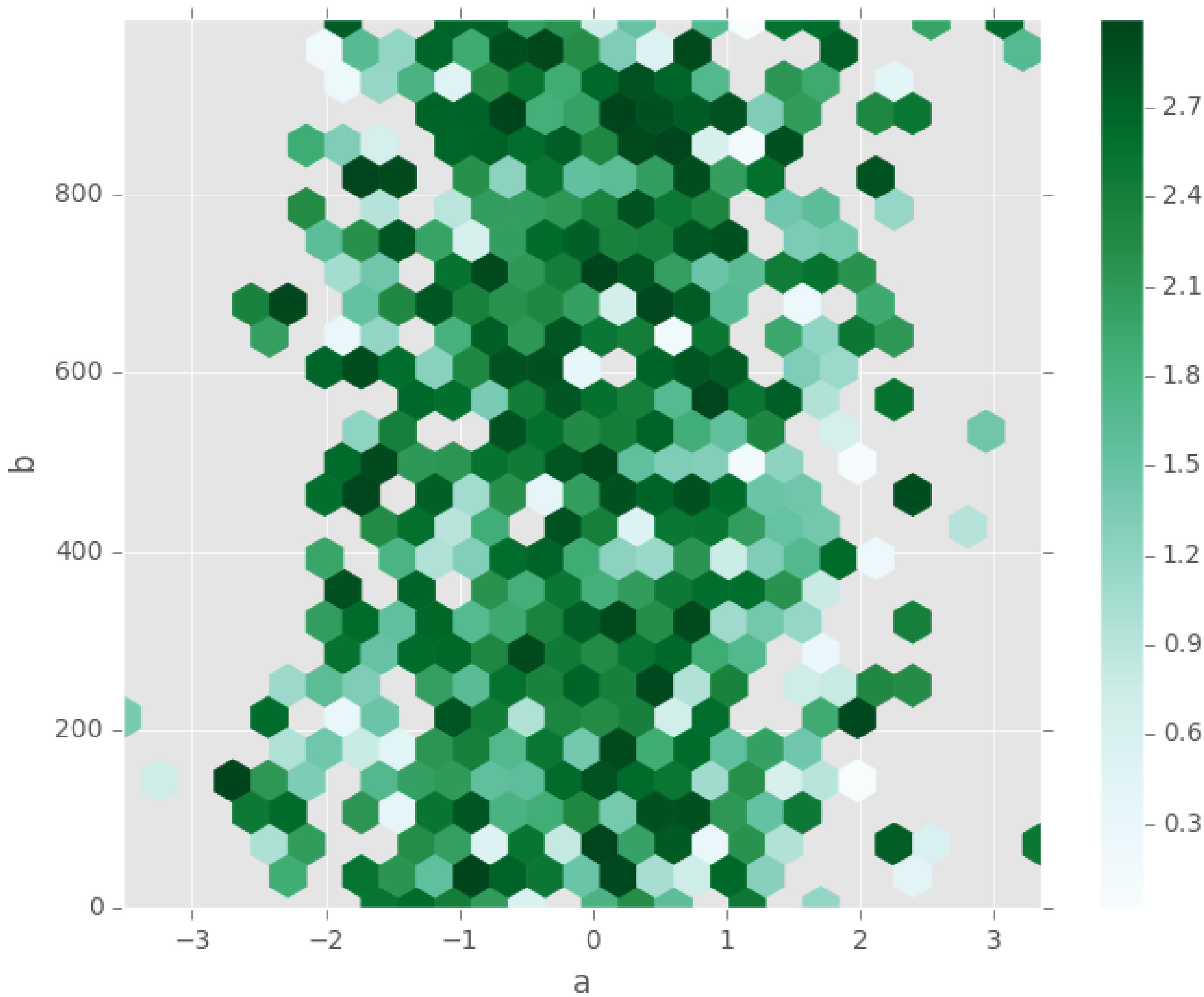
By default, a histogram of the counts around each `(x, y)` point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each `(x, y)` point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g. `mean`, `max`, `sum`, `std`). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with numpy's `max` function.

```
In [65]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

In [66]: df['b'] = df['b'] = df['b'] + np.arange(1000)

In [67]: df['z'] = np.random.uniform(0, 3, 1000)

In [68]: df.plot(kind='hexbin', x='a', y='b', C='z', reduce_C_function=np.max,
   ....:         gridsize=25)
   ....:
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0xadadfb8c>
```



See the `hexbin` method and the matplotlib hexbin documenation for more.

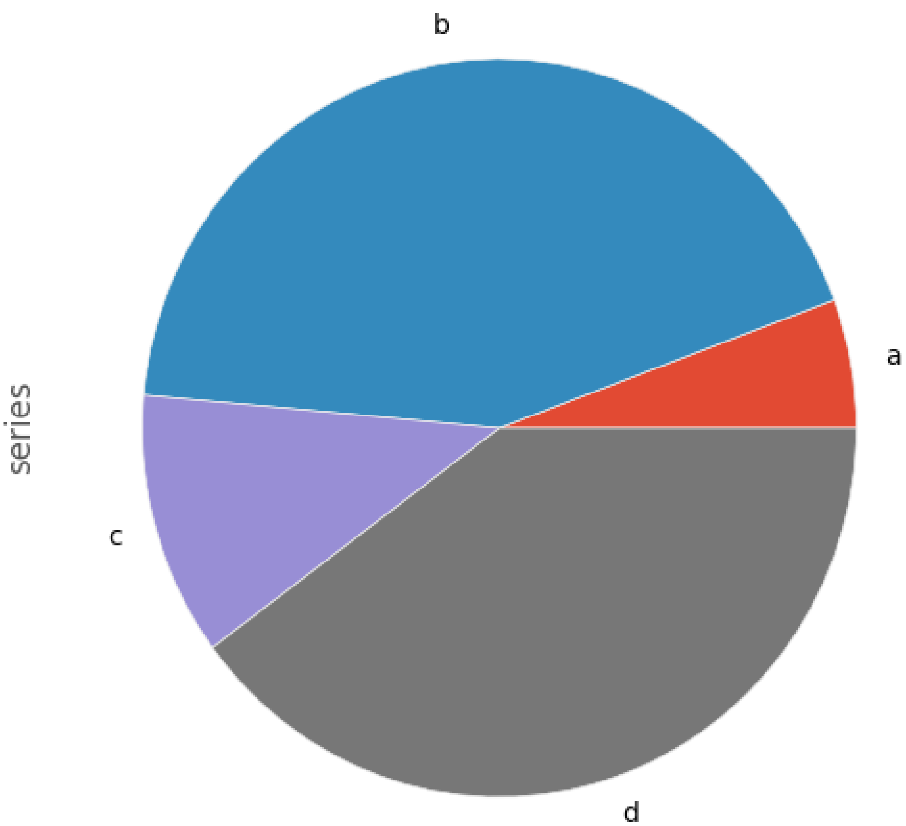
23.2.7 Pie plot

New in version 0.14.

You can create a pie plot with `DataFrame.plot()` or `Series.plot()` with `kind='pie'`. If your data includes any `NaN`, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

```
In [69]: series = pd.Series(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], name='series')

In [70]: series.plot(kind='pie', figsize=(6, 6))
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0xacd2dc4c>
```

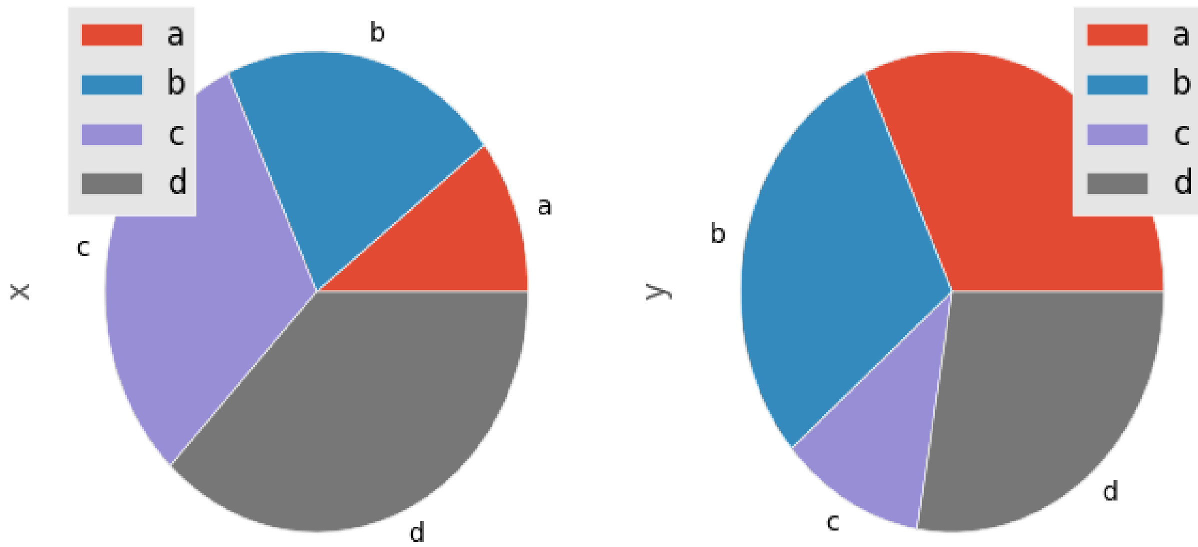


For pie plots it's best to use square figures, one's with an equal aspect ratio. You can create the figure with equal width and height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned `axes` object.

Note that pie plot with `DataFrame` requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```
In [71]: df = pd.DataFrame(3 * np.random.rand(4, 2), index=['a', 'b', 'c', 'd'], columns=['x', 'y'])

In [72]: df.plot(kind='pie', subplots=True, figsize=(8, 4))
Out[72]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0xadae15ec>,
       <matplotlib.axes._subplots.AxesSubplot object at 0xad46114c>], dtype=object)
```

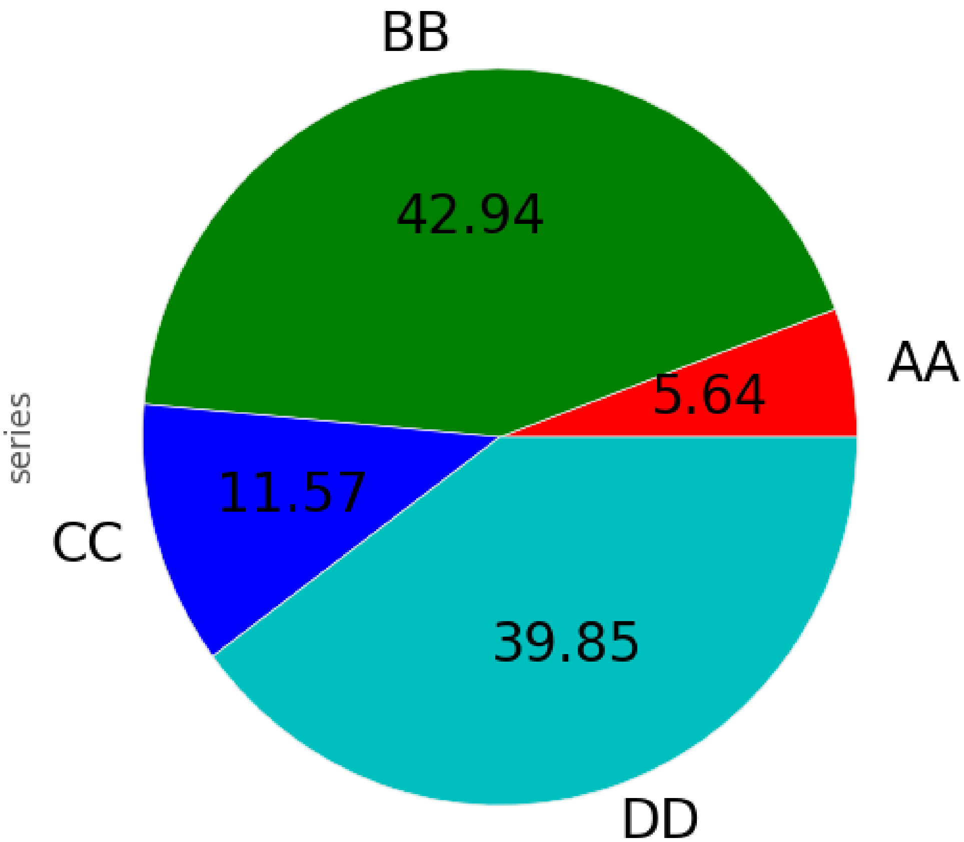


You can use the `labels` and `colors` keywords to specify the labels and colors of each wedge.

> **Warning:** Most pandas plots use the 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.

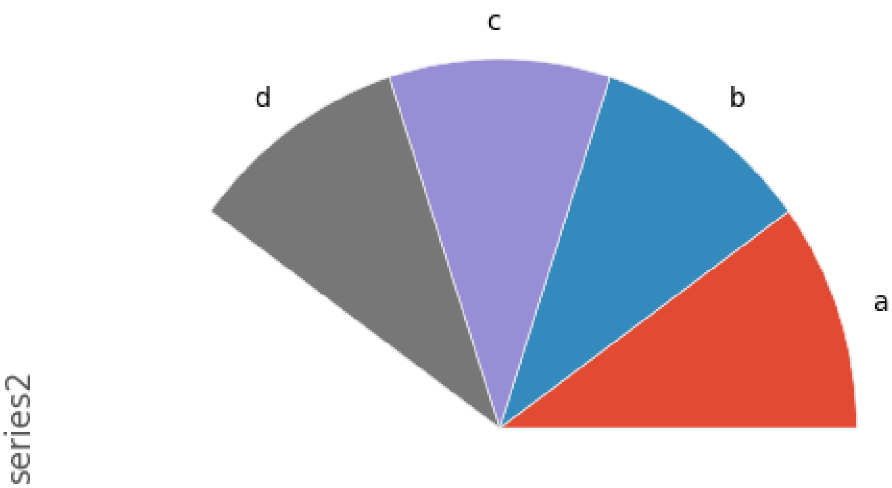
```
In [73]: series.plot(kind='pie', labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
   ....:             autopct='%.2f', fontsize=20, figsize=(6, 6))
   ....:
Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0xadd0558c>
```



If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [74]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')

In [75]: series.plot(kind='pie', figsize=(6, 6))
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0xadcea3ac>
```



See the matplotlib pie documenation for more.

23.3 Plotting with Missing Data

Pandas tries to be pragmatic about plotting DataFrames or Series that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

Plot Type	NaN Handling
Line	Leave gaps at NaNs
Line (stacked)	Fill 0's
Bar	Fill 0's
Scatter	Drop NaNs
Histogram	Drop NaNs (column-wise)
Box	Drop NaNs (column-wise)
Area	Fill 0's
KDE	Drop NaNs (column-wise)
Hexbin	Drop NaNs
Pie	Fill 0's

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using `fillna()` or `dropna()` before plotting.

23.4 Plotting Tools

These functions can be imported from `pandas.tools.plotting` and take a `Series` or `DataFrame` as an argument.

23.4.1 Scatter Matrix Plot

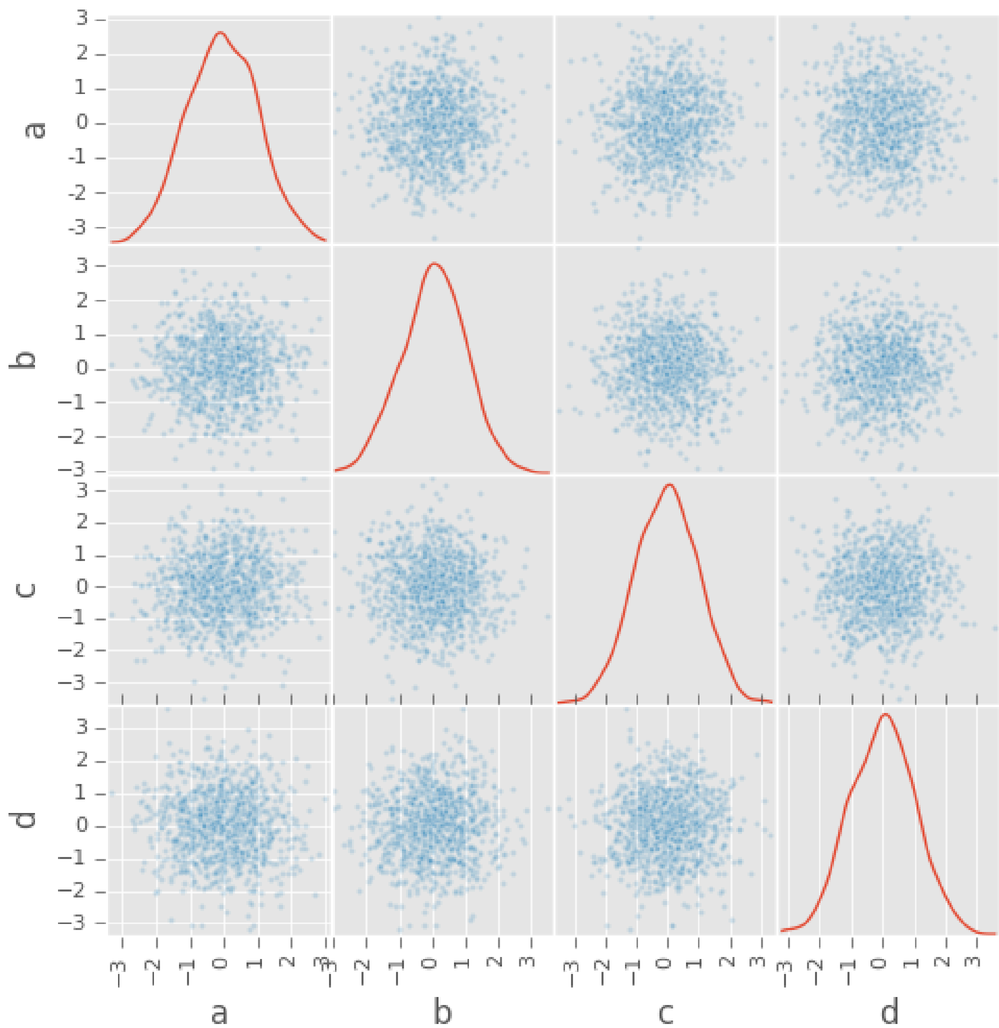
New in version 0.7.3.

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.tools.plotting`:

```
In [76]: from pandas.tools.plotting import scatter_matrix

In [77]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

In [78]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')
Out[78]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0xad5d5ccc>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xac44724c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xac41ce8c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xac3b5f6c>],
        [<matplotlib.axes._subplots.AxesSubplot object at 0xac37c1ac>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xac329b2c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xac2e7a2c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad5504ec>],
        [<matplotlib.axes._subplots.AxesSubplot object at 0xada19e0c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad3c2c2c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad4c044c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad4df24c>],
        [<matplotlib.axes._subplots.AxesSubplot object at 0xacd278ec>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad44ebac>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad397f8c>,
         <matplotlib.axes._subplots.AxesSubplot object at 0xad34d5ec>]], dtype=object)
```



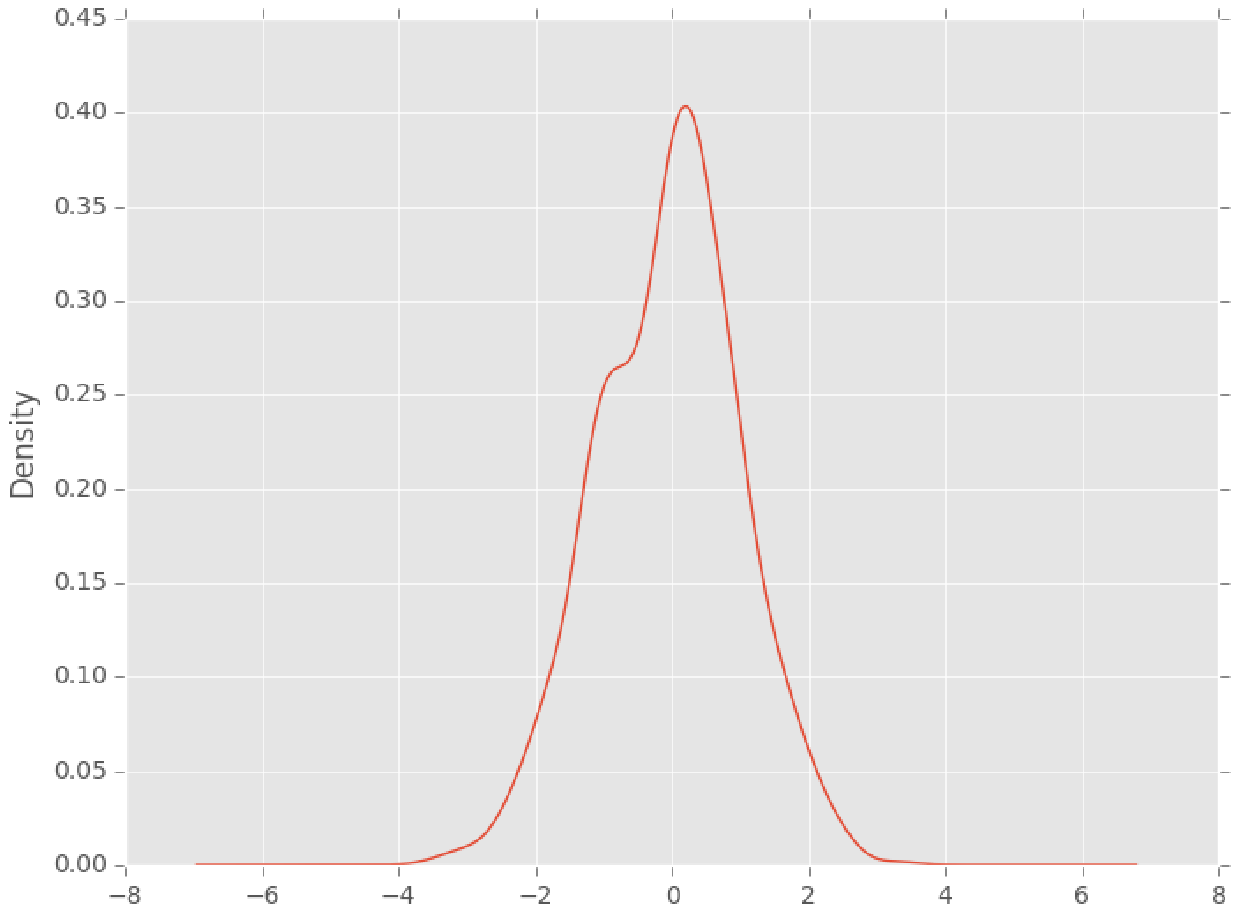
23.4.2 Density Plot

New in version 0.8.0.

You can create density plots using the Series/DataFrame.plot and setting `kind='kde'`:

```
In [79]: ser = pd.Series(np.random.randn(1000))

In [80]: ser.plot(kind='kde')
Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0xa9af7dac>
```



23.4.3 Andrews Curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

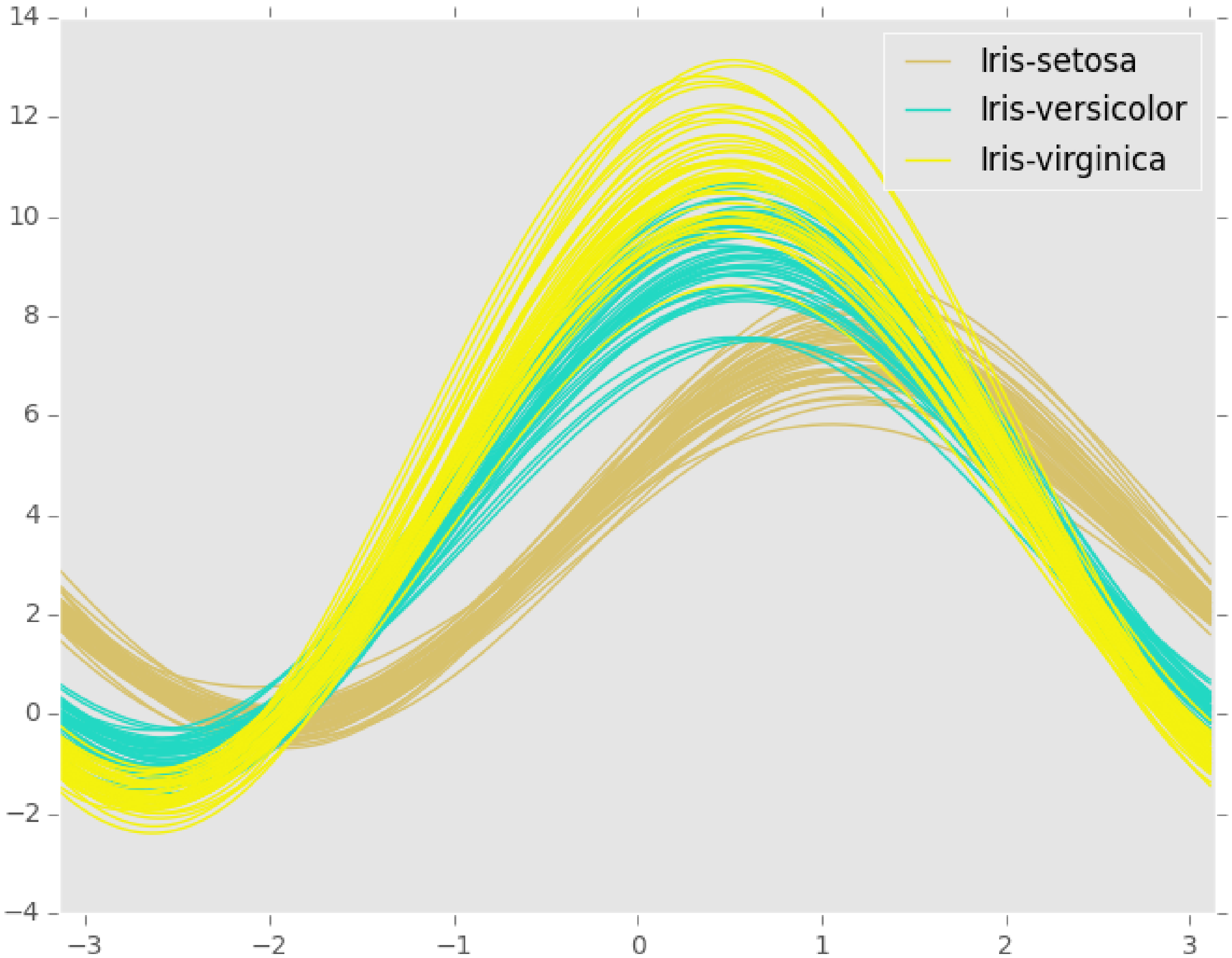
Note: The "Iris" dataset is available here.

```
In [81]: from pandas.tools.plotting import andrews_curves

In [82]: data = pd.read_csv('data/iris.data')

In [83]: plt.figure()
Out[83]: <matplotlib.figure.Figure at 0xa9c6f8cc>

In [84]: andrews_curves(data, 'Name')
Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0xa9c6f96c>
```



23.4.4 Parallel Coordinates

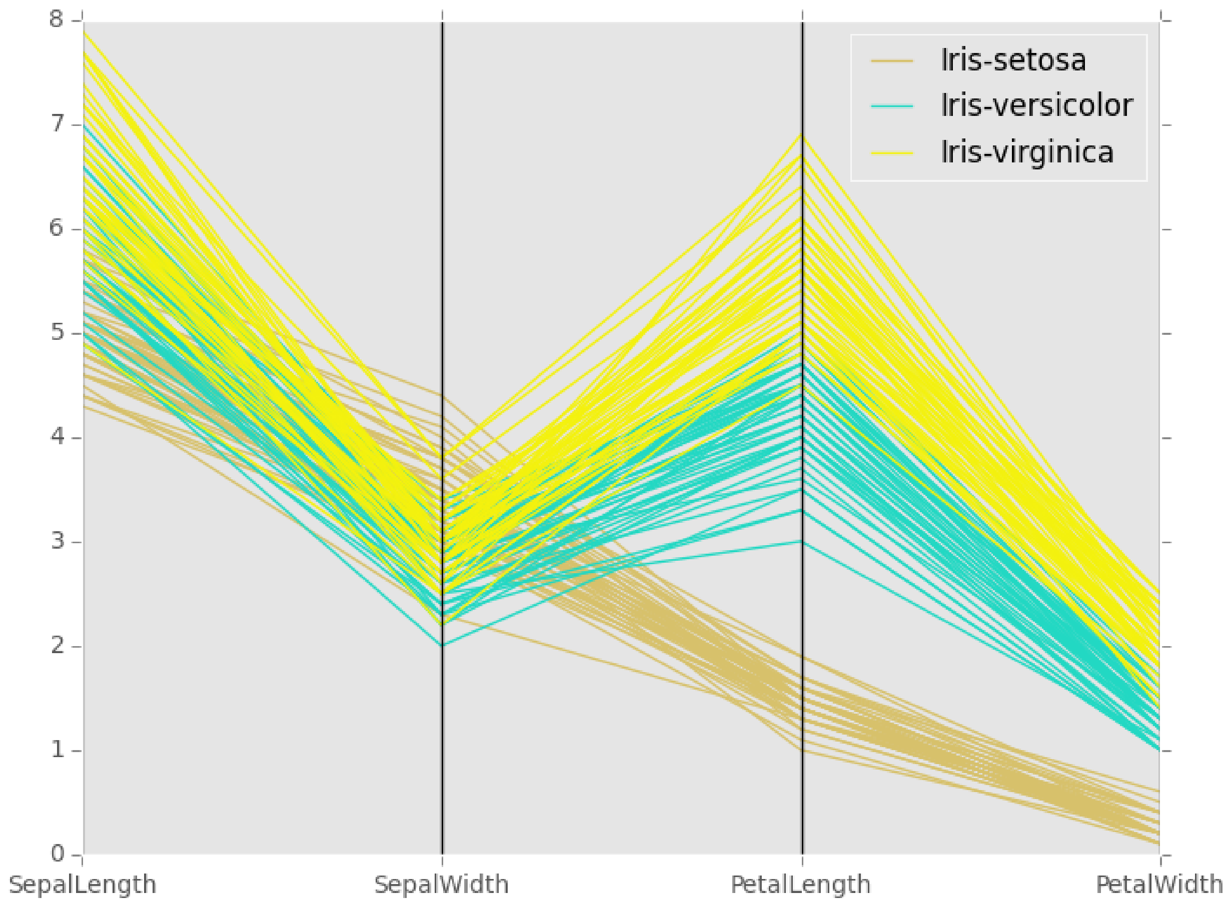
Parallel coordinates is a plotting technique for plotting multivariate data. It allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```
In [85]: from pandas.tools.plotting import parallel_coordinates

In [86]: data = pd.read_csv('data/iris.data')

In [87]: plt.figure()
Out[87]: <matplotlib.figure.Figure at 0xa99a0d2c>

In [88]: parallel_coordinates(data, 'Name')
Out[88]: <matplotlib.axes._subplots.AxesSubplot at 0xa99a57cc>
```



23.4.5 Lag Plot

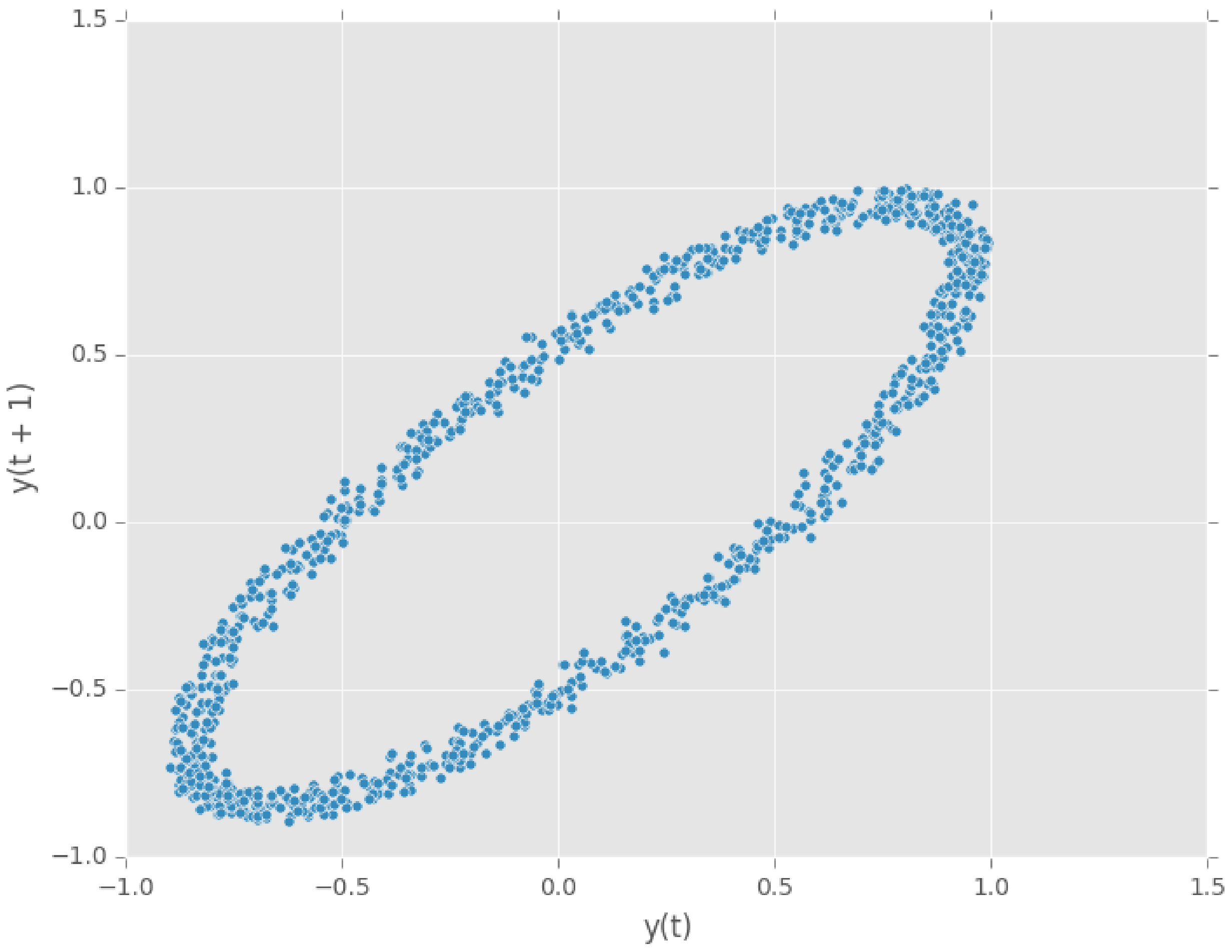
Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random.

```
In [89]: from pandas.tools.plotting import lag_plot

In [90]: plt.figure()
Out[90]: <matplotlib.figure.Figure at 0xa9baf52c>

In [91]: data = pd.Series(0.1 * np.random.rand(1000) +
   ....:     0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))
   ....:

In [92]: lag_plot(data)
Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ba90ec>
```



23.4.6 Autocorrelation Plot

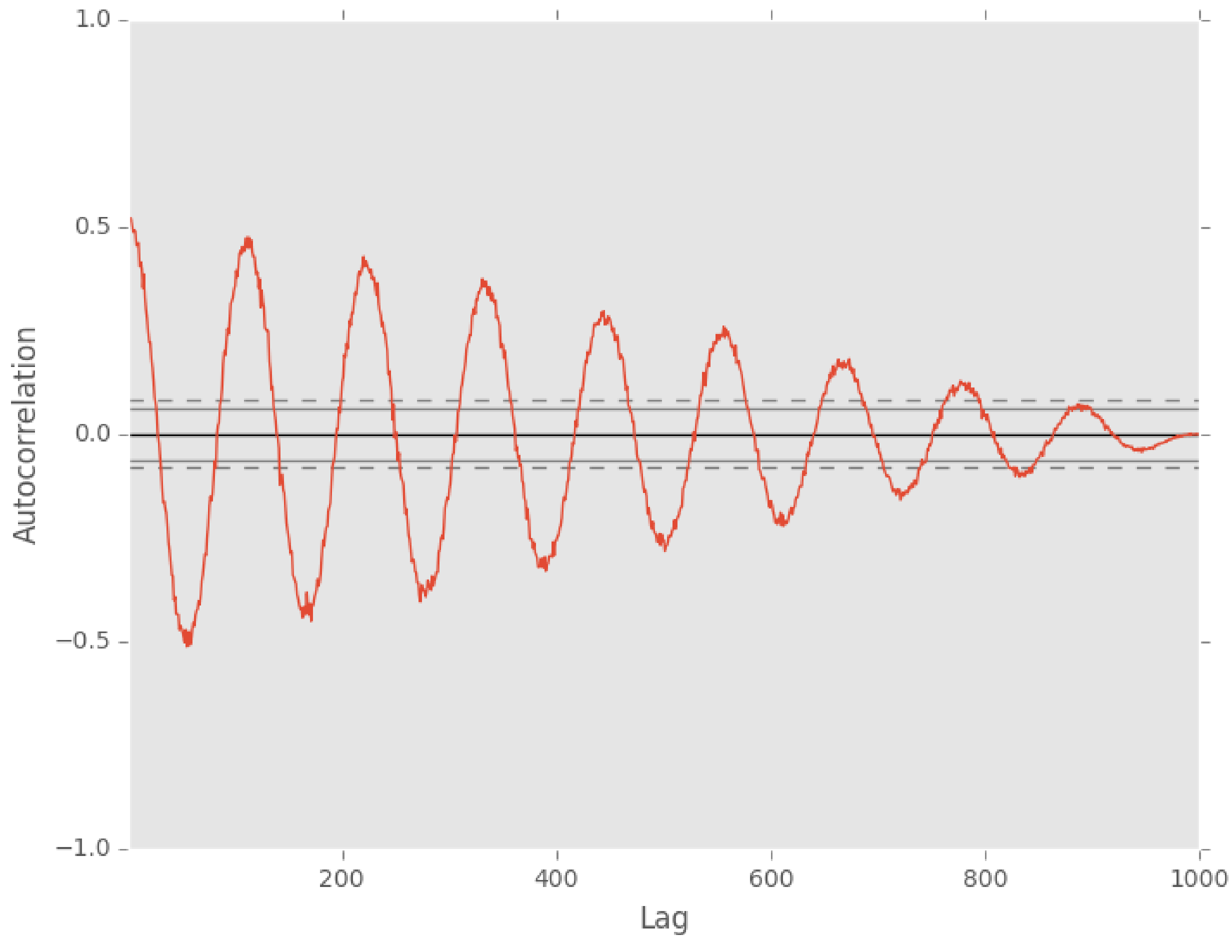
Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band.

```
In [93]: from pandas.tools.plotting import autocorrelation_plot

In [94]: plt.figure()
Out[94]: <matplotlib.figure.Figure at 0xa9ba12cc>

In [95]: data = pd.Series(0.7 * np.random.rand(1000) +
   ....:    0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
   ....:

In [96]: autocorrelation_plot(data)
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0xa9b78c8c>
```



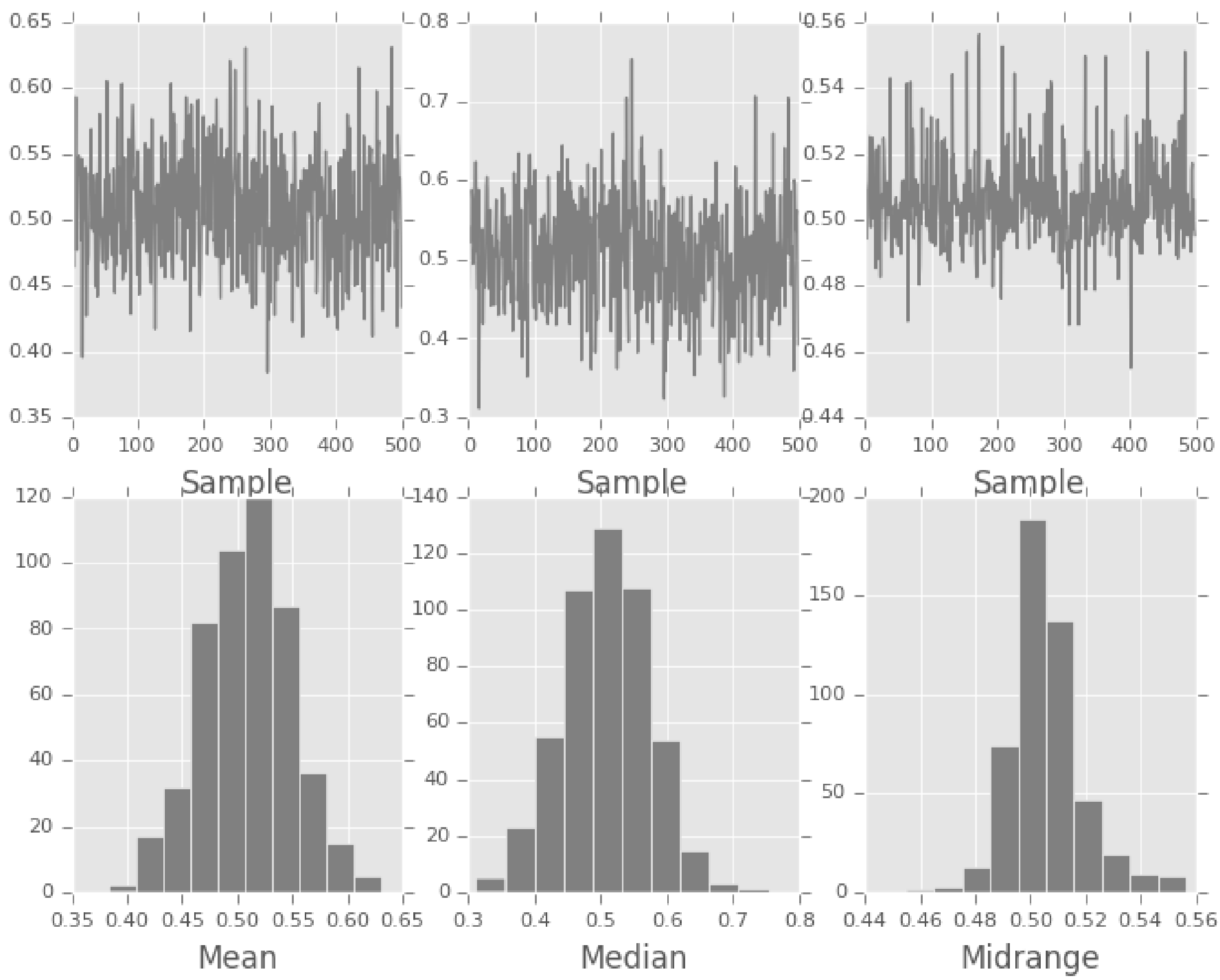
23.4.7 Bootstrap Plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [97]: from pandas.tools.plotting import bootstrap_plot

In [98]: data = pd.Series(np.random.rand(1000))

In [99]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[99]: <matplotlib.figure.Figure at 0xa967668c>
```



23.4.8 RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs it will be colored differently.

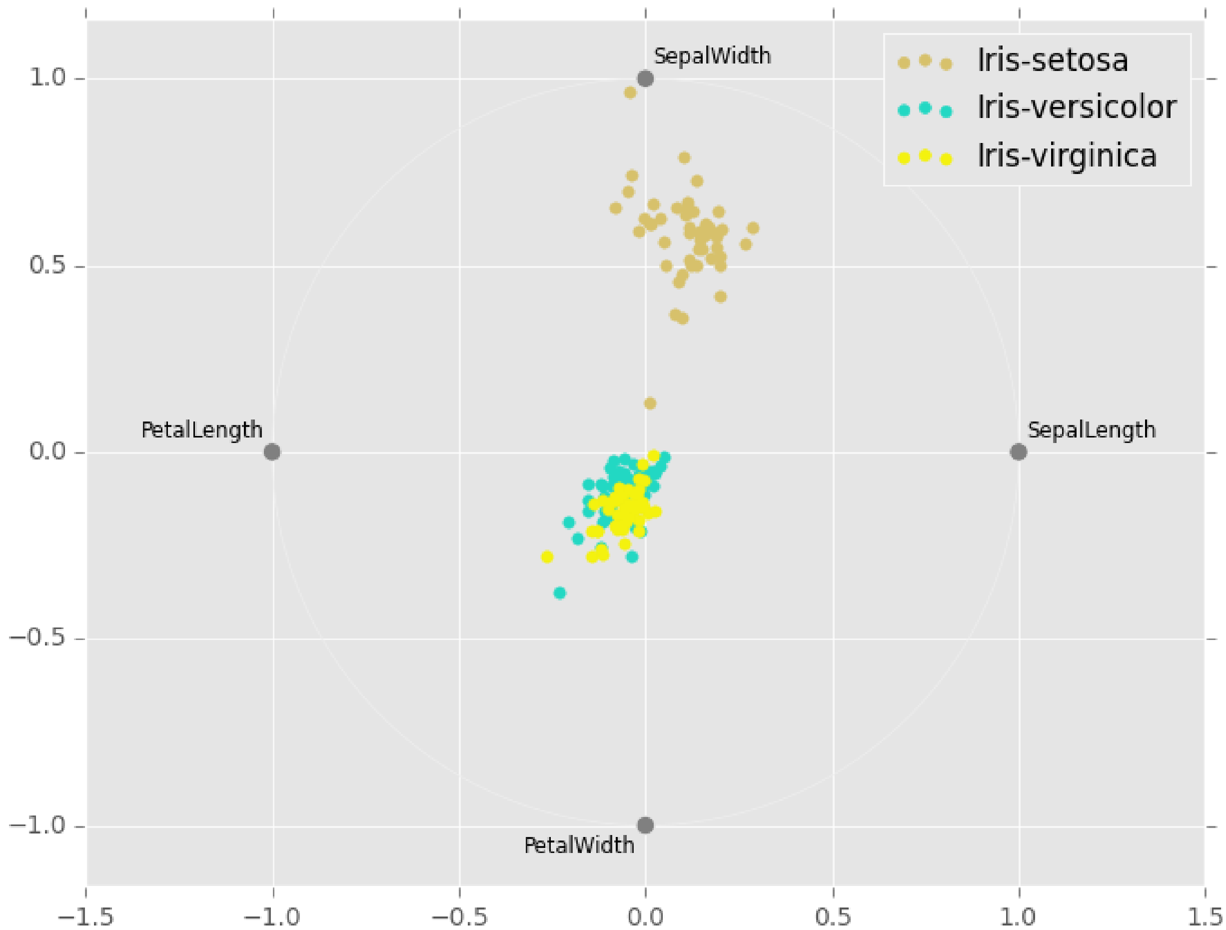
Note: The "Iris" dataset is available here.

```
In [100]: from pandas.tools.plotting import radviz

In [101]: data = pd.read_csv('data/iris.data')

In [102]: plt.figure()
Out[102]: <matplotlib.figure.Figure at 0xa9c2e30c>

In [103]: radviz(data, 'Name')
Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0xa9206c8c>
```



23.5 Plot Formatting

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [104]: plt.figure(); ts.plot(style='k--', label='Series');
```

For each kind of plot (e.g. *line*, *bar*, *scatter*) any additional arguments keywords are passed along to the corresponding matplotlib function (`ax.plot()`, `ax.bar()`, `ax.scatter()`). These can be used to control additional styling, beyond what pandas provides.

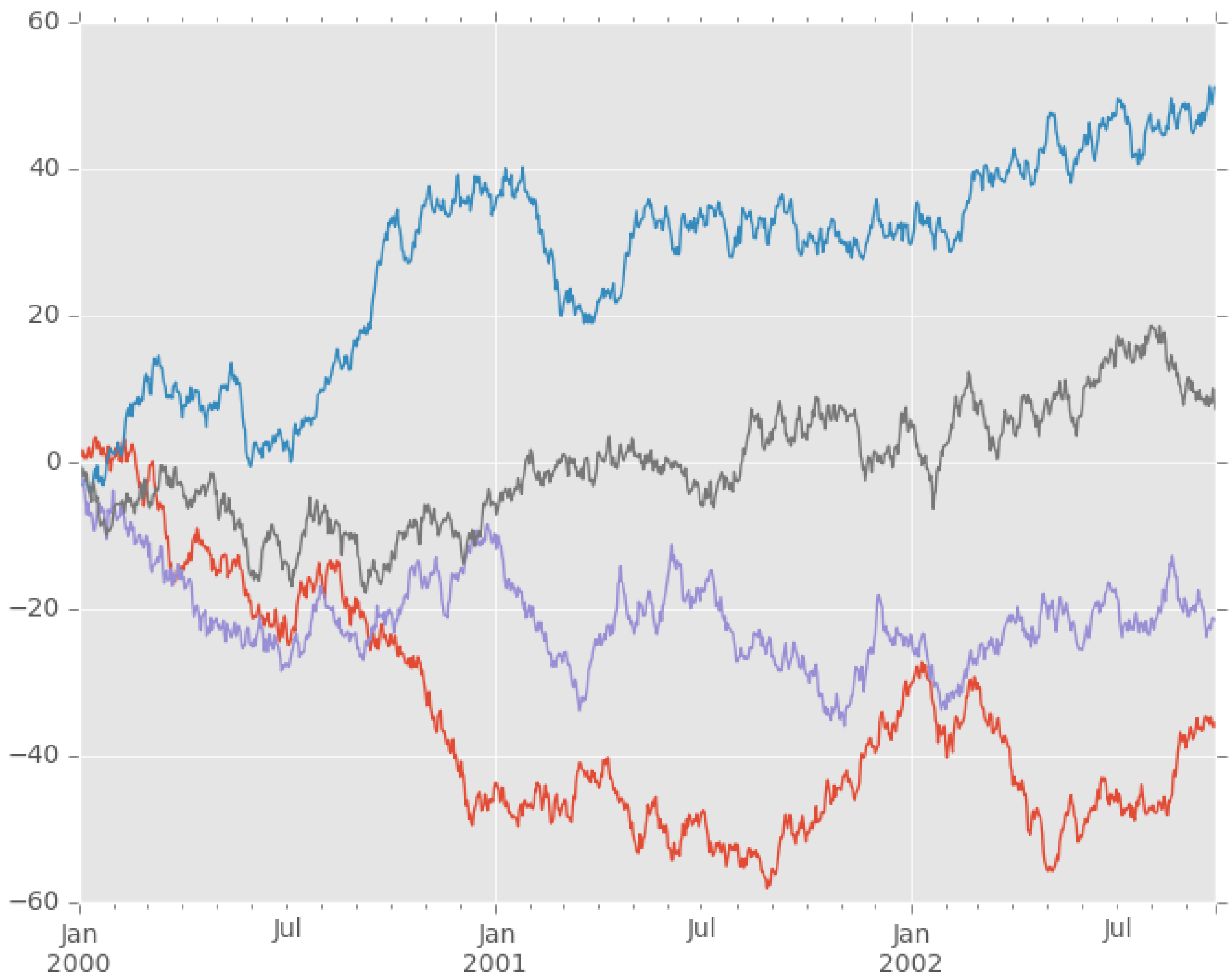
23.5.1 Controlling the Legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```
In [105]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [106]: df = df.cumsum()

In [107]: df.plot(legend=False)
Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0xa8d18ccc>
```



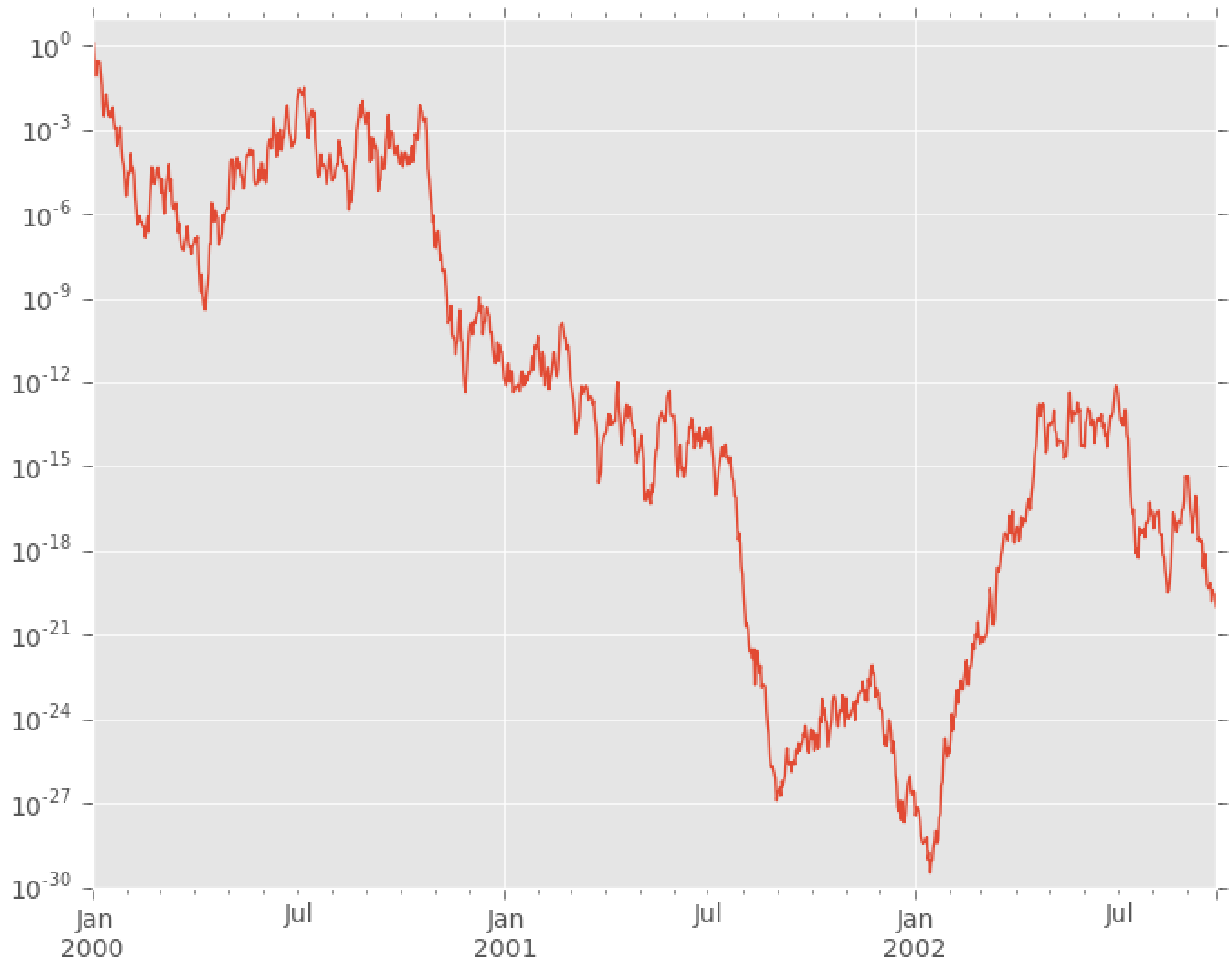
23.5.2 Scales

You may pass `logy` to get a log-scale Y axis.

```
In [108]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [109]: ts = np.exp(ts.cumsum())

In [110]: ts.plot(logy=True)
Out[110]: <matplotlib.axes._subplots.AxesSubplot at 0xa8a67e6c>
```



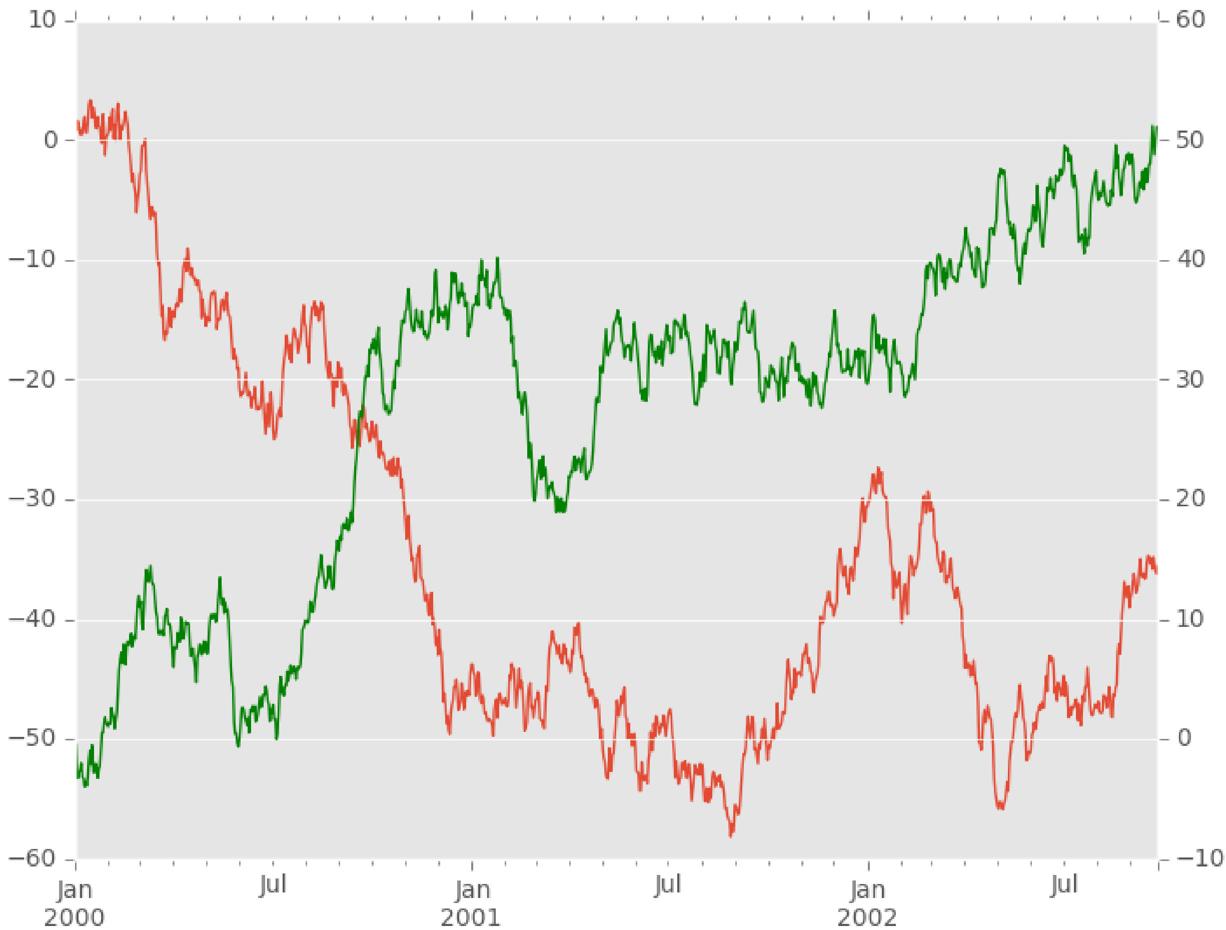
See also the `logx` and `loglog` keyword arguments.

23.5.3 Plotting on a Secondary Y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [111]: df.A.plot()
Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0xa8dc572c>

In [112]: df.B.plot(secondary_y=True, style='g')
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0xa85a228c>
```



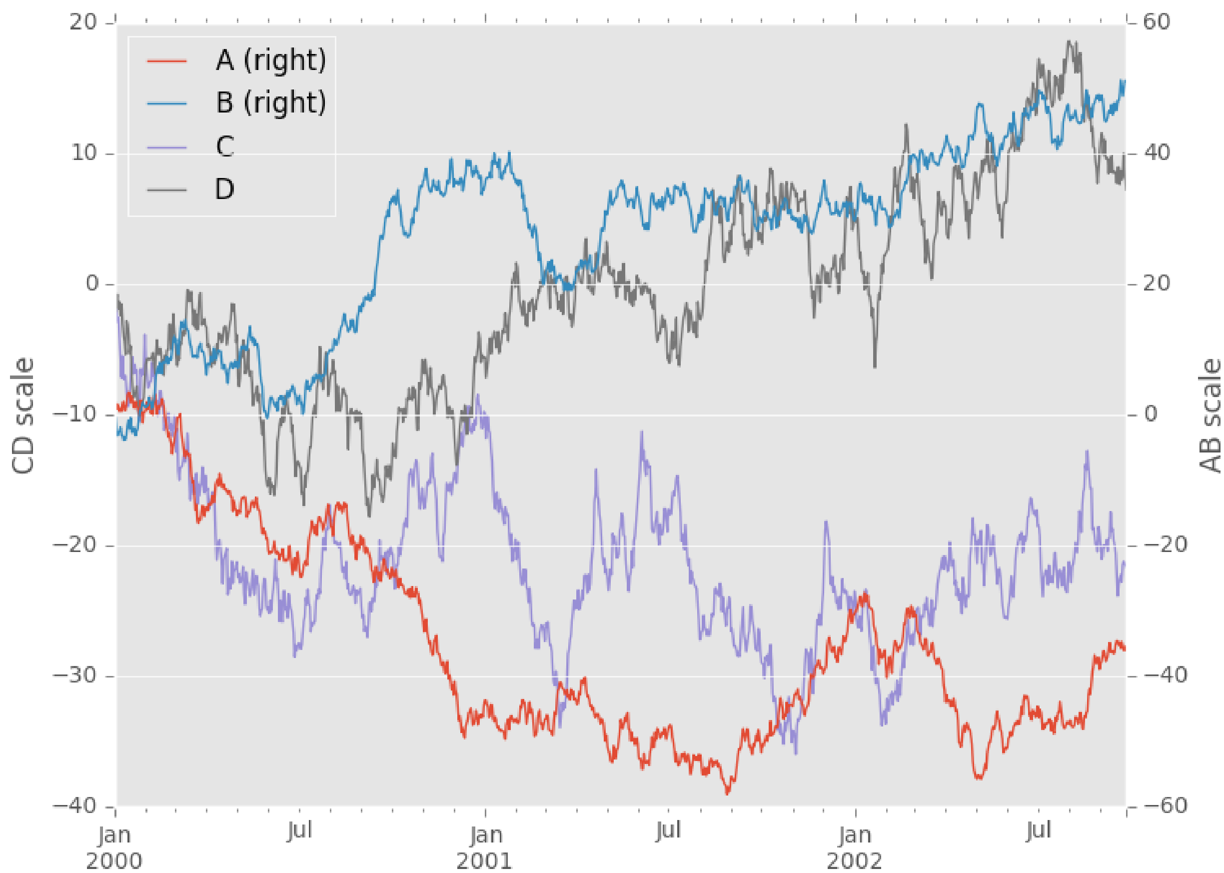
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [113]: plt.figure()
Out[113]: <matplotlib.figure.Figure at 0xa85a960c>

In [114]: ax = df.plot(secondary_y=['A', 'B'])

In [115]: ax.set_ylabel('CD scale')
Out[115]: <matplotlib.text.Text at 0xa894a96c>

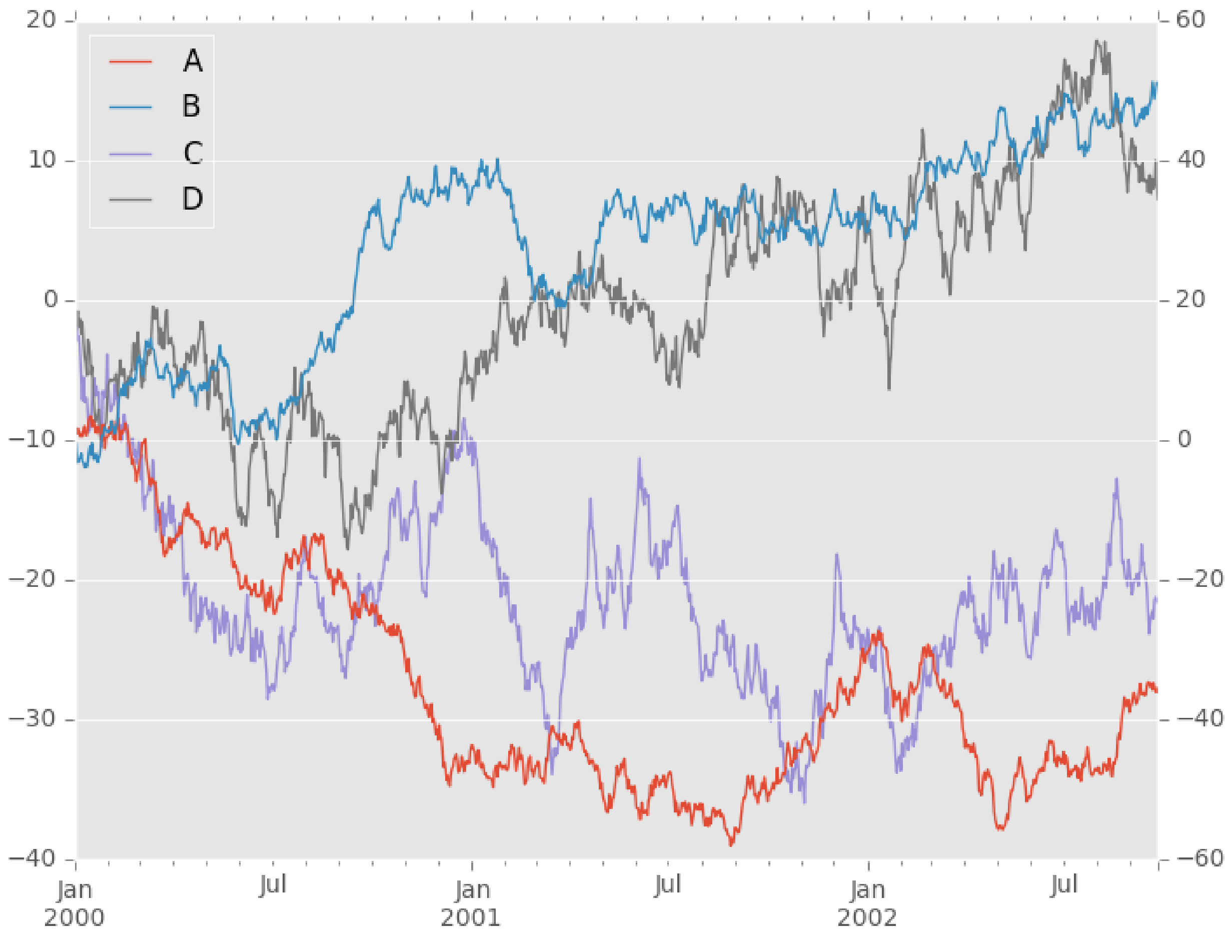
In [116]: ax.right_ax.set_ylabel('AB scale')
Out[116]: <matplotlib.text.Text at 0xa89450ac>
```



Note that the columns plotted on the secondary y-axis is automatically marked with "(right)" in the legend. To turn off the automatic marking, use the `mark_right=False` keyword:

```
In [117]: plt.figure()
Out[117]: <matplotlib.figure.Figure at 0xa8d0d06c>

In [118]: df.plot(secondary_y=['A', 'B'], mark_right=False)
Out[118]: <matplotlib.axes._subplots.AxesSubplot at 0xa847c18c>
```



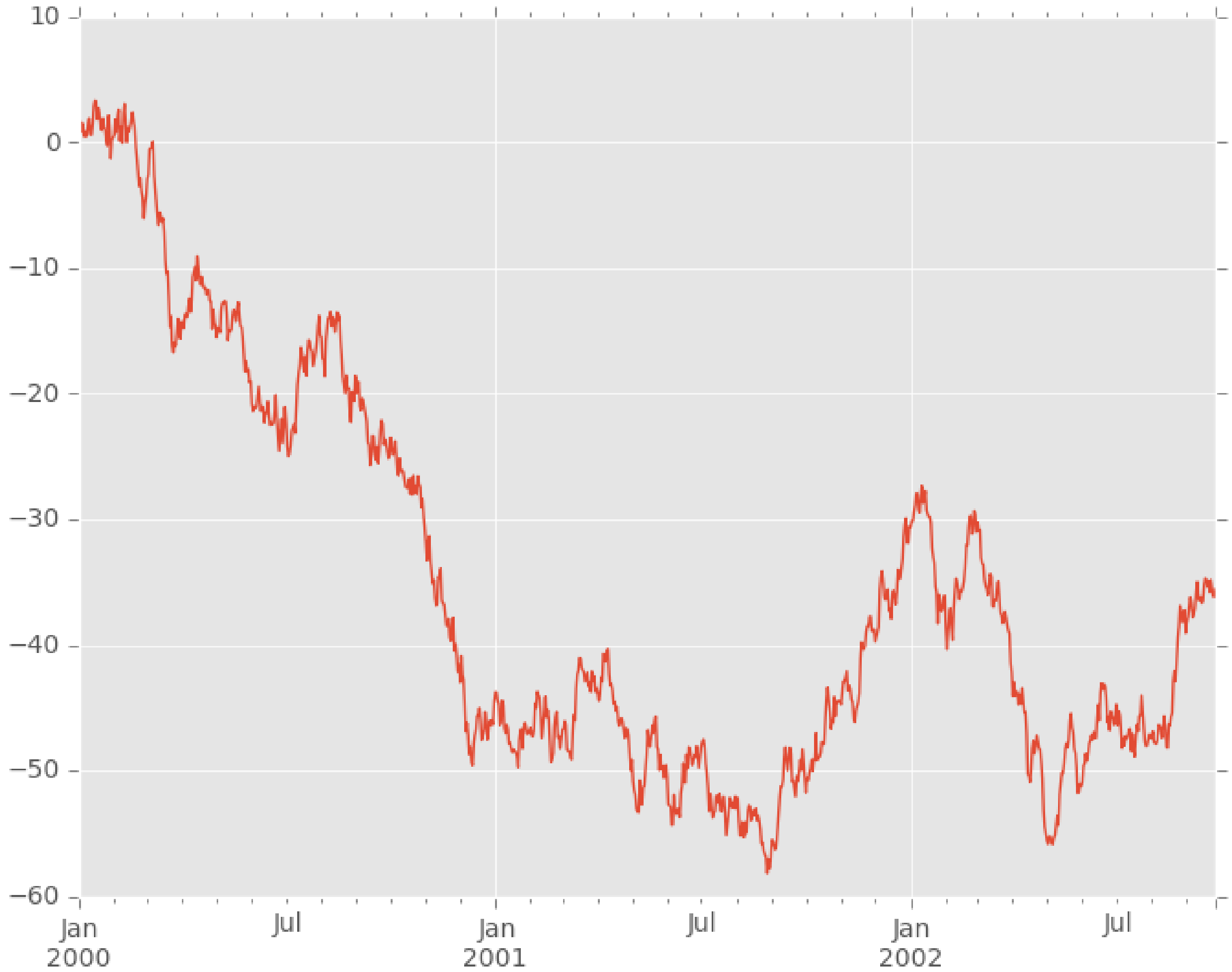
23.5.4 Suppressing Tick Resolution Adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labelling is performed:

```
In [119]: plt.figure()
Out[119]: <matplotlib.figure.Figure at 0xa80a4a0c>

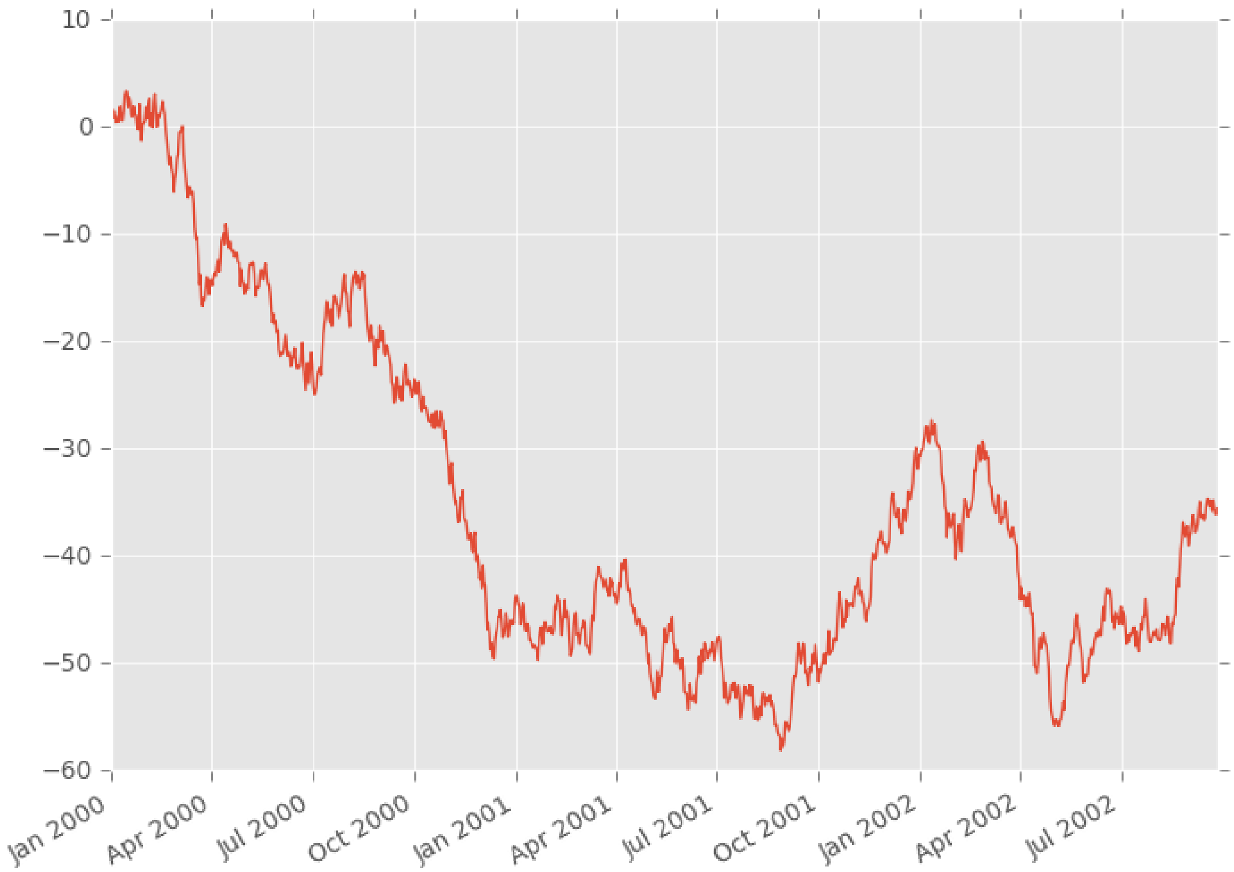
In [120]: df.A.plot()
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0xa809e74c>
```



Using the x_compat parameter, you can suppress this behavior:

```
In [121]: plt.figure()
Out[121]: <matplotlib.figure.Figure at 0xa7fde38c>

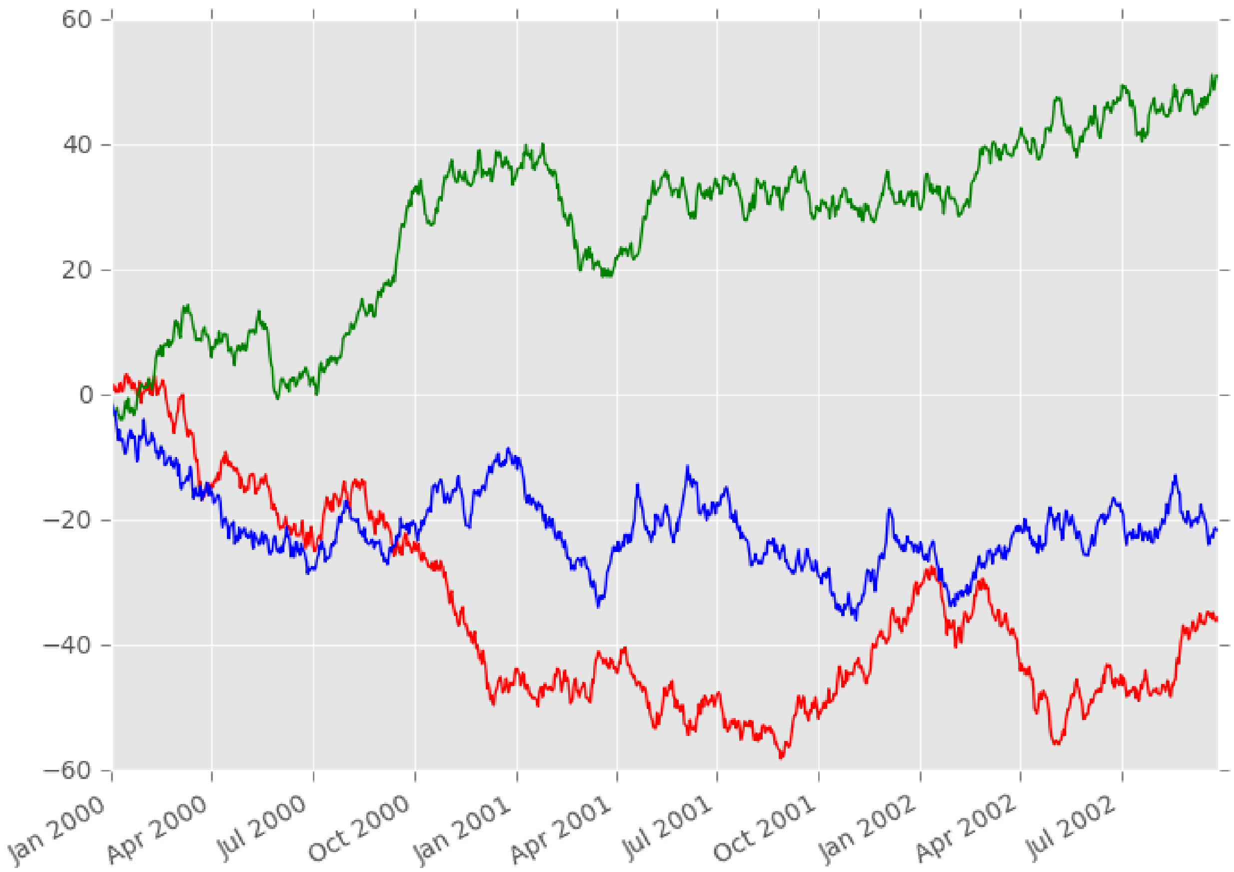
In [122]: df.A.plot(x_compat=True)
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0xa7fe640c>
```



If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plot_params` can be used in a *with statement*:

```
In [123]: plt.figure()
Out[123]: <matplotlib.figure.Figure at 0xa7fc0e2c>

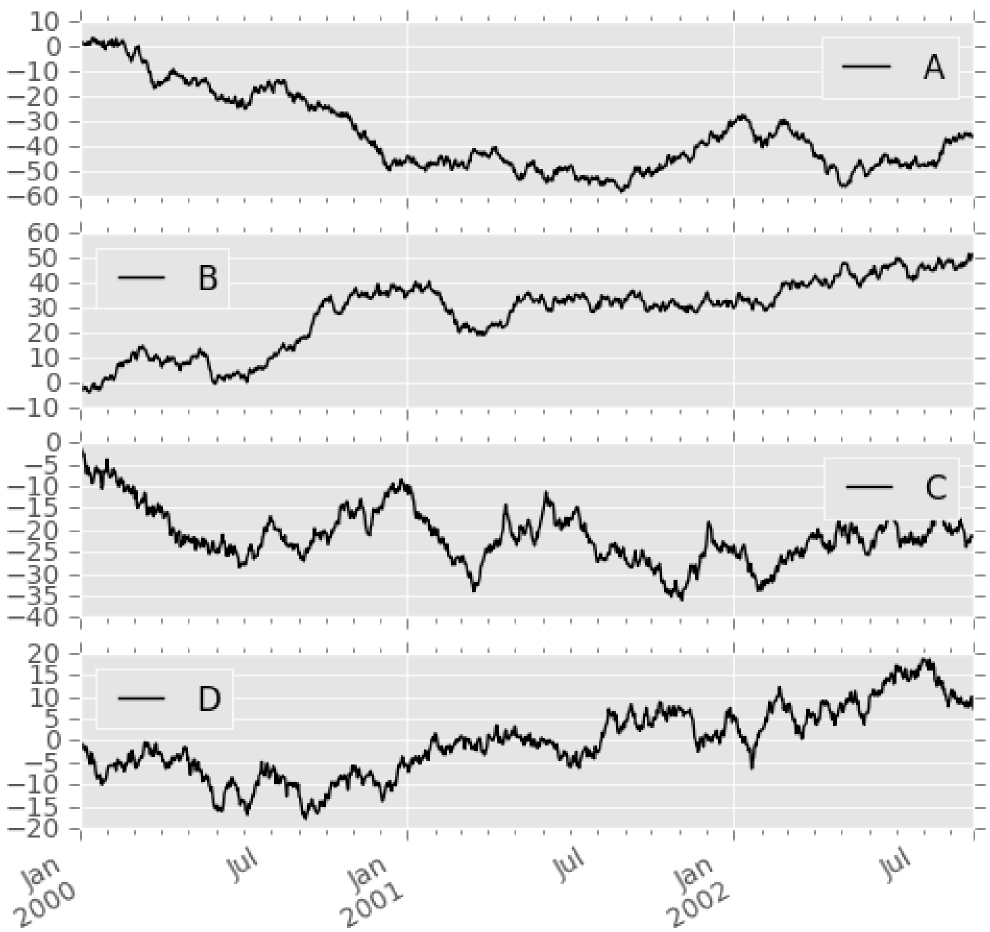
In [124]: with pd.plot_params.use('x_compat', True):
   .....:     df.A.plot(color='r')
   .....:     df.B.plot(color='g')
   .....:     df.C.plot(color='b')
   .....:
```



23.5.5 Subplots

Each Series in a DataFrame can be plotted on a different axis with the `subplots` keyword:

```
In [125]: df.plot(subplots=True, figsize=(6, 6));
```

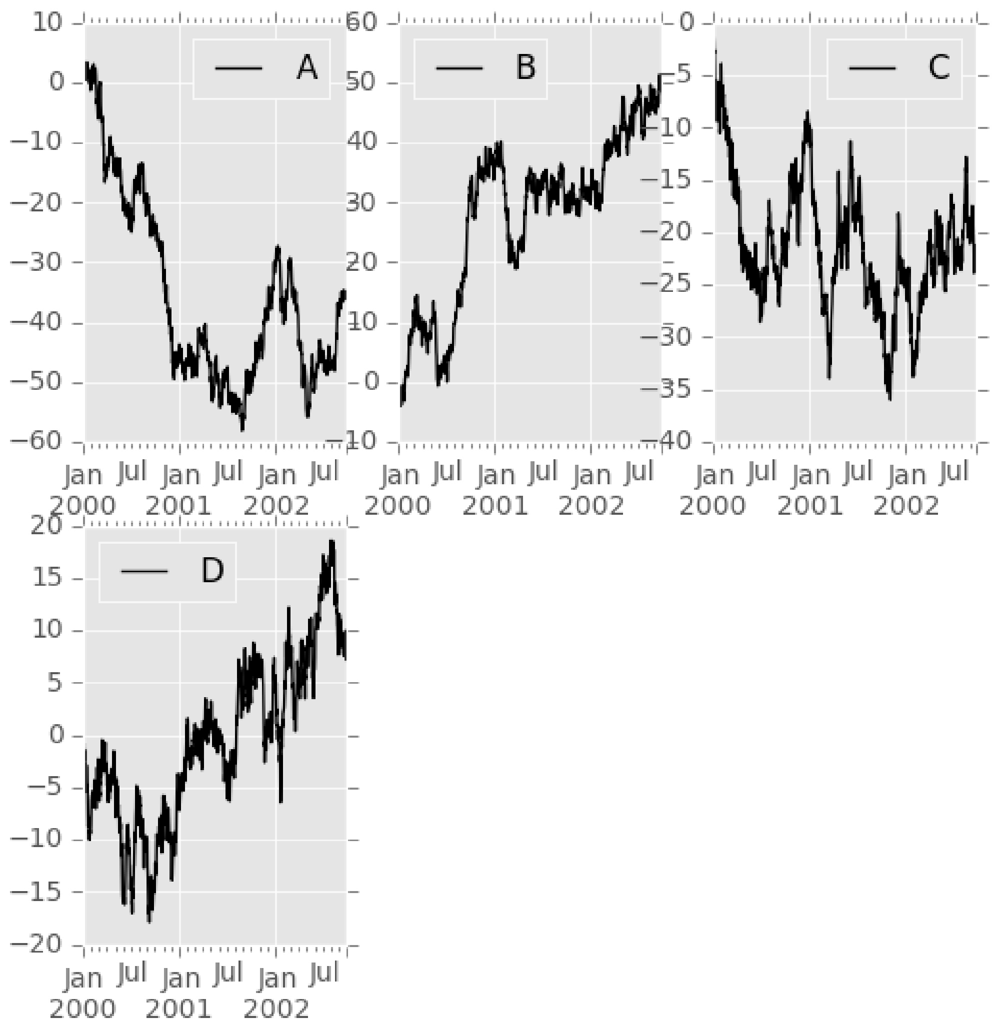


23.5.6 Using Layout and Targetting Multiple Axes

The layout of subplots can be specified by `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If input is invalid, `ValueError` will be raised.

The number of axes which can be contained by rows x columns specified by `layout` must be larger than the number of required subplots. If layout can contain more axes than required, blank axes are not drawn. Similar to a numpy array's `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [126]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```



The above example is identical to using

```
In [127]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

Also, you can pass multiple axes created beforehand as list-like via `ax` keyword. This allows to use more complicated layout. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via `ax` keyword, `layout`, `sharex` and `sharey` keywords don't affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

```
In [128]: fig, axes = plt.subplots(4, 4, figsize=(6, 6));

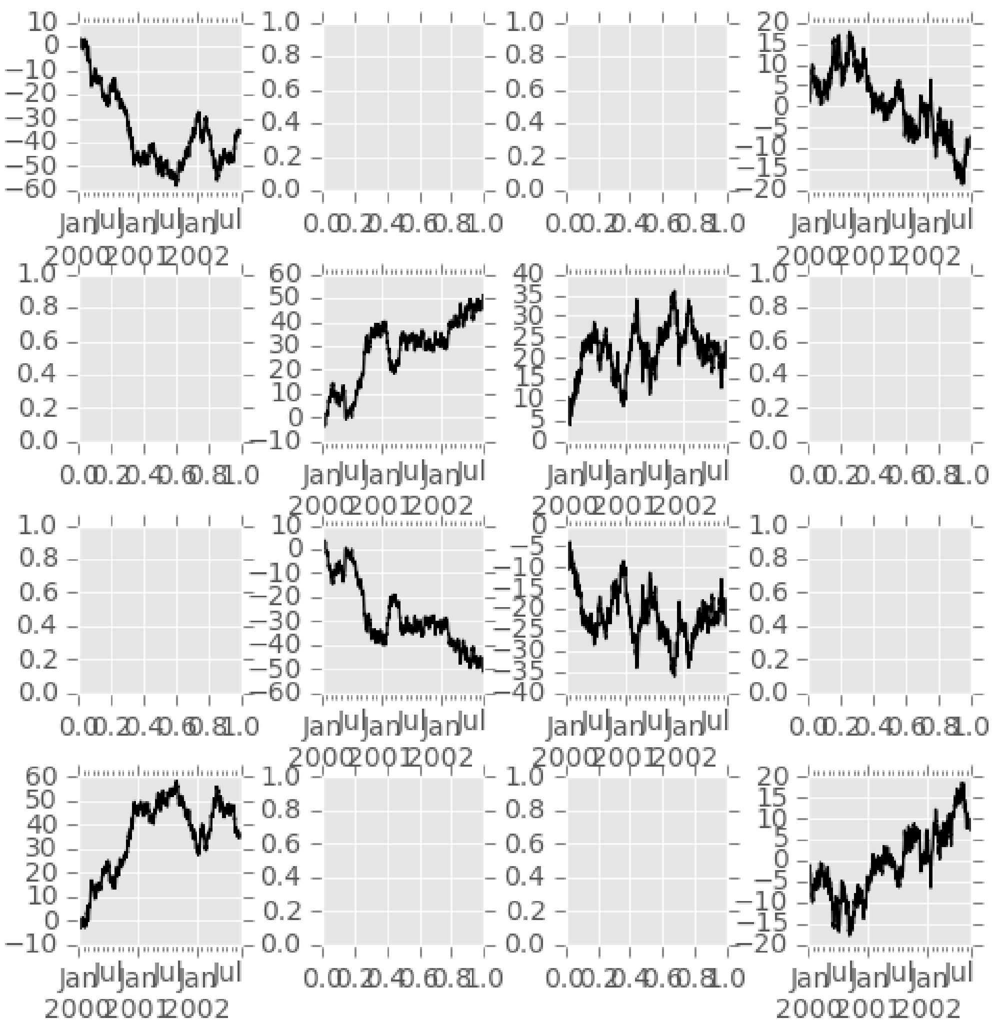
In [129]: plt.subplots_adjust(wspace=0.5, hspace=0.5);

In [130]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]

In [131]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]

In [132]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);

In [133]: (-df).plot(subplots=True, ax=target2, legend=False, sharex=False, sharey=False);
```



Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

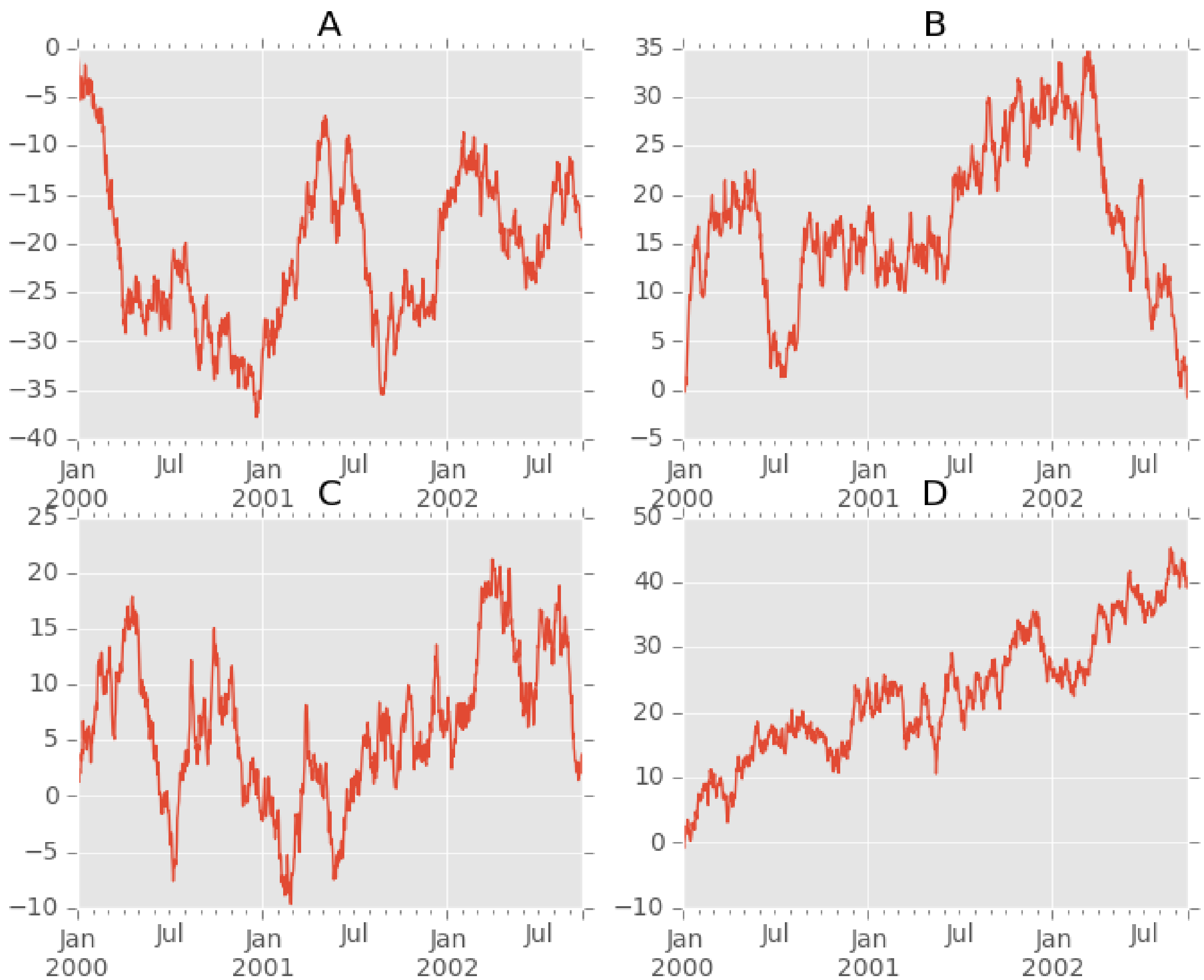
```
In [134]: fig, axes = plt.subplots(nrows=2, ncols=2)

In [135]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A');

In [136]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B');

In [137]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C');

In [138]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D');
```



23.5.7 Plotting With Error Bars

New in version 0.14.

Plotting with error bars is now supported in the `DataFrame.plot()` and `Series.plot()`

Horizontal and vertical errorbars 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 [139]: ix3 = pd.MultiIndex.from_arrays([['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'], ['foo', 'foo',

In [140]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2], 'data2': [6, 5, 7, 5, 4, 5, 6, 5]},

# Group by index labels and take the means and standard deviations for each group
In [141]: gp3 = df3.groupby(level=('letter', 'word'))

In [142]: means = gp3.mean()

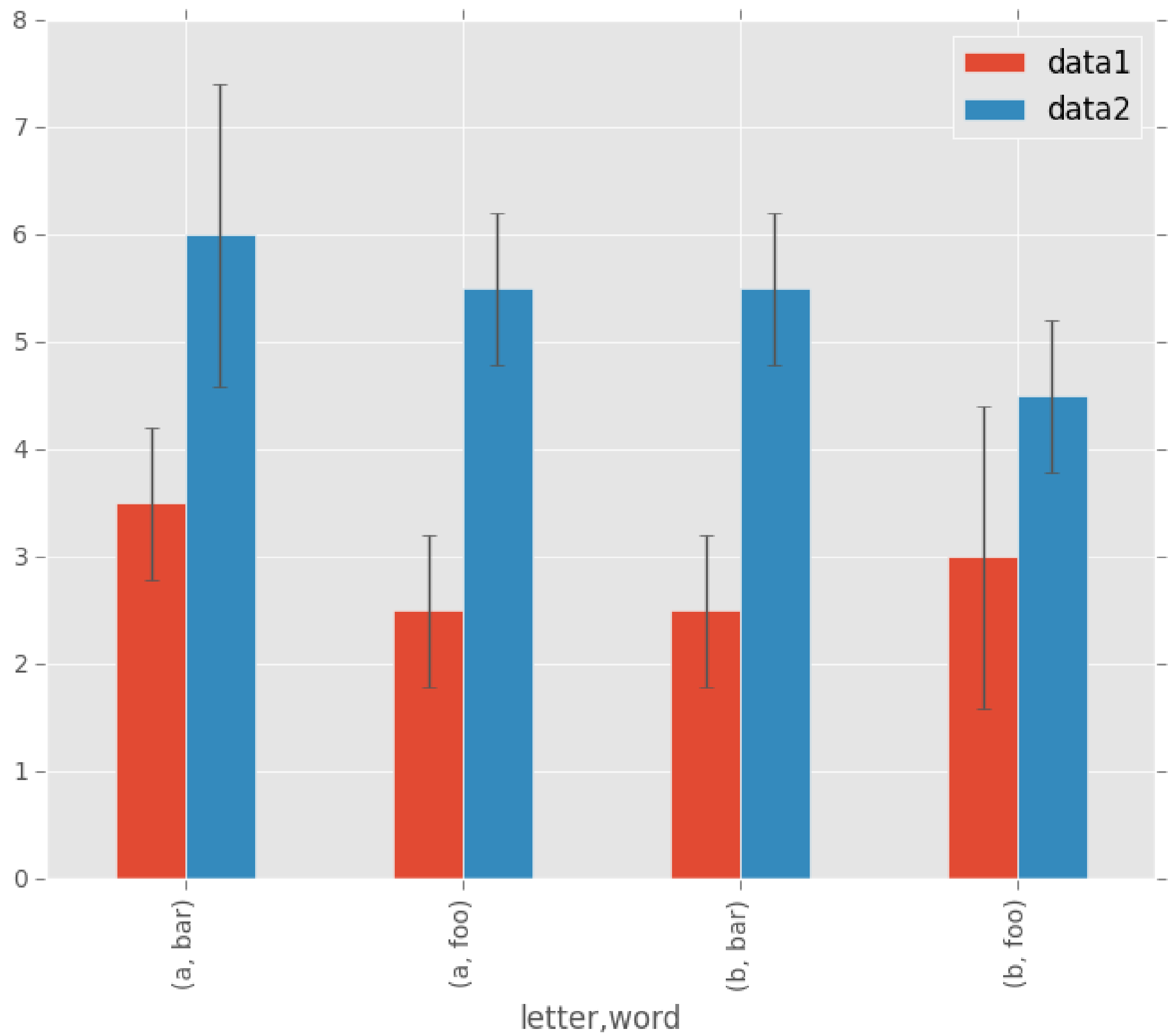
In [143]: errors = gp3.std()

In [144]: means
Out[144]:
             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 [145]: errors
Out[145]:
                data1     data2
letter word
a      bar   0.707107  1.414214
       foo   0.707107  0.707107
b      bar   0.707107  0.707107
       foo   1.414214  0.707107

# Plot
In [146]: fig, ax = plt.subplots()

In [147]: means.plot(yerr=errors, ax=ax, kind='bar')
Out[147]: <matplotlib.axes._subplots.AxesSubplot at 0xa631450c>
```



23.5.8 Plotting Tables

New in version 0.14.

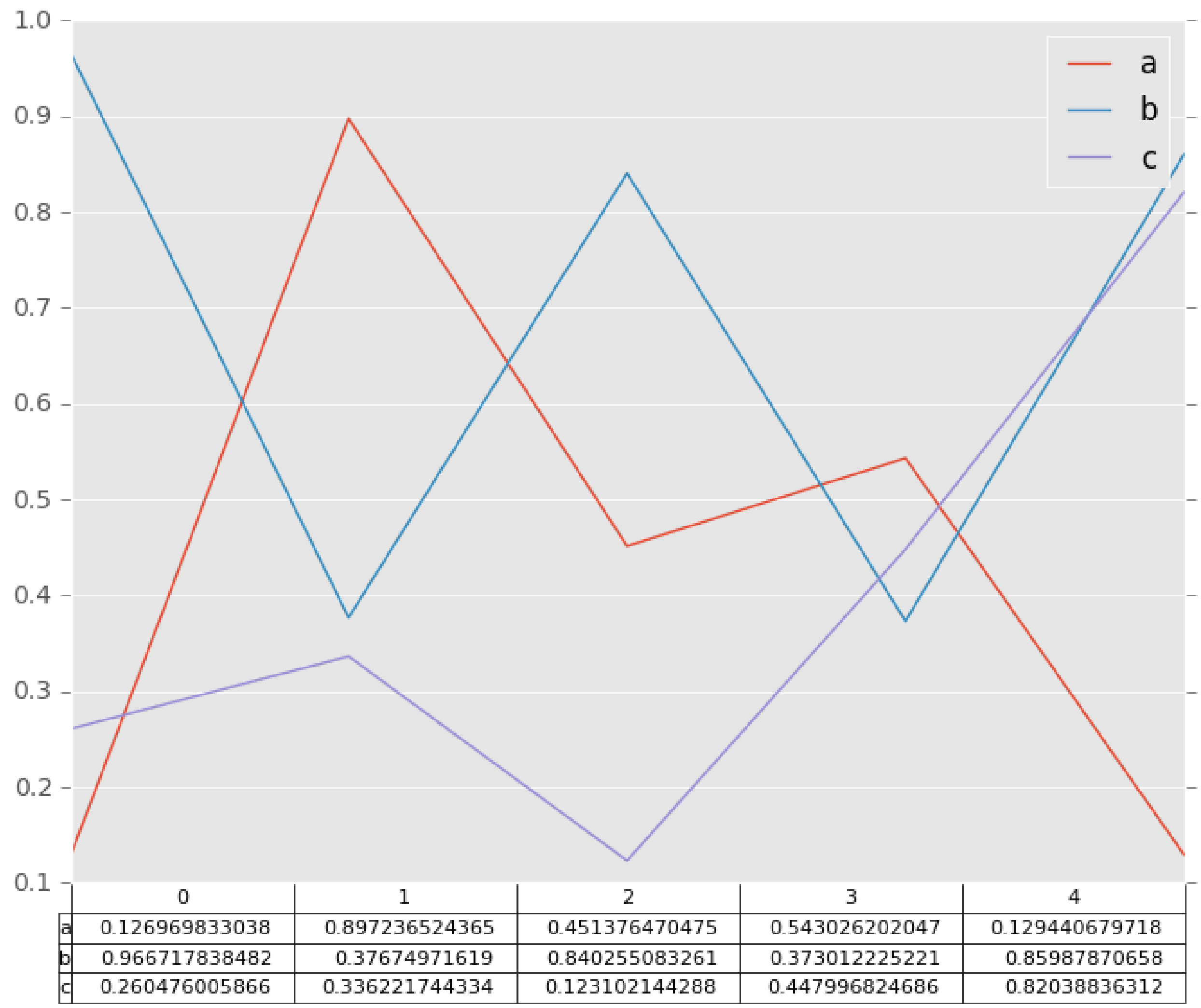
Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

```
In [148]: fig, ax = plt.subplots(1, 1)

In [149]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

In [150]: ax.get_xaxis().set_visible(False)   # Hide Ticks

In [151]: df.plot(table=True, ax=ax)
Out[151]: <matplotlib.axes._subplots.AxesSubplot at 0xa6294eec>
```

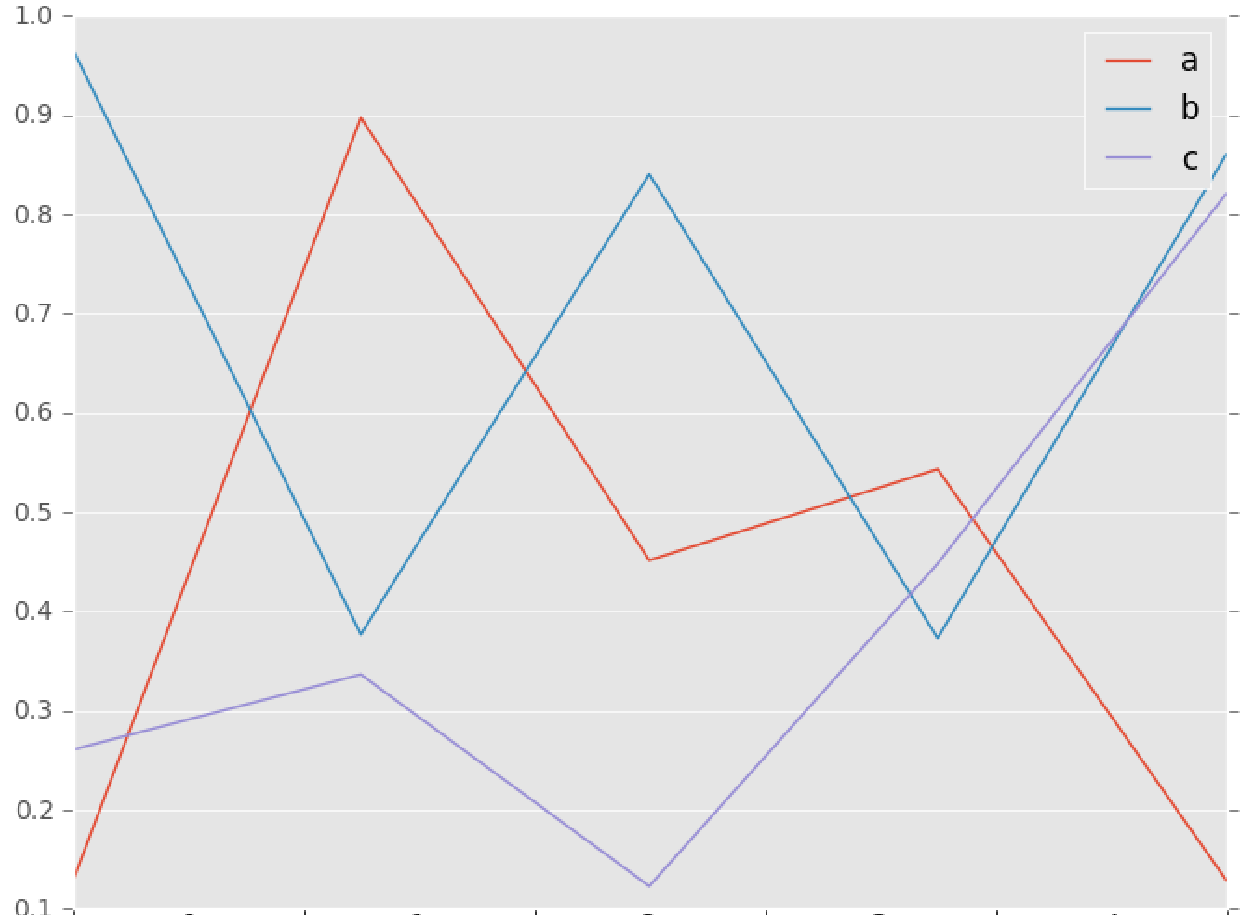


Also, you can pass different `DataFrame` or `Series` for `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as below example.

```
In [152]: fig, ax = plt.subplots(1, 1)

In [153]: ax.get_xaxis().set_visible(False)    # Hide Ticks

In [154]: df.plot(table=np.round(df.T, 2), ax=ax)
Out[154]: <matplotlib.axes._subplots.AxesSubplot at 0xa61a244c>
```



	0	1	2	3	4
a	0.13	0.9	0.45	0.54	0.13
b	0.97	0.38	0.84	0.37	0.86
c	0.26	0.34	0.12	0.45	0.82

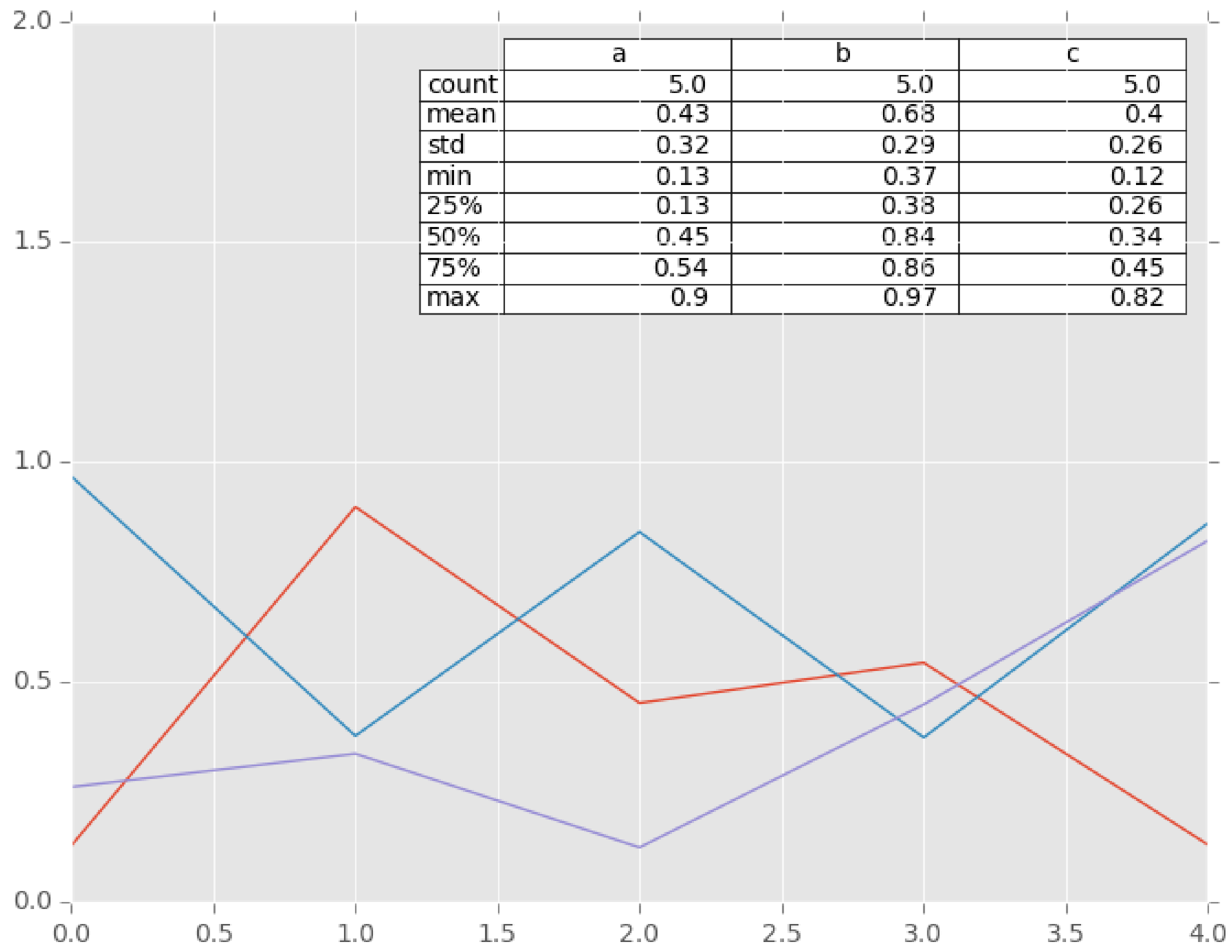
Finally, there is a helper function `pandas.tools.plotting.table` to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`. This function can accept keywords which matplotlib table has.

```
In [155]: from pandas.tools.plotting import table

In [156]: fig, ax = plt.subplots(1, 1)

In [157]: table(ax, np.round(df.describe(), 2),
   .....:       loc='upper right', colWidths=[0.2, 0.2, 0.2])
   .....:
Out[157]: <matplotlib.table.Table at 0xa61db5ac>

In [158]: df.plot(ax=ax, ylim=(0, 2), legend=None)
Out[158]: <matplotlib.axes._subplots.AxesSubplot at 0xa615c3ec>
```



Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the matplotlib table documenation for more.

23.5.9 Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, DataFrame plotting supports the use of the `colormap=` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available here.

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the DataFrame. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

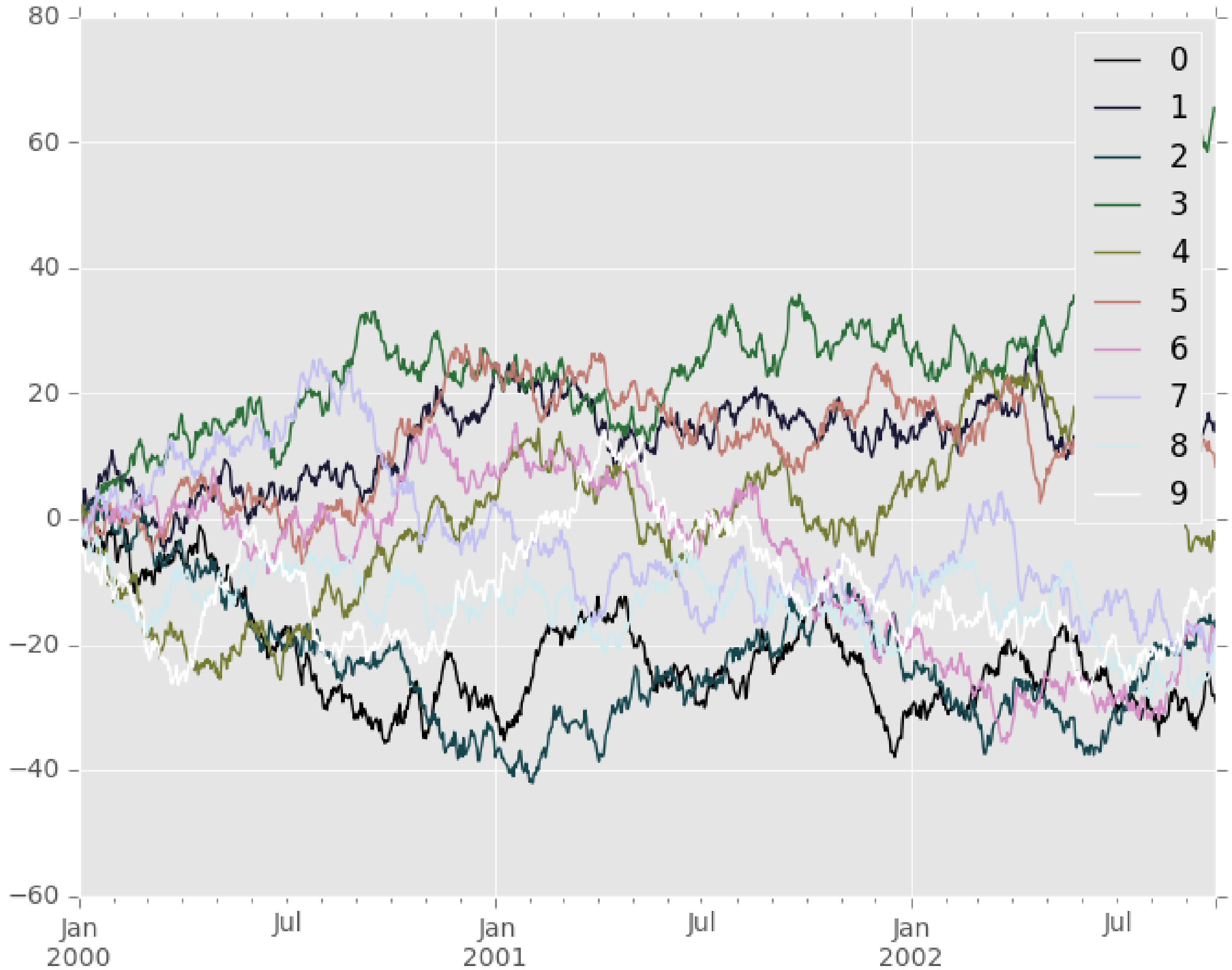
To use the cubehelix colormap, we can simply pass `'cubehelix'` to `colormap=`

```
In [159]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)

In [160]: df = df.cumsum()

In [161]: plt.figure()
Out[161]: <matplotlib.figure.Figure at 0xa5f062cc>
```

```
In [162]: df.plot(colormap='cubehelix')
Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0xa5f0b0ac>
```

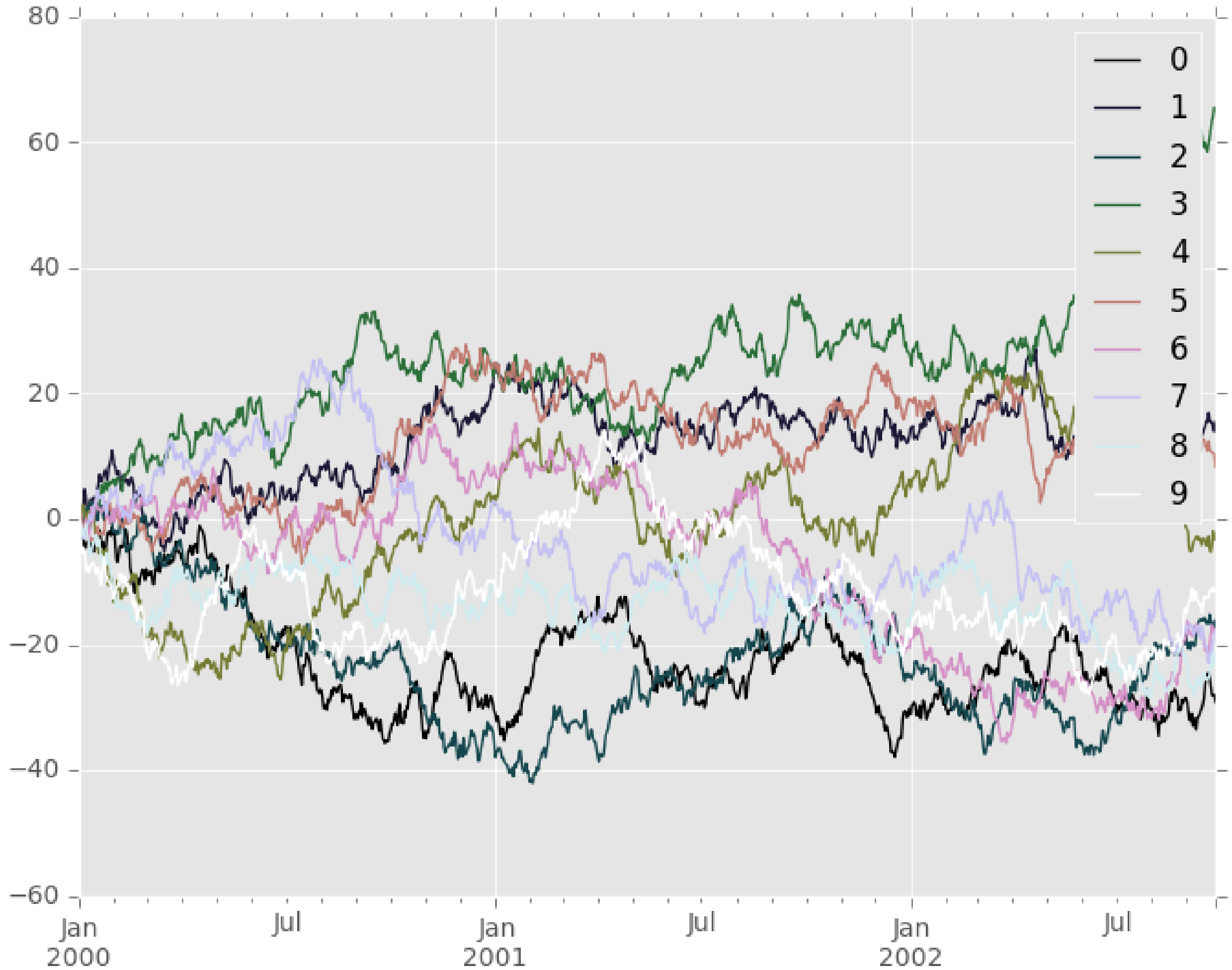


or we can pass the colormap itself

```
In [163]: from matplotlib import cm

In [164]: plt.figure()
Out[164]: <matplotlib.figure.Figure at 0xa591ee2c>

In [165]: df.plot(colormap=cm.cubehelix)
Out[165]: <matplotlib.axes._subplots.AxesSubplot at 0xa5e152ec>
```



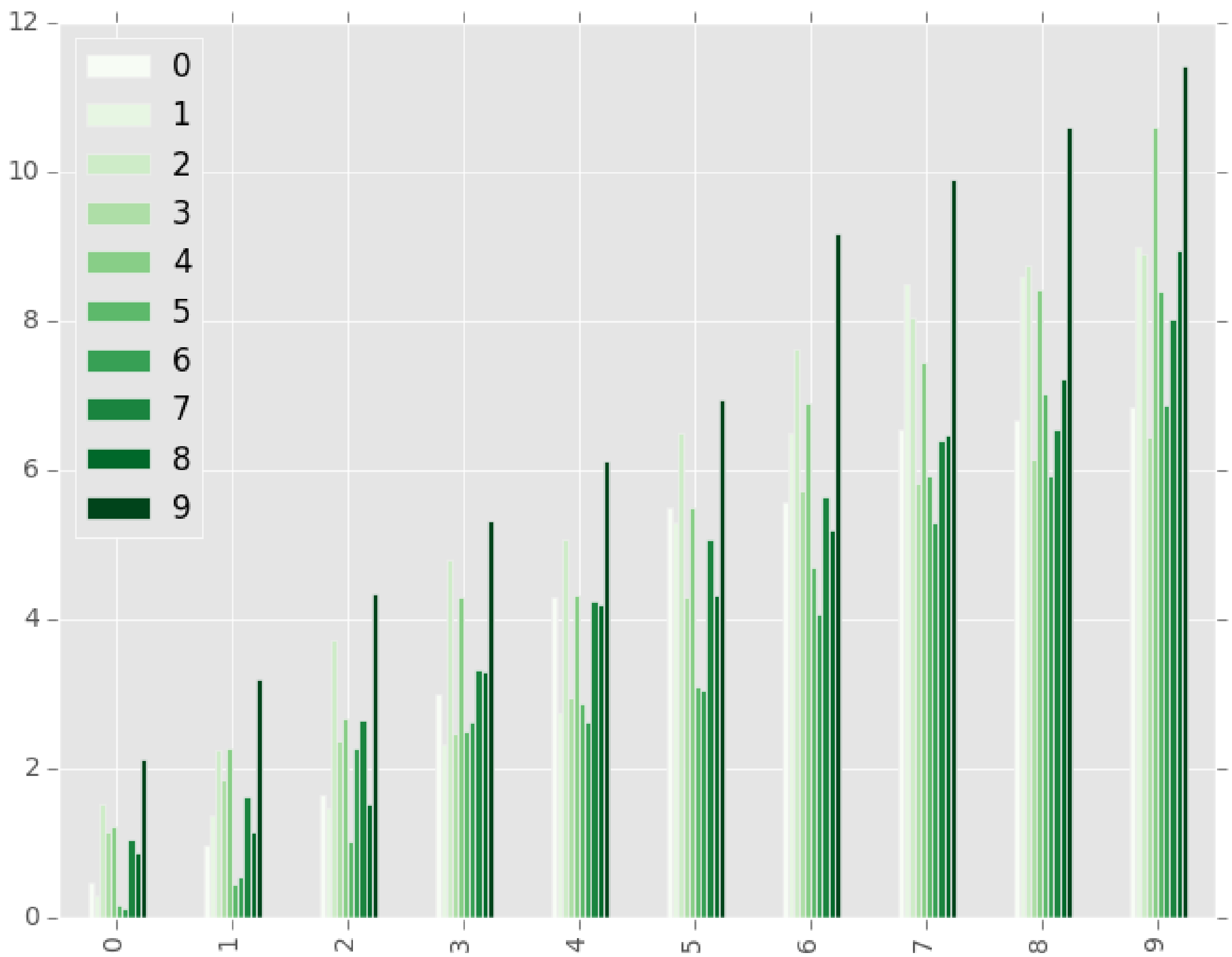
Colormaps can also be used other plot types, like bar charts:

```
In [166]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

In [167]: dd = dd.cumsum()

In [168]: plt.figure()
Out[168]: <matplotlib.figure.Figure at 0xa584e1ec>

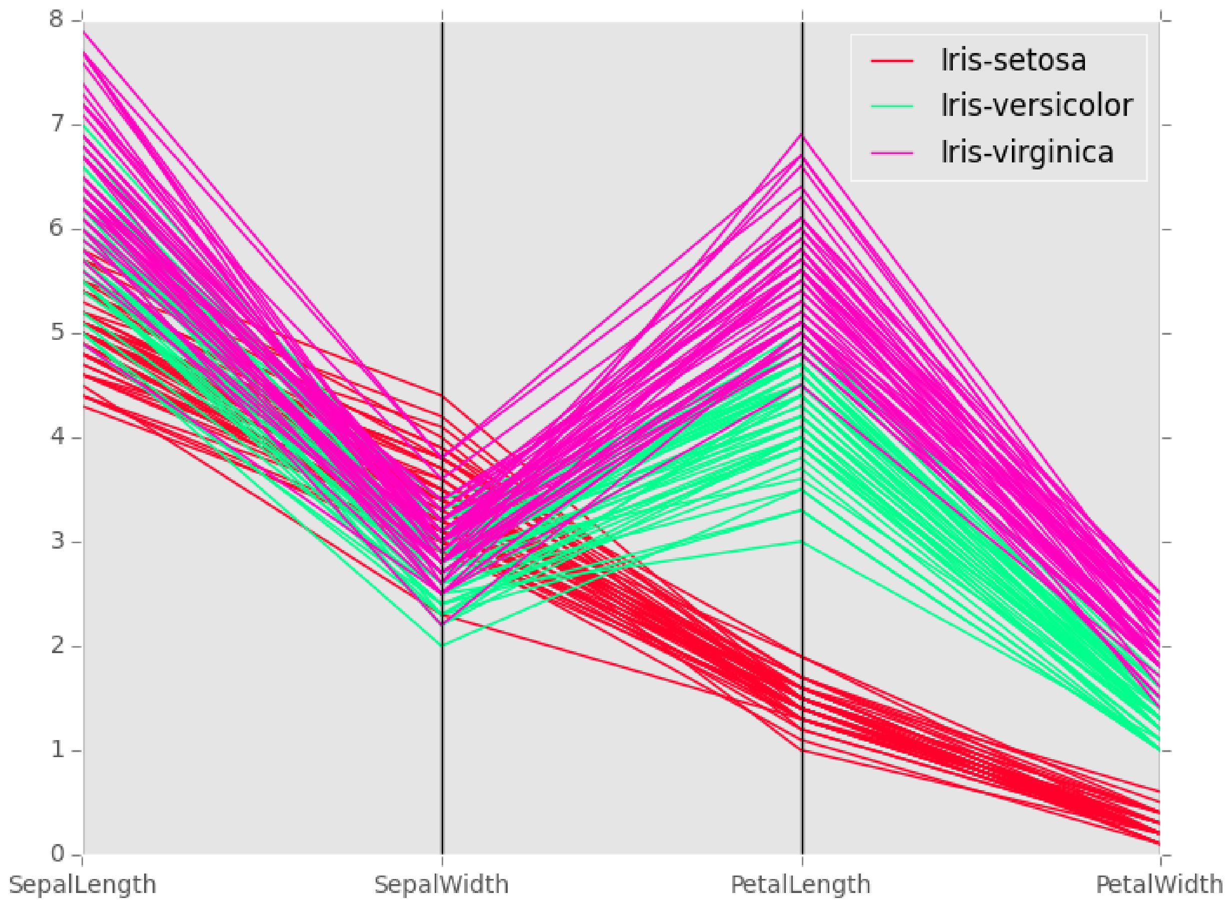
In [169]: dd.plot(kind='bar', colormap='Greens')
Out[169]: <matplotlib.axes._subplots.AxesSubplot at 0xa58355cc>
```



Parallel coordinates charts:

```
In [170]: plt.figure()
Out[170]: <matplotlib.figure.Figure at 0xa55c730c>

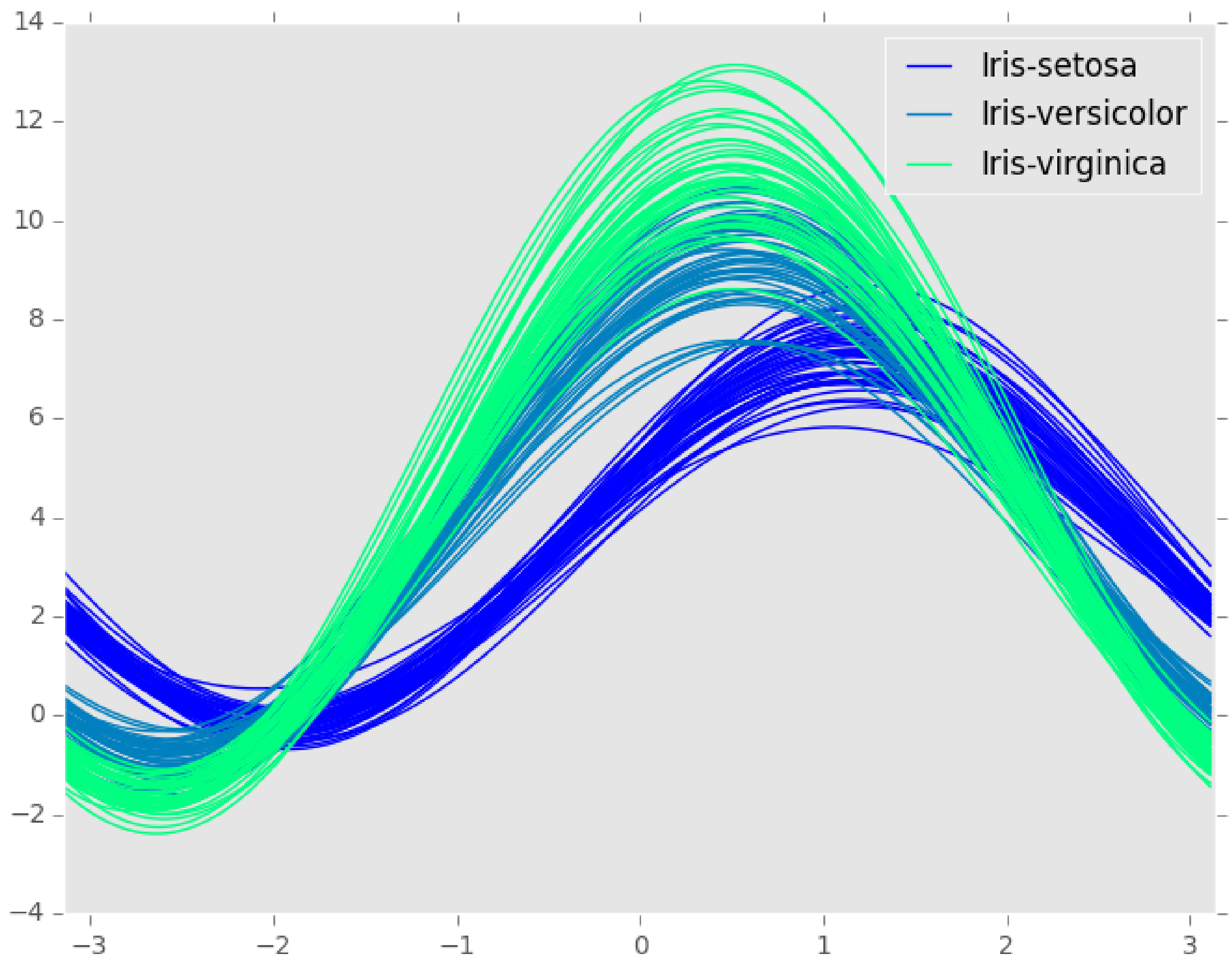
In [171]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
Out[171]: <matplotlib.axes._subplots.AxesSubplot at 0xa55b79cc>
```



Andrews curves charts:

```
In [172]: plt.figure()
Out[172]: <matplotlib.figure.Figure at 0xa4fb712c>

In [173]: andrews_curves(data, 'Name', colormap='winter')
Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0xa4fb7bec>
```



23.6 Plotting directly with matplotlib

In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. Series and DataFrame objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

Note: The speed up for large data sets only applies to pandas 0.14.0 and later.

```
In [174]: price = pd.Series(np.random.randn(150).cumsum(),
   .....:                   index=pd.date_range('2000-1-1', periods=150, freq='B'))
   .....:

In [175]: ma = pd.rolling_mean(price, 20)

In [176]: mstd = pd.rolling_std(price, 20)

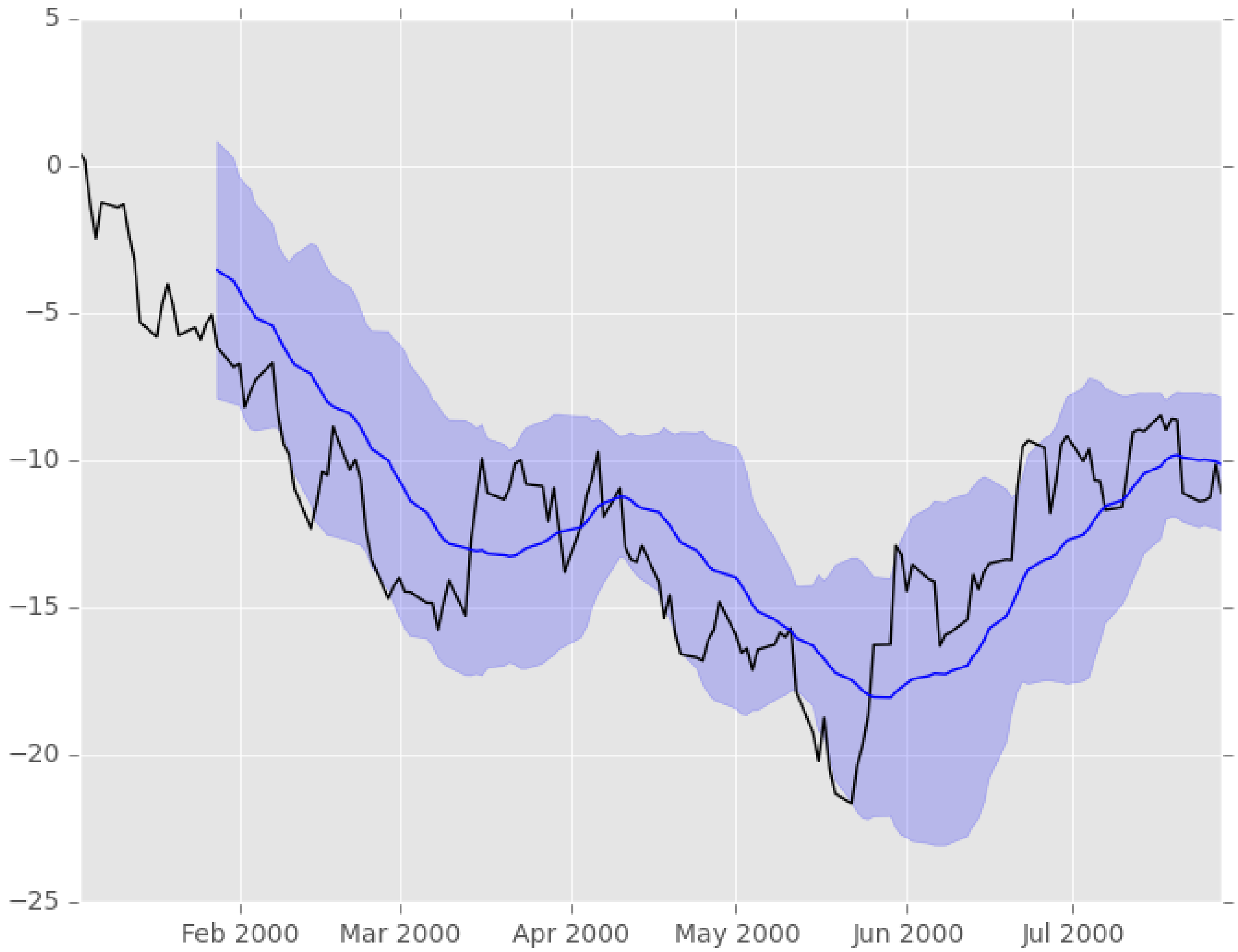
In [177]: plt.figure()
```

```
Out[177]: <matplotlib.figure.Figure at 0xa4cc4eac>

In [178]: plt.plot(price.index, price, 'k')
Out[178]: [<matplotlib.lines.Line2D at 0xa490d18c>]

In [179]: plt.plot(ma.index, ma, 'b')
Out[179]: [<matplotlib.lines.Line2D at 0xa4ac502c>]

In [180]: plt.fill_between(mstd.index, ma-2*mstd, ma+2*mstd, color='b', alpha=0.2)
Out[180]: <matplotlib.collections.PolyCollection at 0xa4ac580c>
```



23.7 Trellis plotting interface

> **Warning:** The `rplot` trellis plotting interface is **deprecated and will be removed in a future version**. We refer to external packages like seaborn for similar but more refined functionality.
> The docs below include some example on how to convert your existing code to `seaborn`.

Note: The tips data set can be downloaded here. Once you download it execute

```
tips_data = pd.read_csv('tips.csv')
```

from the directory where you downloaded the file.

We import the rplot API:

```
In [181]: import pandas.tools.rplot as rplot
```

23.7.1 Examples

RPlot was an API for producing Trellis plots. These plots allow you toµ arrange data in a rectangular grid by values of certain attributes. In the example below, data from the tips data set is arranged by the attributes 'sex' and 'smoker'. Since both of those attributes can take on one of two values, the resulting grid has two columns and two rows. A histogram is displayed for each cell of the grid.

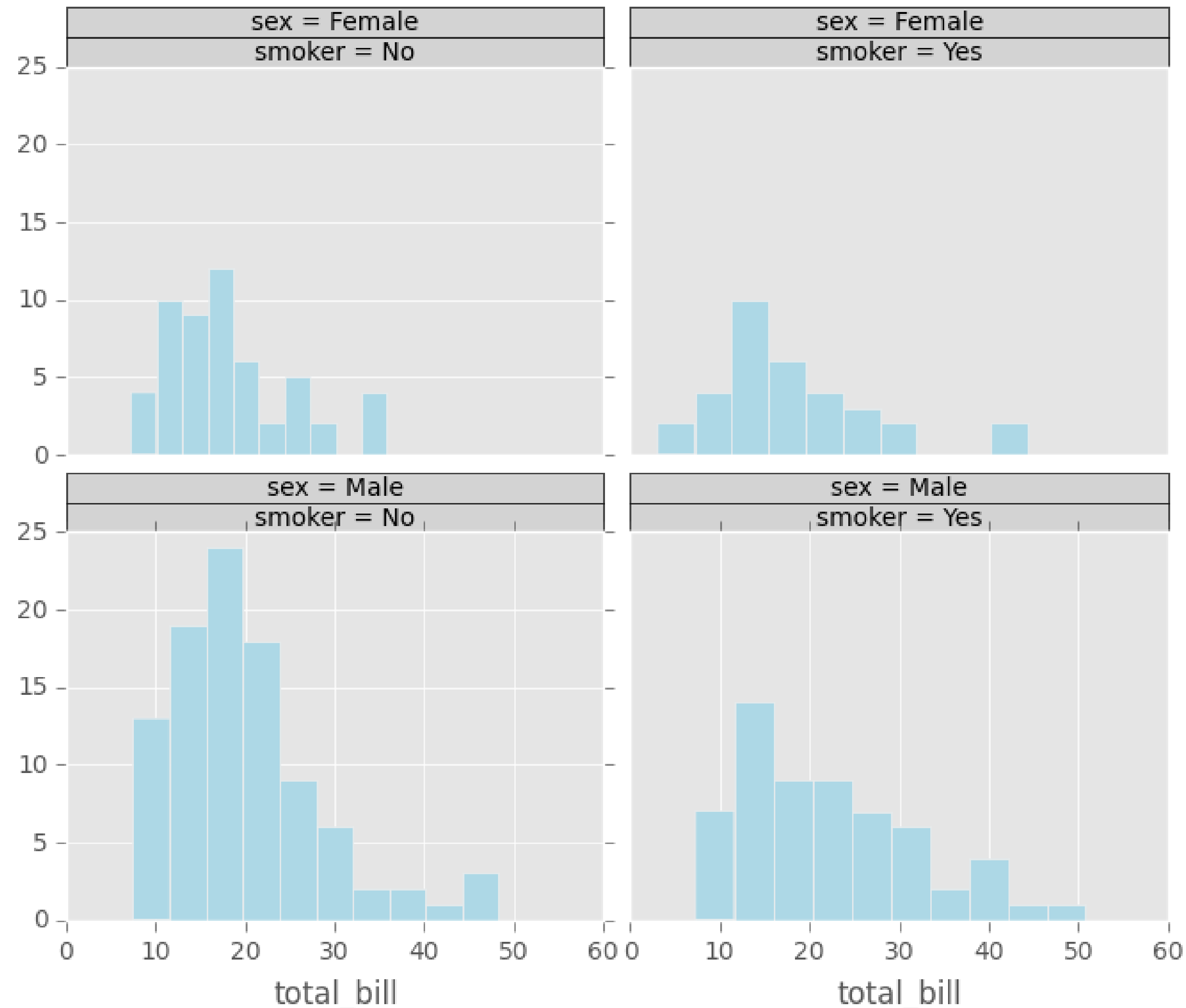
```
In [182]: plt.figure()
Out[182]: <matplotlib.figure.Figure at 0xa474f76c>

In [183]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [184]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

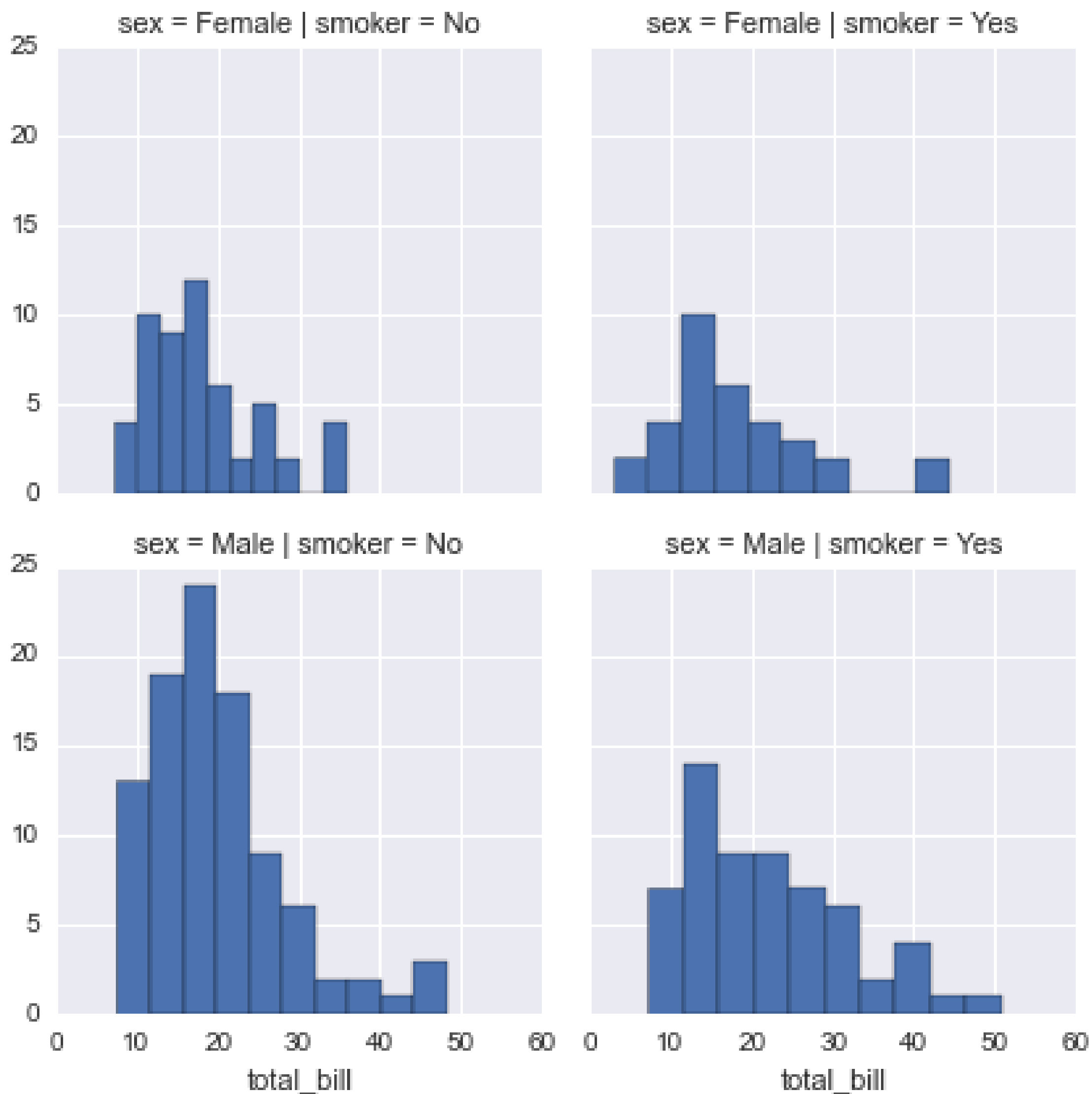
In [185]: plot.add(rplot.GeomHistogram())

In [186]: plot.render(plt.gcf())
Out[186]: <matplotlib.figure.Figure at 0xa474f76c>
```



A similar plot can be made with `seaborn` using the `FacetGrid` object, resulting in the following image:

```
import seaborn as sns
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.hist, "total_bill")
```



Example below is the same as previous except the plot is set to kernel density estimation. A `seaborn` example is included beneath.

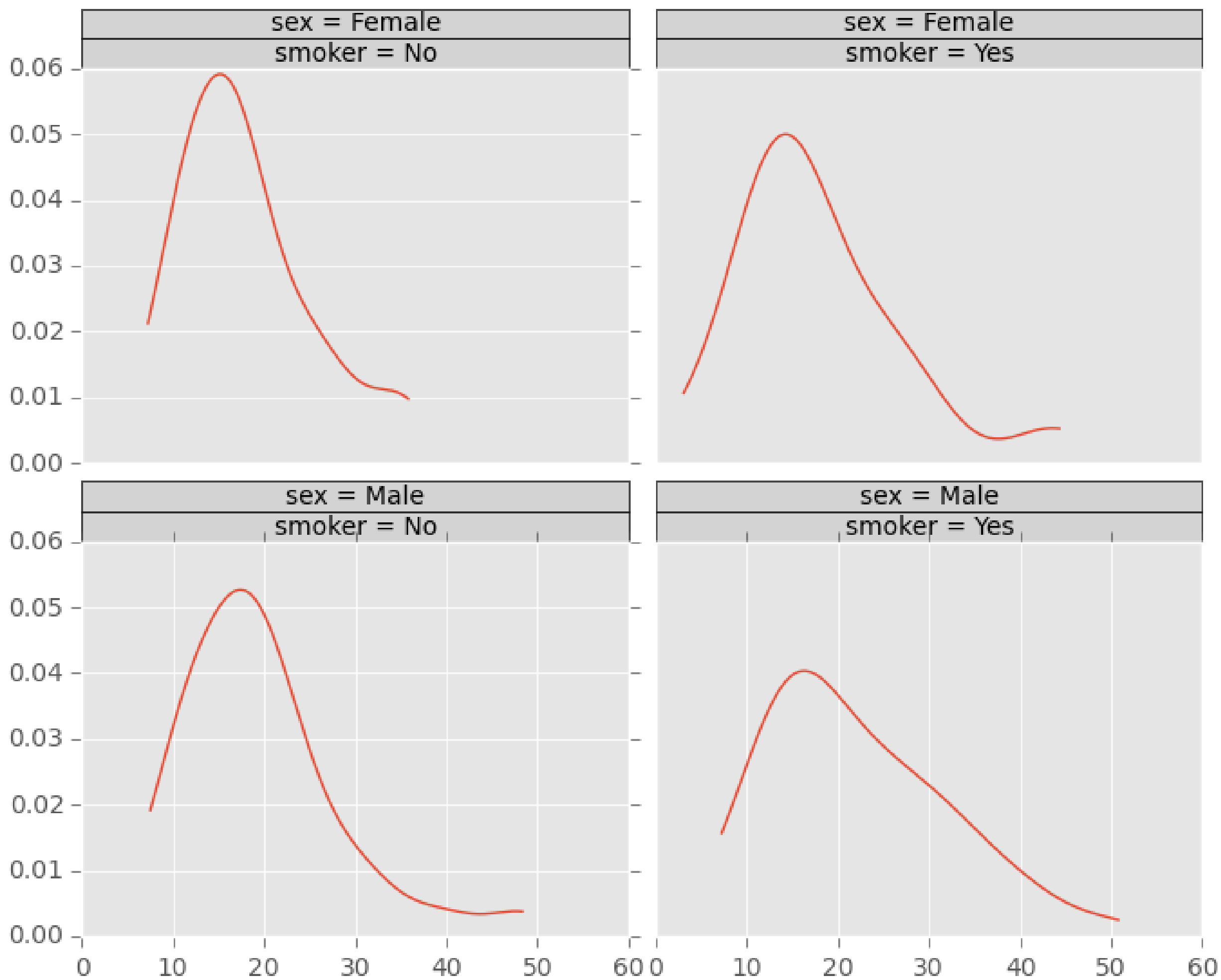
```
In [187]: plt.figure()
Out[187]: <matplotlib.figure.Figure at 0xa475b6cc>

In [188]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

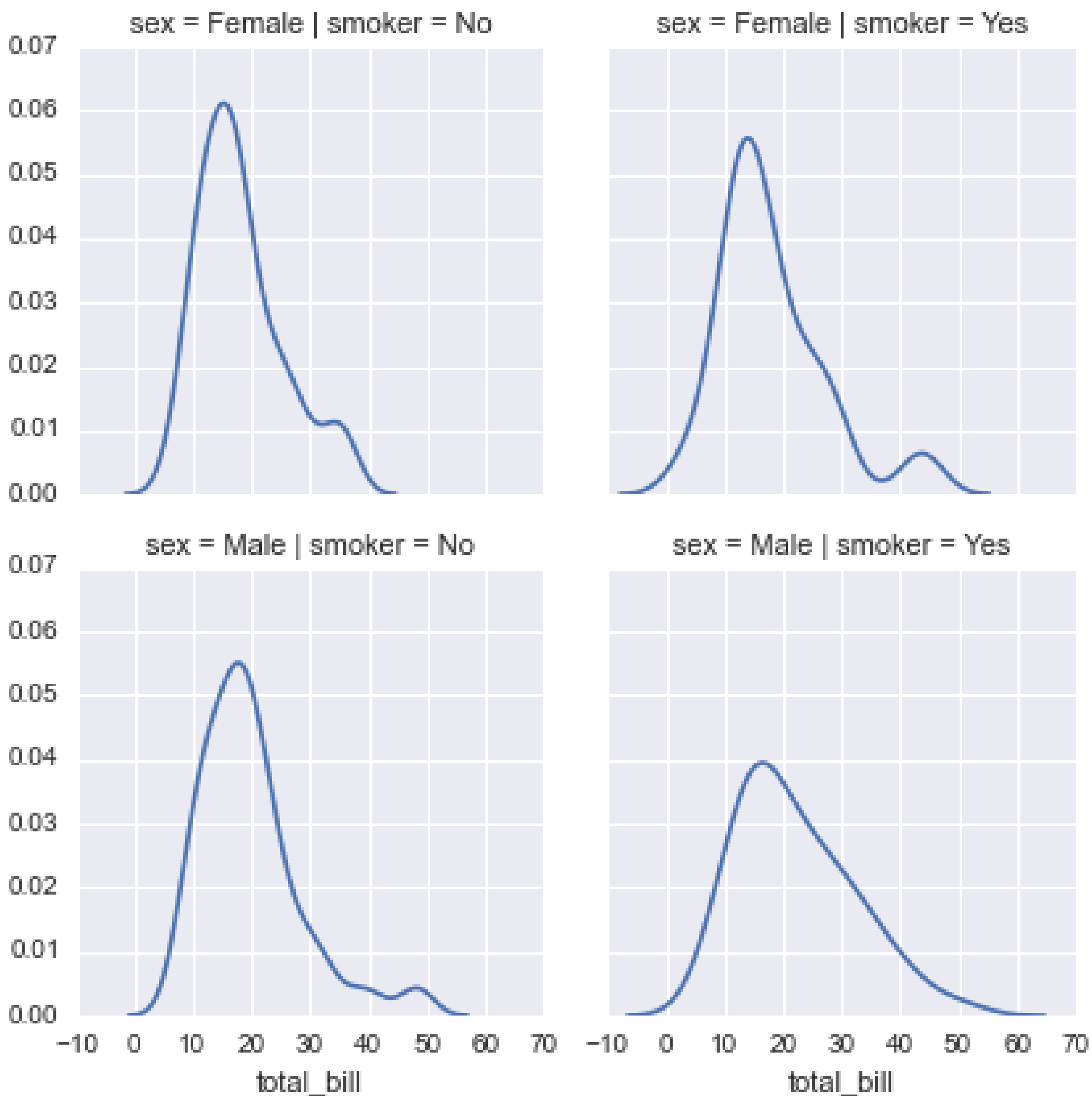
In [189]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [190]: plot.add(rplot.GeomDensity())

In [191]: plot.render(plt.gcf())
Out[191]: <matplotlib.figure.Figure at 0xa475b6cc>
```




```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(sns.kdeplot, "total_bill")
```



The plot below shows that it is possible to have two or more plots for the same data displayed on the same Trellis grid cell.

```
In [192]: plt.figure()
Out[192]: <matplotlib.figure.Figure at 0xa45f6cac>

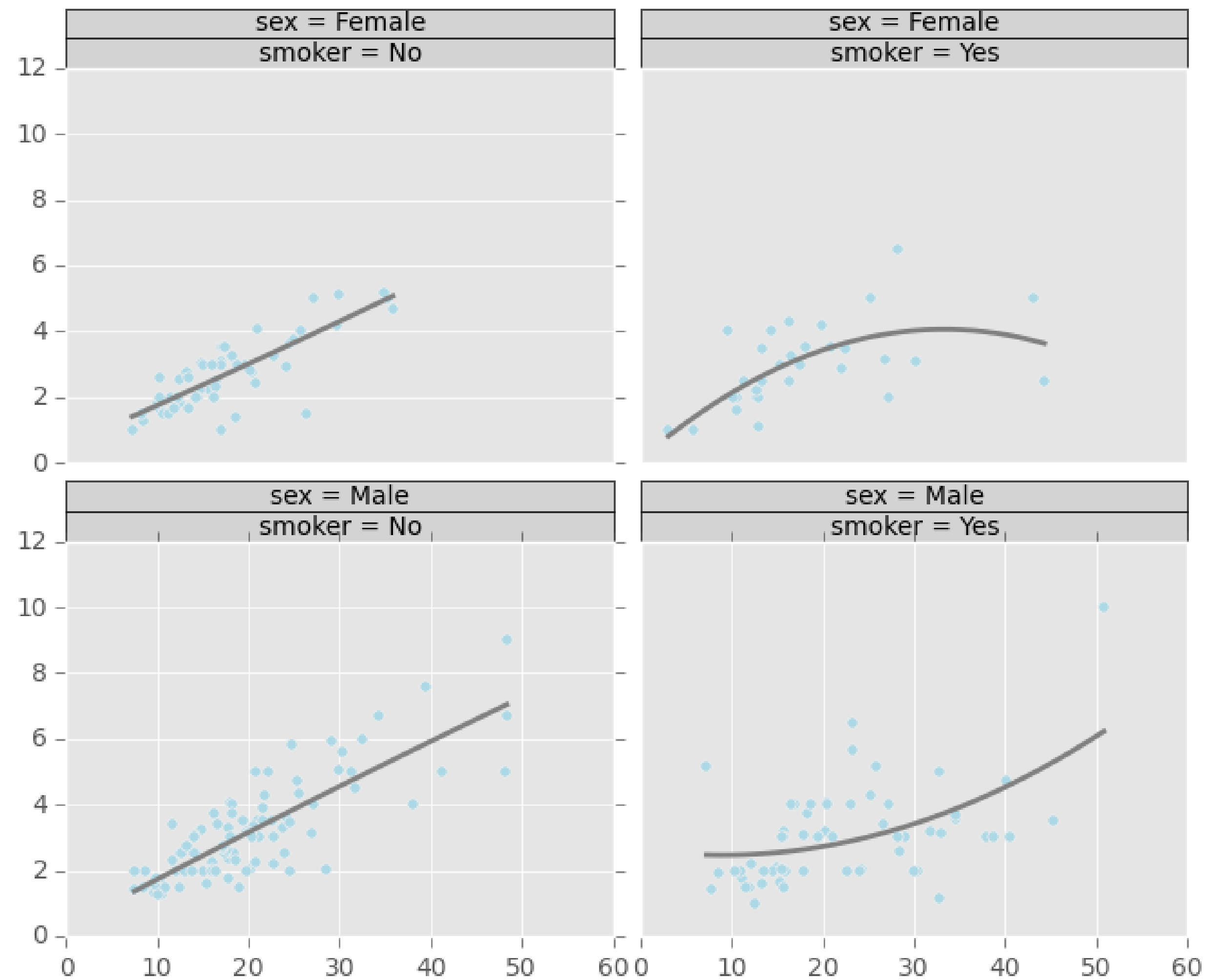
In [193]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [194]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [195]: plot.add(rplot.GeomScatter())

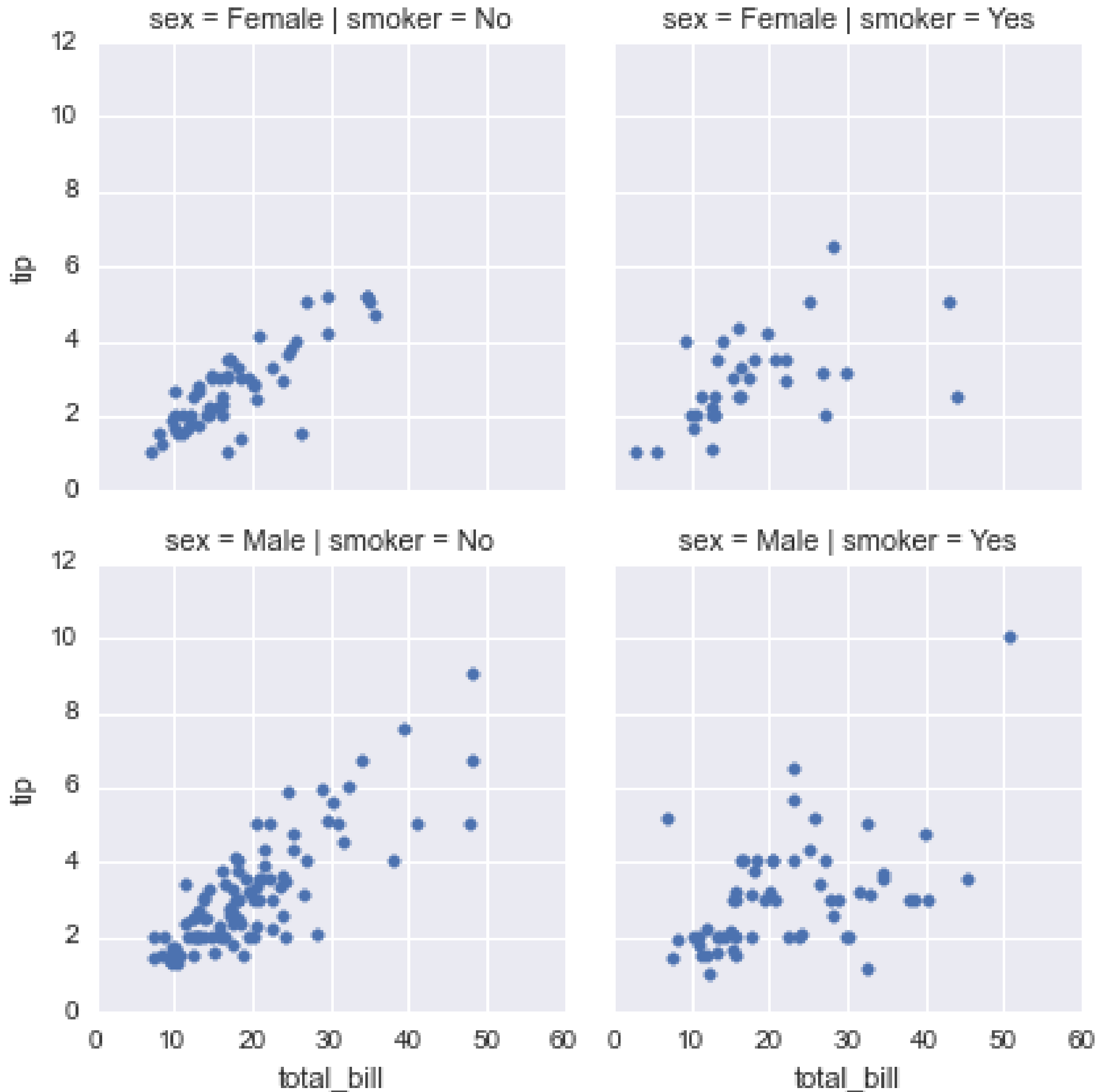
In [196]: plot.add(rplot.GeomPolyFit(degree=2))

In [197]: plot.render(plt.gcf())
Out[197]: <matplotlib.figure.Figure at 0xa45f6cac>
```



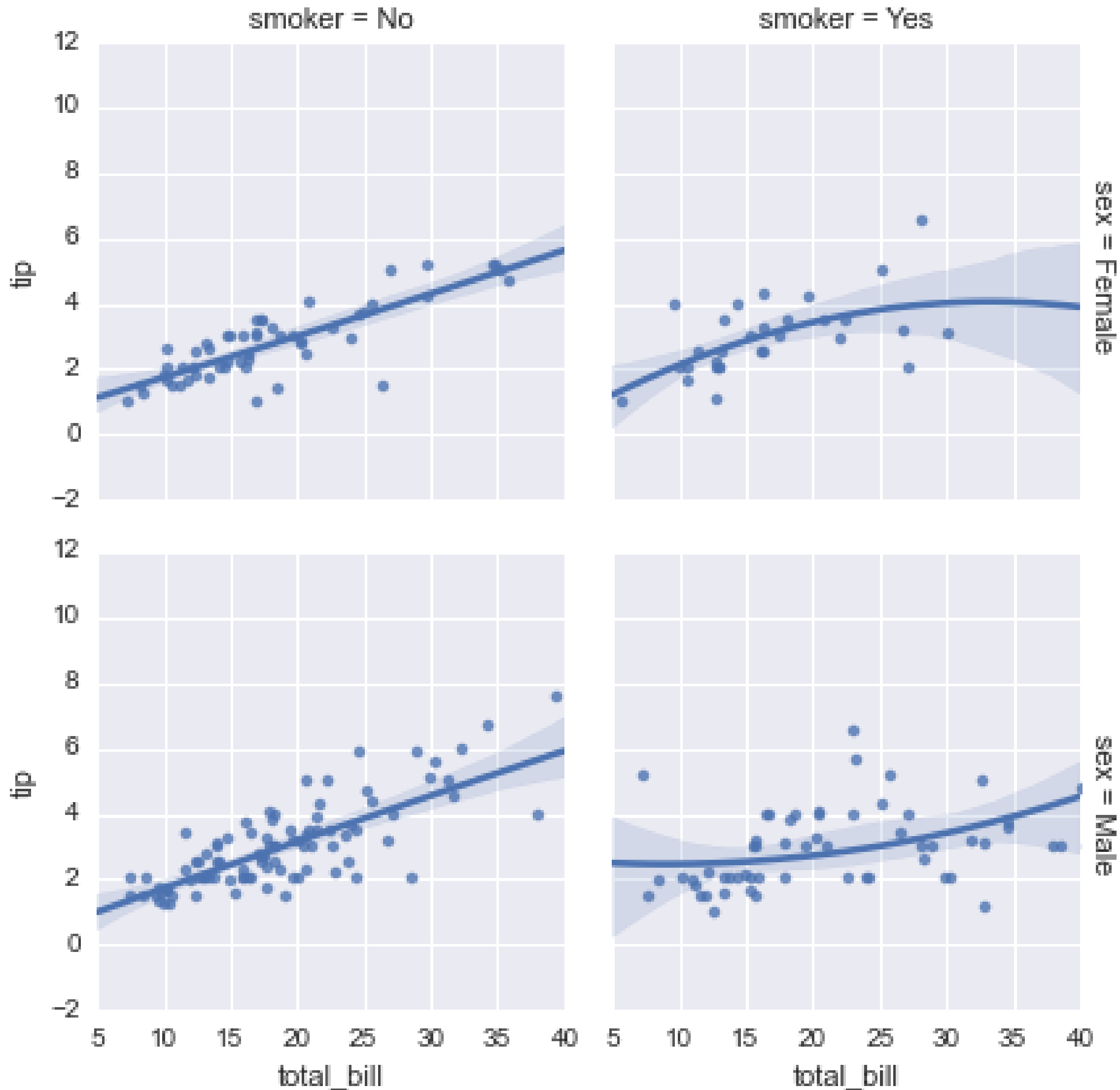
A seaborn equivalent for a simple scatter plot:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
```



and with a regression line, using the dedicated `seaborn regplot` function:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", margin_titles=True)
g.map(sns.regplot, "total_bill", "tip", order=2)
```



Below is a similar plot but with 2D kernel density estimation plot superimposed, followed by a `seaborn` equivalent:

```
In [198]: plt.figure()
Out[198]: <matplotlib.figure.Figure at 0xa4273b2c>

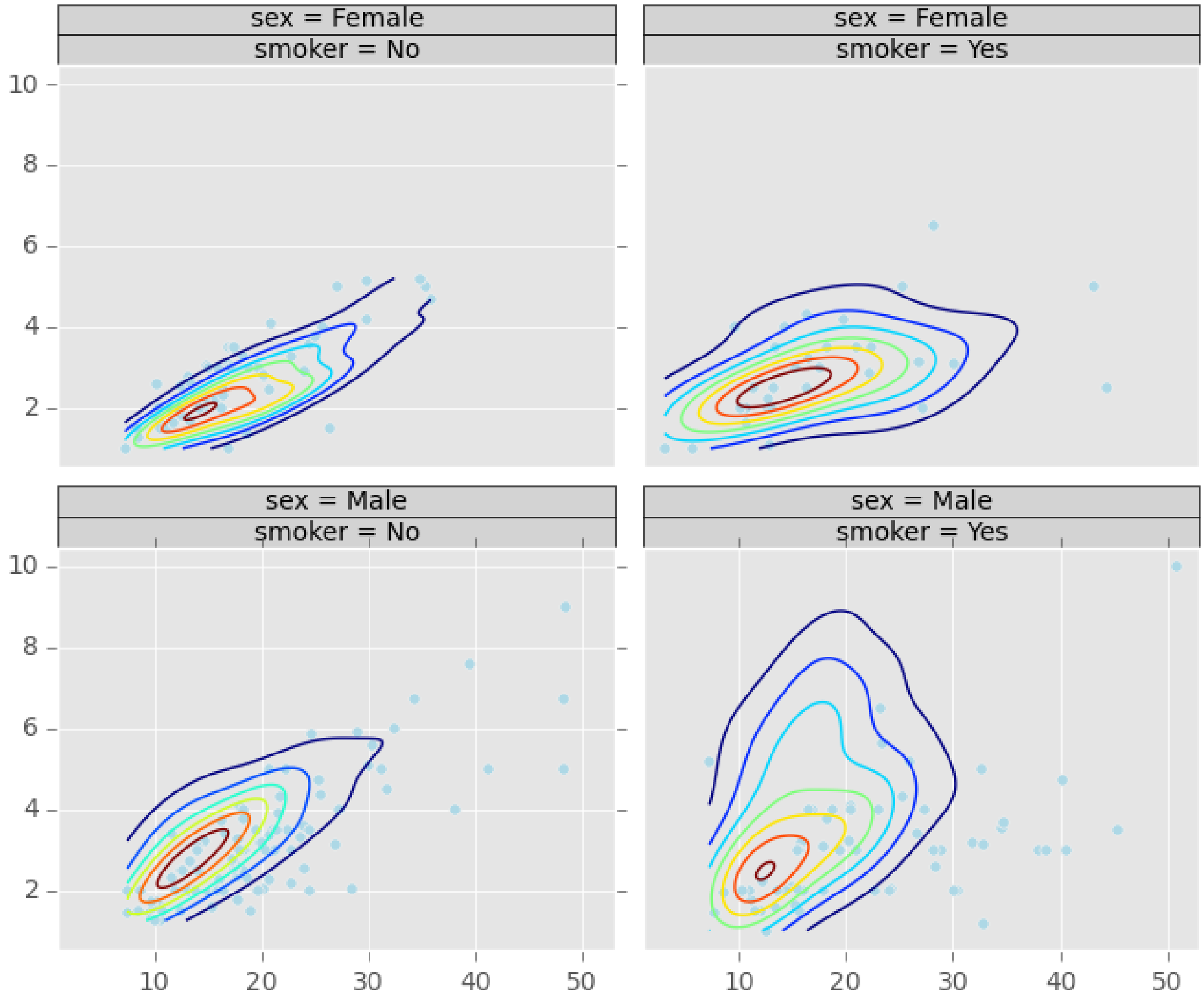
In [199]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [200]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

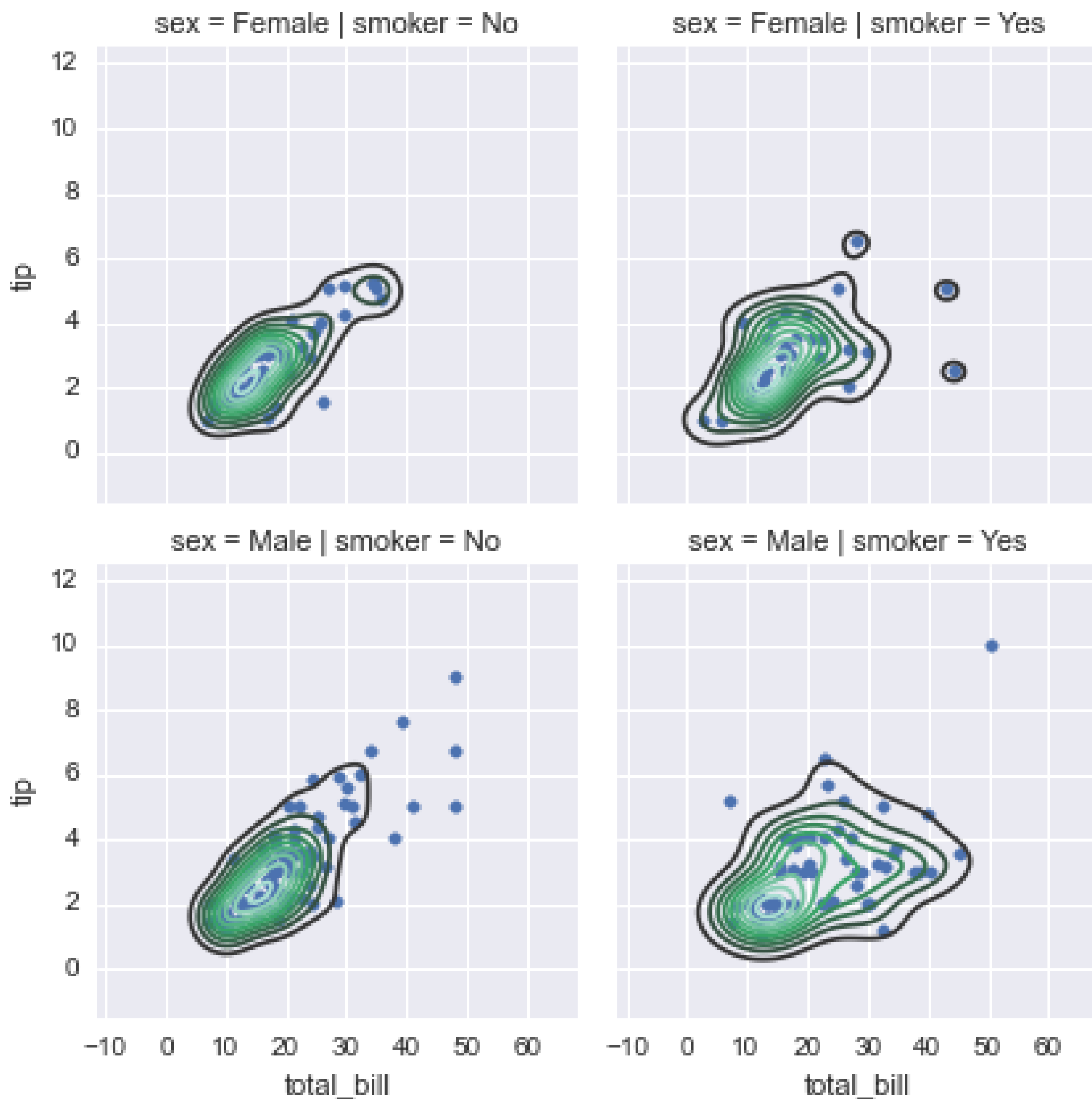
In [201]: plot.add(rplot.GeomScatter())

In [202]: plot.add(rplot.GeomDensity2D())

In [203]: plot.render(plt.gcf())
Out[203]: <matplotlib.figure.Figure at 0xa4273b2c>
```




```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
g.map(sns.kdeplot, "total_bill", "tip")
```



It is possible to only use one attribute for grouping data. The example above only uses 'sex' attribute. If the second grouping attribute is not specified, the plots will be arranged in a column.

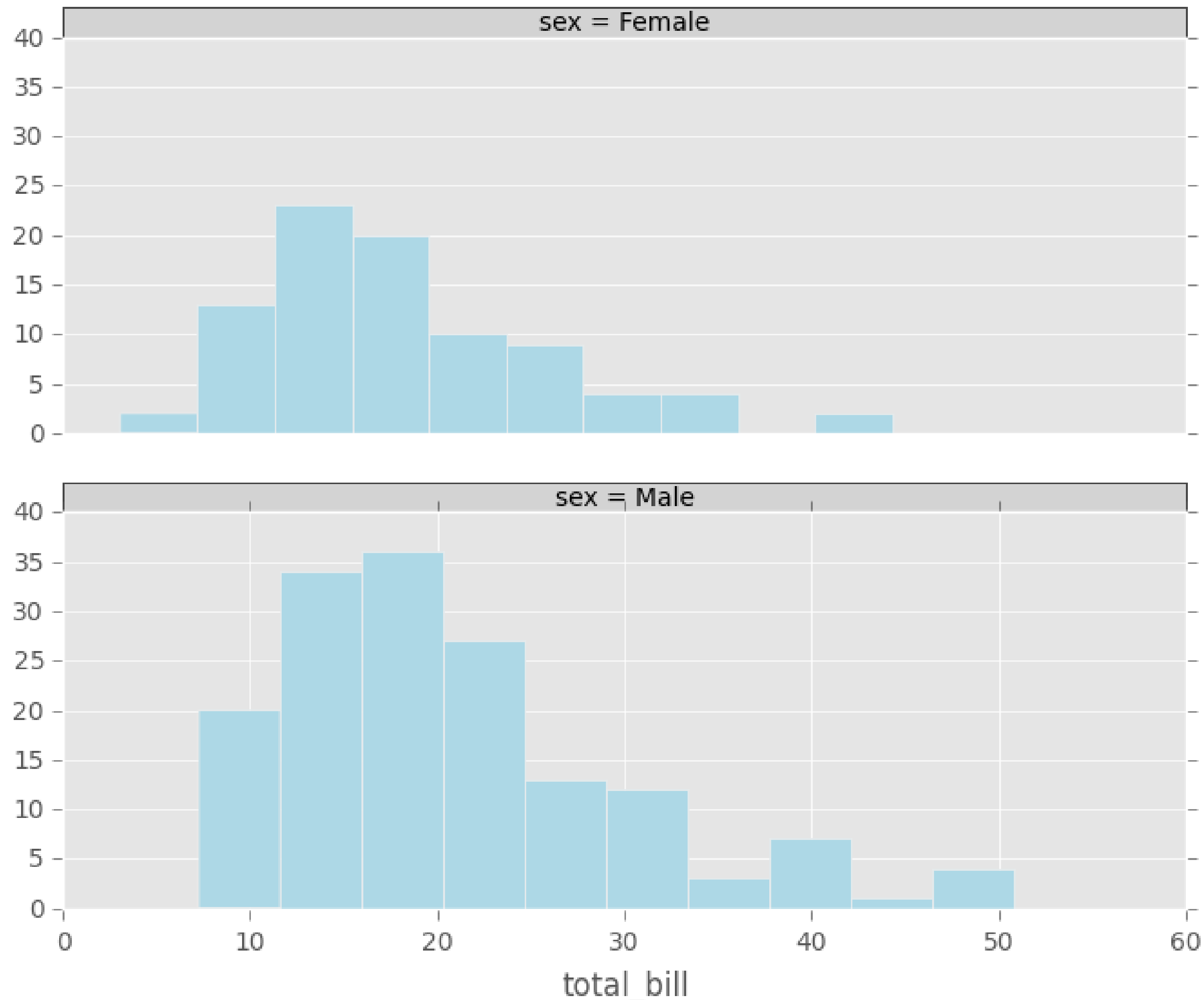
```
In [204]: plt.figure()
Out[204]: <matplotlib.figure.Figure at 0xa420f20c>

In [205]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [206]: plot.add(rplot.TrellisGrid(['sex', '.']))

In [207]: plot.add(rplot.GeomHistogram())

In [208]: plot.render(plt.gcf())
Out[208]: <matplotlib.figure.Figure at 0xa420f20c>
```



If the first grouping attribute is not specified the plots will be arranged in a row.

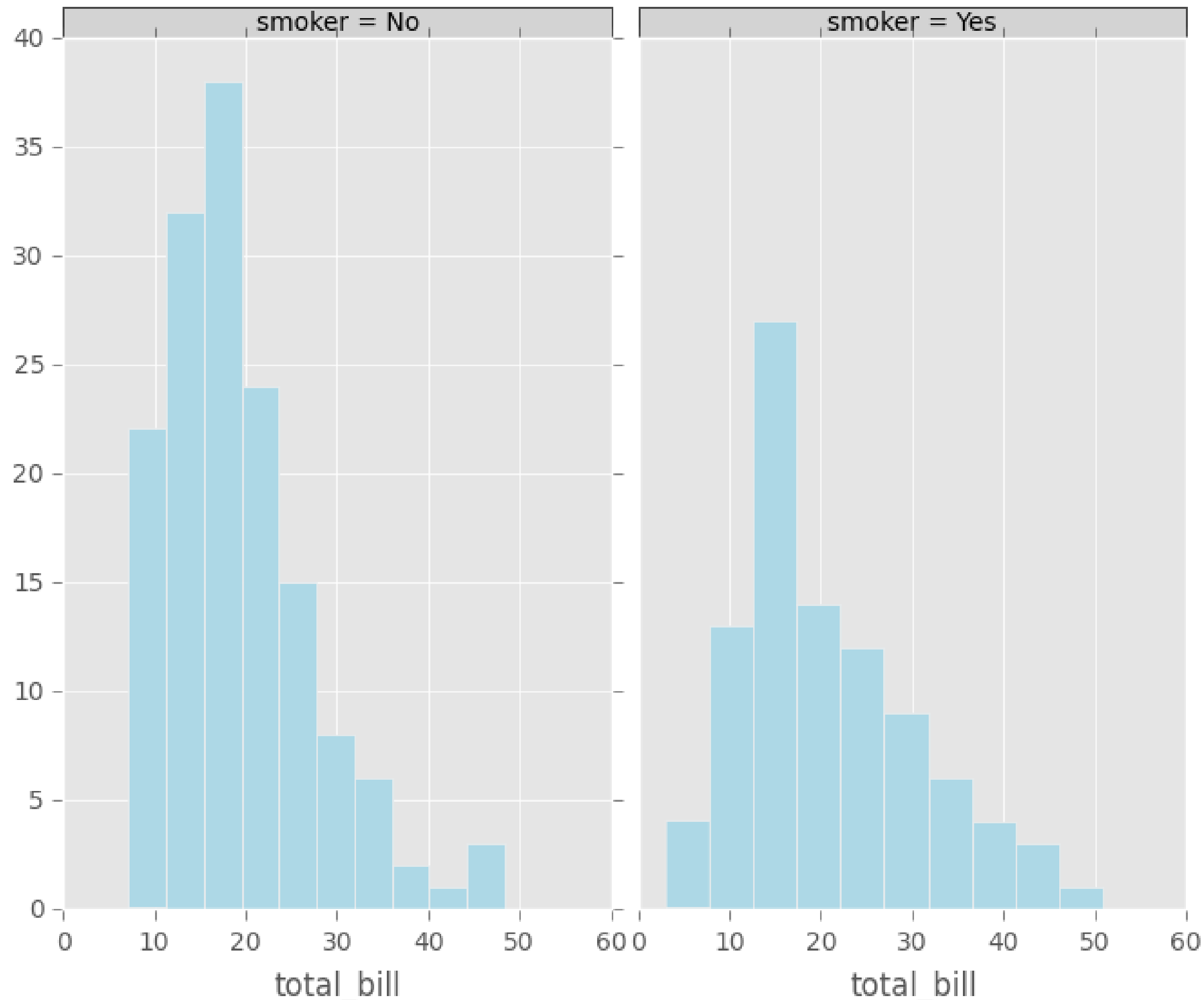
```
In [209]: plt.figure()
Out[209]: <matplotlib.figure.Figure at 0xa3e6e8ec>

In [210]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [211]: plot.add(rplot.TrellisGrid(['.', 'smoker']))

In [212]: plot.add(rplot.GeomHistogram())

In [213]: plot.render(plt.gcf())
Out[213]: <matplotlib.figure.Figure at 0xa3e6e8ec>
```



In seaborn, this can also be done by only specifying one of the row and col arguments.

In the example below the colour and shape of the scatter plot graphical objects is mapped to 'day' and 'size' attributes respectively. You use scale objects to specify these mappings. The list of scale classes is given below with initialization arguments for quick reference.

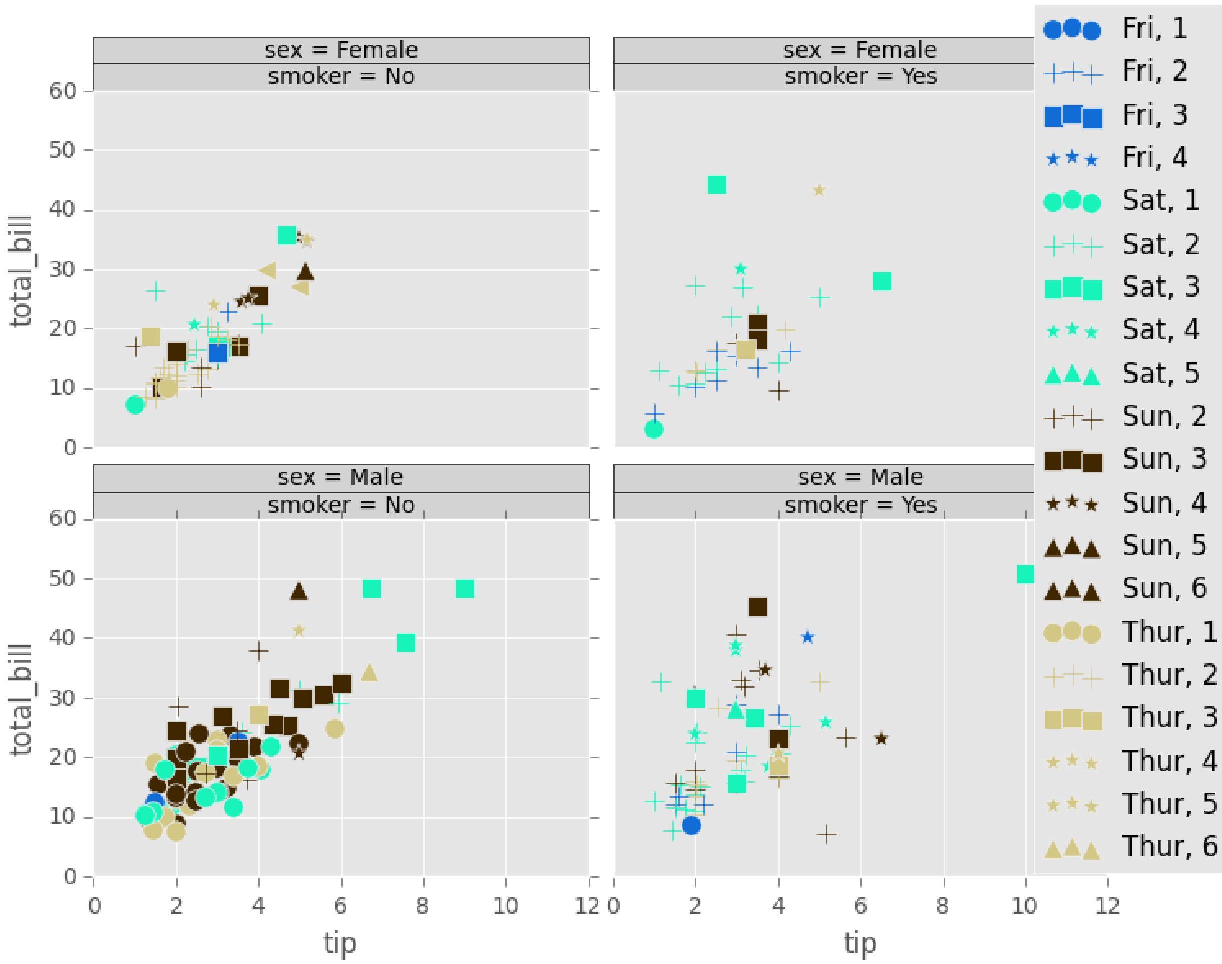
```
In [214]: plt.figure()
Out[214]: <matplotlib.figure.Figure at 0xa3de1f6c>

In [215]: plot = rplot.RPlot(tips_data, x='tip', y='total_bill')

In [216]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

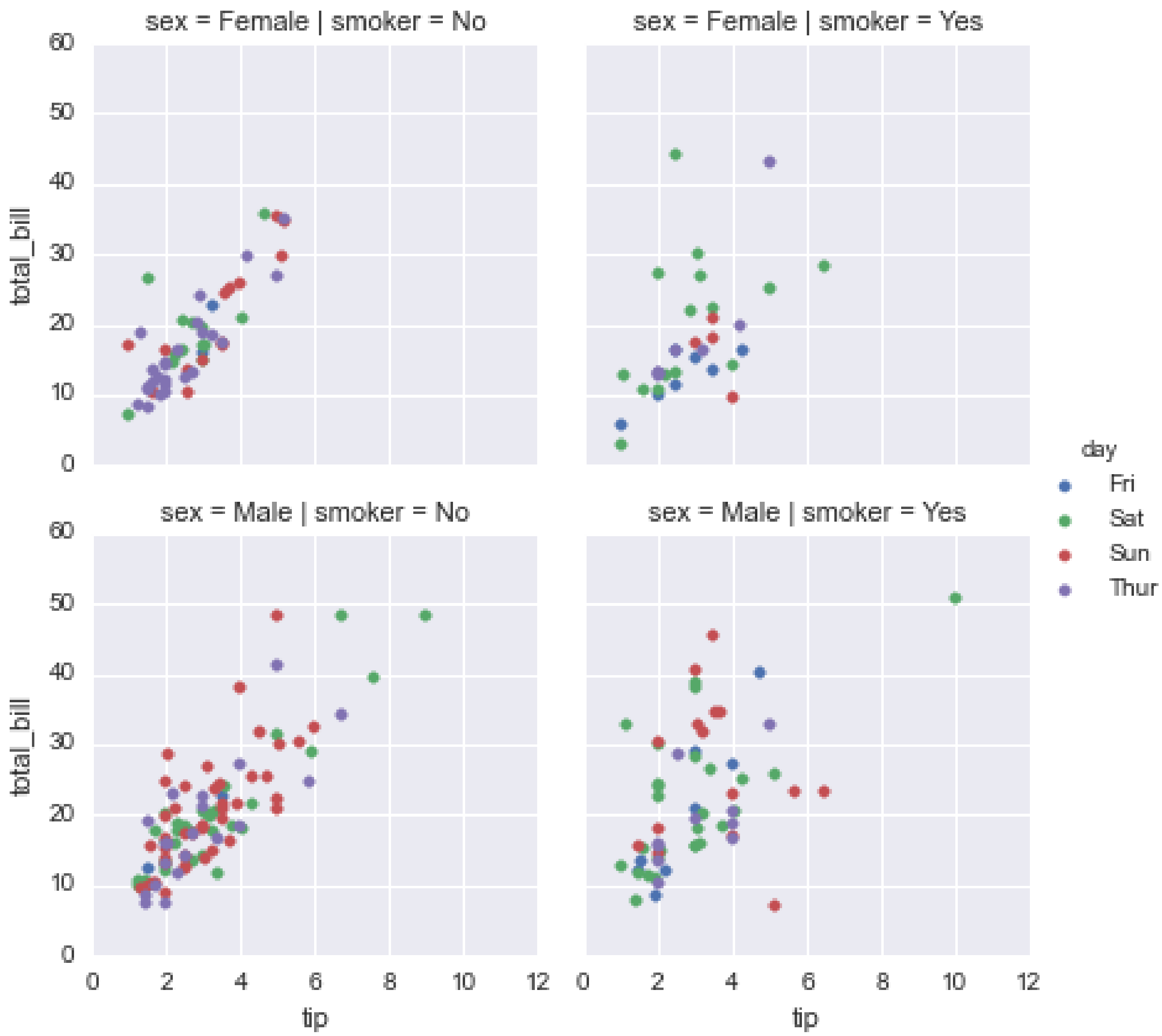
In [217]: plot.add(rplot.GeomPoint(size=80.0, colour=rplot.ScaleRandomColour('day'), shape=rplot.Scal

In [218]: plot.render(plt.gcf())
Out[218]: <matplotlib.figure.Figure at 0xa3de1f6c>
```



This can also be done in `seaborn`, at least for 3 variables:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", hue="day")
g.map(plt.scatter, "tip", "total_bill")
g.add_legend()
```


sex = Female | smoker = No
sex = Female | smoker = Yes
sex = Male | smoker = No
sex = Male | smoker = Yes
total_bill
tip
day
Fri
Sat
Sun
Thur
0
10
20
30
40
50
60
0
2
4
6
8
10
12

CHAPTER

TWENTYFOUR

IO TOOLS (TEXT, CSV, HDF5, ...)

The pandas I/O API is a set of top level `reader` functions accessed like `pd.read_csv()` that generally return a `pandas` object.

- *read_csv*
- *read_excel*
- *read_hdf*
- *read_sql*
- *read_json*
- *read_msgpack* (experimental)
- *read_html*
- *read_gbq* (experimental)
- *read_stata*
- *read_clipboard*
- *read_pickle*

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

- *to_csv*
- *to_excel*
- *to_hdf*
- *to_sql*
- *to_json*
- *to_msgpack* (experimental)
- *to_html*
- *to_gbq* (experimental)
- *to_stata*
- *to_clipboard*
- *to_pickle*

Here is an informal performance comparison for some of these IO methods.

Note: For examples that use the `StringIO` class, make sure you import it according to your Python version, i.e. `from StringIO import StringIO` for Python 2 and `from io import StringIO` for Python 3.

24.1 CSV & Text files

The two workhorse functions for reading text files (a.k.a. flat files) are `read_csv()` and `read_table()`. They both use the same parsing code to intelligently convert tabular data into a DataFrame object. See the *cookbook* for some advanced strategies

They can take a number of arguments:

- `filepath_or_buffer`: Either a string path to a file, URL (including http, ftp, and S3 locations), or any object with a `read` method (such as an open file or `StringIO`).
- `sep` or `delimiter`: A delimiter / separator to split fields on. With `sep=None`, `read_csv` will try to infer the delimiter automatically in some cases by "sniffing". The separator may be specified as a regular expression; for instance you may use '|\s*' to indicate a pipe plus arbitrary whitespace.
- `delim_whitespace`: Parse whitespace-delimited (spaces or tabs) file (much faster than using a regular expression)
- `compression`: decompress `'gzip'` and `'bz2'` formats on the fly. Set to `'infer'` (the default) to guess a format based on the file extension.
- `dialect`: string or `csv.Dialect` instance to expose more ways to specify the file format
- `dtype`: A data type name or a dict of column name to data type. If not specified, data types will be inferred. (Unsupported with `engine='python'`)
- `header`: row number(s) to use as the column names, and the start of the data. Defaults to 0 if no `names` passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True` (the default), so header=0 denotes the first line of data rather than the first line of the file.
- `skip_blank_lines`: whether to skip over blank lines rather than interpreting them as NaN values
- `skiprows`: A collection of numbers for rows in the file to skip. Can also be an integer to skip the first `n` rows
- `index_col`: column number, column name, or list of column numbers/names, to use as the `index` (row labels) of the resulting DataFrame. By default, it will number the rows without using any column, unless there is one more data column than there are headers, in which case the first column is taken as the index.
- `names`: List of column names to use as column names. To replace header existing in file, explicitly pass `header=0`.
- `na_values`: optional list of strings to recognize as NaN (missing values), either in addition to or in lieu of the default set.
- `true_values`: list of strings to recognize as `True`
- `false_values`: list of strings to recognize as `False`
- `keep_default_na`: whether to include the default set of missing values in addition to the ones specified in `na_values`
- `parse_dates`: if True then index will be parsed as dates (False by default). You can specify more complicated options to parse a subset of columns or a combination of columns into a single date column (list of ints or names, list of lists, or dict) [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column [[1, 3]] -> combine columns 1 and 3 and parse as a single date column {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

- `keep_date_col`: if True, then date component columns passed into `parse_dates` will be retained in the output (False by default).
- `date_parser`: function to use to parse strings into datetime objects. If `parse_dates` is True, it defaults to the very robust `dateutil.parser`. Specifying this implicitly sets `parse_dates` as True. You can also use functions from community supported date converters from date_converters.py
- `dayfirst`: if True then uses the DD/MM international/European date format (This is False by default)
- `thousands`: specifies the thousands separator. If not None, this character will be stripped from numeric dtypes. However, if it is the first character in a field, that column will be imported as a string. In the PythonParser, if not None, then parser will try to look for it in the output and parse relevant data to numeric dtypes. Because it has to essentially scan through the data again, this causes a significant performance hit so only use if necessary.
- `lineterminator` : string (length 1), default `None`, Character to break file into lines. Only valid with C parser
- `quotechar` : string, The character to used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.
- `quoting` : int, Controls whether quotes should be recognized. Values are taken from *csv.QUOTE_** values. Acceptable values are 0, 1, 2, and 3 for QUOTE_MINIMAL, QUOTE_ALL, QUOTE_NONE, and QUOTE_NONNUMERIC, respectively.
- `skipinitialspace` : boolean, default `False`, Skip spaces after delimiter
- `escapechar` : string, to specify how to escape quoted data
- `comment`: Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines, fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if comment='#', parsing '#emptyn1,2,3na,b,c' with *header=0* will result in '1,2,3' being treated as the header.
- `nrows`: Number of rows to read out of the file. Useful to only read a small portion of a large file
- `iterator`: If True, return a `TextFileReader` to enable reading a file into memory piece by piece
- `chunksize`: An number of rows to be used to "chunk" a file into pieces. Will cause an `TextFileReader` object to be returned. More on this below in the section on *iterating and chunking*
- `skip_footer`: number of lines to skip at bottom of file (default 0) (Unsupported with `engine='c'`)
- `converters`: a dictionary of functions for converting values in certain columns, where keys are either integers or column labels
- `encoding`: a string representing the encoding to use for decoding unicode data, e.g. `'utf-8`` or `'latin-1'`. Full list of Python standard encodings
- `verbose`: show number of NA values inserted in non-numeric columns
- `squeeze`: if True then output with only one column is turned into Series
- `error_bad_lines`: if False then any lines causing an error will be skipped *bad lines*
- `usecols`: a subset of columns to return, results in much faster parsing time and lower memory usage.
- `mangle_dupe_cols`: boolean, default True, then duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'
- `tupleize_cols`: boolean, default False, if False, convert a list of tuples to a multi-index of columns, otherwise, leave the column index as a list of tuples
- `float_precision` : string, default None. Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, 'high' for the high-precision converter, and 'round_trip' for the round-trip converter.

Consider a typical CSV file containing, in this case, some time series data:

```
In [1]: print(open('foo.csv').read())
date,A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

The default for *read_csv* is to create a DataFrame with simple numbered rows:

```
In [2]: pd.read_csv('foo.csv')
Out[2]:
       date  A  B  C
0  20090101  a  1  2
1  20090102  b  3  4
2  20090103  c  4  5
```

In the case of indexed data, you can pass the column number or column name you wish to use as the index:

```
In [3]: pd.read_csv('foo.csv', index_col=0)
Out[3]:
          A  B  C
date
20090101  a  1  2
20090102  b  3  4
20090103  c  4  5

In [4]: pd.read_csv('foo.csv', index_col='date')
Out[4]:
          A  B  C
date
20090101  a  1  2
20090102  b  3  4
20090103  c  4  5
```

You can also use a list of columns to create a hierarchical index:

```
In [5]: pd.read_csv('foo.csv', index_col=[0, 'A'])
Out[5]:
            B  C
date     A
20090101 a  1  2
20090102 b  3  4
20090103 c  4  5
```

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```
In [6]: print(data)
label1,label2,label3
index1,"a,c,e
index2,b,d,f
```

By default, `read_csv` uses the Excel dialect and treats the double quote as the quote character, which causes it to fail when it finds a newline before it finds the closing double quote.

We can get around this using `dialect`

```
In [7]: dia = csv.excel()

In [8]: dia.quoting = csv.QUOTE_NONE

In [9]: pd.read_csv(StringIO(data), dialect=dia)
Out[9]:
       label1 label2 label3
index1     "a      c      e
index2      b      d      f
```

All of the dialect options can be specified separately by keyword arguments:

```
In [10]: data = 'a,b,c~1,2,3~4,5,6'

In [11]: pd.read_csv(StringIO(data), lineterminator='~')
Out[11]:
   a  b  c
0  1  2  3
1  4  5  6
```

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```
In [12]: data = 'a, b, c\n1, 2, 3\n4, 5, 6'

In [13]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [14]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[14]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to "do the right thing" and not be very fragile. Type inference is a pretty big deal. So if a column can be coerced to integer dtype without altering the contents, it will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

24.1.1 Specifying column data types

Starting with v0.10, you can indicate the data type for the whole DataFrame or individual columns:

```
In [15]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'

In [16]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [17]: df = pd.read_csv(StringIO(data), dtype=object)

In [18]: df
Out[18]:
   a  b  c
0  1  2  3
1  4  5  6
```

```
2  7  8  9

In [19]: df['a'][0]
Out[19]: '1'

In [20]: df = pd.read_csv(StringIO(data), dtype={'b': object, 'c': np.float64})

In [21]: df.dtypes
Out[21]:
a      int64
b     object
c    float64
dtype: object
```

Note: The `dtype` option is currently only supported by the C engine. Specifying `dtype` with `engine` other than 'c' raises a `ValueError`.

24.1.2 Handling column names

A file may or may not have a header row. pandas assumes the first row should be used as the column names:

```
In [22]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'

In [23]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [24]: pd.read_csv(StringIO(data))
Out[24]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

By specifying the `names` argument in conjunction with `header` you can indicate other names to use and whether or not to throw away the header row (if any):

```
In [25]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [26]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[26]:
   foo  bar  baz
0    1    2    3
1    4    5    6
2    7    8    9

In [27]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[27]:
  foo bar baz
0   a   b   c
```

```
1   1   2   3
2   4   5   6
3   7   8   9
```

If the header is in a row other than the first, pass the row number to `header`. This will skip the preceding rows:

```
In [28]: data = 'skip this skip it\na,b,c\n1,2,3\n4,5,6\n7,8,9'

In [29]: pd.read_csv(StringIO(data), header=1)
Out[29]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

24.1.3 Filtering columns (usecols)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names or position numbers:

```
In [30]: data = 'a,b,c,d\n1,2,3,foo\n4,5,6,bar\n7,8,9,baz'

In [31]: pd.read_csv(StringIO(data))
Out[31]:
   a  b  c    d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [32]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[32]:
   b    d
0  2  foo
1  5  bar
2  8  baz

In [33]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[33]:
   a  c    d
0  1  3  foo
1  4  6  bar
2  7  9  baz
```

24.1.4 Ignoring line comments and empty lines

If the `comment` parameter is specified, then completely commented lines will be ignored. By default, completely blank lines will be ignored as well. Both of these are API changes introduced in version 0.15.

```
In [34]: data = '\na,b,c\n  \n# commented line\n1,2,3\n\n4,5,6'

In [35]: print(data)

a,b,c

1,2,3
```

```
4,5,6

# commented line
In [36]: pd.read_csv(StringIO(data), comment='#')
Out[36]:
   a  b  c
0  1  2  3
1  4  5  6
```

If `skip_blank_lines=False`, then `read_csv` will not ignore blank lines:

```
In [37]: data = 'a,b,c\n\n1,2,3\n\n\n4,5,6'

In [38]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[38]:
     a    b    c
0  NaN  NaN  NaN
1    1    2    3
2  NaN  NaN  NaN
3  NaN  NaN  NaN
4    4    5    6
```

Warning: The presence of ignored lines might create ambiguities involving line numbers; the parameter `header` uses row numbers (ignoring commented/empty lines), while `skiprows` uses line numbers (including commented/empty lines):

```
In [39]: data = '#comment\na,b,c\nA,B,C\n1,2,3'

In [40]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[40]:
   A  B  C
0  1  2  3

In [41]: data = 'A,B,C\n#comment\na,b,c\n1,2,3'

In [42]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[42]:
   a  b  c
0  1  2  3
```

If both `header` and `skiprows` are specified, `header` will be relative to the end of `skiprows`. For example:

```
In [43]: data = '# empty\n# second empty line\n# third empty' \

In [43]: 'line\nX,Y,Z\n1,2,3\nA,B,C\n1,2.,4.\n5.,NaN,10.0'

In [44]: print(data)
# empty
# second empty line
# third emptyline
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0

In [45]: pd.read_csv(StringIO(data), comment='#', skiprows=4, header=1)
Out[45]:
   A    B   C
0  1    2   4
1  5  NaN  10
```

24.1.5 Dealing with Unicode Data

The `encoding` argument should be used for encoded unicode data, which will result in byte strings being decoded to unicode in the result:

```
In [46]: data = b'word,length\nTr\xc3\xa4umen,7\nGr\xc3\xbc\xc3\x9fe,5'.decode('utf8').encode('latin-

In [47]: df = pd.read_csv(BytesIO(data), encoding='latin-1')

In [48]: df
Out[48]:
      word  length
0  Träumen       7
1    Grüße       5

In [49]: df['word'][1]
```

```
Out[49]: u'Gr\xfc\xdfe'
```

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

24.1.6 Index columns and trailing delimiters

If a file has one more column of data than the number of column names, the first column will be used as the DataFrame's row names:

```
In [50]: data = 'a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'

In [51]: pd.read_csv(StringIO(data))
Out[51]:
        a    b     c
4   apple  bat   5.7
8  orange  cow  10.0

In [52]: data = 'index,a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'

In [53]: pd.read_csv(StringIO(data), index_col=0)
Out[53]:
            a    b     c
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`:

```
In [54]: data = 'a,b,c\n4,apple,bat,\n8,orange,cow,'

In [55]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [56]: pd.read_csv(StringIO(data))
Out[56]:
        a    b   c
4   apple  bat NaN
8  orange  cow NaN

In [57]: pd.read_csv(StringIO(data), index_col=False)
Out[57]:
   a       b    c
0  4   apple  bat
1  8  orange  cow
```

24.1.7 Specifying Date Columns

To better facilitate working with datetime data, `read_csv()` and `read_table()` uses 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 [58]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)

In [59]: df
Out[59]:
            A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5

# These are python datetime objects
In [60]: df.index
Out[60]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', name=u'dat
```

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:

```
In [61]: 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 [62]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [63]: df
Out[63]:
                  1_2                 1_3     0     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

By default the parser removes the component date columns, but you can choose to retain them via the `keep_date_col` keyword:

```
In [64]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
   ....:                  keep_date_col=True)
   ....:

In [65]: df
Out[65]:
                  1_2                 1_3     0         1          2  \
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  19990127   19:00:00
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  19990127   20:00:00
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD  19990127   21:00:00
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD  19990127   21:00:00
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD  19990127   22:00:00
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD  19990127   23:00:00
```

```
          3     4
0  18:56:00  0.81
1  19:56:00  0.01
2  20:56:00 -0.59
3  21:18:00 -0.99
4  21:56:00 -0.59
5  22:56:00 -0.59
```

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other words, `parse_dates=[1, 2]` indicates that the second and third columns should each be parsed as separate date columns while `parse_dates=[[1, 2]]` means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:

```
In [66]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [67]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)

In [68]: df
Out[68]:
              nominal              actual     0     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

It is important to remember that if multiple text columns are to be parsed into a single date column, then a new column is prepended to the data. The *index_col* specification is based off of this new set of columns rather than the original data columns:

```
In [69]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [70]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
   ....:                  index_col=0) #index is the nominal column
   ....:

In [71]: df
Out[71]:
                                 actual     0     4
nominal
1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

Note: read_csv has a fast_path for parsing datetime strings in iso8601 format, e.g “2000-01-01T00:01:02+00:00” and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

Note: When passing a dict as the *parse_dates* argument, the order of the columns prepended is not guaranteed, because *dict* objects do not impose an ordering on their keys. On Python 2.7+ you may use *collections.OrderedDict* instead of a regular *dict* if this matters to you. Because of this, when using a dict for ‘parse_dates’ in conjunction with the *index_col* argument, it’s best to specify *index_col* as a column label rather then as an index on the resulting frame.

24.1.8 Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```
In [72]: val = '0.3066101993807095471566981359501369297504425048828125'

In [73]: data = 'a,b,c\n1,2,{0}'.format(val)

In [74]: abs(pd.read_csv(StringIO(data), engine='c', float_precision=None)['c'][0] - float(val))
Out[74]: 0.0

In [75]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='high')['c'][0] - float(val))
Out[75]: 5.5511151231257827e-17

In [76]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='round_trip')['c'][0] - float(va
Out[76]: 0.0
```

24.1.9 Date Parsing Functions

Finally, the parser allows you to specify a custom `date_parser` function to take full advantage of the flexibility of the date parsing API:

```
In [77]: import pandas.io.date_converters as conv

In [78]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
   ....:                  date_parser=conv.parse_date_time)
   ....:

In [79]: df
Out[79]: 
              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
```

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.

24.1.10 Inferring Datetime Format

If you have `parse_dates` enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting `infer_datetime_format=True`. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, `infer_datetime_format` should not have any negative consequences if enabled.

Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00)

- "20111230"
- "2011/12/30"
- "20111230 00:00:00"
- "12/30/2011 00:00:00"
- "30/Dec/2011 00:00:00"
- "30/December/2011 00:00:00"

`infer_datetime_format` is sensitive to `dayfirst`. With `dayfirst=True`, it will guess "01/12/2011" to be December 1st. With `dayfirst=False` (default) it will guess "01/12/2011" to be January 12th.

```
# Try to infer the format for the index column
In [80]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
   ....:                  infer_datetime_format=True)
   ....:

In [81]: df
Out[81]:
            A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5
```

24.1.11 International Date Formats

While US date formats tend to be MM/DD/YYYY, many international formats use DD/MM/YYYY instead. For convenience, a `dayfirst` keyword is provided:

```
In [82]: print(open('tmp.csv').read())
date,value,cat
1/6/2000,5,a
```

```
2/6/2000,10,b
3/6/2000,15,c

In [83]: pd.read_csv('tmp.csv', parse_dates=[0])
Out[83]:
        date  value cat
0 2000-01-06      5   a
1 2000-02-06     10   b
2 2000-03-06     15   c

In [84]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
Out[84]:
        date  value cat
0 2000-06-01      5   a
1 2000-06-02     10   b
2 2000-06-03     15   c
```

24.1.12 Thousand Separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings

```
In [85]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [86]: df = pd.read_csv('tmp.csv', sep='|')

In [87]: df
Out[87]:
         ID      level category
0  Patient1    123,000        x
1  Patient2     23,000        y
2  Patient3  1,234,018        z

In [88]: df.level.dtype
Out[88]: dtype('O')
```

The `thousands` keyword allows integers to be parsed correctly

```
In [89]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [90]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')

In [91]: df
Out[91]:
         ID    level category
0  Patient1   123000        x
1  Patient2    23000        y
```

```
2  Patient3  1234018        z

In [92]: df.level.dtype
Out[92]: dtype('int64')
```

24.1.13 NA Values

To control which values are parsed as missing values (which are signified by `NaN`), specifiy a list of strings in `na_values`. If you specify a number (a `float`, like `5.0` or an `integer` like `5`), the corresponding equivalent values will also imply a missing value (in this case effectively `[5.0,5]` are recognized as `NaN`.

To completely override the default values that are recognized as missing, specify `keep_default_na=False`. The default `NaN` recognized values are `['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A','N/A', 'NA', '#NA', 'NULL', 'NaN', '-NaN', 'nan', '-nan']`.

```
read_csv(path, na_values=[5])
```

the default values, in addition to `5` , `5.0` when interpreted as numbers are recognized as `NaN`

```
read_csv(path, keep_default_na=False, na_values=[""])
```

only an empty field will be `NaN`

```
read_csv(path, keep_default_na=False, na_values=["NA", "0"])
```

only `NA` and `0` as strings are `NaN`

```
read_csv(path, na_values=["Nope"])
```

the default values, in addition to the string `"Nope"` are recognized as `NaN`

24.1.14 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`.

24.1.15 Comments

Sometimes comments or meta data may be included in a file:

```
In [93]: 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 parse includes the comments in the output:

```
In [94]: df = pd.read_csv('tmp.csv')

In [95]: df
Out[95]:
         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 [96]: df = pd.read_csv('tmp.csv', comment='#')

In [97]: df
Out[97]:
         ID    level category
0  Patient1   123000        x
1  Patient2    23000        y
2  Patient3  1234018        z
```

24.1.16 Returning Series

Using the `squeeze` keyword, the parser will return output with a single column as a `Series`:

```
In [98]: print(open('tmp.csv').read())
level
Patient1,123000
Patient2,23000
Patient3,1234018

In [99]: output =  pd.read_csv('tmp.csv', squeeze=True)

In [100]: output
Out[100]:
Patient1     123000
Patient2      23000
Patient3    1234018
Name: level, dtype: int64

In [101]: type(output)
Out[101]: pandas.core.series.Series
```

24.1.17 Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Sometime you would want to recognize some other values as being boolean. To do this use the `true_values` and `false_values` options:

```
In [102]: data= 'a,b,c\n1,Yes,2\n3,No,4'

In [103]: print(data)
a,b,c
1,Yes,2
3,No,4

In [104]: pd.read_csv(StringIO(data))
Out[104]:
   a    b  c
0  1  Yes  2
1  3   No  4

In [105]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[105]:
   a      b  c
0  1   True  2
1  3  False  4
```

24.1.18 Handling "bad" lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many will cause an error by default:

```
In [27]: data = 'a,b,c\n1,2,3\n4,5,6,7\n8,9,10'

In [28]: pd.read_csv(StringIO(data))
---------------------------------------------------------------------------
CParserError                              Traceback (most recent call last)
CParserError: Error tokenizing data. C error: Expected 3 fields in line 3, saw 4
```

You can elect to skip bad lines:

```
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
Skipping line 3: expected 3 fields, saw 4

Out[29]:
   a  b   c
0  1  2   3
1  8  9  10
```

24.1.19 Quoting and Escape Characters

Quotes (and other escape characters) in embedded fields can be handled in any number of ways. One way is to use backslashes; to properly parse this data, you should pass the `escapechar` option:

```
In [106]: data = 'a,b\n"hello, \\"Bob\\", nice to see you",5'

In [107]: print(data)
a,b
"hello, \"Bob\", nice to see you",5

In [108]: pd.read_csv(StringIO(data), escapechar='\\')
Out[108]:
                               a  b
0  hello, "Bob", nice to see you  5
```

24.1.20 Files with Fixed Width Columns

While `read_csv` reads delimited data, the `read_fwf()` function works with data files that have known and fixed column widths. The function parameters to `read_fwf` are largely the same as *read_csv* with two extra parameters:

- `colspecs`: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value 'infer' can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behaviour, if not specified, is to infer.
- `widths`: A list of field widths which can be used instead of 'colspecs' if the intervals are contiguous.

Consider a typical fixed-width data file:

```
In [109]: print(open('bar.csv').read())
id8141    360.242940   149.910199   11950.7
id1594    444.953632   166.985655   11788.4
id1849    364.136849   183.628767   11806.2
id1230    413.836124   184.375703   11916.8
id1948    502.953953   173.237159   12468.3
```

In order to parse this file into a DataFrame, we simply need to supply the column specifications to the *read_fwf* function along with the file name:

```
#Column specifications are a list of half-intervals
In [110]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [111]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)

In [112]: df
Out[112]:
                 1           2        3
0
id8141  360.242940  149.910199  11950.7
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
```

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```
#Widths are a list of integers
In [113]: widths = [6, 14, 13, 10]

In [114]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [115]: df
Out[115]:
        0           1           2        3
0  id8141  360.242940  149.910199  11950.7
1  id1594  444.953632  166.985655  11788.4
2  id1849  364.136849  183.628767  11806.2
3  id1230  413.836124  184.375703  11916.8
4  id1948  502.953953  173.237159  12468.3
```

The parser will take care of extra white spaces around the columns so it's ok to have extra separation between the columns in the file.

New in version 0.13.0.

By default, `read_fwf` will try to infer the file's `colspecs` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```
In [116]: df = pd.read_fwf('bar.csv', header=None, index_col=0)

In [117]: df
Out[117]:
                 1           2        3
0
id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

24.1.21 Files with an "implicit" index column

Consider a file with one less entry in the header than the number of data column:

```
In [118]: print(open('foo.csv').read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the DataFrame:

```
In [119]: pd.read_csv('foo.csv')
Out[119]:
          A  B  C
20090101  a  1  2
20090102  b  3  4
20090103  c  4  5
```

Note that the dates weren't automatically parsed. In that case you would need to do as before:

```
In [120]: df = pd.read_csv('foo.csv', parse_dates=True)

In [121]: df.index
Out[121]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', freq=None
```

24.1.22 Reading an index with a `MultiIndex`

Suppose you have data indexed by two columns:

```
In [122]: print(open('data/mindex_ex.csv').read())
year,indiv,zit,xit
1977,"A",1.2,.6
1977,"B",1.5,.5
1977,"C",1.7,.8
1978,"A",.2,.06
1978,"B",.7,.2
1978,"C",.8,.3
1978,"D",.9,.5
1978,"E",1.4,.9
1979,"C",.2,.15
1979,"D",.14,.05
1979,"E",.5,.15
1979,"F",1.2,.5
1979,"G",3.4,1.9
1979,"H",5.4,2.7
1979,"I",6.4,1.2
```

The `index_col` argument to `read_csv` and `read_table` can take a list of column numbers to turn multiple columns into a `MultiIndex` for the index of the returned object:

```
In [123]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0,1])

In [124]: df
Out[124]:
             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

In [125]: df.ix[1978]
Out[125]:
       zit   xit
indiv
A      0.2  0.06
B      0.7  0.20
C      0.8  0.30
D      0.9  0.50
E      1.4  0.90
```

24.1.23 Reading columns with a MultiIndex

By specifying list of row locations for the header argument, you can read in a MultiIndex for the columns. Specifying non-consecutive rows will skip the intervening rows. In order to have the pre-0.13 behavior of tupleizing columns, specify tupleize_cols=True.

```
In [126]: from pandas.util.testing import makeCustomDataframe as mkdf

In [127]: df = mkdf(5,3,r_idx_nlevels=2,c_idx_nlevels=4)

In [128]: df.to_csv('mi.csv')

In [129]: print(open('mi.csv').read())
C0,,C_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 [130]: pd.read_csv('mi.csv',header=[0,1,2,3],index_col=[0,1])
Out[130]:
C0                C_l0_g0 C_l0_g1 C_l0_g2
C1                C_l1_g0 C_l1_g1 C_l1_g2
C2                C_l2_g0 C_l2_g1 C_l2_g2
C3                C_l3_g0 C_l3_g1 C_l3_g2
R0      R1
R_l0_g0 R_l1_g0      R0C0    R0C1    R0C2
R_l0_g1 R_l1_g1      R1C0    R1C1    R1C2
R_l0_g2 R_l1_g2      R2C0    R2C1    R2C2
R_l0_g3 R_l1_g3      R3C0    R3C1    R3C2
```

```
R_l0_g4 R_l1_g4     R4C0     R4C1     R4C2
```

Starting in 0.13.0, `read_csv` will be able to interpret a more common format of multi-columns indices.

```
In [131]: print(open('mi2.csv').read())
,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 [132]: pd.read_csv('mi2.csv',header=[0,1],index_col=0)
Out[132]:
     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*.

24.1.24 Automatically "sniffing" the delimiter

`read_csv` is capable of inferring delimited (not necessarily comma-separated) files, as pandas uses the `csv.Sniffer` class of the csv module. For this, you have to specify `sep=None`.

```
In [133]: print(open('tmp2.sv').read())
:0:1:2:3
0:0.469112299907:-0.282863344329:-1.50905850317:-1.13563237102
1:1.21211202502:-0.173214649053:0.119208711297:-1.04423596628
2:-0.861848963348:-2.10456921889:-0.494929274069:1.07180380704
3:0.721555162244:-0.70677113363:-1.03957498511:0.271859885543
4:-0.424972329789:0.567020349794:0.276232019278:-1.08740069129
5:-0.673689708088:0.113648409689:-1.47842655244:0.524987667115
6:0.40470521868:0.57704598592:-1.71500201611:-1.03926848351
7:-0.370646858236:-1.15789225064:-1.34431181273:0.844885141425
8:1.07576978372:-0.10904997528:1.64356307036:-1.46938795954
9:0.357020564133:-0.67460010373:-1.77690371697:-0.968913812447


In [134]: pd.read_csv('tmp2.sv', sep=None, engine='python')
Out[134]:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
4           4 -0.424972  0.567020  0.276232 -1.087401
5           5 -0.673690  0.113648 -1.478427  0.524988
6           6  0.404705  0.577046 -1.715002 -1.039268
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
```

24.1.25 Iterating through files chunk by chunk

Suppose you wish to iterate through a (potentially very large) file lazily rather than reading the entire file into memory, such as the following:

```
In [135]: print(open('tmp.sv').read())
|0|1|2|3
0|0.469112299907|-0.282863344329|-1.50905850317|-1.13563237102
1|1.21211202502|-0.173214649053|0.119208711297|-1.04423596628
2|-0.861848963348|-2.10456921889|-0.494929274069|1.07180380704
3|0.721555162244|-0.70677113363|-1.03957498511|0.271859885543
4|-0.424972329789|0.567020349794|0.276232019278|-1.08740069129
5|-0.673689708088|0.113648409689|-1.47842655244|0.524987667115
6|0.40470521868|0.57704598592|-1.71500201611|-1.03926848351
7|-0.370646858236|-1.15789225064|-1.34431181273|0.844885141425
8|1.07576978372|-0.10904997528|1.64356307036|-1.46938795954
9|0.357020564133|-0.67460010373|-1.77690371697|-0.968913812447


In [136]: table = pd.read_table('tmp.sv', sep='|')

In [137]: table
Out[137]:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
4           4 -0.424972  0.567020  0.276232 -1.087401
5           5 -0.673690  0.113648 -1.478427  0.524988
6           6  0.404705  0.577046 -1.715002 -1.039268
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
```

By specifying a `chunksize` to `read_csv` or `read_table`, the return value will be an iterable object of type `TextFileReader`:

```
In [138]: reader = pd.read_table('tmp.sv', sep='|', chunksize=4)

In [139]: reader
Out[139]: <pandas.io.parsers.TextFileReader at 0xa561bcec>

In [140]: for chunk in reader:
   .....:     print(chunk)
   .....:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
   Unnamed: 0         0         1         2         3
0           4 -0.424972  0.567020  0.276232 -1.087401
1           5 -0.673690  0.113648 -1.478427  0.524988
2           6  0.404705  0.577046 -1.715002 -1.039268
3           7 -0.370647 -1.157892 -1.344312  0.844885
   Unnamed: 0         0        1         2         3
0           8  1.075770 -0.10905  1.643563 -1.469388
1           9  0.357021 -0.67460 -1.776904 -0.968914
```

Specifying `iterator=True` will also return the `TextFileReader` object:

```
In [141]: reader = pd.read_table('tmp.sv', sep='|', iterator=True)

In [142]: reader.get_chunk(5)
Out[142]:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
4           4 -0.424972  0.567020  0.276232 -1.087401
```

24.1.26 Specifying the parser engine

Under the hood pandas uses a fast and efficient parser implemented in C as well as a python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skip_footer`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

24.1.27 Writing to CSV format

The Series and DataFrame objects have an instance method `to_csv` which allows storing the contents of the object as a comma-separated-values file. The function takes a number of arguments. Only the first is required.

- `path_or_buf`: A string path to the file to write or a StringIO
- `sep` : Field delimiter for the output file (default ",")
- `na_rep`: A string representation of a missing value (default '')
- `float_format`: Format string for floating point numbers
- `cols`: Columns to write (default None)
- `header`: Whether to write out the column names (default True)
- `index`: whether to write row (index) names (default True)
- `index_label`: Column label(s) for index column(s) if desired. If None (default), and *header* and *index* are True, then the index names are used. (A sequence should be given if the DataFrame uses MultiIndex).
- `mode` : Python write mode, default 'w'
- `encoding`: a string representing the encoding to use if the contents are non-ASCII, for python versions prior to 3
- `line_terminator`: Character sequence denoting line end (default '\n')
- `quoting`: Set quoting rules as in csv module (default csv.QUOTE_MINIMAL)
- `quotechar`: Character used to quote fields (default '"')
- `doublequote`: Control quoting of `quotechar` in fields (default True)

- `escapechar`: Character used to escape `sep` and `quotechar` when appropriate (default None)
- `chunksize`: Number of rows to write at a time
- `tupleize_cols`: If False (default), write as a list of tuples, otherwise write in an expanded line format suitable for `read_csv`
- `date_format`: Format string for datetime objects

24.1.28 Writing a formatted string

The DataFrame object has an instance method `to_string` which allows control over the string representation of the object. All arguments are optional:

- `buf` default None, for example a StringIO object
- `columns` default None, which columns to write
- `col_space` default None, minimum width of each column.
- `na_rep` default `NaN`, representation of NA value
- `formatters` default None, a dictionary (by column) of functions each of which takes a single argument and returns a formatted string
- `float_format` default None, a function which takes a single (float) argument and returns a formatted string; to be applied to floats in the DataFrame.
- `sparsify` default True, set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.
- `index_names` default True, will print the names of the indices
- `index` default True, will print the index (ie, row labels)
- `header` default True, will print the column labels
- `justify` default `left`, will print column headers left- or right-justified

The Series object also has a `to_string` method, but with only the `buf`, `na_rep`, `float_format` arguments. There is also a `length` argument which, if set to `True`, will additionally output the length of the Series.

24.2 JSON

Read and write `JSON` format files and strings.

24.2.1 Writing JSON

A `Series` or `DataFrame` can be converted to a valid JSON string. Use `to_json` with optional parameters:

- `path_or_buf` : the pathname or buffer to write the output This can be `None` in which case a JSON string is returned
- `orient` :

  Series :

  - default is `index`
  - allowed values are {`split`, `records`, `index`}

DataFrame

- default is columns
- allowed values are {split, records, index, columns, values}

The format of the JSON string

split	dict like {index -> [index], columns -> [columns], data -> [values]}
records	list like [{column -> value}, ... , {column -> value}]
index	dict like {index -> {column -> value}}
columns	dict like {column -> {index -> value}}
values	just the values array

- date_format : string, type of date conversion, 'epoch' for timestamp, 'iso' for ISO8601.
- double_precision : The number of decimal places to use when encoding floating point values, default 10.
- force_ascii : force encoded string to be ASCII, default True.
- date_unit : The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us' or 'ns' for seconds, milliseconds, microseconds and nanoseconds respectively. Default 'ms'.
- default_handler : The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.

Note NaN's, NaT's and None will be converted to null and datetime objects will be converted based on the date_format and date_unit parameters.

```
In [143]: dfj = DataFrame(randn(5, 2), columns=list('AB'))

In [144]: json = dfj.to_json()

In [145]: json
Out[145]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.0061535699,"4":0.895717
```

Orient Options

There are a number of different options for the format of the resulting JSON file / string. Consider the following DataFrame and Series:

```
In [146]: dfjo = DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),
   .....:                  columns=list('ABC'), index=list('xyz'))
   .....:

In [147]: dfjo
Out[147]:
   A  B  C
x  1  4  7
y  2  5  8
z  3  6  9

In [148]: sjo = Series(dict(x=15, y=16, z=17), name='D')

In [149]: sjo
Out[149]:
x    15
y    16
z    17
Name: D, dtype: int64
```

Column oriented (the default for `DataFrame`) serializes the data as nested JSON objects with column labels acting as the primary index:

```
In [150]: dfjo.to_json(orient="columns")
Out[150]: '{"A":{"x":1,"y":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:

```
In [151]: dfjo.to_json(orient="index")
Out[151]: '{"x":{"A":1,"B":4,"C":7},"y":{"A":2,"B":5,"C":8},"z":{"A":3,"B":6,"C":9}}'

In [152]: sjo.to_json(orient="index")
Out[152]: '{"x":15,"y":16,"z":17}'
```

Record oriented serializes the data to a JSON array of column -> value records, index labels are not included. This is useful for passing DataFrame data to plotting libraries, for example the JavaScript library d3.js:

```
In [153]: dfjo.to_json(orient="records")
Out[153]: '[{"A":1,"B":4,"C":7},{"A":2,"B":5,"C":8},{"A":3,"B":6,"C":9}]'

In [154]: sjo.to_json(orient="records")
Out[154]: '[15,16,17]'
```

Value oriented is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

```
In [155]: dfjo.to_json(orient="values")
Out[155]: '[[1,4,7],[2,5,8],[3,6,9]]'
```

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for `Series`:

```
In [156]: dfjo.to_json(orient="split")
Out[156]: '{"columns":["A","B","C"],"index":["x","y","z"],"data":[[1,4,7],[2,5,8],[3,6,9]]}'

In [157]: sjo.to_json(orient="split")
Out[157]: '{"name":"D","index":["x","y","z"],"data":[15,16,17]}'
```

Note: Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the *split* option as it uses ordered containers.

Date Handling

Writing in ISO date format

```
In [158]: dfd = DataFrame(randn(5, 2), columns=list('AB'))

In [159]: dfd['date'] = Timestamp('20130101')

In [160]: dfd = dfd.sort_index(1, ascending=False)

In [161]: json = dfd.to_json(date_format='iso')

In [162]: json
Out[162]: '{"date":{"0":"2013-01-01T00:00:00.000Z","1":"2013-01-01T00:00:00.000Z","2":"2013-01-01T00
```

Writing in ISO date format, with microseconds

```
In [163]: json = dfd.to_json(date_format='iso', date_unit='us')

In [164]: json
Out[164]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z","2":"2013-01-
```

Epoch timestamps, in seconds

```
In [165]: json = dfd.to_json(date_format='epoch', date_unit='s')

In [166]: json
Out[166]: '{"date":{"0":1356998400,"1":1356998400,"2":1356998400,"3":1356998400,"4":1356998400},"B":
```

Writing to a file, with a date index and a date column

```
In [167]: dfj2 = dfj.copy()

In [168]: dfj2['date'] = Timestamp('20130101')

In [169]: dfj2['ints'] = list(range(5))

In [170]: dfj2['bools'] = True

In [171]: dfj2.index = date_range('20130101', periods=5)

In [172]: dfj2.to_json('test.json')

In [173]: open('test.json').read()
Out[173]: '{"A":{"1356998400000":-1.2945235903,"1357084800000":0.2766617129,"1357171200000":-0.01395
```

Fallback Behavior

If the JSON serializer cannot handle the container contents directly it will fallback in the following manner:

- if a `toDict` method is defined by the unrecognised object then that will be called and its returned `dict` will be JSON serialized.
- if a `default_handler` has been passed to `to_json` that will be called to convert the object.
- otherwise an attempt is made to convert the object to a `dict` by parsing its contents. However if the object is complex this will often fail with an `OverflowError`.

Your best bet when encountering `OverflowError` during serialization is to specify a `default_handler`. For example `timedelta` can cause problems:

```
In [141]: from datetime import timedelta

In [142]: dftd = DataFrame([timedelta(23), timedelta(seconds=5), 42])

In [143]: dftd.to_json()

---------------------------------------------------------------------------
OverflowError                             Traceback (most recent call last)
OverflowError: Maximum recursion level reached
```

which can be dealt with by specifying a simple `default_handler`:

```
In [174]: dftd.to_json(default_handler=str)
Out[174]: '{"0":{"0":1987200000,"1":5000,"2":42}}'
```

```
In [175]: def my_handler(obj):
   .....:     return obj.total_seconds()
   .....:
```

24.2.2 Reading JSON

Reading a JSON string to pandas object can take a number of parameters. The parser will try to parse a `DataFrame` if `typ` is not supplied or is `None`. To explicitly force `Series` parsing, pass `typ=series`

- `filepath_or_buffer` : a **VALID** JSON string or file handle / StringIO. The string could be a URL. Valid URL schemes include http, ftp, S3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.json
- `typ` : type of object to recover (series or frame), default 'frame'
- `orient` :

  Series :

  - default is `index`
  - allowed values are {`split`, `records`, `index`}

  DataFrame

  - default is `columns`
  - allowed values are {`split`, `records`, `index`, `columns`, `values`}

  The format of the JSON string

`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

- `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.

The parser will raise one of `ValueError/TypeError/AssertionError` if the JSON is not parseable.

If a non-default `orient` was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see Orient Options for an overview.

Data Conversion

The default of `convert_axes=True`, `dtype=True`, and `convert_dates=True` will try to parse the axes, and all of the data into appropriate types, including dates. If you need to override specific dtypes, pass a dict to `dtype`. `convert_axes` should only be set to `False` if you need to preserve string-like numbers (e.g. '1', '2') in an axes.

Note: Large integer values may be converted to dates if `convert_dates=True` and the data and / or column labels appear 'date-like'. The exact threshold depends on the `date_unit` specified.

Warning: When reading JSON data, automatic coercing into dtypes has some quirks:

- an index can be reconstructed in a different order from serialization, that is, the returned order is not guaranteed to be the same as before serialization
- a column that was `float` data will be converted to `integer` if it can be done safely, e.g. a column of `1.`
- bool columns will be converted to `integer` on reconstruction

Thus there are times where you may want to specify specific dtypes via the `dtype` keyword argument.

Reading from a JSON string:

```
In [176]: pd.read_json(json)
Out[176]:
          A         B       date
0 -1.206412  2.565646 2013-01-01
1  1.431256  1.340309 2013-01-01
2 -1.170299 -0.226169 2013-01-01
3  0.410835  0.813850 2013-01-01
4  0.132003 -0.827317 2013-01-01
```

Reading from a file:

```
In [177]: pd.read_json('test.json')
Out[177]:
                   A         B bools       date  ints
2013-01-01 -1.294524  0.413738  True 2013-01-01     0
2013-01-02  0.276662 -0.472035  True 2013-01-01     1
2013-01-03 -0.013960 -0.362543  True 2013-01-01     2
2013-01-04 -0.006154 -0.923061  True 2013-01-01     3
2013-01-05  0.895717  0.805244  True 2013-01-01     4
```

Don't convert any data (but still convert axes and dates):

```
In [178]: pd.read_json('test.json', dtype=object).dtypes
Out[178]:
A        object
B        object
bools    object
date     object
ints     object
dtype: object
```

Specify dtypes for conversion:

```
In [179]: pd.read_json('test.json', dtype={'A' : 'float32', 'bools' : 'int8'}).dtypes
Out[179]:
A               float32
B               float64
bools              int8
date     datetime64[ns]
```

```
ints              int64
dtype: object
```

Preserve string indices:

```
In [180]: si = DataFrame(np.zeros((4, 4)),
   .....:           columns=list(range(4)),
   .....:           index=[str(i) for i in range(4)])
   .....:

In [181]: si
Out[181]:
   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 [182]: si.index
Out[182]: Index([u'0', u'1', u'2', u'3'], dtype='object')

In [183]: si.columns
Out[183]: Int64Index([0, 1, 2, 3], dtype='int64')

In [184]: json = si.to_json()

In [185]: sij = pd.read_json(json, convert_axes=False)

In [186]: sij
Out[186]:
   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 [187]: sij.index
Out[187]: Index([u'0', u'1', u'2', u'3'], dtype='object')

In [188]: sij.columns
Out[188]: Index([u'0', u'1', u'2', u'3'], dtype='object')
```

Dates written in nanoseconds need to be read back in nanoseconds:

```
In [189]: json = dfj2.to_json(date_unit='ns')

# Try to parse timestamps as millseconds -> Won't Work
In [190]: dfju = pd.read_json(json, date_unit='ms')

In [191]: dfju
Out[191]:
                     A         B bools                 date  ints
1.356998e+18 -1.294524  0.413738  True  1356998400000000000     0
1.357085e+18  0.276662 -0.472035  True  1356998400000000000     1
1.357171e+18 -0.013960 -0.362543  True  1356998400000000000     2
1.357258e+18 -0.006154 -0.923061  True  1356998400000000000     3
1.357344e+18  0.895717  0.805244  True  1356998400000000000     4

# Let pandas detect the correct precision
```

```
In [192]: dfju = pd.read_json(json)

In [193]: dfju
Out[193]:
                   A         B bools       date  ints
2013-01-01 -1.294524  0.413738  True 2013-01-01     0
2013-01-02  0.276662 -0.472035  True 2013-01-01     1
2013-01-03 -0.013960 -0.362543  True 2013-01-01     2
2013-01-04 -0.006154 -0.923061  True 2013-01-01     3
2013-01-05  0.895717  0.805244  True 2013-01-01     4

# Or specify that all timestamps are in nanoseconds
In [194]: dfju = pd.read_json(json, date_unit='ns')

In [195]: dfju
Out[195]:
                   A         B bools       date  ints
2013-01-01 -1.294524  0.413738  True 2013-01-01     0
2013-01-02  0.276662 -0.472035  True 2013-01-01     1
2013-01-03 -0.013960 -0.362543  True 2013-01-01     2
2013-01-04 -0.006154 -0.923061  True 2013-01-01     3
2013-01-05  0.895717  0.805244  True 2013-01-01     4
```

The Numpy Parameter

Note: This supports numeric data only. Index and columns labels may be non-numeric, e.g. strings, dates etc.

If `numpy=True` is passed to `read_json` an attempt will be made to sniff an appropriate dtype during deserialization and to subsequently decode directly to numpy arrays, bypassing the need for intermediate Python objects.

This can provide speedups if you are deserialising a large amount of numeric data:

```
In [196]: randfloats = np.random.uniform(-100, 1000, 10000)

In [197]: randfloats.shape = (1000, 10)

In [198]: dffloats = DataFrame(randfloats, columns=list('ABCDEFGHIJ'))

In [199]: jsonfloats = dffloats.to_json()

In [200]: timeit read_json(jsonfloats)
10 loops, best of 3: 23.4 ms per loop

In [201]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 6.39 ms per loop
```

The speedup is less noticeable for smaller datasets:

```
In [202]: jsonfloats = dffloats.head(100).to_json()

In [203]: timeit read_json(jsonfloats)
100 loops, best of 3: 6 ms per loop

In [204]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 3.38 ms per loop
```

Warning: Direct numpy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The dtype is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.

24.2.3 Normalization

New in version 0.13.0.

pandas provides a utility function to take a dict or list of dicts and *normalize* this semi-structured data into a flat table.

```
In [205]: from pandas.io.json import json_normalize

In [206]: data = [{'state': 'Florida',
   .....:           'shortname': 'FL',
   .....:           'info': {
   .....:                'governor': 'Rick Scott'
   .....:           },
   .....:           'counties': [{'name': 'Dade', 'population': 12345},
   .....:                       {'name': 'Broward', 'population': 40000},
   .....:                       {'name': 'Palm Beach', 'population': 60000}]},
   .....:          {'state': 'Ohio',
   .....:           'shortname': 'OH',
   .....:           'info': {
   .....:                'governor': 'John Kasich'
   .....:           },
   .....:           'counties': [{'name': 'Summit', 'population': 1234},
   .....:                        {'name': 'Cuyahoga', 'population': 1337}]}]
   .....:

In [207]: json_normalize(data, 'counties', ['state', 'shortname', ['info', 'governor']])
Out[207]:
         name  population info.governor    state shortname
0        Dade       12345    Rick Scott  Florida        FL
1     Broward       40000    Rick Scott  Florida        FL
2  Palm Beach       60000    Rick Scott  Florida        FL
3      Summit        1234   John Kasich     Ohio        OH
4    Cuyahoga        1337   John Kasich     Ohio        OH
```

24.3 HTML

24.3.1 Reading HTML Content

Warning: We **highly encourage** you to read the *HTML parsing gotchas* regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

New in version 0.12.0.

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

```
In [208]: url = 'http://www.fdic.gov/bank/individual/failed/banklist.html'

In [209]: dfs = read_html(url)

In [210]: dfs
Out[210]:
[                                 Bank Name         City  ST   CERT  \
 0                           Edgebrook Bank      Chicago  IL  57772
 1                     Doral BankEn Espanol     San Juan  PR  32102
 2        Capitol City Bank & Trust Company      Atlanta  GA  33938
 3                  Highland Community Bank      Chicago  IL  20290
 4         First National Bank of Crestview    Crestview  FL  17557
 5                       Northern Star Bank      Mankato  MN  34983
 6    Frontier Bank, FSB D/B/A El Paseo Bank  Palm Desert  CA  34738
 ..                                     ...          ...  ..    ...
 532               Hamilton Bank, NAEn Espanol        Miami  FL  24382
 533                   Sinclair National Bank     Gravette  AR  34248
 534                       Superior Bank, FSB     Hinsdale  IL  32646
 535                      Malta National Bank        Malta  OH   6629
 536          First Alliance Bank & Trust Co.   Manchester  NH  34264
 537        National State Bank of Metropolis   Metropolis  IL   3815
 538                         Bank of Honolulu     Honolulu  HI  21029

                   Acquiring Institution       Closing Date  \
 0                Republic Bank of Chicago        May 8, 2015
 1            Banco Popular de Puerto Rico  February 27, 2015
 2    First-Citizens Bank & Trust Company  February 13, 2015
 3               United Fidelity Bank, fsb   January 23, 2015
 4                          First NBC Bank   January 16, 2015
 5                               BankVista  December 19, 2014
 6      Bank of Southern California, N.A.   November 7, 2014
 ..                                    ...                ...
 532     Israel Discount Bank of New York   January 11, 2002
 533                  Delta Trust & Bank  September 7, 2001
 534                 Superior Federal, FSB      July 27, 2001
 535                    North Valley Bank        May 3, 2001
 536 Southern New Hampshire Bank & Trust   February 2, 2001
 537                Banterra Bank of Marion  December 14, 2000
 538                   Bank of the Orient   October 13, 2000

          Updated Date Loss Share Type Agreement Terminated Termination Date
 0        May 19, 2015             NaN                  NaN              NaN
 1        May 13, 2015             NaN                  NaN              NaN
 2      April 21, 2015            none                  NaN              NaN
 3      April 21, 2015            none                  NaN              NaN
 4      April 21, 2015            none                  NaN              NaN
 5      March 26, 2015            none                  NaN              NaN
 6      March 26, 2015            none                  NaN              NaN
 ..                ...             ...                  ...              ...
 532      June 5, 2012            none                  NaN              NaN
```

```
533  February 10, 2004           none               NaN              NaN
534    August 19, 2014           none               NaN              NaN
535  November 18, 2002           none               NaN              NaN
536  February 18, 2003           none               NaN              NaN
537     March 17, 2005           none               NaN              NaN
538     March 17, 2005           none               NaN              NaN

[539 rows x 10 columns]
```

Note: The data from the above URL changes every Monday so the resulting data above and the data below may be slightly different.

Read in the content of the file from the above URL and pass it to `read_html` as a string

```
In [211]: with open(file_path, 'r') as f:
   .....:     dfs = read_html(f.read())
   .....:

In [212]: dfs
Out[212]:
[                                    Bank Name          City  ST   CERT  \
 0    Banks of Wisconsin d/b/a Bank of Kenosha       Kenosha  WI  35386
 1                        Central Arizona Bank    Scottsdale  AZ  34527
 2                                Sunrise Bank      Valdosta  GA  58185
 3                       Pisgah Community Bank     Asheville  NC  58701
 4                         Douglas County Bank  Douglasville  GA  21649
 5                                Parkway Bank        Lenoir  NC  57158
 6                      Chipola Community Bank      Marianna  FL  58034
 ..                                        ...           ...  ..    ...
 499               Hamilton Bank, NAEn Espanol         Miami  FL  24382
 500                    Sinclair National Bank      Gravette  AR  34248
 501                        Superior Bank, FSB      Hinsdale  IL  32646
 502                       Malta National Bank         Malta  OH   6629
 503           First Alliance Bank & Trust Co.    Manchester  NH  34264
 504         National State Bank of Metropolis    Metropolis  IL   3815
 505                          Bank of Honolulu      Honolulu  HI  21029

                   Acquiring Institution       Closing Date       Updated Date
 0                   North Shore Bank, FSB       May 31, 2013       May 31, 2013
 1                      Western State Bank       May 14, 2013       May 20, 2013
 2                            Synovus Bank       May 10, 2013       May 21, 2013
 3                      Capital Bank, N.A.       May 10, 2013       May 14, 2013
 4                     Hamilton State Bank     April 26, 2013       May 16, 2013
 5       CertusBank, National Association     April 26, 2013       May 17, 2013
 6          First Federal Bank of Florida     April 19, 2013       May 16, 2013
 ..                                    ...                ...                ...
 499     Israel Discount Bank of New York   January 11, 2002       June 5, 2012
 500                   Delta Trust & Bank  September 7, 2001  February 10, 2004
 501                 Superior Federal, FSB      July 27, 2001       June 5, 2012
 502                     North Valley Bank        May 3, 2001  November 18, 2002
 503  Southern New Hampshire Bank & Trust   February 2, 2001  February 18, 2003
 504               Banterra Bank of Marion  December 14, 2000     March 17, 2005
 505                   Bank of the Orient   October 13, 2000     March 17, 2005

 [506 rows x 7 columns]]
```

You can even pass in an instance of `StringIO` if you so desire

```
In [213]: with open(file_path, 'r') as f:
   .....:     sio = StringIO(f.read())
   .....:

In [214]: dfs = read_html(sio)

In [215]: dfs
Out[215]:
[                                   Bank Name          City  ST   CERT  \
 0    Banks of Wisconsin d/b/a Bank of Kenosha       Kenosha  WI  35386
 1                        Central Arizona Bank    Scottsdale  AZ  34527
 2                                Sunrise Bank      Valdosta  GA  58185
 3                       Pisgah Community Bank     Asheville  NC  58701
 4                         Douglas County Bank  Douglasville  GA  21649
 5                                Parkway Bank        Lenoir  NC  57158
 6                      Chipola Community Bank      Marianna  FL  58034
 ..                                        ...           ...  ..    ...
 499              Hamilton Bank, NAEn Espanol         Miami  FL  24382
 500                     Sinclair National Bank      Gravette  AR  34248
 501                         Superior Bank, FSB      Hinsdale  IL  32646
 502                        Malta National Bank         Malta  OH   6629
 503            First Alliance Bank & Trust Co.    Manchester  NH  34264
 504          National State Bank of Metropolis    Metropolis  IL   3815
 505                           Bank of Honolulu      Honolulu  HI  21029

                   Acquiring Institution       Closing Date       Updated Date
 0                   North Shore Bank, FSB       May 31, 2013       May 31, 2013
 1                      Western State Bank       May 14, 2013       May 20, 2013
 2                            Synovus Bank       May 10, 2013       May 21, 2013
 3                      Capital Bank, N.A.       May 10, 2013       May 14, 2013
 4                     Hamilton State Bank     April 26, 2013       May 16, 2013
 5       CertusBank, National Association     April 26, 2013       May 17, 2013
 6          First Federal Bank of Florida     April 19, 2013       May 16, 2013
 ..                                    ...                ...                ...
 499     Israel Discount Bank of New York   January 11, 2002        June 5, 2012
 500                   Delta Trust & Bank  September 7, 2001   February 10, 2004
 501                 Superior Federal, FSB      July 27, 2001        June 5, 2012
 502                     North Valley Bank        May 3, 2001  November 18, 2002
 503  Southern New Hampshire Bank & Trust    February 2, 2001  February 18, 2003
 504                 Banterra Bank of Marion  December 14, 2000     March 17, 2005
 505                    Bank of the Orient   October 13, 2000     March 17, 2005

 [506 rows x 7 columns]]
```

Note: The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn't run, please do not hesitate to report it over on pandas GitHub issues page.

Read a URL and match a table that contains specific text

```
match = 'Metcalf Bank'
df_list = read_html(url, match=match)
```

Specify a header row (by default `<th>` elements are used to form the column index); if specified, the header row is taken from the data minus the parsed header elements (`<th>` elements).

```
dfs = read_html(url, header=0)
```

Specify an index column

```
dfs = read_html(url, index_col=0)
```

Specify a number of rows to skip

```
dfs = read_html(url, skiprows=0)
```

Specify a number of rows to skip using a list (`xrange` (Python 2 only) works as well)

```
dfs = read_html(url, skiprows=range(2))
```

Don't infer numeric and date types

```
dfs = read_html(url, infer_types=False)
```

Specify an HTML attribute

```
dfs1 = read_html(url, attrs={'id': 'table'})
dfs2 = read_html(url, attrs={'class': 'sortable'})
print(np.array_equal(dfs1[0], dfs2[0]))  # Should be True
```

Use some combination of the above

```
dfs = read_html(url, match='Metcalf Bank', index_col=0)
```

Read in pandas `to_html` output (with some loss of floating point precision)

```
df = DataFrame(randn(2, 2))
s = df.to_html(float_format='{0:.40g}'.format)
dfin = read_html(s, index_col=0)
```

The `lxml` backend will raise an error on a failed parse if that is the only parser you provide (if you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings)

```
dfs = read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml'])
```

or

```
dfs = read_html(url, 'Metcalf Bank', index_col=0, flavor='lxml')
```

However, if you have bs4 and html5lib installed and pass `None` or `['lxml', 'bs4']` then the parse will most likely succeed. Note that *as soon as a parse succeeds, the function will return*.

```
dfs = read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml', 'bs4'])
```

24.3.2 Writing to HTML files

`DataFrame` objects have an instance method `to_html` which renders the contents of the `DataFrame` as an HTML table. The function arguments are as in the method `to_string` described above.

Note: Not all of the possible options for `DataFrame.to_html` are shown here for brevity's sake. See `to_html()` for the full set of options.

```
In [216]: df = DataFrame(randn(2, 2))

In [217]: df
Out[217]:
          0         1
0 -0.184744  0.496971
1 -0.856240  1.857977

In [218]: print(df.to_html())  # raw html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

HTML:

The `columns` argument will limit the columns shown

```
In [219]: print(df.to_html(columns=[0]))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
    </tr>
  </tbody>
</table>
```

HTML:

`float_format` takes a Python callable to control the precision of floating point values

```
In [220]: print(df.to_html(float_format='{0:.10f}'.format))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.1847438576</td>
      <td>0.4969711327</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.8562396763</td>
      <td>1.8579766508</td>
    </tr>
  </tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off

```
In [221]: print(df.to_html(bold_rows=False))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <td>0</td>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <td>1</td>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

The `classes` argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are *appended* to the existing `'dataframe'` class.

```
In [222]: print(df.to_html(classes=['awesome_table_class', 'even_more_awesome_class']))
<table border="1" class="dataframe awesome_table_class even_more_awesome_class">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
```

```
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

Finally, the `escape` argument allows you to control whether the "<", ">" and "&" characters escaped in the resulting HTML (by default it is `True`). So to get the HTML without escaped characters pass `escape=False`

```
In [223]: df = DataFrame({'a': list('&<>'), 'b': randn(3)})
```

Escaped:

```
In [224]: print(df.to_html())
<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>
```

Not escaped:

```
In [225]: 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>&</td>
      <td>-0.474063</td>
    </tr>
    <tr>
      <th>1</th>
      <td><</td>
      <td>-0.230305</td>
    </tr>
    <tr>
      <th>2</th>
      <td>></td>
      <td>-0.400654</td>
    </tr>
  </tbody>
</table>
```

Note: Some browsers may not show a difference in the rendering of the previous two HTML tables.

24.4 Excel files

The `read_excel()` method can read Excel 2003 (`.xls`) and Excel 2007 (`.xlsx`) files using the `xlrd` Python module and use the same parsing code as the above to convert tabular data into a DataFrame. See the *cookbook* for some advanced strategies

24.4.1 Reading Excel Files

New in version 0.16.

`read_excel` can read more than one sheet, by setting `sheetname` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets.

New in version 0.13.

Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

New in version 0.12.

`ExcelFile` has been moved to the top level namespace.

There are two approaches to reading an excel file. The `read_excel` function and the `ExcelFile` class. `read_excel` is for reading one file with file-specific arguments (ie. identical data formats across sheets). `ExcelFile` is for reading one file with sheet-specific arguments (ie. various data formats across sheets). Choosing the approach is largely a question of code readability and execution speed.

Equivalent class and function approaches to read a single sheet:

```
# using the ExcelFile class
xls = pd.ExcelFile('path_to_file.xls')
data = xls.parse('Sheet1', index_col=None, na_values=['NA'])
```

```
# using the read_excel function
data = read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Equivalent class and function approaches to read multiple sheets:

```
data = {}
# For when Sheet1's format differs from Sheet2
xls = pd.ExcelFile('path_to_file.xls')
data['Sheet1'] = xls.parse('Sheet1', index_col=None, na_values=['NA'])
data['Sheet2'] = xls.parse('Sheet2', index_col=1)

# For when Sheet1's format is identical to Sheet2
data = read_excel('path_to_file.xls', ['Sheet1','Sheet2'], index_col=None, na_values=['NA'])
```

Specifying Sheets

Note: The second argument is `sheetname`, not to be confused with `ExcelFile.sheet_names`

Note: An ExcelFile's attribute `sheet_names` provides access to a list of sheets.

- The arguments `sheetname` allows specifying the sheet or sheets to read.
- The default value for `sheetname` is 0, indicating to read the first sheet
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a `None` to return a dictionary of all available sheets.

```
# Returns a DataFrame
read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Using the sheet index:

```
# Returns a DataFrame
read_excel('path_to_file.xls', 0, index_col=None, na_values=['NA'])
```

Using all default values:

```
# Returns a DataFrame
read_excel('path_to_file.xls')
```

Using None to get all sheets:

```
# Returns a dictionary of DataFrames
read_excel('path_to_file.xls',sheetname=None)
```

Using a list to get multiple sheets:

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
read_excel('path_to_file.xls',sheetname=['Sheet1',3])
```

Parsing Specific Columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. *read_excel* takes a *parse_cols* keyword to allow you to specify a subset of columns to parse.

If *parse_cols* is an integer, then it is assumed to indicate the last column to be parsed.

```
read_excel('path_to_file.xls', 'Sheet1', parse_cols=2)
```

If *parse_cols* is a list of integers, then it is assumed to be the file column indices to be parsed.

```
read_excel('path_to_file.xls', 'Sheet1', parse_cols=[0, 2, 3])
```

Cell Converters

It is possible to transform the contents of Excel cells via the *converters* option. For instance, to convert a column to boolean:

```
read_excel('path_to_file.xls', 'Sheet1', converters={'MyBools': bool})
```

This options handles missing values and treats exceptions in the converters as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```
cfun = lambda x: int(x) if x else -1
read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

24.4.2 Writing Excel Files

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:

```
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The DataFrame will be written in a way that tries to mimic the REPL output. One difference from 0.12.0 is that the `index_label` will be placed in the second row instead of the first. You can get the previous behaviour by setting the `merge_cells` option in `to_excel()` to `False`:

```
df.to_excel('path_to_file.xlsx', index_label='label', merge_cells=False)
```

The Panel class also has a `to_excel` instance method, which writes each DataFrame in the Panel to a separate sheet.

In order to write separate DataFrames to separate sheets in a single Excel file, one can pass an `ExcelWriter`.

```
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.

24.4.3 Excel writer engines

New in version 0.13.

pandas chooses an Excel writer via two methods:

1. the engine keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the XlsxWriter for .xlsx and openpyxl for .xlsm files and xlwt for .xls files. If you have multiple engines installed, you can set the default engine through *setting the config options* io.excel.xlsx.writer and io.excel.xls.writer. pandas will fall back on openpyxl for .xlsx files if Xlsxwriter is not available.

To specify which writer you want to use, you can pass an engine keyword argument to to_excel and to ExcelWriter. The built-in engines are:

- openpyxl: This includes stable support for OpenPyxl 1.6.1 up to but not including 2.0.0, and experimental support for OpenPyxl 2.0.0 and later.
- xlsxwriter
- xlwt

```
# By setting the 'engine' in the DataFrame and Panel 'to_excel()' methods.
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1', engine='xlsxwriter')

# By setting the 'engine' in the ExcelWriter constructor.
writer = ExcelWriter('path_to_file.xlsx', engine='xlsxwriter')

# Or via pandas configuration.
from pandas import options
options.io.excel.xlsx.writer = 'xlsxwriter'

df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

24.5 Clipboard

A handy way to grab data is to use the read_clipboard method, which takes the contents of the clipboard buffer and passes them to the read_table method. For instance, you can copy the following text to the clipboard (CTRL-C on many operating systems):

```
  A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

And then import the data directly to a DataFrame by calling:

```
clipdf = pd.read_clipboard()
```

```
In [226]: clipdf
Out[226]:
   A  B  C
x  1  4  p
y  2  5  q
z  3  6  r
```

The `to_clipboard` method can be used to write the contents of a DataFrame to the clipboard. Following which you can paste the clipboard contents into other applications (CTRL-V on many operating systems). Here we illustrate writing a DataFrame into clipboard and reading it back.

```
In [227]: df=pd.DataFrame(randn(5,3))

In [228]: df
Out[228]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129

In [229]: df.to_clipboard()

In [230]: pd.read_clipboard()
Out[230]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129
```

We can see that we got the same content back, which we had earlier written to the clipboard.

Note: You may need to install xclip or xsel (with gtk or PyQt4 modules) on Linux to use these methods.

24.6 Pickling

All pandas objects are equipped with `to_pickle` methods which use Python's `cPickle` module to save data structures to disk using the pickle format.

```
In [231]: df
Out[231]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129

In [232]: df.to_pickle('foo.pkl')
```

The `read_pickle` function in the `pandas` namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```
In [233]: read_pickle('foo.pkl')
Out[233]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
```

```
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129
```

Warning: Loading pickled data received from untrusted sources can be unsafe.
See: http://docs.python.org/2.7/library/pickle.html

Warning: Several internal refactorings, 0.13 (*Series Refactoring*), and 0.15 (*Index Refactoring*), preserve compatibility with pickles created prior to these versions. However, these must be read with `pd.read_pickle`, rather than the default python `pickle.load`. See this question for a detailed explanation.

Note: These methods were previously `pd.save` and `pd.load`, prior to 0.12.0, and are now deprecated.

24.7 msgpack (experimental)

New in version 0.13.0.

Starting in 0.13.0, pandas is supporting the `msgpack` format for object serialization. This is a lightweight portable binary format, similar to binary JSON, that is highly space efficient, and provides good performance both on the writing (serialization), and reading (deserialization).

Warning: This is a very new feature of pandas. We intend to provide certain optimizations in the io of the `msgpack` data. Since this is marked as an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```
In [234]: df = DataFrame(np.random.rand(5,2),columns=list('AB'))

In [235]: df.to_msgpack('foo.msg')

In [236]: pd.read_msgpack('foo.msg')
Out[236]:
          A         B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
3  0.290293  0.710783
4  0.988593  0.062106

In [237]: s = Series(np.random.rand(5),index=date_range('20130101',periods=5))
```

You can pass a list of objects and you will receive them back on deserialization.

```
In [238]: pd.to_msgpack('foo.msg', df, 'foo', np.array([1,2,3]), s)

In [239]: pd.read_msgpack('foo.msg')
Out[239]:
[          A         B
 0  0.154336  0.710999
 1  0.398096  0.765220
 2  0.586749  0.293052
 3  0.290293  0.710783
 4  0.988593  0.062106, u'foo', array([1, 2, 3]), 2013-01-01    0.690810
 2013-01-02    0.235907
 2013-01-03    0.712756
```

```
 2013-01-04    0.119599
 2013-01-05    0.023493
 Freq: D, dtype: float64]
```

You can pass `iterator=True` to iterate over the unpacked results

```
In [240]: for o in pd.read_msgpack('foo.msg',iterator=True):
   .....:     print o
   .....:
          A         B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
3  0.290293  0.710783
4  0.988593  0.062106
foo
[1 2 3]
2013-01-01    0.690810
2013-01-02    0.235907
2013-01-03    0.712756
2013-01-04    0.119599
2013-01-05    0.023493
Freq: D, dtype: float64
```

You can pass `append=True` to the writer to append to an existing pack

```
In [241]: df.to_msgpack('foo.msg',append=True)

In [242]: pd.read_msgpack('foo.msg')
Out[242]:
[          A         B
 0  0.154336  0.710999
 1  0.398096  0.765220
 2  0.586749  0.293052
 3  0.290293  0.710783
 4  0.988593  0.062106, u'foo', array([1, 2, 3]), 2013-01-01    0.690810
 2013-01-02    0.235907
 2013-01-03    0.712756
 2013-01-04    0.119599
 2013-01-05    0.023493
 Freq: D, dtype: float64,           A         B
 0  0.154336  0.710999
 1  0.398096  0.765220
 2  0.586749  0.293052
 3  0.290293  0.710783
 4  0.988593  0.062106]
```

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.

```
In [243]: pd.to_msgpack('foo2.msg', { 'dict' : [ { 'df' : df }, { 'string' : 'foo' }, { 'scalar' : 1

In [244]: pd.read_msgpack('foo2.msg')
Out[244]:
{u'dict': ({u'df':           A         B
   0  0.154336  0.710999
   1  0.398096  0.765220
   2  0.586749  0.293052
```

```
   3  0.290293  0.710783
   4  0.988593  0.062106},
  {u'string': u'foo'},
  {u'scalar': 1.0},
  {u's': 2013-01-01    0.690810
   2013-01-02    0.235907
   2013-01-03    0.712756
   2013-01-04    0.119599
   2013-01-05    0.023493
   Freq: D, dtype: float64})}
```

24.7.1 Read/Write API

Msgpacks can also be read from and written to strings.

```
In [245]: df.to_msgpack()
Out[245]: '\x84\xa6blocks\x91\x86\xa5items\x86\xa4name\xc0\xa5dtype\x11\xa8compress\xc0\xa4data\x92\x
```

Furthermore you can concatenate the strings to produce a list of the original objects.

```
In [246]: pd.read_msgpack(df.to_msgpack() + s.to_msgpack())
Out[246]:
[          A         B
 0  0.154336  0.710999
 1  0.398096  0.765220
 2  0.586749  0.293052
 3  0.290293  0.710783
 4  0.988593  0.062106, 2013-01-01    0.690810
 2013-01-02    0.235907
 2013-01-03    0.712756
 2013-01-04    0.119599
 2013-01-05    0.023493
 Freq: D, dtype: float64]
```

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: As of version 0.15.0, pandas requires PyTables >= 3.0.0. Stores written with prior versions of pandas / PyTables >= 2.3 are fully compatible (this was the previous minimum PyTables required version).

Warning: There is a PyTables indexing bug which may appear when querying stores using an index. If you see a subset of results being returned, upgrade to PyTables >= 3.2. Stores created previously will need to be rewritten using the updated version.

```
In [247]: store = HDFStore('store.h5')

In [248]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
Empty
```

Objects can be written to the file just like adding key-value pairs to a dict:

```
In [249]: np.random.seed(1234)

In [250]: index = date_range('1/1/2000', periods=8)

In [251]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [252]: df = DataFrame(randn(8, 3), index=index,
   .....:                columns=['A', 'B', 'C'])
   .....:

In [253]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   .....:            major_axis=date_range('1/1/2000', periods=5),
   .....:            minor_axis=['A', 'B', 'C', 'D'])
   .....:

# store.put('s', s) is an equivalent method
In [254]: store['s'] = s

In [255]: store['df'] = df

In [256]: store['wp'] = wp

# the type of stored data
In [257]: store.root.wp._v_attrs.pandas_type
Out[257]: 'wide'

In [258]: store
Out[258]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame        (shape->[8,3])
/s             series       (shape->[5])
/wp            wide         (shape->[2,5,4])
```

In a current or later Python session, you can retrieve stored objects:

```
# store.get('df') is an equivalent method
In [259]: store['df']
Out[259]:
                   A         B         C
2000-01-01  0.887163  0.859588 -0.636524
2000-01-02  0.015696 -2.242685  1.150036
2000-01-03  0.991946  0.953324 -2.021255
2000-01-04 -0.334077  0.002118  0.405453
2000-01-05  0.289092  1.321158 -1.546906
2000-01-06 -0.202646 -0.655969  0.193421
2000-01-07  0.553439  1.318152 -0.469305
2000-01-08  0.675554 -1.817027 -0.183109

# dotted (attribute) access provides get as well
In [260]: store.df
Out[260]:
                   A         B         C
2000-01-01  0.887163  0.859588 -0.636524
2000-01-02  0.015696 -2.242685  1.150036
2000-01-03  0.991946  0.953324 -2.021255
2000-01-04 -0.334077  0.002118  0.405453
```

```
2000-01-05  0.289092  1.321158 -1.546906
2000-01-06 -0.202646 -0.655969  0.193421
2000-01-07  0.553439  1.318152 -0.469305
2000-01-08  0.675554 -1.817027 -0.183109
```

Deletion of the object specified by the key

```
# store.remove('wp') is an equivalent method
In [261]: del store['wp']

In [262]: store
Out[262]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df             frame        (shape->[8,3])
/s              series       (shape->[5])
```

Closing a Store, Context Manager

```
In [263]: store.close()

In [264]: store
Out[264]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
File is CLOSED

In [265]: store.is_open
Out[265]: False

# Working with, and automatically closing the store with the context
# manager
In [266]: with HDFStore('store.h5') as store:
   .....:     store.keys()
   .....:
```

24.8.1 Read/Write API

`HDFStore` supports an top-level API using `read_hdf` for reading and `to_hdf` for writing, similar to how `read_csv` and `to_csv` work. (new in 0.11.0)

```
In [267]: df_tl = DataFrame(dict(A=list(range(5)), B=list(range(5))))

In [268]: df_tl.to_hdf('store_tl.h5','table',append=True)

In [269]: read_hdf('store_tl.h5', 'table', where = ['index>2'])
Out[269]:
   A  B
3  3  3
4  4  4
```

24.8.2 Fixed Format

Note: This was prior to 0.13.0 the `Storer` format.

The examples above show storing using `put`, which write the HDF5 to `PyTables` in a fixed array format, called the `fixed` format. These types of stores are are **not** appendable once written (though you can simply remove them and rewrite). Nor are they **queryable**; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The `fixed` format stores offer very fast writing and slightly faster reading than `table` stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`

Warning: A `fixed` format will raise a `TypeError` if you try to retrieve using a `where` .

```
DataFrame(randn(10,2)).to_hdf('test_fixed.h5','df')

pd.read_hdf('test_fixed.h5','df',where='index>5')
TypeError: cannot pass a where specification when reading a fixed format.
           this store must be selected in its entirety
```

24.8.3 Table Format

`HDFStore` supports another `PyTables` format on disk, the `table` format. Conceptually a `table` is shaped very much like a DataFrame, with rows and columns. A `table` may be appended to in the same or other sessions. In addition, delete & query type operations are supported. This format is specified by `format='table'` or `format='t'` to `append` or `put` or `to_hdf`

New in version 0.13.

This format can be set as an option as well `pd.set_option('io.hdf.default_format','table')` to enable `put/append/to_hdf` to by default store in the `table` format.

```
In [270]: store = HDFStore('store.h5')

In [271]: df1 = df[0:4]

In [272]: df2 = df[4:]

# append data (creates a table automatically)
In [273]: store.append('df', df1)

In [274]: store.append('df', df2)

In [275]: store
Out[275]: 
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# select the entire object
In [276]: store.select('df')
Out[276]: 
                   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 [277]: store.root.df._v_attrs.pandas_type
Out[277]: '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*.

```
In [278]: store.put('foo/bar/bah', df)

In [279]: store.append('food/orange', df)

In [280]: store.append('food/apple',  df)

In [281]: store
Out[281]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                     frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah            frame        (shape->[8,3])
/food/apple             frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# a list of keys are returned
In [282]: store.keys()
Out[282]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [283]: store.remove('food')

In [284]: store
Out[284]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                     frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah            frame        (shape->[8,3])
```

24.8.5 Storing Mixed Types in a Table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent appends will truncate strings at this length.

Passing `min_itemsize={`values`: size}` as a parameter to append will set a larger minimum for the string columns. Storing `floats, strings, ints, bools, datetime64` are currently supported. For string columns, passing `nan_rep = 'nan'` to append will change the default nan representation on disk (which converts to/from *np.nan*), this defaults to *nan*.

```
In [285]: df_mixed = DataFrame({ 'A' : randn(8),
   .....:                        'B' : randn(8),
```

```
   .....:                          'C' : np.array(randn(8),dtype='float32'),
   .....:                          'string' :'string',
   .....:                          'int' : 1,
   .....:                          'bool' : True,
   .....:                          'datetime64' : Timestamp('20010102')},
   .....:                        index=list(range(8)))
   .....:

In [286]: df_mixed.ix[3:5,['A', 'B', 'string', 'datetime64']] = np.nan

In [287]: store.append('df_mixed', df_mixed, min_itemsize = {'values': 50})

In [288]: df_mixed1 = store.select('df_mixed')

In [289]: df_mixed1
Out[289]:
          A         B         C  bool datetime64  int  string
0  0.704721 -1.152659 -0.430096  True 2001-01-02    1  string
1 -0.785435  0.631979  0.767369  True 2001-01-02    1  string
2  0.462060  0.039513  0.984920  True 2001-01-02    1  string
3       NaN       NaN  0.270836  True        NaT    1     NaN
4       NaN       NaN  1.391986  True        NaT    1     NaN
5       NaN       NaN  0.079842  True        NaT    1     NaN
6  2.007843  0.152631 -0.399965  True 2001-01-02    1  string
7  0.226963  0.164530 -1.027851  True 2001-01-02    1  string

In [290]: df_mixed1.get_dtype_counts()
Out[290]:
bool              1
datetime64[ns]    1
float32           1
float64           2
int64             1
object            1
dtype: int64

# we have provided a minimum string column size
In [291]: store.root.df_mixed.table
Out[291]:
/df_mixed/table (Table(8,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=1),
  "values_block_1": Float32Col(shape=(1,), dflt=0.0, pos=2),
  "values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
  "values_block_3": Int64Col(shape=(1,), dflt=0, pos=4),
  "values_block_4": BoolCol(shape=(1,), dflt=False, pos=5),
  "values_block_5": StringCol(itemsize=50, shape=(1,), dflt='', pos=6)}
  byteorder := 'little'
  chunkshape := (689,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

24.8.6 Storing Multi-Index DataFrames

Storing multi-index dataframes as tables is very similar to storing/selecting from homogeneous index DataFrames.

```
In [292]: 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 [293]: df_mi = DataFrame(np.random.randn(10, 3), index=index,
   .....:                   columns=['A', 'B', 'C'])
   .....:

In [294]: df_mi
Out[294]:
                  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 [295]: store.append('df_mi',df_mi)

In [296]: store.select('df_mi')
Out[296]:
                  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

# the levels are automatically included as data columns
In [297]: store.select('df_mi', 'foo=bar')
Out[297]:
                A         B         C
foo bar
bar one  0.503592  0.285296  0.484288
    two  1.363482 -0.781105 -0.468018
```

24.8.7 Querying a Table

Warning: This query capabilities have changed substantially starting in `0.13.0`. Queries from prior version are accepted (with a `DeprecationWarning`) printed if its not string-like.

`select` and `delete` operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the `Term` class under the hood, as a boolean expression.

- `index` and `columns` are supported indexers of a DataFrame
- `major_axis`, `minor_axis`, and `items` are supported indexers of the Panel
- if `data_columns` are specified, these can be used as additional indexers

Valid comparison operators are:

- `=, ==, !=, >, >=, <, <=`

Valid boolean expressions are combined with:

- `|` : or
- `&` : and
- `(` and `)` : for grouping

These rules are similar to how boolean expressions are used in pandas for indexing.

Note:

- = will be automatically expanded to the comparison operator ==
- ~ is the not operator, but can only be used in very limited circumstances
- If a list/tuple of expressions is passed they will be combined via `&`

The following are valid expressions:

- `’index>=date’`
- `"columns=[’A’, ’D’]"`
- `"columns in [’A’, ’D’]"`
- `’columns=A’`
- `’columns==A’`
- `"~(columns=[’A’,’B’])"`
- `’index>df.index[3] & string="bar"’`
- `’(index>df.index[3] & index<=df.index[6]) | string="bar"’`
- `"ts>=Timestamp(’2012-02-01’)"`
- `"major_axis>=20130101"`

The `indexers` are on the left-hand side of the sub-expression:

- `columns`, `major_axis`, `ts`

The right-hand side of the sub-expression (after a comparison operator) can be:

- functions that will be evaluated, e.g. `Timestamp(’2012-02-01’)`
- strings, e.g. `"bar"`
- date-like, e.g. `20130101`, or `"20130101"`
- lists, e.g. `"[’A’,’B’]"`
- variables that are defined in the local names space, e.g. `date`

Note: Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this

```
string = "HolyMoly'"
store.select('df', 'index == string')
```

instead of this

```
string = "HolyMoly'"
store.select('df',  'index == %s' % string)
```

The latter will **not** work and will raise a `SyntaxError`.Note that there's a single quote followed by a double quote in the `string` variable.

If you *must* interpolate, use the `'%r'` format specifier

```
store.select('df', 'index == %r' % string)
```

which will quote `string`.

Here are some examples:

```
In [298]: dfq = DataFrame(randn(10,4),columns=list('ABCD'),index=date_range('20130101',periods=10))

In [299]: store.append('dfq',dfq,format='table',data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [300]: store.select('dfq',"index>Timestamp('20130104') & columns=['A', 'B']")
Out[300]:
                   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 [301]: store.select('dfq',where="A>0 or C>0")
Out[301]:
                   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 [302]: store.append('wp',wp)

In [303]: store
Out[303]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

```
/df                        frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df_mi                     frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed                  frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfq                       frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C
/foo/bar/bah               frame        (shape->[8,3])
/wp                        wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_

In [304]: store.select('wp', "major_axis>Timestamp('20000102') & minor_axis=['A', 'B']")
Out[304]:
<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 [305]: store.select('df', "columns=['A', 'B']")
Out[305]:
                   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.

```
# this is effectively what the storage of a Panel looks like
In [306]: wp.to_frame()
Out[306]:
                     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
In [307]: store.select('wp',"major_axis>20000102 & minor_axis=['A','B']",
   .....:              start=0, stop=10)
```

```
   .....:
Out[307]:
<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.

Using timedelta64[ns]

New in version 0.13.

Beginning in 0.13.0, you can store and query using the `timedelta64[ns]` type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be `D,s,ms,us,ns` for the timedelta. Here's an example:

Warning: This requires `numpy >= 1.7`

```
In [308]: from datetime import timedelta

In [309]: dftd = DataFrame(dict(A = Timestamp('20130101'), B = [ Timestamp('20130101') + timedelta(da

In [310]: dftd['C'] = dftd['A']-dftd['B']

In [311]: dftd
Out[311]:
           A                   B                  C
0 2013-01-01 2013-01-01 00:00:10  -1 days +23:59:50
1 2013-01-01 2013-01-02 00:00:10  -2 days +23:59:50
2 2013-01-01 2013-01-03 00:00:10  -3 days +23:59:50
3 2013-01-01 2013-01-04 00:00:10  -4 days +23:59:50
4 2013-01-01 2013-01-05 00:00:10  -5 days +23:59:50
5 2013-01-01 2013-01-06 00:00:10  -6 days +23:59:50
6 2013-01-01 2013-01-07 00:00:10  -7 days +23:59:50
7 2013-01-01 2013-01-08 00:00:10  -8 days +23:59:50
8 2013-01-01 2013-01-09 00:00:10  -9 days +23:59:50
9 2013-01-01 2013-01-10 00:00:10 -10 days +23:59:50

In [312]: store.append('dftd',dftd,data_columns=True)

In [313]: store.select('dftd',"C<'-3.5D'")
Out[313]:
           A                   B                  C
4 2013-01-01 2013-01-05 00:00:10  -5 days +23:59:50
5 2013-01-01 2013-01-06 00:00:10  -6 days +23:59:50
6 2013-01-01 2013-01-07 00:00:10  -7 days +23:59:50
7 2013-01-01 2013-01-08 00:00:10  -8 days +23:59:50
8 2013-01-01 2013-01-09 00:00:10  -9 days +23:59:50
9 2013-01-01 2013-01-10 00:00:10 -10 days +23:59:50
```

24.8.8 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 (starting `0.10.1`) on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

```
# we have automagically already created an index (in the first section)
In [314]: i = store.root.df.table.cols.index.index

In [315]: i.optlevel, i.kind
Out[315]: (6, 'medium')

# change an index by passing new parameters
In [316]: store.create_table_index('df', optlevel=9, kind='full')

In [317]: i = store.root.df.table.cols.index.index

In [318]: i.optlevel, i.kind
Out[318]: (9, 'full')
```

See here for how to create a completely-sorted-index (CSI) on an existing store.

24.8.9 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 [319]: df_dc = df.copy()

In [320]: df_dc['string'] = 'foo'

In [321]: df_dc.ix[4:6,'string'] = np.nan

In [322]: df_dc.ix[7:9,'string'] = 'bar'

In [323]: df_dc['string2'] = 'cool'

In [324]: df_dc.ix[1:3,['B','C']] = 1.0

In [325]: df_dc
Out[325]:
                   A         B         C string string2
2000-01-01  0.887163  0.859588 -0.636524    foo    cool
2000-01-02  0.015696  1.000000  1.000000    foo    cool
2000-01-03  0.991946  1.000000  1.000000    foo    cool
2000-01-04 -0.334077  0.002118  0.405453    foo    cool
2000-01-05  0.289092  1.321158 -1.546906    NaN    cool
2000-01-06 -0.202646 -0.655969  0.193421    NaN    cool
2000-01-07  0.553439  1.318152 -0.469305    foo    cool
2000-01-08  0.675554 -1.817027 -0.183109    bar    cool
```

```
# on-disk operations
In [326]: store.append('df_dc', df_dc, data_columns = ['B', 'C', 'string', 'string2'])

In [327]: store.select('df_dc', [ Term('B>0') ])
Out[327]:
                   A         B         C string string2
2000-01-01  0.887163  0.859588 -0.636524    foo    cool
2000-01-02  0.015696  1.000000  1.000000    foo    cool
2000-01-03  0.991946  1.000000  1.000000    foo    cool
2000-01-04 -0.334077  0.002118  0.405453    foo    cool
2000-01-05  0.289092  1.321158 -1.546906    NaN    cool
2000-01-07  0.553439  1.318152 -0.469305    foo    cool

# getting creative
In [328]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')
Out[328]:
                   A         B         C string string2
2000-01-02  0.015696  1.000000  1.000000    foo    cool
2000-01-03  0.991946  1.000000  1.000000    foo    cool
2000-01-04 -0.334077  0.002118  0.405453    foo    cool

# this is in-memory version of this type of selection
In [329]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
Out[329]:
                   A         B         C string string2
2000-01-02  0.015696  1.000000  1.000000    foo    cool
2000-01-03  0.991946  1.000000  1.000000    foo    cool
2000-01-04 -0.334077  0.002118  0.405453    foo    cool

# we have automagically created this index and the B/C/string/string2
# columns are stored separately as ``PyTables`` columns
In [330]: store.root.df_dc.table
Out[330]:
/df_dc/table (Table(8,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
  "B": Float64Col(shape=(), dflt=0.0, pos=2),
  "C": Float64Col(shape=(), dflt=0.0, pos=3),
  "string": StringCol(itemsize=3, shape=(), dflt='', pos=4),
  "string2": StringCol(itemsize=4, shape=(), dflt='', pos=5)}
  byteorder := 'little'
  chunkshape := (1680,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

There is some performance degradation by making lots of columns into *data columns*, so it is up to the user to designate these. In addition, you cannot change data columns (nor indexables) after the first append/put operation (Of course you can simply read in the data and create a new table!)

24.8.10 Iterator

Starting in `0.11.0`, you can pass, `iterator=True` or `chunksize=number_in_a_chunk` to `select` and `select_as_multiple` to return an iterator on the results. The default is 50,000 rows returned in a chunk.

```
In [331]: 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: New in version 0.12.0.

You can also use the iterator with `read_hdf` which will open, then automatically close the store when finished iterating.

```
for df in read_hdf('store.h5','df', chunksize=3):
    print(df)
```

Note, that the chunksize keyword applies to the **source** rows. So if you are doing a query, then the chunksize will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```
In [332]: dfeq = DataFrame({'number': np.arange(1,11)})

In [333]: dfeq
Out[333]:
   number
0       1
1       2
2       3
3       4
4       5
5       6
6       7
7       8
8       9
9      10

In [334]: store.append('dfeq', dfeq, data_columns=['number'])

In [335]: def chunks(l, n):
   .....:      return [l[i:i+n] for i in range(0, len(l), n)]
   .....:

In [336]: evens = [2,4,6,8,10]

In [337]: coordinates = store.select_as_coordinates('dfeq','number=evens')
```

```
In [338]: for c in chunks(coordinates, 2):
   .....:      print store.select('dfeq',where=c)
   .....:
   number
1       2
3       4
   number
5       6
7       8
   number
9      10
```

24.8.11 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 [339]: store.select_column('df_dc', 'index')
Out[339]:
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
dtype: datetime64[ns]

In [340]: store.select_column('df_dc', 'string')
Out[340]:
0    foo
1    foo
2    foo
3    foo
4    NaN
5    NaN
6    foo
7    bar
dtype: object
```

Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```
In [341]: df_coord = DataFrame(np.random.randn(1000,2),index=date_range('20000101',periods=1000))

In [342]: store.append('df_coord',df_coord)

In [343]: c = store.select_as_coordinates('df_coord','index>20020101')

In [344]: c.summary()
Out[344]: u'Int64Index: 268 entries, 732 to 999'
```

```
In [345]: store.select('df_coord',where=c)
Out[345]:
                   0         1
2002-01-02 -0.667994 -0.368175
2002-01-03  0.020119 -0.823208
2002-01-04 -0.165481  0.720866
2002-01-05  1.295919 -0.527767
2002-01-06 -0.463393 -0.150792
2002-01-07 -1.139341 -0.954387
2002-01-08  0.051837 -0.147048
...              ...       ...
2002-09-20  0.058626 -0.489107
2002-09-21 -0.356873 -0.437071
2002-09-22 -0.243534 -0.093778
2002-09-23 -0.615983  0.414649
2002-09-24  0.202096 -0.297561
2002-09-25  0.681661  0.538311
2002-09-26 -0.614051  0.769058

[268 rows x 2 columns]
```

Selecting using a where mask

Sometime your query can involve creating a list of rows to select. Usually this `mask` would be a resulting `index` from an indexing operation. This example selects the months of a datetimeindex which are 5.

```
In [346]: df_mask = DataFrame(np.random.randn(1000,2),index=date_range('20000101',periods=1000))

In [347]: store.append('df_mask',df_mask)

In [348]: c = store.select_column('df_mask','index')

In [349]: where = c[DatetimeIndex(c).month==5].index

In [350]: store.select('df_mask',where=where)
Out[350]:
                   0         1
2000-05-01 -0.098554 -0.280782
2000-05-02  0.739851  1.627182
2000-05-03  0.030132 -0.145601
2000-05-04  0.227530  1.048856
2000-05-05  1.773939  1.116887
2000-05-06  1.081251  1.509416
2000-05-07 -0.498694 -0.913155
...              ...       ...
2002-05-25 -0.497252  0.348099
2002-05-26 -1.287350 -1.488122
2002-05-27 -0.726220  0.507747
2002-05-28  0.189871  0.980528
2002-05-29  0.555156  0.369371
2002-05-30 -0.637441 -3.434819
2002-05-31 -0.070283 -0.278044

[93 rows x 2 columns]
```

Storer Object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this programmatically to say get the number of rows in an object.

```
In [351]: store.get_storer('df_dc').nrows
Out[351]: 8
```

24.8.12 Multiple Table Queries

New in 0.10.1 are the methods `append_to_multiple` and `select_as_multiple`, that can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table's index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of 'columns' you want in that table. If *None* is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which table is the selector table (which you can make queries from). The argument `dropna` will drop rows from the input DataFrame to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely `np.NaN`, that row will be dropped from all tables.

If `dropna` is False, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES**. Remember that 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 [352]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
   .....:                                columns=['A', 'B', 'C', 'D', 'E', 'F'])
   .....:

In [353]: df_mt['foo'] = 'bar'

In [354]: df_mt.ix[1, ('A', 'B')] = np.nan

# you can also create the tables individually
In [355]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None },
   .....:                           df_mt, selector='df1_mt')
   .....:

In [356]: store
Out[356]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                frame_table  (typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt                frame_table  (typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord              frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc                 frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,st
/df_mask               frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi                 frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq                  frame_table  (typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe
/dfq                   frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C
/dftd                  frame_table  (typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C
/foo/bar/bah           frame        (shape->[8,3])
/wp                    wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_

# individual tables were created
In [357]: store.select('df1_mt')
```

```
Out[357]:
                   A         B
2000-01-01 -0.816310  1.282296
2000-01-03  0.684353 -1.755306
2000-01-04 -1.315814  1.455079
2000-01-05 -0.027564  0.046757
2000-01-06 -0.416244 -0.821168
2000-01-07  0.665090  1.084344
2000-01-08  0.607460  0.790907

In [358]: store.select('df2_mt')
Out[358]:
                   C         D         E         F  foo
2000-01-01 -1.521825 -0.428670 -1.550209  0.826839  bar
2000-01-03  1.236974 -1.328279  0.662291  1.894976  bar
2000-01-04 -0.746478  0.851039  1.415686 -0.929096  bar
2000-01-05 -1.452287  1.575492 -0.197377 -0.219901  bar
2000-01-06  1.190342  2.115021  0.148762  1.073931  bar
2000-01-07 -0.709897 -2.022441  0.714697  0.318215  bar
2000-01-08  0.852225  0.096696 -0.379903  0.929313  bar

# as a multiple
In [359]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'],
   .....:                           selector = 'df1_mt')
   .....:
Out[359]:
                  A         B         C         D         E         F  foo
2000-01-07  0.66509  1.084344 -0.709897 -2.022441  0.714697  0.318215  bar
2000-01-08  0.60746  0.790907  0.852225  0.096696 -0.379903  0.929313  bar
```

24.8.13 Delete from a Table

You can delete from a table selectively by specifying a `where`. In deleting rows, it is important to understand the `PyTables` deletes rows by erasing the rows, then **moving** the following data. Thus deleting can potentially be a very expensive operation depending on the orientation of your data. This is especially true in higher dimensional objects (`Panel` and `Panel4D`). To get optimal performance, it's worthwhile to have the dimension you are deleting be the first of the `indexables`.

Data is ordered (on the disk) in terms of the `indexables`. Here's a simple use case. You store panel-type data, with dates in the `major_axis` and ids in the `minor_axis`. The data is then interleaved like this:

- **date_1**
  - id_1
  - id_2
  - .
  - id_n
- **date_2**
  - id_1
  - .
  - id_n

It should be clear that a delete operation on the `major_axis` will be fairly quick, as one chunk is removed, then the following data moved. On the other hand a delete operation on the `minor_axis` will be very expensive. In this case it would almost certainly be faster to rewrite the table using a `where` that selects all but the missing data.

```
# returns the number of rows deleted
In [360]: store.remove('wp', 'major_axis>20000102' )
Out[360]: 12

In [361]: store.select('wp')
Out[361]:
<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
```

Please note that HDF5 **DOES NOT RECLAIM SPACE** in the h5 files automatically. Thus, repeatedly deleting (or removing nodes) and adding again **WILL TEND TO INCREASE THE FILE SIZE**. To *clean* the file, use `ptrepack` (see below).

24.8.14 Compression

`PyTables` allows the stored data to be compressed. This applies to all kinds of stores, not just tables.

- Pass `complevel=int` for a compression level (1-9, with 0 being no compression, and the default)
- Pass `complib=lib` where lib is any of `zlib, bzip2, lzo, blosc` for whichever compression library you prefer.

`HDFStore` will use the file based compression scheme if no overriding `complib` or `complevel` options are provided. `blosc` offers very fast compression, and is my most used. Note that `lzo` and `bzip2` may not be installed (by Python) by default.

Compression for all objects within the file

- `store_compressed = HDFStore('store_compressed.h5', complevel=9, complib='blosc')`

Or on-the-fly compression (this only applies to tables). You can turn off file compression for a specific table by passing `complevel=0`

- `store.append('df', df, complib='zlib', complevel=5)`

ptrepack

`PyTables` offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied `PyTables` utility `ptrepack`. In addition, `ptrepack` can change compression levels after the fact.

- `ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5`

Furthermore `ptrepack in.h5 out.h5` will *repack* the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the `copy` method.

24.8.15 Notes & Caveats

- Once a `table` is created its items (Panel) / columns (DataFrame) are fixed; only exactly the same columns can be appended

- If a row has `np.nan` for **EVERY COLUMN** (having a `nan` in a string, or a `NaT` in a datetime-like column counts as having a value), then those rows **WILL BE DROPPED IMPLICITLY**. This limitation *may* be addressed in the future.
- `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 issue (*:2397*) 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.
- `PyTables` only supports fixed-width string columns in `tables`. The sizes of a string based indexing column (e.g. *columns* or *minor_axis*) are determined as the maximum size of the elements in that axis or by passing the parameter
- 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. Generally identifiers that have spaces, start with numbers, or _, or have - embedded are not considered *natural*. These types of identifiers cannot be used in a `where` clause and are generally a bad idea.

24.8.16 DataTypes

`HDFStore` will map an object dtype to the `PyTables` underlying dtype. This means the following types are known to work:

- floating : `float64, float32, float16` *(using* `np.nan` *to represent invalid values)*
- integer : `int64, int32, int8, uint64, uint32, uint8`
- bool
- datetime64[ns] *(using* `NaT` *to represent invalid values)*
- object : `strings` *(using* `np.nan` *to represent invalid values)*

Currently, `unicode` and `datetime` columns (represented with a dtype of `object`), **WILL FAIL**. In addition, even though a column may look like a `datetime64[ns]`, if it contains `np.nan`, this **WILL FAIL**. You can try to convert datetimelike columns to proper `datetime64[ns]` columns, that possibly contain `NaT` to represent invalid values. (Some of these issues have been addressed and these conversion may not be necessary in future versions of pandas)

```
In [362]: import datetime

In [363]: df = DataFrame(dict(datelike=Series([datetime.datetime(2001, 1, 1),
   .....:                                      datetime.datetime(2001, 1, 2), np.nan])))
   .....:

In [364]: df
Out[364]:
    datelike
0 2001-01-01
1 2001-01-02
2        NaT
```

```
In [365]: df.dtypes
Out[365]:
datelike    datetime64[ns]
dtype: object

# to convert
In [366]: df['datelike'] = Series(df['datelike'].values, dtype='M8[ns]')

In [367]: df
Out[367]:
    datelike
0 2001-01-01
1 2001-01-02
2        NaT

In [368]: df.dtypes
Out[368]:
datelike    datetime64[ns]
dtype: object
```

24.8.17 Categorical Data

New in version 0.15.2.

Writing data to a `HDFStore` that contains a `category` dtype was implemented in 0.15.2. Queries work the same as if it was an object array. However, the `category` dtyped data is stored in a more efficient manner.

```
In [369]: dfcat = DataFrame({ 'A' : Series(list('aabbcdba')).astype('category'),
   .....:                     'B' : np.random.randn(8) })
   .....:

In [370]: dfcat
Out[370]:
   A         B
0  a  0.811031
1  a -0.356817
2  b  1.047085
3  b  0.664705
4  c -0.086919
5  d  0.416905
6  b -0.764381
7  a -0.287229

In [371]: dfcat.dtypes
Out[371]:
A    category
B     float64
dtype: object

In [372]: cstore = pd.HDFStore('cats.h5', mode='w')

In [373]: cstore.append('dfcat', dfcat, format='table', data_columns=['A'])

In [374]: result = cstore.select('dfcat', where="A in ['b','c']")

In [375]: result
Out[375]:
```

```
   A         B
2  b  1.047085
3  b  0.664705
4  c -0.086919
6  b -0.764381

In [376]: result.dtypes
Out[376]:
A    category
B     float64
dtype: object
```

Warning: The format of the `Categorical` is readable by prior versions of pandas (< 0.15.2), but will retrieve the data as an integer based column (e.g. the `codes`). However, the `categories` *can* be retrieved but require the user to select them manually using the explicit meta path.

The data is stored like so:

```
In [377]: cstore
Out[377]:
<class 'pandas.io.pytables.HDFStore'>
File path: cats.h5
/dfcat                          frame_table  (typ->appendable,nrows->8,ncols->2,indexers->[index],dc-
/dfcat/meta/A/meta              series_table (typ->appendable,nrows->4,ncols->1,indexers->[index],dc-

# to get the categories
In [378]: cstore.select('dfcat/meta/A/meta')
Out[378]:
0    a
1    b
2    c
3    d
dtype: object
```

24.8.18 String Columns

min_itemsize

The underlying implementation of `HDFStore` uses a fixed column width (itemsize) for string columns. A string column itemsize is calculated as the maximum of the length of data (for that column) that is passed to the `HDFStore`, **in the first append**. Subsequent appends, may introduce a string for a column **larger** than the column can hold, an Exception will be raised (otherwise you could have a silent truncation of these columns, leading to loss of information). In the future we may relax this and allow a user-specified truncation to occur.

Pass `min_itemsize` on the first table creation to a-priori specify the minimum length of a particular string column. `min_itemsize` can be an integer, or a dict mapping a column name to an integer. You can pass `values` as a key to allow all *indexables* or *data_columns* to have this min_itemsize.

Starting in 0.11.0, passing a `min_itemsize` dict will cause all passed columns to be created as *data_columns* automatically.

Note: If you are not passing any *data_columns*, then the min_itemsize will be the maximum of the length of any string passed

```
In [379]: dfs = DataFrame(dict(A = 'foo', B = 'bar'),index=list(range(5)))
```

```
In [380]: dfs
Out[380]:
     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 [381]: store.append('dfs', dfs, min_itemsize = 30)

In [382]: store.get_storer('dfs').table
Out[382]:
/dfs/table (Table(5,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsize=30, shape=(2,), dflt='', pos=1)}
  byteorder := 'little'
  chunkshape := (963,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

# A is created as a data_column with a size of 30
# B is size is calculated
In [383]: store.append('dfs2', dfs, min_itemsize = { 'A' : 30 })

In [384]: store.get_storer('dfs2').table
Out[384]:
/dfs2/table (Table(5,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsize=3, shape=(1,), dflt='', pos=1),
  "A": StringCol(itemsize=30, shape=(), dflt='', pos=2)}
  byteorder := 'little'
  chunkshape := (1598,)
  autoindex := True
  colindexes := {
    "A": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

nan_rep

String columns will serialize a `np.nan` (a missing value) with the `nan_rep` string representation. This defaults to the string value `nan`. You could inadvertently turn an actual `nan` value into a missing value.

```
In [385]: dfss = DataFrame(dict(A = ['foo','bar','nan']))

In [386]: dfss
Out[386]:
     A
0  foo
1  bar
2  nan

In [387]: store.append('dfss', dfss)

In [388]: store.select('dfss')
```

```
Out[388]:
     A
0  foo
1  bar
2  NaN

# here you need to specify a different nan rep
In [389]: store.append('dfss2', dfss, nan_rep='_nan_')

In [390]: store.select('dfss2')
Out[390]:
     A
0  foo
1  bar
2  nan
```

24.8.19 External Compatibility

HDFStore writes table format objects in specific formats suitable for producing loss-less round trips to pandas objects. For external compatibility, HDFStore can read native PyTables format tables.

It is possible to write an HDFStore object that can easily be imported into R using the rhdf5 library (Package website). Create a table format store like this:

```
In [391]: np.random.seed(1)

In [392]: 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 [393]: df_for_r.head()
Out[393]:
   class     first    second
0      0  0.417022  0.326645
1      0  0.720324  0.527058
2      1  0.000114  0.885942
3      1  0.302333  0.357270
4      1  0.146756  0.908535

In [394]: store_export = HDFStore('export.h5')

In [395]: store_export.append('df_for_r', df_for_r, data_columns=df_dc.columns)

In [396]: store_export
Out[396]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
/df_for_r            frame_table  (typ->appendable,nrows->100,ncols->3,indexers->[index])
```

In R this file can be read into a data.frame object using the rhdf5 library. The following example function reads the corresponding column names and data values from the values and assembles them into a data.frame:

```
# Load values and column names for all datasets from corresponding nodes and
# insert them into one data.frame object.
```

```
library(rhdf5)

loadhdf5data <- function(h5File) {

listing <- h5ls(h5File)
# Find all data nodes, values are stored in *_values and corresponding column
# titles in *_items
data_nodes <- grep("_values", listing$name)
name_nodes <- grep("_items", listing$name)
data_paths = paste(listing$group[data_nodes], listing$name[data_nodes], sep = "/")
name_paths = paste(listing$group[name_nodes], listing$name[name_nodes], sep = "/")
columns = list()
for (idx in seq(data_paths)) {
  # NOTE: matrices returned by h5read have to be transposed to to obtain
  # required Fortran order!
  data <- data.frame(t(h5read(h5File, data_paths[idx])))
  names <- t(h5read(h5File, name_paths[idx]))
  entry <- data.frame(data)
  colnames(entry) <- names
  columns <- append(columns, entry)
}

data <- data.frame(columns)

return(data)
}
```

Now you can import the `DataFrame` into R:

```
> 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.

24.8.20 Backwards Compatibility

0.10.1 of `HDFStore` can read tables created in a prior version of pandas, however query terms using the prior (undocumented) methodology are unsupported. `HDFStore` will issue a warning if you try to use a legacy-format file. You must read in the entire file and write it out using the new format, using the method `copy` to take advantage of the updates. The group attribute `pandas_version` contains the version information. `copy` takes a number of options, please see the docstring.

```
# a legacy store
In [397]: legacy_store = HDFStore(legacy_file_path,'r')

In [398]: legacy_store
Out[398]:
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: /home/joris/scipy/pandas/doc/source/_static/legacy_0.10.h5
/a                      series       (shape->[30])
/b                      frame        (shape->[30,4])
/df1_mixed              frame_table [0.10.0] (typ->appendable,nrows->30,ncols->11,indexers->[index])
/foo/bar                wide         (shape->[3,30,4])
/p1_mixed               wide_table  [0.10.0] (typ->appendable,nrows->120,ncols->9,indexers->[major_axis
/p4d_mixed              ndim_table  [0.10.0] (typ->appendable,nrows->360,ncols->9,indexers->[items,majo

# copy (and return the new handle)
In [399]: new_store = legacy_store.copy('store_new.h5')

In [400]: new_store
Out[400]:
<class 'pandas.io.pytables.HDFStore'>
File path: store_new.h5
/a                      series       (shape->[30])
/b                      frame        (shape->[30,4])
/df1_mixed              frame_table  (typ->appendable,nrows->30,ncols->11,indexers->[index])
/foo/bar                wide         (shape->[3,30,4])
/p1_mixed               wide_table   (typ->appendable,nrows->120,ncols->9,indexers->[major_axis,minor_a
/p4d_mixed              wide_table   (typ->appendable,nrows->360,ncols->9,indexers->[items,major_axis,m

In [401]: new_store.close()
```

24.8.21 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.

24.8.22 Experimental

HDFStore supports `Panel4D` storage.

```
In [402]: p4d = Panel4D({ 'l1' : wp })

In [403]: p4d
Out[403]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 1 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: l1 to l1
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

```
In [404]: store.append('p4d', p4d)

In [405]: store
Out[405]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                frame_table  (typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt                frame_table  (typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord              frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc                 frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,st
/df_mask               frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi                 frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq                  frame_table  (typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe
/dfq                   frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C
/dfs                   frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2                  frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfss                  frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dfss2                 frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dftd                  frame_table  (typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C
/foo/bar/bah           frame        (shape->[8,3])
/p4d                   wide_table   (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,
/wp                    wide_table   (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_a
```

These, by default, index the three axes `items, major_axis, minor_axis`. On an `AppendableTable` it is possible to setup with the first append a different indexing scheme, depending on how you want to store your data. Pass the `axes` keyword with a list of dimensions (currently must by exactly 1 less than the total dimensions of the object). This cannot be changed after table creation.

```
In [406]: store.append('p4d2', p4d, axes=['labels', 'major_axis', 'minor_axis'])

In [407]: store
Out[407]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                frame_table  (typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt                frame_table  (typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord              frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc                 frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,st
/df_mask               frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi                 frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq                  frame_table  (typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe
/dfq                   frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C
/dfs                   frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2                  frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfss                  frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dfss2                 frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dftd                  frame_table  (typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C
/foo/bar/bah           frame        (shape->[8,3])
/p4d                   wide_table   (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,
/p4d2                  wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[labels,major_axis
/wp                    wide_table   (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_a

In [408]: store.select('p4d2', [ Term('labels=l1'), Term('items=Item1'), Term('minor_axis=A_big_strin
Out[408]:
```

```
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 0 (labels) x 1 (items) x 0 (major_axis) x 0 (minor_axis)
Labels axis: None
Items axis: Item1 to Item1
Major_axis axis: None
Minor_axis axis: None
```

24.9 SQL Queries

The `pandas.io.sql` module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed, in addition you will need a driver library for your database.

New in version 0.14.0.

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the Python DB-API.

See also some *cookbook examples* for some advanced strategies.

The key functions are:

`read_sql_table`(table_name, con[, schema, ...])	Read SQL database table into a DataFrame.
`read_sql_query`(sql, con[, index_col, ...])	Read SQL query into a DataFrame.
`read_sql`(sql, con[, index_col, ...])	Read SQL query or database table into a DataFrame.
`DataFrame.to_sql`(name, con[, flavor, ...])	Write records stored in a DataFrame to a SQL database.

24.9.1 pandas.read_sql_table

`pandas.`**`read_sql_table`**(*table_name*, *con*, *schema=None*, *index_col=None*, *coerce_float=True*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy engine, returns a DataFrame. This function does not support DBAPI connections.

Parameters **table_name** : string

Name of SQL table in database

con : SQLAlchemy engine

Sqlite DBAPI connection mode not supported

schema : string, default None

Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

index_col : string, optional

Column to set as index

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

parse_dates : list or dict

- 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

List of column names to select from sql table

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

`read_sql_query` Read SQL query into a DataFrame.

`read_sql`

Notes

Any datetime values with time zone information will be converted to UTC

24.9.2 pandas.read_sql_query

`pandas.`**`read_sql_query`**(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *chunksize=None*)

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

Parameters **sql** : string

SQL query to be executed

con : SQLAlchemy engine or sqlite3 DBAPI2 connection

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

Column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

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

- 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

`read_sql`

Notes

Any datetime values with time zone information parsed via the *parse_dates* parameter will be converted to UTC

24.9.3 pandas.read_sql

pandas.**read_sql**(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL query or database table into a DataFrame.

Parameters **sql** : string

SQL query to be executed or database table name.

con : SQLAlchemy engine or DBAPI2 connection (fallback mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

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

- 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

List of column names to select from sql table (only used when reading a table).

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

`read_sql_table` Read SQL database table into a DataFrame

`read_sql_query` Read SQL query into a DataFrame

Notes

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

24.9.4 pandas.DataFrame.to_sql

`DataFrame.`**`to_sql`**(*name*, *con*, *flavor='sqlite'*, *schema=None*, *if_exists='fail'*, *index=True*, *index_label=None*, *chunksize=None*, *dtype=None*)

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

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

```
In [409]: from sqlalchemy import create_engine

# Create your connection.
In [410]: engine = create_engine('sqlite:///:memory:')
```

24.9.5 Writing DataFrames

Assuming the following data is in a DataFrame `data`, we can insert it into the database using `to_sql()`.

id	Date	Col_1	Col_2	Col_3
26	2012-10-18	X	25.7	True
42	2012-10-19	Y	-12.4	False
63	2012-10-20	Z	5.73	True

```
In [411]: data.to_sql('data', engine)
```

With some databases, writing large DataFrames can result in errors due to packet size limitations being exceeded. This can be avoided by setting the `chunksize` parameter when calling `to_sql`. For example, the following writes `data` to the database in batches of 1000 rows at a time:

```
In [412]: data.to_sql('data_chunked', engine, chunksize=1000)
```

SQL data types

`to_sql()` will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype `object`, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the sqlite3 fallback mode). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
In [413]: from sqlalchemy.types import String

In [414]: data.to_sql('data_dtype', engine, dtype={'Col_1': String})
```

Note: Due to the limited support for timedelta's in the different database flavors, columns with type `timedelta64` will be written as integer values as nanoseconds to the database and a warning will be raised.

Note: Columns of `category` dtype will be converted to the dense representation as you would get with `np.asarray(categorical)` (e.g. for string categories this gives an array of strings). Because of this, reading the database table back in does **not** generate a categorical.

24.9.6 Reading Tables

`read_sql_table()` will read a database table given the table name and optionally a subset of columns to read.

Note: In order to use `read_sql_table()`, you **must** have the SQLAlchemy optional dependency installed.

```
In [415]: pd.read_sql_table('data', engine)
Out[415]:
   index  id       Date Col_1  Col_2  Col_3
0      0  26 2010-10-18     X  27.50   True
1      1  42 2010-10-19     Y -12.50  False
2      2  63 2010-10-20     Z   5.73   True
```

You can also specify the name of the column as the DataFrame index, and specify a subset of columns to be read.

```
In [416]: pd.read_sql_table('data', engine, index_col='id')
Out[416]:
    index       Date Col_1  Col_2  Col_3
id
26      0 2010-10-18     X  27.50   True
42      1 2010-10-19     Y -12.50  False
63      2 2010-10-20     Z   5.73   True

In [417]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
Out[417]:
  Col_1  Col_2
0     X  27.50
```

```
1     Y -12.50
2     Z   5.73
```

And you can explicitly force columns to be parsed as dates:

```
In [418]: pd.read_sql_table('data', engine, parse_dates=['Date'])
Out[418]:
   index  id       Date Col_1  Col_2  Col_3
0      0  26 2010-10-18     X  27.50   True
1      1  42 2010-10-19     Y -12.50  False
2      2  63 2010-10-20     Z   5.73   True
```

If needed you can explicitly specify a format string, or a dict of arguments to pass to `pandas.to_datetime()`:

```
pd.read_sql_table('data', engine, parse_dates={'Date': '%Y-%m-%d'})
pd.read_sql_table('data', engine, parse_dates={'Date': {'format': '%Y-%m-%d %H:%M:%S'}})
```

You can check if a table exists using `has_table()`

24.9.7 Schema support

New in version 0.15.0.

Reading from and writing to different schema's is supported through the `schema` keyword in the `read_sql_table()` and `to_sql()` functions. Note however that this depends on the database flavor (sqlite does not have schema's). For example:

```
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

24.9.8 Querying

You can query using raw SQL in the `read_sql_query()` function. In this case you must use the SQL variant appropriate for your database. When using SQLAlchemy, you can also pass SQLAlchemy Expression language constructs, which are database-agnostic.

```
In [419]: pd.read_sql_query('SELECT * FROM data', engine)
Out[419]:
   index  id                        Date Col_1  Col_2  Col_3
0      0  26  2010-10-18 00:00:00.000000     X  27.50      1
1      1  42  2010-10-19 00:00:00.000000     Y -12.50      0
2      2  63  2010-10-20 00:00:00.000000     Z   5.73      1
```

Of course, you can specify a more "complex" query.

```
In [420]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)
Out[420]:
   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 [421]: df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))

In [422]: df.to_sql('data_chunks', engine, index=False)
```

```
In [423]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine, chunksize=5):
   .....:     print(chunk)
   .....:
          a         b         c
0  0.280665 -0.073113  1.160339
1  0.369493  1.904659  1.111057
2  0.659050 -1.627438  0.602319
3  0.420282  0.810952  1.044442
4 -0.400878  0.824006 -0.562305
          a         b         c
0  1.954878 -1.331952 -1.760689
1 -1.650721 -0.890556 -1.119115
2  1.956079 -0.326499 -1.342676
3  1.114383 -0.586524 -1.236853
4  0.875839  0.623362 -0.434957
          a         b         c
0  1.407540  0.129102  1.616950
1  0.502741  1.558806  0.109403
2 -1.219744  2.449369 -0.545774
3 -0.198838 -0.700399 -0.203394
4  0.242669  0.201830  0.661020
          a         b         c
0  1.792158 -0.120465 -1.233121
1 -1.182318 -0.665755 -1.674196
2  0.825030 -0.498214 -0.310985
3 -0.001891 -1.396620 -0.861316
4  0.674712  0.618539 -0.443172
```

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.

```
from pandas.io import sql
sql.execute('SELECT * FROM table_name', engine)
sql.execute('INSERT INTO table_name VALUES(?, ?, ?)', engine, params=[('id', 1, 12.2, True)])
```

24.9.9 Engine connection examples

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to.

```
from sqlalchemy import create_engine

engine = create_engine('postgresql://scott:tiger@localhost:5432/mydatabase')

engine = create_engine('mysql+mysqldb://scott:tiger@localhost/foo')

engine = create_engine('oracle://scott:tiger@127.0.0.1:1521/sidname')

engine = create_engine('mssql+pyodbc://mydsn')

# sqlite://<nohostname>/<path>
# where <path> is relative:
engine = create_engine('sqlite:///foo.db')

# or absolute, starting with a slash:
engine = create_engine('sqlite:////absolute/path/to/foo.db')
```

For more information see the examples the SQLAlchemy documentation

24.9.10 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:

```
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)
```

24.10 Google BigQuery (Experimental)

New in version 0.13.0.

The `pandas.io.gbq` module provides a wrapper for Google's BigQuery analytics web service to simplify retrieving results from BigQuery tables using SQL-like queries. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table. Additionally, DataFrames can be appended to existing BigQuery tables if the destination table is the same shape as the DataFrame.

For specifics on the service itself, see here

As an example, suppose you want to load all data from an existing BigQuery table : *test_dataset.test_table* into a DataFrame using the `read_gbq()` function.

```
# Insert your BigQuery Project ID Here
# Can be found in the Google web console
projectid = "xxxxxxxx"

data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table', project_id = projectid)
```

You will then be authenticated to the specified BigQuery account via Google's Oauth2 mechanism. In general, this is as simple as following the prompts in a browser window which will be opened for you. Should the browser not be available, or fail to launch, a code will be provided to complete the process manually. Additional information on the authentication mechanism can be found here

You can define which column from BigQuery to use as an index in the destination DataFrame as well as a preferred column order as follows:

```
data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table',
                          index_col='index_column_name',
                          col_order=['col1', 'col2', 'col3'], project_id = projectid)
```

Finally, you can append data to a BigQuery table from a pandas DataFrame using the `to_gbq()` function. This function uses the Google streaming API which requires that your destination table exists in BigQuery. Given the BigQuery table already exists, your DataFrame should match the destination table in column order, structure, and data types. DataFrame indexes are not supported. By default, rows are streamed to BigQuery in chunks of 10,000 rows, but you can pass other chuck values via the `chunksize` argument. You can also see the progess of your post via the `verbose` flag which defaults to `True`. The http response code of Google BigQuery can be successful (200) even if the append failed. For this reason, if there is a failure to append to the table, the complete error response from BigQuery is returned which can be quite long given it provides a status for each row. You may want to start with smaller chunks to test that the size and types of your dataframe match your destination table to make debugging simpler.

```
df = pandas.DataFrame({'string_col_name' : ['hello'],
      'integer_col_name' : [1],
      'boolean_col_name' : [True]})
df.to_gbq('my_dataset.my_table', project_id = projectid)
```

The BigQuery SQL query language has some oddities, see here

While BigQuery uses SQL-like syntax, it has some important differences from traditional databases both in functionality, API limitations (size and quantity of queries or uploads), and how Google charges for use of the service. You should refer to Google documentation often as the service seems to be changing and evolving. BiqQuery is best for analyzing large sets of data quickly, but it is not a direct replacement for a transactional database.

You can access the management console to determine project id's by: <https://code.google.com/apis/console/b/0/?noredirect>

As of 0.15.2, the gbq module has a function `generate_bq_schema` which will produce the dictionary representation of the schema.

```
df = pandas.DataFrame({'A': [1.0]})
gbq.generate_bq_schema(df, default_type='STRING')
```

Warning: To use this module, you will need a valid BigQuery account. See <https://cloud.google.com/products/big-query> for details on the service.

24.11 Stata Format

New in version 0.12.0.

24.11.1 Writing to Stata format

The method `to_stata()` will write a DataFrame into a .dta file. The format version of this file is always 115 (Stata 12).

```
In [424]: df = DataFrame(randn(10, 2), columns=list('AB'))

In [425]: 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`.

24.11.2 Reading from Stata format

The top-level function `read_stata` will read a dta file and return either a DataFrame or a `StataReader` that can be used to read the file incrementally.

```
In [426]: pd.read_stata('stata.dta')
Out[426]:
   index         A         B
0      0  1.810535 -1.305727
1      1 -0.344987 -0.230840
2      2 -2.793085  1.937529
3      3  0.366332 -1.044589
4      4  2.051173  0.585662
5      5  0.429526 -0.606998
6      6  0.106223 -1.525680
7      7  0.795026 -0.374438
8      8  0.134048  1.202055
9      9  0.284748  0.262467
```

New in version 0.16.0.

Specifying a `chunksize` yields a `StataReader` instance that can be used to read `chunksize` lines from the file at a time. The `StataReader` object can be used as an iterator.

```
In [427]: reader = pd.read_stata('stata.dta', chunksize=3)

In [428]: for df in reader:
   .....:     print(df.shape)
   .....:
(3, 3)
(3, 3)
(3, 3)
(1, 3)
```

For more fine-grained control, use `iterator=True` and specify `chunksize` with each call to `read()`.

```
In [429]: reader = pd.read_stata('stata.dta', iterator=True)

In [430]: chunk1 = reader.read(5)

In [431]: 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.

`read_stata()` and `StataReader` supports .dta formats 104, 105, 108, 113-115 (Stata 10-12) and 117 (Stata 13+).

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.

24.11.3 Categorical Data

New in version 0.15.2.

`Categorical` data can be exported to *Stata* data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. *Stata* does not have an explicit equivalent to a `Categorical` and information about *whether* the variable is ordered is lost when exporting.

Warning: *Stata* only supports string value labels, and so `str` is called on the categories when exporting data. Exporting `Categorical` variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from *Stata* data files as `Categorical` variables using the keyword argument `convert_categoricals` (`True` by default). The keyword argument `order_categoricals` (`True` by default) determines whether imported `Categorical` variables are ordered.

Note: When importing categorical data, the values of the variables in the *Stata* data file are not preserved since `Categorical` variables always use integer data types between `-1` and `n-1` where `n` is the number of categories. If the original values in the *Stata* data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original *Stata* data values and the category codes of imported Categorical variables: missing values are assigned code `-1`, and the smallest original value is assigned `0`, the second smallest is assigned `1` and so on until the largest original value is assigned the code `n-1`.

Note: *Stata* supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a `Categorial` with string categories for the values that are labeled and numeric categories for values with no label.

24.12 Other file formats

pandas itself only supports IO with a limited set of file formats that map cleanly to its tabular data model. For reading and writing other file formats into and from pandas, we recommend these packages from the broader community.

24.12.1 netCDF

xray provides data structures inspired by the pandas DataFrame for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

24.13 Performance Considerations

This is an informal comparison of various IO methods, using pandas 0.13.1.

```
In [3]: df = DataFrame(randn(1000000,2),columns=list('AB'))
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A    1000000  non-null values
B    1000000  non-null values
dtypes: float64(2)
```

Writing

```
In [14]: %timeit test_sql_write(df)
1 loops, best of 3: 6.24 s per loop

In [15]: %timeit test_hdf_fixed_write(df)
1 loops, best of 3: 237 ms per loop

In [26]: %timeit test_hdf_fixed_write_compress(df)
1 loops, best of 3: 245 ms per loop

In [16]: %timeit test_hdf_table_write(df)
1 loops, best of 3: 901 ms per loop

In [27]: %timeit test_hdf_table_write_compress(df)
1 loops, best of 3: 952 ms per loop

In [17]: %timeit test_csv_write(df)
1 loops, best of 3: 3.44 s per loop
```

Reading

```
In [18]: %timeit test_sql_read()
1 loops, best of 3: 766 ms per loop

In [19]: %timeit test_hdf_fixed_read()
10 loops, best of 3: 19.1 ms per loop

In [28]: %timeit test_hdf_fixed_read_compress()
10 loops, best of 3: 36.3 ms per loop

In [20]: %timeit test_hdf_table_read()
10 loops, best of 3: 39 ms per loop

In [29]: %timeit test_hdf_table_read_compress()
10 loops, best of 3: 60.6 ms per loop

In [22]: %timeit test_csv_read()
1 loops, best of 3: 620 ms per loop
```

Space on disk (in bytes)

```
25843712 Apr  8 14:11 test.sql
24007368 Apr  8 14:11 test_fixed.hdf
15580682 Apr  8 14:11 test_fixed_compress.hdf
24458444 Apr  8 14:11 test_table.hdf
```

```
16797283 Apr  8 14:11 test_table_compress.hdf
46152810 Apr  8 14:11 test.csv
```

And here's the code

```
import sqlite3
import os
from pandas.io import sql

df = DataFrame(randn(1000000,2),columns=list('AB'))

def test_sql_write(df):
    if os.path.exists('test.sql'):
        os.remove('test.sql')
    sql_db = sqlite3.connect('test.sql')
    df.to_sql(name='test_table', con=sql_db)
    sql_db.close()

def test_sql_read():
    sql_db = sqlite3.connect('test.sql')
    pd.read_sql_query("select * from test_table", sql_db)
    sql_db.close()

def test_hdf_fixed_write(df):
    df.to_hdf('test_fixed.hdf','test',mode='w')

def test_hdf_fixed_read():
    pd.read_hdf('test_fixed.hdf','test')

def test_hdf_fixed_write_compress(df):
    df.to_hdf('test_fixed_compress.hdf','test',mode='w',complib='blosc')

def test_hdf_fixed_read_compress():
    pd.read_hdf('test_fixed_compress.hdf','test')

def test_hdf_table_write(df):
    df.to_hdf('test_table.hdf','test',mode='w',format='table')

def test_hdf_table_read():
    pd.read_hdf('test_table.hdf','test')

def test_hdf_table_write_compress(df):
    df.to_hdf('test_table_compress.hdf','test',mode='w',complib='blosc',format='table')

def test_hdf_table_read_compress():
    pd.read_hdf('test_table_compress.hdf','test')

def test_csv_write(df):
    df.to_csv('test.csv',mode='w')

def test_csv_read():
    pd.read_csv('test.csv',index_col=0)
```

CHAPTER

TWENTYFIVE

REMOTE DATA ACCESS

Warning: In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable pandas-datareader package. This will allow the data modules to be independently updated to your pandas installation. The API for `pandas-datareader v0.1.1` is the same as in `pandas v0.16.1`. (GH8961)

You should replace the imports of the following:

```
from pandas.io import data, wb
```

With:

```
from pandas_datareader import data, wb
```

Functions from `pandas.io.data` and `pandas.io.ga` extract data from various Internet sources into a DataFrame. Currently the following sources are supported:

- *Yahoo! Finance*
- *Google Finance*
- *St.Louis FED (FRED)*
- *Kenneth French's data library*
- *World Bank*
- *Google Analytics*

It should be noted, that various sources support different kinds of data, so not all sources implement the same methods and the data elements returned might also differ.

25.1 Yahoo! Finance

```
In [1]: import pandas.io.data as web

In [2]: import datetime

In [3]: start = datetime.datetime(2010, 1, 1)

In [4]: end = datetime.datetime(2013, 1, 27)

In [5]: f = web.DataReader("F", 'yahoo', start, end)

In [6]: f.ix['2010-01-04']
Out[6]:
Open              10.170000
```

```
High                10.280000
Low                 10.050000
Close               10.280000
Volume        60855800.000000
Adj Close            9.338676
Name: 2010-01-04 00:00:00, dtype: float64
```

25.2 Yahoo! Finance Options

Experimental

The `Options` class allows the download of options data from Yahoo! Finance.

The `get_all_data` method downloads and caches option data for all expiry months and provides a formatted `DataFrame` with a hierarchical index, so it is easy to get to the specific option you want.

```
In [7]: from pandas.io.data import Options

In [8]: aapl = Options('aapl', 'yahoo')

In [9]: data = aapl.get_all_data()

In [10]: data.iloc[0:5, 0:5]
Out[10]: 
                                             Last    Bid    Ask   Chg   PctChg
Strike Expiry     Type Symbol                                                
34.29  2016-01-15 call AAPL160115C00034290  97.55  92.10  94.30  0.00    0.00%
                  put  AAPL160115P00034290   0.02   0.01   0.03  0.01  100.00%
35.71  2016-01-15 call AAPL160115C00035710  88.30  90.80  91.95  0.00    0.00%
                  put  AAPL160115P00035710   0.01   0.01   0.04  0.00    0.00%
37.14  2016-01-15 call AAPL160115C00037140  90.70  88.50  90.55  0.60    0.67%

# Show the $100 strike puts at all expiry dates:
In [11]: data.loc[(100, slice(None), 'put'),:].iloc[0:5, 0:5]
Out[11]: 
                                            Last   Bid   Ask   Chg   PctChg
Strike Expiry     Type Symbol                                              
100    2015-06-19 put  AAPL150619P00100000  0.01     0  0.01  0.00    0.00%
       2015-06-26 put  AAPL150626P00100000  0.02  0.01  0.02 -0.02  -50.00%
       2015-07-17 put  AAPL150717P00100000  0.03  0.03  0.04 -0.01  -25.00%
       2015-08-21 put  AAPL150821P00100000  0.22  0.22  0.24  0.03   15.79%
       2015-10-16 put  AAPL151016P00100000  0.60   0.6  0.62  0.07   13.21%

# Show the volume traded of $100 strike puts at all expiry dates:
In [12]: data.loc[(100, slice(None), 'put'),'Vol'].head()
Out[12]: 
Strike  Expiry      Type  Symbol             
100     2015-06-19  put   AAPL150619P00100000    263
        2015-06-26  put   AAPL150626P00100000      8
        2015-07-17  put   AAPL150717P00100000     52
        2015-08-21  put   AAPL150821P00100000     23
        2015-10-16  put   AAPL151016P00100000    126
Name: Vol, dtype: int64
```

If you don’t want to download all the data, more specific requests can be made.

```
In [13]: import datetime

In [14]: expiry = datetime.date(2016, 1, 1)

In [15]: data = aapl.get_call_data(expiry=expiry)

In [16]: data.iloc[0:5:, 0:5]
Out[16]:
                                                Last    Bid    Ask  Chg PctChg
Strike Expiry     Type Symbol
34.29  2016-01-15 call AAPL160115C00034290  97.55  92.10  94.30  0.0  0.00%
35.71  2016-01-15 call AAPL160115C00035710  88.30  90.80  91.95  0.0  0.00%
37.14  2016-01-15 call AAPL160115C00037140  90.70  88.50  90.55  0.6  0.67%
38.57  2016-01-15 call AAPL160115C00038570  86.45  87.40  89.95  0.0  0.00%
40.00  2016-01-15 call AAPL160115C00040000  89.40  86.00  87.75  0.0  0.00%
```

Note that if you call `get_all_data` first, this second call will happen much faster, as the data is cached.

If a given expiry date is not available, data for the next available expiry will be returned (January 15, 2015 in the above example).

Available expiry dates can be accessed from the `expiry_dates` property.

```
In [17]: aapl.expiry_dates
Out[17]:
[datetime.date(2015, 6, 19),
 datetime.date(2015, 6, 26),
 datetime.date(2015, 7, 2),
 datetime.date(2015, 7, 10),
 datetime.date(2015, 7, 17),
 datetime.date(2015, 7, 24),
 datetime.date(2015, 7, 31),
 datetime.date(2015, 8, 21),
 datetime.date(2015, 10, 16),
 datetime.date(2015, 12, 18),
 datetime.date(2016, 1, 15),
 datetime.date(2016, 6, 17),
 datetime.date(2017, 1, 20)]

In [18]: data = aapl.get_call_data(expiry=aapl.expiry_dates[0])

In [19]: data.iloc[0:5:, 0:5]
Out[19]:
                                                Last    Bid    Ask   Chg   PctChg
Strike Expiry     Type Symbol
65     2015-06-19 call AAPL150619C00065000  64.25  61.95  62.35  0.00   0.00%
70     2015-06-19 call AAPL150619C00070000  60.72  56.85  57.35  0.00   0.00%
75     2015-06-19 call AAPL150619C00075000  57.21  51.85  52.45  0.00   0.00%
80     2015-06-19 call AAPL150619C00080000  47.50  46.80  47.40 -1.36  -2.78%
85     2015-06-19 call AAPL150619C00085000  42.50  41.85  42.40  0.00   0.00%
```

A list-like object containing dates can also be passed to the expiry parameter, returning options data for all expiry dates in the list.

```
In [20]: data = aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3])

In [21]: data.iloc[0:5:, 0:5]
Out[21]:
                                               Last   Bid   Ask   Chg   PctChg
Strike Expiry     Type Symbol
```

```
127    2015-06-26 call AAPL150626C00127000  2.00  1.98  2.00 -0.96  -32.43%
       2015-07-02 call AAPL150702C00127000  2.36  2.34  2.40 -0.94  -28.48%
128    2015-06-19 call AAPL150619C00128000  0.88  0.88  0.89 -0.87  -49.71%
       2015-06-26 call AAPL150626C00128000  1.48  1.47  1.51 -0.85  -36.48%
       2015-07-02 call AAPL150702C00128000  1.88  1.85  1.89 -0.84  -30.88%
```

The `month` and `year` parameters can be used to get all options data for a given month.

25.3 Google Finance

```
In [22]: import pandas.io.data as web

In [23]: import datetime

In [24]: start = datetime.datetime(2010, 1, 1)

In [25]: end = datetime.datetime(2013, 1, 27)

In [26]: f = web.DataReader("F", 'google', start, end)

In [27]: f.ix['2010-01-04']
Out[27]:
Open            10.17
High            10.28
Low             10.05
Close           10.28
Volume    60855796.00
Name: 2010-01-04 00:00:00, dtype: float64
```

25.4 FRED

```
In [28]: import pandas.io.data as web

In [29]: import datetime

In [30]: start = datetime.datetime(2010, 1, 1)

In [31]: end = datetime.datetime(2013, 1, 27)

In [32]: gdp=web.DataReader("GDP", "fred", start, end)

In [33]: gdp.ix['2013-01-01']
Out[33]:
GDP    16502.4
Name: 2013-01-01 00:00:00, dtype: float64

# Multiple series:
In [34]: inflation = web.DataReader(["CPIAUCSL", "CPILFESL"], "fred", start, end)

In [35]: inflation.head()
Out[35]:
            CPIAUCSL  CPILFESL
DATE
2010-01-01   217.488   220.633
```

```
2010-02-01   217.281   220.731
2010-03-01   217.353   220.783
2010-04-01   217.403   220.822
2010-05-01   217.290   220.962
```

25.5 Fama/French

Dataset names are listed at Fama/French Data Library.

```
In [36]: import pandas.io.data as web

In [37]: ip = web.DataReader("5_Industry_Portfolios", "famafrench")

In [38]: ip[4].ix[192607]
Out[38]:
1 Cnsmr    5.43
2 Manuf    2.73
3 HiTec    1.83
4 Hlth     1.77
5 Other    2.16
Name: 192607, dtype: float64
```

25.6 World Bank

pandas users can easily access thousands of panel data series from the World Bank's World Development Indicators by using the wb I/O functions.

25.6.1 Indicators

Either from exploring the World Bank site, or using the search function included, every world bank indicator is accessible.

For example, if you wanted to compare the Gross Domestic Products per capita in constant dollars in North America, you would use the search function:

```
In [1]: from pandas.io import wb

In [2]: wb.search('gdp.*capita.*const').iloc[:,:2]
Out[2]:
                     id                                               name
3242            GDPPCKD             GDP per Capita, constant US$, millions
5143     NY.GDP.PCAP.KD                 GDP per capita (constant 2005 US$)
5145     NY.GDP.PCAP.KN                      GDP per capita (constant LCU)
5147  NY.GDP.PCAP.PP.KD  GDP per capita, PPP (constant 2005 internation...
```

Then you would use the download function to acquire the data from the World Bank's servers:

```
In [3]: dat = wb.download(indicator='NY.GDP.PCAP.KD', country=['US', 'CA', 'MX'], start=2005, end=20

In [4]: print(dat)
                      NY.GDP.PCAP.KD
country       year
Canada        2008  36005.5004978584
```

```
               2007  36182.9138439757
               2006  35785.9698172849
               2005  35087.8925933298
Mexico         2008  8113.10219480083
               2007  8119.21298908649
               2006  7961.96818458178
               2005  7666.69796097264
United States  2008  43069.5819857208
               2007  43635.5852068142
               2006   43228.111147107
               2005  42516.3934699993
```

The resulting dataset is a properly formatted `DataFrame` with a hierarchical index, so it is easy to apply `.groupby` transformations to it:

```
In [6]: dat['NY.GDP.PCAP.KD'].groupby(level=0).mean()
Out[6]:
country
Canada           35765.569188
Mexico            7965.245332
United States    43112.417952
dtype: float64
```

Now imagine you want to compare GDP to the share of people with cellphone contracts around the world.

```
In [7]: wb.search('cell.*%').iloc[:,:2]
Out[7]:
                     id                                               name
3990  IT.CEL.SETS.FE.ZS  Mobile cellular telephone users, female (% of ...
3991  IT.CEL.SETS.MA.ZS  Mobile cellular telephone users, male (% of po...
4027      IT.MOB.COV.ZS  Population coverage of mobile cellular telepho...
```

Notice that this second search was much faster than the first one because `pandas` now has a cached list of available data series.

```
In [13]: ind = ['NY.GDP.PCAP.KD', 'IT.MOB.COV.ZS']
In [14]: dat = wb.download(indicator=ind, country='all', start=2011, end=2011).dropna()
In [15]: dat.columns = ['gdp', 'cellphone']
In [16]: print(dat.tail())
                        gdp  cellphone
country   year
Swaziland 2011  2413.952853       94.9
Tunisia   2011  3687.340170      100.0
Uganda    2011   405.332501      100.0
Zambia    2011   767.911290       62.0
Zimbabwe  2011   419.236086       72.4
```

Finally, we use the `statsmodels` package to assess the relationship between our two variables using ordinary least squares regression. Unsurprisingly, populations in rich countries tend to use cellphones at a higher rate:

```
In [17]: import numpy as np
In [18]: import statsmodels.formula.api as smf
In [19]: mod = smf.ols("cellphone ~ np.log(gdp)", dat).fit()
In [20]: print(mod.summary())
                            OLS Regression Results
==============================================================================
Dep. Variable:              cellphone   R-squared:                       0.297
Model:                            OLS   Adj. R-squared:                  0.274
Method:                 Least Squares   F-statistic:                     13.08
```

```
Date:                Thu, 25 Jul 2013   Prob (F-statistic):          0.00105
Time:                        15:24:42   Log-Likelihood:              -139.16
No. Observations:                  33   AIC:                           282.3
Df Residuals:                      31   BIC:                           285.3
Df Model:                           1
================================================================================
                  coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------
Intercept      16.5110     19.071      0.866      0.393       -22.384    55.406
np.log(gdp)     9.9333      2.747      3.616      0.001         4.331    15.535
==============================================================================
Omnibus:                       36.054   Durbin-Watson:                   2.071
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              119.133
Skew:                          -2.314   Prob(JB):                     1.35e-26
Kurtosis:                      11.077   Cond. No.                         45.8
==============================================================================
```

25.6.2 Country Codes

New in version 0.15.1.

The `country` argument accepts a string or list of mixed two or three character ISO country codes, as well as dynamic World Bank exceptions to the ISO standards.

For a list of the the hard-coded country codes (used solely for error handling logic) see `pandas.io.wb.country_codes`.

25.6.3 Problematic Country Codes & Indicators

Note: The World Bank's country list and indicators are dynamic. As of 0.15.1, `wb.download()` is more flexible. To achieve this, the warning and exception logic changed.

The world bank converts some country codes in their response, which makes error checking by pandas difficult. Retired indicators still persist in the search.

Given the new flexibility of 0.15.1, improved error handling by the user may be necessary for fringe cases.

To help identify issues:

There are at least 4 kinds of country codes:

1. Standard (2/3 digit ISO) - returns data, will warn and error properly.
2. Non-standard (WB Exceptions) - returns data, but will falsely warn.
3. Blank - silently missing from the response.
4. Bad - causes the entire response from WB to fail, always exception inducing.

There are at least 3 kinds of indicators:

1. Current - Returns data.
2. Retired - Appears in search results, yet won't return data.
3. Bad - Will not return data.

Use the `errors` argument to control warnings and exceptions. Setting errors to ignore or warn, won't stop failed responses. (ie, 100% bad indicators, or a single "bad" (#4 above) country code).

See docstrings for more info.

25.7 Google Analytics

The ga module provides a wrapper for Google Analytics API to simplify retrieving traffic data. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table.

25.7.1 Configuring Access to Google Analytics

The first thing you need to do is to setup accesses to Google Analytics API. Follow the steps below:

1. **In the Google Developers Console**
   (a) enable the Analytics API
   (b) create a new project
   (c) create a new Client ID for an "Installed Application" (in the "APIs & auth / Credentials section" of the newly created project)
   (d) download it (JSON file)
2. **On your machine**
   (a) rename it to `client_secrets.json`
   (b) move it to the `pandas/io` module directory

The first time you use the `read_ga()` funtion, a browser window will open to ask you to authentify to the Google API. Do proceed.

25.7.2 Using the Google Analytics API

The following will fetch users and pageviews (metrics) data per day of the week, for the first semester of 2014, from a particular property.

```
import pandas.io.ga as ga
ga.read_ga(
    account_id  = "2360420",
    profile_id  = "19462946",
    property_id = "UA-2360420-5",
    metrics     = ['users', 'pageviews'],
    dimensions  = ['dayOfWeek'],
    start_date  = "2014-01-01",
    end_date    = "2014-08-01",
    index_col   = 0,
    filters     = "pagePath=~aboutus;ga:country==France",
)
```

The only mandatory arguments are `metrics,` `dimensions` and `start_date`. We strongly recommend that you always specify the `account_id`, `profile_id` and `property_id` to avoid accessing the wrong data bucket in Google Analytics.

The `index_col` argument indicates which dimension(s) has to be taken as index.

The `filters` argument indicates the filtering to apply to the query. In the above example, the page URL has to contain `aboutus` AND the visitors country has to be France.

Detailed information in the following:

- pandas & google analytics, by yhat
- Google Analytics integration in pandas, by Chang She
- Google Analytics Dimensions and Metrics Reference

CHAPTER

TWENTYSIX

ENHANCING PERFORMANCE

26.1 Cython (Writing C extensions for pandas)

For many use cases writing pandas in pure python and numpy is sufficient. In some computationally heavy applications however, it can be possible to achieve sizeable speed-ups by offloading work to cython.

This tutorial assumes you have refactored as much as possible in python, for example trying to remove for loops and making use of numpy vectorization, it's always worth optimising in python first.

This tutorial walks through a "typical" process of cythonizing a slow computation. We use an example from the cython documentation but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure python.

26.1.1 Pure python

We have a DataFrame to which we want to apply a function row-wise.

```
In [1]: df = DataFrame({'a': randn(1000), 'b': randn(1000),'N': randint(100, 1000, (1000)), 'x': 'x'

In [2]: df
Out[2]:
       N         a         b  x
0    585  0.469112 -0.218470  x
1    841 -0.282863 -0.061645  x
2    251 -1.509059 -0.723780  x
3    972 -1.135632  0.551225  x
4    181  1.212112 -0.497767  x
5    458 -0.173215  0.837519  x
6    159  0.119209  1.103245  x
..   ...       ...       ... ..
993  190  0.131892  0.290162  x
994  931  0.342097  0.215341  x
995  374 -1.512743  0.874737  x
996  246  0.933753  1.120790  x
997  157 -0.308013  0.198768  x
998  977 -0.079915  1.757555  x
999  770 -1.010589 -1.115680  x

[1000 rows x 4 columns]
```

Here's the function in pure python:

```
In [3]: def f(x):
   ...:     return x * (x - 1)
```

```
   ...:

In [4]: def integrate_f(a, b, N):
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f(a + i * dx)
   ...:     return s * dx
   ...:
```

We achieve our result by using `apply` (row-wise):

```
In [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:

```
In [5]: %prun -l 4 df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
         611748 function calls (609735 primitive calls) in 0.561 seconds

   Ordered by: internal time
   List reduced from 102 to 4 due to restriction <4>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     1000    0.306    0.000    0.492    0.000 <ipython-input-4-91e33489f136>:1(integrate_f)
   552423    0.179    0.000    0.179    0.000 <ipython-input-3-bc41a25943f6>:1(f)
     1000    0.007    0.000    0.007    0.000 {range}
     3000    0.007    0.000    0.047    0.000 series.py:519(__getitem__)
```

By far the majority of time is spend inside either `integrate_f` or `f`, hence we'll concentrate our efforts cythonizing these two functions.

Note: In python 2 replacing the `range` with its generator counterpart (`xrange`) would mean the `range` line would vanish. In python 3 `range` is already a generator.

26.1.2 Plain cython

First we're going to need to import the cython magic function to ipython:

```
In [6]: %load_ext cythonmagic
```

Now, let's simply copy our functions over to cython as is (the suffix is here to distinguish between function versions):

```
In [7]: %%cython
   ...: def f_plain(x):
   ...:     return x * (x - 1)
   ...: def integrate_f_plain(a, b, N):
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f_plain(a + i * dx)
   ...:     return s * dx
   ...:
```

Note: If you're having trouble pasting the above into your ipython, you may need to be using bleeding edge ipython for paste to play well with cell magics.

```
In [4]: %timeit df.apply(lambda x: integrate_f_plain(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 85.5 ms per loop
```

Already this has shaved a third off, not too bad for a simple copy and paste.

26.1.3 Adding type

We get another huge improvement simply by providing type information:

```
In [8]: %%cython
   ...: cdef double f_typed(double x) except? -2:
   ...:     return x * (x - 1)
   ...: cpdef double integrate_f_typed(double a, double b, int N):
   ...:     cdef int i
   ...:     cdef double s, dx
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f_typed(a + i * dx)
   ...:     return s * dx
   ...:
```

```
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:

```
In [9]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
         58325 function calls (56312 primitive calls) in 0.078 seconds

   Ordered by: internal time
   List reduced from 100 to 4 due to restriction <4>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     3000    0.008    0.000    0.052    0.000 series.py:519(__getitem__)
     3000    0.007    0.000    0.017    0.000 internals.py:3481(get_values)
     3000    0.007    0.000    0.039    0.000 index.py:1582(get_value)
     6000    0.007    0.000    0.026    0.000 {pandas.lib.values_from_object}
```

26.1.4 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 minimise 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 co
   ....:     assert (col_a.dtype == np.float and col_b.dtype == np.float and col_N.dtype == np.int)
   ....:     cdef Py_ssize_t i, n = len(col_N)
   ....:     assert (len(col_a) == len(col_b) == n)
   ....:     cdef np.ndarray[double] res = np.empty(n)
   ....:     for i in range(len(col_a)):
   ....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
   ....:     return res
   ....:
```

The implementation is simple, it creates an array of zeros and loops over the rows, applying our `integrate_f_typed`, and putting this in the zeros array.

> **Warning:** In 0.13.0 since `Series` has internaly been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, you can **not pass** a `Series` directly as a `ndarray` typed parameter to a cython function. Instead pass the actual `ndarray` using the `.values` attribute of the Series.
>
> Prior to 0.13.0
>
> ```
> apply_integrate_f(df['a'], df['b'], df['N'])
> ```
>
> Use `.values` to get the underlying `ndarray`
>
> ```
> apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
> ```

Note: Loops like this would be *extremely* slow in python, but in Cython looping over numpy arrays is *fast*.

```
In [4]: %timeit apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
1000 loops, best of 3: 1.25 ms per loop
```

We've gotten another big improvement. Let's check again where the time is spent:

```
In [11]: %prun -l 4 apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
         190 function calls in 0.003 seconds

   Ordered by: internal time
   List reduced from 49 to 4 due to restriction <4>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
        1    0.002    0.002    0.002    0.002 {_cython_magic_073e22cb442403aaff864a05d833c10b.apply_i
        3    0.000    0.000    0.000    0.000 internals.py:2872(iget)
        6    0.000    0.000    0.000    0.000 generic.py:2152(__setattr__)
        3    0.000    0.000    0.000    0.000 generic.py:1079(_get_item_cache)
```

As one might expect, the majority of the time is now spent in `apply_integrate_f`, so if we wanted to make anymore efficiencies we must continue to concentrate our efforts here.

26.1.5 More advanced techniques

There is still hope for improvement. Here's an example of using some more advanced cython techniques:

```
In [12]: %%cython
   ....: cimport cython
   ....: cimport numpy as np
   ....: import numpy as np
   ....: cdef double f_typed(double x) except? -2:
   ....:     return x * (x - 1)
   ....: cpdef double integrate_f_typed(double a, double b, int N):
   ....:     cdef int i
   ....:     cdef double s, dx
   ....:     s = 0
   ....:     dx = (b - a) / N
   ....:     for i in range(N):
   ....:         s += f_typed(a + i * dx)
   ....:     return s * dx
   ....: @cython.boundscheck(False)
   ....: @cython.wraparound(False)
   ....: cpdef np.ndarray[double] apply_integrate_f_wrap(np.ndarray[double] col_a, np.ndarray[double]
   ....:     cdef Py_ssize_t i, n = len(col_N)
   ....:     assert len(col_a) == len(col_b) == n
   ....:     cdef np.ndarray[double] res = np.empty(n)
   ....:     for i in range(n):
   ....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
   ....:     return res
   ....:
```

```
In [4]: %timeit apply_integrate_f_wrap(df['a'].values, df['b'].values, df['N'].values)
1000 loops, best of 3: 987 us per loop
```

Even faster, with the caveat that a bug in our cython code (an off-by-one error, for example) might cause a segfault because memory access isn't checked.

26.2 Using numba

A recent alternative to statically compiling cython code, is to use a *dynamic jit-compiler*, numba.

Numba gives you the power to speed up your applications with high performance functions written directly in Python. With a few annotations, array-oriented and math-heavy Python code can be just-in-time compiled to native machine instructions, similar in performance to C, C++ and Fortran, without having to switch languages or Python interpreters.

Numba works by generating optimized machine code using the LLVM compiler infrastructure at import time, runtime, or statically (using the included pycc tool). Numba supports compilation of Python to run on either CPU or GPU hardware, and is designed to integrate with the Python scientific software stack.

Note: You will need to install numba. This is easy with conda, by using: conda install numba, see *installing using miniconda*.

We simply take the plain python code from above and annotate with the @jit decorator.

```
import numba

@numba.jit
def f_plain(x):
```

```
    return x * (x - 1)

@numba.jit
def integrate_f_numba(a, b, N):
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f_plain(a + i * dx)
    return s * dx

@numba.jit
def apply_integrate_f_numba(col_a, col_b, col_N):
    n = len(col_N)
    result = np.empty(n, dtype='float64')
    assert len(col_a) == len(col_b) == n
    for i in range(n):
       result[i] = integrate_f_numba(col_a[i], col_b[i], col_N[i])
    return result

def compute_numba(df):
    result = apply_integrate_f_numba(df['a'].values, df['b'].values, df['N'].values)
    return Series(result, index=df.index, name='result')
```

Similar to above, we directly pass `numpy` arrays directly to the numba function. Further we are wrapping the results to provide a nice interface by passing/returning pandas objects.

```
In [4]: %timeit compute_numba(df)
1000 loops, best of 3: 798 us per loop
```

Read more in the numba docs.

26.3 Expression Evaluation via `eval()` (Experimental)

New in version 0.13.

The top-level function `pandas.eval()` implements expression evaluation of `Series` and `DataFrame` objects.

Note: To benefit from using `eval()` you need to install `numexpr`. See the *recommended dependencies section* for more details.

The point of using `eval()` for expression evaluation rather than plain Python is two-fold: 1) large `DataFrame` objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default `numexpr` is used for evaluation).

Note: You should not use `eval()` for simple expressions or for expressions involving small DataFrames. In fact, `eval()` is many orders of magnitude slower for smaller expressions/objects than plain ol' Python. A good rule of thumb is to only use `eval()` when you have a `DataFrame` with more than 10,000 rows.

`eval()` supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

Note: The larger the frame and the larger the expression the more speedup you will see from using `eval()`.

26.3.1 Supported Syntax

These operations are supported by `pandas.eval()`:

- 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)

This Python syntax is **not** allowed:

- Expressions
  - Function calls
  - `is`/`is not` operations
  - `if` expressions
  - `lambda` expressions
  - `list`/`set`/`dict` comprehensions
  - Literal `dict` and `set` expressions
  - `yield` expressions
  - Generator expressions
  - Boolean expressions consisting of only scalar values
- Statements
  - Neither simple nor compound statements are allowed. This includes things like `for`, `while`, and `if`.

26.3.2 `eval()` Examples

`pandas.eval()` works well with expressions containing large arrays.

First let's create a few decent-sized arrays to play with:

```
In [13]: import pandas as pd

In [14]: from pandas import DataFrame, Series

In [15]: from numpy.random import randn

In [16]: import numpy as np

In [17]: nrows, ncols = 20000, 100

In [18]: df1, df2, df3, df4 = [DataFrame(randn(nrows, ncols)) for _ in range(4)]
```

Now let's compare adding them together using plain ol' Python versus `eval()`:

```
In [19]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 24.4 ms per loop

In [20]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 13.8 ms per loop
```

Now let's do the same thing but with comparisons:

```
In [21]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
10 loops, best of 3: 71.4 ms per loop

In [22]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
10 loops, best of 3: 24.5 ms per loop
```

`eval()` also works with unaligned pandas objects:

```
In [23]: s = Series(randn(50))

In [24]: %timeit df1 + df2 + df3 + df4 + s
10 loops, best of 3: 80.5 ms per loop

In [25]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
10 loops, best of 3: 57 ms per loop
```

Note: Operations such as

```
1 and 2  # would parse to 1 & 2, but should evaluate to 2
3 or 4  # would parse to 3 | 4, but should evaluate to 3
~1  # this is okay, but slower when using eval
```

should be performed in Python. An exception will be raised if you try to perform any boolean/bitwise operations with scalar operands that are not of type `bool` or `np.bool_`. Again, you should perform these kinds of operations in plain Python.

26.3.3 The `DataFrame.eval` method (Experimental)

New in version 0.13.

In addition to the top level `pandas.eval()` function you can also evaluate an expression in the "context" of a `DataFrame`.

```
In [26]: df = DataFrame(randn(5, 2), columns=['a', 'b'])

In [27]: df.eval('a + b')
Out[27]:
0   -0.246747
1    0.867786
2   -1.626063
3   -1.134978
4   -1.027798
dtype: float64
```

Any expression that is a valid `pandas.eval()` expression is also a valid `DataFrame.eval()` expression, with the added benefit that you don't have to prefix the name of the `DataFrame` to the column(s) you're interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for *formulaic evaluation*. Only a single assignment is permitted. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

```
In [28]: df = DataFrame(dict(a=range(5), b=range(5, 10)))

In [29]: df.eval('c = a + b')

In [30]: df.eval('d = a + b + c')

In [31]: df.eval('a = 1')

In [32]: df
Out[32]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26
```

The equivalent in standard Python would be

```
In [33]: df = DataFrame(dict(a=range(5), b=range(5, 10)))

In [34]: df['c'] = df.a + df.b

In [35]: df['d'] = df.a + df.b + df.c

In [36]: df['a'] = 1

In [37]: df
Out[37]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26
```

26.3.4 Local Variables

In pandas version 0.14 the local variable API has changed. In pandas 0.13.x, you could refer to local variables the same way you would in standard Python. For example,

```
df = DataFrame(randn(5, 2), columns=['a', 'b'])
newcol = randn(len(df))
df.eval('b + newcol')

UndefinedVariableError: name 'newcol' is not defined
```

As you can see from the exception generated, this syntax is no longer allowed. You must *explicitly reference* any local variable that you want to use in an expression by placing the `@` character in front of the name. For example,

```
In [38]: df = DataFrame(randn(5, 2), columns=list('ab'))

In [39]: newcol = randn(len(df))
```

```
In [40]: df.eval('b + @newcol')
Out[40]:
0   -0.173926
1    2.493083
2   -0.881831
3   -0.691045
4    1.334703
dtype: float64

In [41]: df.query('b < @newcol')
Out[41]:
          a         b
0  0.863987 -0.115998
2 -2.621419 -1.297879
```

If you don't prefix the local variable with `@`, pandas will raise an exception telling you the variable is undefined.

When using `DataFrame.eval()` and `DataFrame.query()`, this allows you to have a local variable and a `DataFrame` column with the same name in an expression.

```
In [42]: a = randn()

In [43]: df.query('@a < a')
Out[43]:
          a         b
0  0.863987 -0.115998

In [44]: df.loc[a < df.a]  # same as the previous expression
Out[44]:
          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 [45]: a, b = 1, 2

In [46]: pd.eval('@a + b')
  File "<string>", line unknown
SyntaxError: The '@' prefix is not allowed in top-level eval calls,
please refer to your variables by name without the '@' prefix
```

In this case, you should simply refer to the variables like you would in standard Python.

```
In [47]: pd.eval('a + b')
Out[47]: 3
```

26.3.5 `pandas.eval()` Parsers

There are two different parsers and two different engines you can use as the backend.

The default `'pandas'` parser allows a more intuitive syntax for expressing query-like operations (comparisons, conjunctions and disjunctions). In particular, the precedence of the `&` and `|` operators is made equal to the precedence of the corresponding boolean operations `and` and `or`.

For example, the above conjunction can be written without parentheses. Alternatively, you can use the `'python'` parser to enforce strict Python semantics.

```
In [48]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'

In [49]: x = pd.eval(expr, parser='python')

In [50]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'

In [51]: y = pd.eval(expr_no_parens, parser='pandas')

In [52]: np.all(x == y)
Out[52]: True
```

The same expression can be "anded" together with the word `and` as well:

```
In [53]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'

In [54]: x = pd.eval(expr, parser='python')

In [55]: expr_with_ands = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'

In [56]: y = pd.eval(expr_with_ands, parser='pandas')

In [57]: np.all(x == y)
Out[57]: True
```

The `and` and `or` operators here have the same precedence that they would in vanilla Python.

26.3.6 `pandas.eval()` Backends

There's also the option to make `eval()` operate identical to plain ol' Python.

Note: Using the `'python'` engine is generally *not* useful, except for testing other evaluation engines against it. You will acheive **no** performance benefits using `eval()` with `engine='python'` and in fact may incur a performance hit.

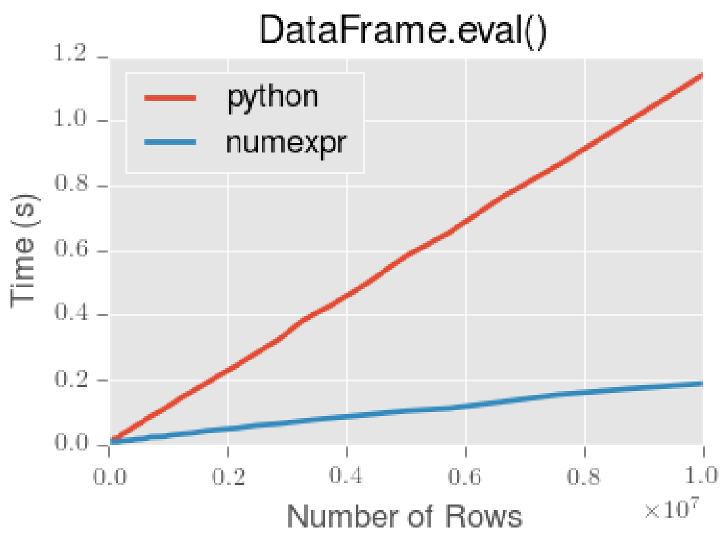
You can see this by using `pandas.eval()` with the `'python'` engine. It is a bit slower (not by much) than evaluating the same expression in Python

```
In [58]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 24.3 ms per loop

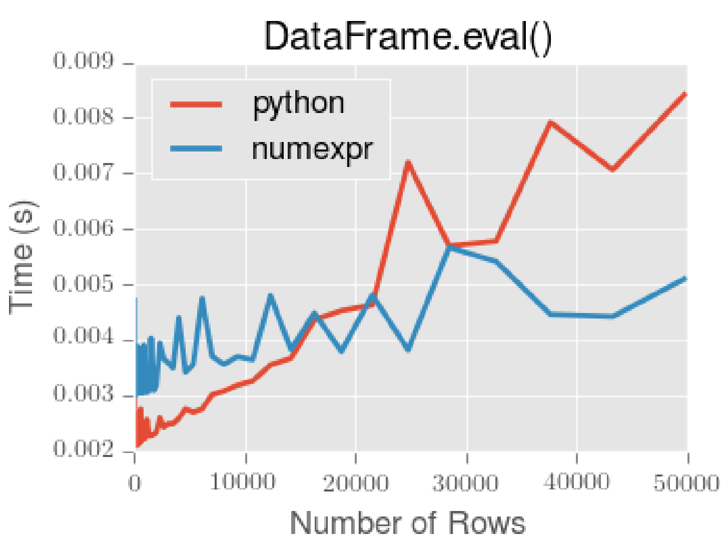
In [59]: %timeit pd.eval('df1 + df2 + df3 + df4', engine='python')
10 loops, best of 3: 26.1 ms per loop
```

26.3.7 `pandas.eval()` Performance

`eval()` is intended to speed up certain kinds of operations. In particular, those operations involving complex expressions with large `DataFrame`/`Series` objects should see a significant performance benefit. Here is a plot showing the running time of `pandas.eval()` as function of the size of the frame involved in the computation. The two lines are two different engines.



Note: Operations with smallish objects (around 15k-20k rows) are faster using plain Python:



This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

26.3.8 Technical Minutia Regarding Expression Evaluation

Expressions that would result in an object dtype or involve datetime operations (because of `NaT`) must be evaluated in Python space. The main reason for this behavior is to maintain backwards compatbility 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 [60]: df = DataFrame({'strings': np.repeat(list('cba'), 3),
   ....:                 'nums': np.repeat(range(3), 3)})
   ....:

In [61]: df
Out[61]:
   nums strings
0     0       c
1     0       c
2     0       c
3     1       b
4     1       b
5     1       b
6     2       a
7     2       a
8     2       a

In [62]: df.query('strings == "a" and nums == 1')
Out[62]:
Empty DataFrame
Columns: [nums, strings]
Index: []
```

the numeric part of the comparison (`nums == 1`) will be evaluated by `numexpr`.

In general, `DataFrame.query()`/`pandas.eval()` will evaluate the subexpressions that *can* be evaluated by `numexpr` and those that must be evaluated in Python space transparently to the user. This is done by inferring the result type of an expression from its arguments and operators.

CHAPTER

TWENTYSEVEN

SPARSE DATA STRUCTURES

We have implemented "sparse" versions of Series, DataFrame, and Panel. These are not sparse in the typical "mostly 0". You can view these objects as being "compressed" where any data matching a specific value (NaN/missing by default, though any value can be chosen) is omitted. A special `SparseIndex` object tracks where data has been "sparsified". This will make much more sense in an example. All of the standard pandas data structures have a `to_sparse` method:

```
In [1]: ts = Series(randn(10))

In [2]: ts[2:-2] = np.nan

In [3]: sts = ts.to_sparse()

In [4]: sts
Out[4]:
0    0.469112
1   -0.282863
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8   -0.861849
9   -2.104569
dtype: float64
BlockIndex
Block locations: array([0, 8])
Block lengths: array([2, 2])
```

The `to_sparse` method takes a `kind` argument (for the sparse index, see below) and a `fill_value`. So if we had a mostly zero Series, we could convert it to sparse with `fill_value=0`:

```
In [5]: ts.fillna(0).to_sparse(fill_value=0)
Out[5]:
0    0.469112
1   -0.282863
2    0.000000
3    0.000000
4    0.000000
5    0.000000
6    0.000000
7    0.000000
8   -0.861849
9   -2.104569
dtype: float64
```

```
BlockIndex
Block locations: array([0, 8])
Block lengths: array([2, 2])
```

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```
In [6]: df = DataFrame(randn(10000, 4))

In [7]: df.ix[:9998] = np.nan

In [8]: sdf = df.to_sparse()

In [9]: sdf
Out[9]:
             0         1         2         3
0          NaN       NaN       NaN       NaN
1          NaN       NaN       NaN       NaN
2          NaN       NaN       NaN       NaN
3          NaN       NaN       NaN       NaN
4          NaN       NaN       NaN       NaN
5          NaN       NaN       NaN       NaN
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       NaN       NaN       NaN       NaN
9999  0.280249 -1.648493  1.490865 -0.890819

[10000 rows x 4 columns]

In [10]: sdf.density
Out[10]: 0.0001
```

As you can see, the density (% of values that have not been "compressed") is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter. Functionally, their behavior should be nearly identical to their dense counterparts.

Any sparse object can be converted back to the standard dense form by calling `to_dense`:

```
In [11]: sts.to_dense()
Out[11]:
0    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
```

27.1 SparseArray

`SparseArray` is the base layer for all of the sparse indexed data structures. It is a 1-dimensional ndarray-like object storing only values distinct from the `fill_value`:

```
In [12]: arr = np.random.randn(10)

In [13]: arr[2:5] = np.nan; arr[7:8] = np.nan

In [14]: sparr = SparseArray(arr)

In [15]: sparr
Out[15]:
[-1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9])
```

Like the indexed objects (SparseSeries, SparseDataFrame, SparsePanel), a `SparseArray` can be converted back to a regular ndarray by calling `to_dense`:

```
In [16]: sparr.to_dense()
Out[16]:
array([-1.9557, -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,
           nan,  0.606 ,  1.3342])
```

27.2 SparseList

`SparseList` is a list-like data structure for managing a dynamic collection of SparseArrays. To create one, simply call the `SparseList` constructor with a `fill_value` (defaulting to `NaN`):

```
In [17]: spl = SparseList()

In [18]: spl
Out[18]: <pandas.sparse.list.SparseList object at 0x9c67e74c>
```

The two important methods are `append` and `to_array`. `append` can accept scalar values or any 1-dimensional sequence:

```
In [19]: from numpy import nan

In [20]: spl.append(np.array([1., nan, nan, 2., 3.]))

In [21]: spl.append(5)

In [22]: spl.append(sparr)

In [23]: spl
Out[23]:
<pandas.sparse.list.SparseList object at 0x9c67e74c>
[1.0, nan, nan, 2.0, 3.0]
Fill: nan
IntIndex
Indices: array([0, 3, 4])

[5.0]
```

```
Fill: nan
IntIndex
Indices: array([0])

[-1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9])
```

As you can see, all of the contents are stored internally as a list of memory-efficient `SparseArray` objects. Once you've accumulated all of the data, you can call `to_array` to get a single `SparseArray` with all the data:

```
In [24]: spl.to_array()
Out[24]:
[1.0, nan, nan, 2.0, 3.0, 5.0, -1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297
Fill: nan
IntIndex
Indices: array([ 0,  3,  4,  5,  6,  7, 11, 12, 14, 15])
```

27.3 SparseIndex objects

Two kinds of `SparseIndex` are implemented, `block` and `integer`. We recommend using `block` as it's more memory efficient. The `integer` format keeps an 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.

27.4 Interaction with scipy.sparse

Experimental api to transform between sparse pandas and scipy.sparse structures.

A `SparseSeries.to_coo()` method is implemented for transforming a `SparseSeries` indexed by a `MultiIndex` to a `scipy.sparse.coo_matrix`.

The method requires a `MultiIndex` with two or more levels.

```
In [25]: from numpy import nan

In [26]: s = Series([3.0, nan, 1.0, 3.0, nan, nan])

In [27]: s.index = MultiIndex.from_tuples([(1, 2, 'a', 0),
   ....:                                    (1, 2, 'a', 1),
   ....:                                    (1, 1, 'b', 0),
   ....:                                    (1, 1, 'b', 1),
   ....:                                    (2, 1, 'b', 0),
   ....:                                    (2, 1, 'b', 1)],
   ....:                                    names=['A', 'B', 'C', 'D'])
   ....:

In [28]: s
Out[28]:
A  B  C  D
1  2  a  0      3
         1    NaN
   1  b  0      1
         1      3
```

```
2  1  b  0    NaN
         1    NaN
dtype: float64

# SparseSeries
In [29]: ss = s.to_sparse()

In [30]: ss
Out[30]:
A  B  C  D
1  2  a  0      3
         1    NaN
   1  b  0      1
         1      3
2  1  b  0    NaN
         1    NaN
dtype: float64
BlockIndex
Block locations: array([0, 2])
Block lengths: array([1, 2])
```

In 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 [31]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
   ....:                              column_levels=['C', 'D'],
   ....:                              sort_labels=True)
   ....:

In [32]: A
Out[32]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
	with 3 stored elements in COOrdinate format>

In [33]: A.todense()
Out[33]:
matrix([[ 0.,  0.,  1.,  3.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])

In [34]: rows
Out[34]: [(1L, 1L), (1L, 2L), (2L, 1L)]

In [35]: columns
Out[35]: [('a', 0L), ('a', 1L), ('b', 0L), ('b', 1L)]
```

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

```
In [36]: A, rows, columns = ss.to_coo(row_levels=['A', 'B', 'C'],
   ....:                              column_levels=['D'],
   ....:                              sort_labels=False)
   ....:

In [37]: A
Out[37]:
<3x2 sparse matrix of type '<type 'numpy.float64'>'
	with 3 stored elements in COOrdinate format>
```

```
In [38]: A.todense()
Out[38]:
matrix([[ 3.,  0.],
        [ 1.,  3.],
        [ 0.,  0.]])

In [39]: rows
Out[39]: [(1L, 2L, 'a'), (1L, 1L, 'b'), (2L, 1L, 'b')]

In [40]: columns
Out[40]: [0, 1]
```

A convenience method `SparseSeries.from_coo()` is implemented for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`.

```
In [41]: from scipy import sparse

In [42]: A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
   ....:                          shape=(3, 4))
   ....:

In [43]: A
Out[43]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>

In [44]: A.todense()
Out[44]:
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.

```
In [45]: ss = SparseSeries.from_coo(A)

In [46]: ss
Out[46]:
0  2    1
   3    2
1  0    3
dtype: float64
BlockIndex
Block locations: array([0])
Block lengths: array([3])
```

Specifying `dense_index=True` will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to `dense_index=False`) if the sparse matrix is large (and sparse) enough.

```
In [47]: ss_dense = SparseSeries.from_coo(A, dense_index=True)

In [48]: ss_dense
Out[48]:
0  0   NaN
   1   NaN
   2     1
   3     2
```

```
1  0     3
   1   NaN
   2   NaN
   3   NaN
2  0   NaN
   1   NaN
   2   NaN
   3   NaN
dtype: float64
BlockIndex
Block locations: array([2])
Block lengths: array([3])
```

CHAPTER

TWENTYEIGHT

CAVEATS AND GOTCHAS

28.1 Using If/Truth Statements with pandas

pandas follows the numpy convention of raising an error when you try to convert something to a `bool`. This happens in a `if` or when using the boolean operations, `and`, `or`, or `not`. It is not clear what the result of

```
>>> if Series([False, True, False]):
     ...
```

should be. Should it be `True` because it's not zero-length? `False` because there are `False` values? It is unclear, so instead, pandas raises a `ValueError`:

```
>>> if pd.Series([False, True, False]):
    print("I was true")
Traceback
    ...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

If you see that, you need to explicitly choose what you want to do with it (e.g., use *any()*, *all()* or *empty*). or, you might want to compare if the pandas object is `None`

```
>>> if pd.Series([False, True, False]) is not None:
       print("I was not None")
>>> I was not None
```

or return if `any` value is `True`.

```
>>> if pd.Series([False, True, False]).any():
       print("I am any")
>>> I am any
```

To evaluate single-element pandas objects in a boolean context, use the method `.bool()`:

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

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

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

In [4]: DataFrame([[False]]).bool()
Out[4]: False
```

28.1.1 Bitwise boolean

Bitwise boolean operators like == and != will 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.

28.1.2 Using the in operator

Using the Python in operator on a Series tests for membership in the index, not membership among the values.

If this behavior is surprising, keep in mind that using in on a Python dictionary tests keys, not values, and Series are dict-like. To test for membership in the values, use the method isin():

For DataFrames, likewise, in applies to the column axis, testing for membership in the list of column names.

28.2 NaN, Integer NA values and NA type promotions

28.2.1 Choice of NA representation

For lack of NA (missing) support from the ground up in NumPy and Python in general, we were given the difficult choice between either

- A *masked array* solution: an array of data and an array of boolean values indicating whether a value
- Using a special sentinel value, bit pattern, or set of sentinel values to denote NA across the dtypes

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value NaN (Not-A-Number) is used everywhere as the NA value, and there are API functions isnull and notnull which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

28.2.2 Support for integer NA

In the absence of high performance NA support being built into NumPy from the ground up, the primary casualty is the ability to represent NAs in integer arrays. For example:

```
In [5]: s = Series([1, 2, 3, 4, 5], index=list('abcde'))

In [6]: s
Out[6]:
a    1
b    2
c    3
```

```
d    4
e    5
dtype: int64

In [7]: s.dtype
Out[7]: dtype('int64')

In [8]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])

In [9]: s2
Out[9]:
a     1
b     2
c     3
f   NaN
u   NaN
dtype: float64

In [10]: s2.dtype
Out[10]: 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.

28.2.3 `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. These are summarized by this table:

Typeclass	Promotion dtype for storing NAs
`floating`	no change
`object`	no change
`integer`	cast to `float64`
`boolean`	cast to `object`

While this may seem like a heavy trade-off, in practice I have found very few cases where this is an issue in practice. Some explanation for the motivation here in the next section.

28.2.4 Why not make NumPy like R?

Many people have suggested that NumPy should simply emulate the `NA` support present in the more domain-specific statistical programming language R. Part of the reason is the NumPy type hierarchy:

Typeclass	Dtypes
`numpy.floating`	`float16, float32, float64, float128`
`numpy.integer`	`int8, int16, int32, int64`
`numpy.unsignedinteger`	`uint8, uint16, uint32, uint64`
`numpy.object_`	`object_`
`numpy.bool_`	`bool_`
`numpy.character`	`string_, unicode_`

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.

28.3 Integer indexing

Label-based indexing with integer axis labels is a thorny topic. It has been discussed heavily on mailing lists and among various members of the scientific Python community. In pandas, our general viewpoint is that labels matter more than integer locations. Therefore, with an integer axis index *only* label-based indexing is possible with the standard tools like .ix. The following code will generate exceptions:

```
s = Series(range(5))
s[-1]
df = DataFrame(np.random.randn(5, 4))
df
df.ix[-2:]
```

This deliberate decision was made to prevent ambiguities and subtle bugs (many users reported finding bugs when the API change was made to stop "falling back" on position-based indexing).

28.4 Label-based slicing conventions

28.4.1 Non-monotonic indexes require exact matches

28.4.2 Endpoints are inclusive

Compared with standard Python sequence slicing in which the slice endpoint is not inclusive, label-based slicing in pandas **is inclusive**. The primary reason for this is that it is often not possible to easily determine the "successor" or next element after a particular label in an index. For example, consider the following Series:

```
In [11]: s = Series(randn(6), index=list('abcdef'))

In [12]: s
Out[12]:
a   -0.345411
b    1.721799
c    0.171342
d    1.222367
e    1.228721
f    0.549175
dtype: float64
```

Suppose we wished to slice from c to e, using integers this would be

```
In [13]: s[2:5]
Out[13]:
c    0.171342
d    1.222367
```

```
e    1.228721
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.ix['c':'e'+1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design design to make label-based slicing include both endpoints:

```
In [14]: s.ix['c':'e']
Out[14]:
c    0.171342
d    1.222367
e    1.228721
dtype: float64
```

This is most definitely a "practicality beats purity" sort of thing, but it is something to watch out for if you expect label-based slicing to behave exactly in the way that standard Python integer slicing works.

28.5 Miscellaneous indexing gotchas

28.5.1 Reindex versus ix gotchas

Many users will find themselves using the ix indexing capabilities as a concise means of selecting data from a pandas object:

```
In [15]: df = DataFrame(randn(6, 4), columns=['one', 'two', 'three', 'four'],
   ....:                index=list('abcdef'))
   ....:

In [16]: df
Out[16]:
        one       two     three      four
a -1.982099 -0.366112 -0.228622 -1.663680
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
d -0.077343  1.052958  1.528472  0.644673
e -1.261108  1.265039  0.424791  0.385124
f -1.176251 -0.074802 -0.384239  1.075475

In [17]: df.ix[['b', 'c', 'e']]
Out[17]:
        one       two     three      four
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
e -1.261108  1.265039  0.424791  0.385124
```

This is, of course, completely equivalent *in this case* to using th reindex method:

```
In [18]: df.reindex(['b', 'c', 'e'])
Out[18]:
        one       two     three      four
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
e -1.261108  1.265039  0.424791  0.385124
```

Some might conclude that `ix` and `reindex` are 100% equivalent based on this. This is indeed true **except in the case of integer indexing**. For example, the above operation could alternately have been expressed as:

```
In [19]: df.ix[[1, 2, 4]]
Out[19]:
        one       two     three      four
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
e -1.261108  1.265039  0.424791  0.385124
```

If you pass `[1, 2, 4]` to `reindex` you will get another thing entirely:

```
In [20]: df.reindex([1, 2, 4])
Out[20]:
   one  two  three  four
1  NaN  NaN    NaN   NaN
2  NaN  NaN    NaN   NaN
4  NaN  NaN    NaN   NaN
```

So it's important to remember that `reindex` is **strict label indexing only**. This can lead to some potentially surprising results in pathological cases where an index contains, say, both integers and strings:

```
In [21]: s = Series([1, 2, 3], index=['a', 0, 1])

In [22]: s
Out[22]:
a    1
0    2
1    3
dtype: int64

In [23]: s.ix[[0, 1]]
Out[23]:
0    2
1    3
dtype: int64

In [24]: s.reindex([0, 1])
Out[24]:
0    2
1    3
dtype: int64
```

Because the index in this case does not contain solely integers, `ix` falls back on integer indexing. By contrast, `reindex` only looks for the values passed in the index, thus finding the integers `0` and `1`. While it would be possible to insert some logic to check whether a passed sequence is all contained in the index, that logic would exact a very high cost in large data sets.

28.5.2 Reindex potentially changes underlying Series dtype

The use of `reindex_like` can potentially change the dtype of a `Series`.

```
In [25]: series = Series([1, 2, 3])

In [26]: x = Series([True])

In [27]: x.dtype
Out[27]: dtype('bool')
```

```
In [28]: x = Series([True]).reindex_like(series)

In [29]: x.dtype
Out[29]: dtype('O')
```

This is because `reindex_like` silently inserts `NaNs` and the `dtype` changes accordingly. This can cause some issues when using `numpy` `ufuncs` such as `numpy.logical_and`.

See the this old issue for a more detailed discussion.

28.6 Timestamp limitations

28.6.1 Minimum and maximum timestamps

Since pandas represents timestamps in nanosecond resolution, the timespan that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [30]: begin = Timestamp.min

In [31]: begin
Out[31]: Timestamp('1677-09-22 00:12:43.145225')

In [32]: end = Timestamp.max

In [33]: end
Out[33]: Timestamp('2262-04-11 23:47:16.854775807')
```

See *here* for ways to represent data outside these bound.

28.7 Parsing Dates from Text Files

When parsing multiple text file columns into a single date column, the new date column is prepended to the data and then *index_col* specification is indexed off of the new set of columns rather than the original ones:

```
In [34]: print(open('tmp.csv').read())
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900

In [35]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [36]: df = read_csv('tmp.csv', header=None,
   ....:                  parse_dates=date_spec,
   ....:                  keep_date_col=True,
   ....:                  index_col=0)
   ....:

# index_col=0 refers to the combined column "nominal" and not the original
# first column of 'KORD' strings
In [37]: df
```

```
Out[37]:
                                actual     0         1         2         3  \
nominal
1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  19990127   19:00:00   18:56:00
1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  19990127   20:00:00   19:56:00
1999-01-27 21:00:00 1999-01-27 20:56:00  KORD  19990127   21:00:00   20:56:00
1999-01-27 21:00:00 1999-01-27 21:18:00  KORD  19990127   21:00:00   21:18:00
1999-01-27 22:00:00 1999-01-27 21:56:00  KORD  19990127   22:00:00   21:56:00
1999-01-27 23:00:00 1999-01-27 22:56:00  KORD  19990127   23:00:00   22:56:00

                        4
nominal
1999-01-27 19:00:00  0.81
1999-01-27 20:00:00  0.01
1999-01-27 21:00:00 -0.59
1999-01-27 21:00:00 -0.99
1999-01-27 22:00:00 -0.59
1999-01-27 23:00:00 -0.59
```

28.8 Differences with NumPy

For Series and DataFrame objects, `var` normalizes by `N-1` to produce unbiased estimates of the sample variance, while NumPy's `var` normalizes by N, which measures the variance of the sample. Note that `cov` normalizes by `N-1` in both pandas and NumPy.

28.9 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the `DataFrame.copy` method. If you are doing a lot of copying of DataFrame objects shared among threads, we recommend holding locks inside the threads where the data copying occurs.

See this link for more information.

28.10 HTML Table Parsing

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas io function `read_html`.

Issues with lxml

- Benefits
  - **lxml** is very fast
  - **lxml** requires Cython to install correctly.
- Drawbacks
  - **lxml** does *not* make any guarantees about the results of it's parse *unless* it is given **strictly valid markup**.
  - In light of the above, we have chosen to allow you, the user, to use the **lxml** backend, but **this backend will use html5lib** if **lxml** fails to parse

  - It is therefore *highly recommended* that you install both **BeautifulSoup4** and **html5lib**, so that you will still get a valid result (provided everything else is valid) even if **lxml** fails.

Issues with BeautifulSoup4 using lxml as a backend

- The above issues hold here as well since **BeautifulSoup4** is essentially just a wrapper around a parser backend.

Issues with BeautifulSoup4 using html5lib as a backend

- Benefits
  - **html5lib** is far more lenient than **lxml** and consequently deals with *real-life markup* in a much saner way rather than just, e.g., dropping an element without notifying you.
  - **html5lib** *generates valid HTML5 markup from invalid markup automatically*. This is extremely important for parsing HTML tables, since it guarantees a valid document. However, that does NOT mean that it is "correct", since the process of fixing markup does not have a single definition.
  - **html5lib** is pure Python and requires no additional build steps beyond its own installation.
- Drawbacks
  - The biggest drawback to using **html5lib** is that it is slow as molasses. However consider the fact that many tables on the web are not big enough for the parsing algorithm runtime to matter. It is more likely that the bottleneck will be in the process of reading the raw text from the URL over the web, i.e., IO (input-output). For very large tables, this might not be true.

Issues with using Anaconda

- Anaconda ships with lxml version 3.2.0; the following workaround for Anaconda was successfully used to deal with the versioning issues surrounding lxml and BeautifulSoup4.

Note: Unless you have *both*:

- A strong restriction on the upper bound of the runtime of some code that incorporates `read_html()`
- Complete knowledge that the HTML you will be parsing will be 100% valid at all times

then you should install html5lib and things will work swimmingly without you having to muck around with *conda*. If you want the best of both worlds then install both html5lib and lxml. If you do install lxml then you need to perform the following commands to ensure that lxml will work correctly:

```
# remove the included version
conda remove lxml

# install the latest version of lxml
pip install 'git+git://github.com/lxml/lxml.git'

# install the latest version of beautifulsoup4
pip install 'bzr+lp:beautifulsoup'
```

Note that you need bzr and git installed to perform the last two operations.

28.11 Byte-Ordering Issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like

```
Traceback
    ...
ValueError: Big-endian buffer not supported on little-endian compiler
```

To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to Series/DataFrame/Panel constructors using something similar to the following:

```
In [38]: x = np.array(list(range(10)), '>i4') # big endian

In [39]: newx = x.byteswap().newbyteorder() # force native byteorder

In [40]: s = Series(newx)
```

See the NumPy documentation on byte order for more details.

CHAPTER

TWENTYNINE

RPY2 / R INTERFACE

> **Warning:** In v0.16.0, the `pandas.rpy` interface has been **deprecated and will be removed in a future version**. Similar functionality can be accessed through the rpy2 project. See the *updating* section for a guide to port your code from the `pandas.rpy` to `rpy2` functions.

29.1 Updating your code to use rpy2 functions

In v0.16.0, the `pandas.rpy` module has been **deprecated** and users are pointed to the similar functionality in `rpy2` itself (rpy2 >= 2.4).

Instead of importing `import pandas.rpy.common as com`, the following imports should be done to activate the pandas conversion support in rpy2:

```
from rpy2.robjects import pandas2ri
pandas2ri.activate()
```

Converting data frames back and forth between rpy2 and pandas should be largely automated (no need to convert explicitly, it will be done on the fly in most rpy2 functions).

To convert explicitly, the functions are `pandas2ri.py2ri()` and `pandas2ri.ri2py()`. So these functions can be used to replace the existing functions in pandas:

- `com.convert_to_r_dataframe(df)` should be replaced with `pandas2ri.py2ri(df)`
- `com.convert_robj(rdf)` should be replaced with `pandas2ri.ri2py(rdf)`

Note: these functions are for the latest version (rpy2 2.5.x) and were called `pandas2ri.pandas2ri()` and `pandas2ri.ri2pandas()` previously.

Some of the other functionality in *pandas.rpy* can be replaced easily as well. For example to load R data as done with the `load_data` function, the current method:

```
df_iris = com.load_data('iris')
```

can be replaced with:

```
from rpy2.robjects import r
r.data('iris')
df_iris = pandas2ri.ri2py(r[name])
```

The `convert_to_r_matrix` function can be replaced by the normal `pandas2ri.py2ri` to convert dataframes, with a subsequent call to R `as.matrix` function.

Warning: Not all conversion functions in rpy2 are working exactly the same as the current methods in pandas. If you experience problems or limitations in comparison to the ones in pandas, please report this at the issue tracker.

See also the documentation of the rpy2 project.

29.2 R interface with rpy2

If your computer has R and rpy2 (> 2.2) installed (which will be left to the reader), you will be able to leverage the below functionality. On Windows, doing this is quite an ordeal at the moment, but users on Unix-like systems should find it quite easy. rpy2 evolves in time, and is currently reaching its release 2.3, while the current interface is designed for the 2.2.x series. We recommend to use 2.2.x over other series unless you are prepared to fix parts of the code, yet the rpy2-2.3.0 introduces improvements such as a better R-Python bridge memory management layer so it might be a good idea to bite the bullet and submit patches for the few minor differences that need to be fixed.

```
# if installing for the first time
hg clone http://bitbucket.org/lgautier/rpy2

cd rpy2
hg pull
hg update version_2.2.x
sudo python setup.py install
```

Note: To use R packages with this interface, you will need to install them inside R yourself. At the moment it cannot install them for you.

Once you have done installed R and rpy2, you should be able to import `pandas.rpy.common` without a hitch.

29.3 Transferring R data sets into Python

The **load_data** function retrieves an R data set and converts it to the appropriate pandas object (most likely a DataFrame):

```
In [1]: import pandas.rpy.common as com

In [2]: infert = com.load_data('infert')

In [3]: infert.head()
Out[3]:
  education  age  parity  induced  case  spontaneous  stratum  pooled.stratum
1    0-5yrs   26       6        1     1            2        1               3
2    0-5yrs   42       1        1     1            0        2               1
3    0-5yrs   39       6        2     1            0        3               4
4    0-5yrs   34       4        2     1            0        4               2
5   6-11yrs   35       3        1     1            1        5              32
```

29.4 Converting DataFrames into R objects

New in version 0.8.

Starting from pandas 0.8, there is **experimental** support to convert DataFrames into the equivalent R object (that is, **data.frame**):

```
In [4]: from pandas import DataFrame

In [5]: df = DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C':[7,8,9]},
   ...:                index=["one", "two", "three"])
   ...:

In [6]: r_dataframe = com.convert_to_r_dataframe(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.

You can also use **convert_to_r_matrix** to obtain a `Matrix` instance, but bear in mind that it will only work with homogeneously-typed DataFrames (as R matrices bear no information on the data type):

```
In [9]: r_matrix = com.convert_to_r_matrix(df)

In [10]: print(type(r_matrix))
<class 'rpy2.robjects.vectors.Matrix'>

In [11]: print(r_matrix)
      A B C
one   1 4 7
two   2 5 8
three 3 6 9
```

29.5 Calling R functions with pandas objects

29.6 High-level interface to R estimators

CHAPTER

THIRTY

PANDAS ECOSYSTEM

Increasingly, packages are being built on top of pandas to address specific needs in data preparation, analysis and visualization. This is encouraging because it means pandas is not only helping users to handle their data tasks but also that it provides a better starting point for developers to build powerful and more focused data tools. The creation of libraries that complement pandas' functionality also allows pandas development to remain focused around it's original requirements.

This is an in-exhaustive list of projects that build on pandas in order to provide tools in the PyData space.

We'd like to make it easier for users to find these project, if you know of other substantial projects that you feel should be on this list, please let us know.

30.1 Statistics and Machine Learning

30.1.1 Statsmodels

Statsmodels is the prominent python "statistics and econometrics library" and it has a long-standing special relationship with pandas. Statsmodels provides powerful statistics, econometrics, analysis and modeling functionality that is out of pandas' scope. Statsmodels leverages pandas objects as the underlying data container for computation.

30.1.2 sklearn-pandas

Use pandas DataFrames in your scikit-learn ML pipeline.

30.2 Visualization

30.2.1 Bokeh

Bokeh is a Python interactive visualization library for large datasets that natively uses the latest web technologies. Its goal is to provide elegant, concise construction of novel graphics in the style of Protovis/D3, while delivering high-performance interactivity over large data to thin clients.

30.2.2 yhat/ggplot

Hadley Wickham's ggplot2 is a foundational exploratory visualization package for the R language. Based on "The Grammar of Graphics" it provides a powerful, declarative and extremely general way to generate bespoke plots of any kind of data. It's really quite incredible. Various implementations to other languages are available, but a faithful implementation for python users has long been missing. Although still young (as of Jan-2014), the yhat/ggplot project has been progressing quickly in that direction.

30.2.3 Seaborn

Although pandas has quite a bit of "just plot it" functionality built-in, visualization and in particular statistical graphics is a vast field with a long tradition and lots of ground to cover. The Seaborn project builds on top of pandas and matplotlib to provide easy plotting of data which extends to more advanced types of plots then those offered by pandas.

30.2.4 Vincent

The Vincent project leverages Vega (that in turn, leverages d3) to create plots . It has great support for pandas data objects.

30.3 IDE

30.3.1 IPython

IPython is an interactive command shell and distributed computing environment. IPython Notebook is a web application for creating IPython notebooks. An IPython notebook is a JSON document containing an ordered list of input/output cells which can contain code, text, mathematics, plots and rich media. IPython notebooks can be converted to a number of open standard output formats (HTML, HTML presentation slides, LaTeX, PDF, ReStructuredText, Markdown, Python) through 'Download As' in the web interface and `ipython nbconvert` in a shell.

Pandas DataFrames implement `_repr_html_` methods which are utilized by IPython Notebook for displaying (abbreviated) HTML tables. (Note: HTML tables may or may not be compatible with non-HTML IPython output formats.)

30.3.2 quantopian/qgrid

qgrid is "an interactive grid for sorting and filtering DataFrames in IPython Notebook" built with SlickGrid.

30.3.3 Spyder

Spyder is a cross-platform Qt-based open-source Python IDE with editing, testing, debugging, and introspection features. Spyder can now introspect and display Pandas DataFrames and show both "column wise min/max and global min/max coloring."

30.4 API

30.4.1 quandl/Python

Quandl API for Python wraps the Quandl REST API to return Pandas DataFrames with timeseries indexes.

30.4.2 pydatastream

PyDatastream is a Python interface to the Thomson Dataworks Enterprise (DWE/Datastream) SOAP API to return indexed Pandas DataFrames or Panels with financial data. This package requires valid credentials for this API (non free).

30.4.3 pandaSDMX

pandaSDMX is an extensible library to retrieve and acquire statistical data and metadata disseminated in SDMX 2.1. This standard is currently supported by the European statistics office (Eurostat) and the European Central Bank (ECB). Datasets may be returned as pandas Series or multi-indexed DataFrames.

30.4.4 fredapi

fredapi is a Python interface to the Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis. It works with both the FRED database and ALFRED database that contains point-in-time data (i.e. historic data revisions). fredapi provides a wrapper in python to the FRED HTTP API, and also provides several conveninent methods for parsing and analyzing point-in-time data from ALFRED. fredapi makes use of pandas and returns data in a Series or DataFrame. This module requires a FRED API key that you can obtain for free on the FRED website.

30.5 Domain Specific

30.5.1 Geopandas

Geopandas extends pandas data objects to include geographic information which support geometric operations. If your work entails maps and geographical coordinates, and you love pandas, you should take a close look at Geopandas.

30.5.2 xray

xray brings the labeled data power of pandas to the physical sciences by providing N-dimensional variants of the core pandas data structures. It aims to provide a pandas-like and pandas-compatible toolkit for analytics on multi-dimensional arrays, rather than the tabular data for which pandas excels.

30.6 Out-of-core

30.6.1 Blaze

Blaze provides a standard API for doing computations with various in-memory and on-disk backends: NumPy, Pandas, SQLAlchemy, MongoDB, PyTables, PySpark.

CHAPTER

THIRTYONE

COMPARISON WITH R / R LIBRARIES

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

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

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

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

31.1 Base R

31.1.1 Slicing with R's `c`

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

```
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

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

Selecting multiple columns by name in `pandas` is straightforward

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list('abc'))

In [2]: df[['a', 'c']]
Out[2]:
          a         c
0 -1.039575 -0.424972
1  0.567020 -1.087401
2 -0.673690 -1.478427
3  0.524988  0.577046
4 -1.715002 -0.370647
5 -1.157892  0.844885
6  1.075770  1.643563
```

```
7 -1.469388 -0.674600
8 -1.776904 -1.294524
9  0.413738 -0.472035

In [3]: df.loc[:, ['a', 'c']]
Out[3]:
          a         c
0 -1.039575 -0.424972
1  0.567020 -1.087401
2 -0.673690 -1.478427
3  0.524988  0.577046
4 -1.715002 -0.370647
5 -1.157892  0.844885
6  1.075770  1.643563
7 -1.469388 -0.674600
8 -1.776904 -1.294524
9  0.413738 -0.472035
```

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

```
In [4]: named = list('abcdefg')

In [5]: n = 30

In [6]: columns = named + np.arange(len(named), n).tolist()

In [7]: df = pd.DataFrame(np.random.randn(n, n), columns=columns)

In [8]: df.iloc[:, np.r_[:10, 24:30]]
Out[8]:
           a         b         c         d         e         f         g  \
0  -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
1   0.545952 -1.219217 -1.226825  0.769804 -1.281247 -0.727707 -0.121306
2   2.396780  0.014871  3.357427 -0.317441 -1.236269  0.896171 -0.487602
3  -0.988387  0.094055  1.262731  1.289997  0.082423 -0.055758  0.536580
4  -1.340896  1.846883 -1.328865  1.682706 -1.717693  0.888782  0.228440
5   0.464000  0.227371 -0.496922  0.306389 -2.290613 -1.134623 -1.561819
6  -0.507516 -0.230096  0.394500 -1.934370 -1.652499  1.488753 -0.896484
..       ...       ...       ...       ...       ...       ...       ...
23 -0.083272 -0.273955 -0.772369 -1.242807 -0.386336 -0.182486  0.164816
24  2.071413 -1.364763  1.122066  0.066847  1.751987  0.419071 -1.118283
25  0.036609  0.359986  1.211905  0.850427  1.554957 -0.888463 -1.508808
26 -1.179240  0.238923  1.756671 -0.747571  0.543625 -0.159609 -0.051458
27  0.025645  0.932436 -1.694531 -0.182236 -1.072710  0.466764 -0.072673
28  0.439086  0.812684 -0.128932 -0.142506 -1.137207  0.462001 -0.159466
29 -0.909806 -0.312006  0.383630 -0.631606  1.321415 -0.004799 -2.008210

           7         8         9        24        25        26        27  \
0   2.565646  1.431256  1.340309  0.875906 -2.211372  0.974466 -2.006747
1  -0.097883  0.695775  0.341734 -1.743161 -0.826591 -0.345352  1.314232
2  -0.082240 -2.182937  0.380396  1.266143  0.299368 -0.863838  0.408204
3  -0.489682  0.369374 -0.034571  0.221471 -0.744471  0.758527  1.729689
4   0.901805  1.171216  0.520260  0.650776 -1.461665 -1.137707 -0.891060
5  -0.260838  0.281957  1.523962 -0.008434  1.952541 -1.056652  0.533946
6   0.576897  1.146000  1.487349  2.015523 -1.833722  1.771740 -0.670027
..       ...       ...       ...       ...       ...       ...       ...
23  0.065624  0.307665 -1.898358  1.389045 -0.873585 -0.699862  0.812477
```

```
24  1.010694  0.877138 -0.611561 -1.040389 -0.796211  0.241596  0.385922
25 -0.617855  0.536164  2.175585  1.872601 -2.513465 -0.139184  0.810491
26  0.937882  0.617547  0.287918 -1.584814  0.307941  1.809049  0.296237
27 -0.026233 -0.051744  0.001402  0.150664 -3.060395  0.040268  0.066091
28 -1.788308  0.753604  0.918071  0.922729  0.869610  0.364726 -0.226101
29 -0.481634 -2.056211 -2.106095  0.039227  0.211283  1.440190 -0.989193

          28        29
0  -0.410001 -0.078638
1   0.690579  0.995761
2  -1.048089 -0.025747
3  -0.964980 -0.845696
4  -0.693921  1.613616
5  -1.226970  0.040403
6   0.049307 -0.521493
..       ...       ...
23 -0.469503  1.142702
24 -0.486078  0.433042
25  0.571599 -0.000676
26 -0.143550  0.289401
27 -0.192862  1.979055
28 -0.657647 -0.952699
29  0.313335 -0.399709

[30 rows x 16 columns]
```

31.1.2 aggregate

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

```
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.

```
In [9]: df = pd.DataFrame({
   ...:   'v1': [1,3,5,7,8,3,5,np.nan,4,5,7,9],
   ...:   'v2': [11,33,55,77,88,33,55,np.nan,44,55,77,99],
   ...:   'by1': ["red", "blue", 1, 2, np.nan, "big", 1, 2, "red", 1, np.nan, 12],
   ...:   'by2': ["wet", "dry", 99, 95, np.nan, "damp", 95, 99, "red", 99, np.nan,
   ...:           np.nan]
   ...: })
   ...:

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

In [11]: g[['v1','v2']].mean()
Out[11]:
          v1  v2
by1  by2
1    95    5  55
     99    5  55
```

```
2    95      7  77
     99    NaN NaN
big  damp    3  33
blue dry     3  33
red  red     4  44
     wet     1  11
```

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

31.1.3 `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:

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

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

```
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:

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

The `apply()` method can be used to replicate this:

```
In [14]: s = pd.Series(np.arange(5),dtype=np.float32)

In [15]: pd.Series(pd.match(s,[2,4],np.nan))
Out[15]:
0   NaN
1   NaN
2     0
3   NaN
4     1
dtype: float64
```

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

31.1.4 `tapply`

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

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

tapply(baseball$batting.average, baseball.example$team,
       max)
```

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

```
In [16]: import random

In [17]: import string

In [18]: baseball = pd.DataFrame({
   ....:     'team': ["team %d" % (x+1) for x in range(5)]*5,
   ....:     'player': random.sample(list(string.ascii_lowercase),25),
   ....:     'batting avg': np.random.uniform(.200, .400, 25)
   ....:     })
   ....:

In [19]: baseball.pivot_table(values='batting avg', columns='team', aggfunc=np.max)
Out[19]:
team
team 1    0.394457
team 2    0.395730
team 3    0.343015
team 4    0.388863
team 5    0.377379
Name: batting avg, dtype: float64
```

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

31.1.5 subset

New in version 0.13.

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

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

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

```
In [20]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})

In [21]: df.query('a <= b')
Out[21]:
          a         b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479
```

```
In [22]: df[df.a <= df.b]
Out[22]:
          a         b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479

In [23]: df.loc[df.a <= df.b]
Out[23]:
          a         b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479
```

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

31.1.6 with

New in version 0.13.

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

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
df$a + df$b  # same as the previous expression
```

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

```
In [24]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})

In [25]: df.eval('a + b')
Out[25]:
0   -0.920205
1   -0.860236
2    1.154370
3    0.188140
4   -1.163718
5    0.001397
6   -0.825694
7   -1.138198
8   -1.708034
9    1.148616
dtype: float64

In [26]: df.a + df.b  # same as the previous expression
Out[26]:
0   -0.920205
1   -0.860236
2    1.154370
3    0.188140
4   -1.163718
5    0.001397
6   -0.825694
```

```
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*.

31.2 zoo

31.3 xts

31.4 plyr

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

R	Python
array	list
lists	dictionary or list of objects
data.frame	dataframe

31.4.1 `ddply`

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

```
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:

```
In [27]: df = pd.DataFrame({
   ....:     'x': np.random.uniform(1., 168., 120),
   ....:     'y': np.random.uniform(7., 334., 120),
   ....:     'z': np.random.uniform(1.7, 20.7, 120),
   ....:     'month': [5,6,7,8]*30,
   ....:     'week': np.random.randint(1,4, 120)
   ....: })
   ....:

In [28]: grouped = df.groupby(['month','week'])
```

```
In [29]: print grouped['x'].agg([np.mean, np.std])
                   mean        std
month week
5     1       71.840596  52.886392
      2       71.904794  55.786805
      3       89.845632  49.892367
6     1       97.730877  52.442172
      2       93.369836  47.178389
      3       96.592088  58.773744
7     1       59.255715  43.442336
      2       69.634012  28.607369
      3       84.510992  59.761096
8     1      104.787666  31.745437
      2       69.717872  53.747188
      3       79.892221  52.950459
```

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

31.5 reshape / reshape2

31.5.1 `melt.array`

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

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

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

```
In [30]: a = np.array(list(range(1,24))+[np.NAN]).reshape(2,3,4)

In [31]: pd.DataFrame([tuple(list(x)+[val]) for x, val in np.ndenumerate(a)])
Out[31]:
    0  1  2    3
0   0  0  0    1
1   0  0  1    2
2   0  0  2    3
3   0  0  3    4
4   0  1  0    5
5   0  1  1    6
6   0  1  2    7
.. .. .. ..   ..
17  1  1  1   18
18  1  1  2   19
19  1  1  3   20
20  1  2  0   21
21  1  2  1   22
22  1  2  2   23
23  1  2  3  NaN

[24 rows x 4 columns]
```

31.5.2 `melt.list`

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

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

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

```
In [32]: a = list(enumerate(list(range(1,5))+[np.NAN]))

In [33]: pd.DataFrame(a)
Out[33]:
   0    1
0  0    1
1  1    2
2  2    3
3  3    4
4  4  NaN
```

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

31.5.3 `melt.data.frame`

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

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

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

```
In [34]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
   ....:                        'last' : ['Doe', 'Bo'],
   ....:                        'height' : [5.5, 6.0],
   ....:                        'weight' : [130, 150]})
   ....:

In [35]: pd.melt(cheese, id_vars=['first', 'last'])
Out[35]:
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [36]: cheese.set_index(['first', 'last']).stack() # alternative way
Out[36]:
first  last
John   Doe   height      5.5
             weight    130.0
Mary   Bo    height      6.0
             weight    150.0
dtype: float64
```

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

31.5.4 cast

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

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

In [38]: mdf = pd.melt(df, id_vars=['month', 'week'])

In [39]: pd.pivot_table(mdf, values='value', index=['variable','week'],
   ....:                  columns=['month'], aggfunc=np.mean)
   ....:
Out[39]:
month                  5           6           7
variable week
x        1    114.001700  132.227290   65.808204
         2    124.669553  147.495706   82.882820
y        1    225.636630  301.864228   91.706834
         2     57.692665  215.851669  218.004383
z        1     17.793871    7.124644   17.679823
         2     15.068355   13.873974    9.394966
```

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

```
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()`:

```
In [40]: df = pd.DataFrame({
   ....:     'Animal': ['Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
   ....:                'Animal2', 'Animal3'],
```

```
   ....:     'FeedType': ['A', 'B', 'A', 'A', 'B', 'B', 'A'],
   ....:     'Amount': [10, 7, 4, 2, 5, 6, 2],
   ....: })
   ....:

In [41]: df.pivot_table(values='Amount', index='Animal', columns='FeedType', aggfunc='sum')
Out[41]:
FeedType   A   B
Animal
Animal1   10   5
Animal2    2  13
Animal3    6 NaN
```

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

```
In [42]: df.groupby(['Animal','FeedType'])['Amount'].sum()
Out[42]:
Animal   FeedType
Animal1  A           10
         B            5
Animal2  A            2
         B           13
Animal3  A            6
Name: Amount, dtype: int64
```

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

31.5.5 `factor`

New in version 0.15.

pandas has a data type for categorical data.

```
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 [43]: pd.cut(pd.Series([1,2,3,4,5,6]), 3)
Out[43]:
0    (0.995, 2.667]
1    (0.995, 2.667]
2    (2.667, 4.333]
3    (2.667, 4.333]
4        (4.333, 6]
5        (4.333, 6]
dtype: category
Categories (3, object): [(0.995, 2.667] < (2.667, 4.333] < (4.333, 6]]

In [44]: pd.Series([1,2,3,2,2,3]).astype("category")
Out[44]:
0    1
1    2
2    3
3    2
4    2
5    3
```

```
dtype: category
Categories (3, int64): [1, 2, 3]
```

For more details and examples see *categorical introduction* and the *API documentation*. There is also a documentation regarding the *differences to R's factor*.

CHAPTER

THIRTYTWO

COMPARISON WITH SQL

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

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

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

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

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

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

```
In [3]: url = 'https://raw.github.com/pydata/pandas/master/pandas/tests/data/tips.csv'

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

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

32.1 SELECT

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

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

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

```
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
Out[6]:
   total_bill   tip smoker    time
0       16.99  1.01     No  Dinner
1       10.34  1.66     No  Dinner
2       21.01  3.50     No  Dinner
```

```
3       23.68  3.31     No  Dinner
4       24.59  3.61     No  Dinner
```

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

32.2 WHERE

Filtering in SQL is done via a WHERE clause.

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

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

```
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.

```
In [8]: is_dinner = tips['time'] == 'Dinner'

In [9]: is_dinner.value_counts()
Out[9]:
True     176
False     68
dtype: int64

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).

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

```
# tips of more than $5.00 at Dinner meals
In [11]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
Out[11]:
     total_bill    tip     sex smoker  day    time  size
23        39.42   7.58    Male     No  Sat  Dinner     4
```

```
44         30.40   5.60    Male     No  Sun  Dinner     4
47         32.40   6.00    Male     No  Sun  Dinner     4
52         34.81   5.20  Female     No  Sun  Dinner     4
59         48.27   6.73    Male     No  Sat  Dinner     4
116        29.93   5.07    Male     No  Sun  Dinner     4
155        29.85   5.14  Female     No  Sun  Dinner     5
170        50.81  10.00    Male    Yes  Sat  Dinner     3
172         7.25   5.15    Male    Yes  Sun  Dinner     2
181        23.33   5.65    Male    Yes  Sun  Dinner     2
183        23.17   6.50    Male    Yes  Sun  Dinner     4
211        25.89   5.16    Male    Yes  Sat  Dinner     4
212        48.33   9.00    Male     No  Sat  Dinner     4
214        28.17   6.50  Female    Yes  Sat  Dinner     3
239        29.03   5.92    Male     No  Sat  Dinner     3
```

```
-- tips by parties of at least 5 diners OR bill total was more than $45
SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;
```

```
# tips by parties of at least 5 diners OR bill total was more than $45
In [12]: tips[(tips['size'] >= 5) | (tips['total_bill'] > 45)]
Out[12]:
     total_bill    tip     sex smoker   day    time  size
59        48.27   6.73    Male     No   Sat  Dinner     4
125       29.80   4.20  Female     No  Thur   Lunch     6
141       34.30   6.70    Male     No  Thur   Lunch     6
142       41.19   5.00    Male     No  Thur   Lunch     5
143       27.05   5.00  Female     No  Thur   Lunch     6
155       29.85   5.14  Female     No   Sun  Dinner     5
156       48.17   5.00    Male     No   Sun  Dinner     6
170       50.81  10.00    Male    Yes   Sat  Dinner     3
182       45.35   3.50    Male    Yes   Sun  Dinner     3
185       20.69   5.00    Male     No   Sun  Dinner     5
187       30.46   2.00    Male    Yes   Sun  Dinner     5
212       48.33   9.00    Male     No   Sat  Dinner     4
216       28.15   3.00    Male    Yes   Sat  Dinner     5
```

NULL checking is done using the `notnull()` and `isnull()` methods.

```
In [13]: frame = pd.DataFrame({'col1': ['A', 'B', np.NaN, 'C', 'D'],
   ....:                       'col2': ['F', np.NaN, 'G', 'H', 'I']})
   ....:

In [14]: frame
Out[14]:
  col1 col2
0    A    F
1    B  NaN
2  NaN    G
3    C    H
4    D    I
```

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

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

```
In [15]: frame[frame['col2'].isnull()]
Out[15]:
  col1 col2
1    B  NaN
```

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

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

```
In [16]: frame[frame['col1'].notnull()]
Out[16]:
  col1 col2
0    A    F
1    B  NaN
3    C    H
4    D    I
```

32.3 GROUP BY

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

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

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

The pandas equivalent would be:

```
In [17]: tips.groupby('sex').size()
Out[17]:
sex
Female     87
Male      157
dtype: int64
```

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

```
In [18]: tips.groupby('sex').count()
Out[18]:
        total_bill  tip  smoker  day  time  size
sex
Female          87   87      87   87    87    87
Male           157  157     157  157   157   157
```

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

```
In [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]:
             tip
            size      mean
smoker day
No     Fri     4  2.812500
       Sat    45  3.102889
       Sun    57  3.167895
       Thur   45  2.673778
Yes    Fri    15  2.714000
       Sat    42  2.875476
       Sun    19  3.516842
```

```
   Thur    17   3.030000
```

32.4 JOIN

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

```
In [22]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
   ....:                     'value': np.random.randn(4)})
   ....:

In [23]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
   ....:                     'value': np.random.randn(4)})
   ....:
```

Assume we have two database tables of the same name and structure as our DataFrames.

Now let's go over the various types of JOINs.

32.4.1 INNER JOIN

```
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]:
  key   value_x   value_y
0   B  1.075416 -0.227314
1   D  1.065735  2.102726
2   D  1.065735 -0.092796
```

`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)
Out[26]:
  key   value_x   value_y
1   B  1.075416 -0.227314
3   D  1.065735  2.102726
3   D  1.065735 -0.092796
```

32.4.2 LEFT OUTER JOIN

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

```
# show all records from df1
In [27]: pd.merge(df1, df2, on='key', how='left')
Out[27]:
  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
```

32.4.3 RIGHT JOIN

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

```
# show all records from df2
In [28]: pd.merge(df1, df2, on='key', how='right')
Out[28]:
  key   value_x   value_y
0   B  1.075416 -0.227314
1   D  1.065735  2.102726
2   D  1.065735 -0.092796
3   E       NaN  0.094694
```

32.4.4 FULL JOIN

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

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

```
# show all records from both frames
In [29]: pd.merge(df1, df2, on='key', how='outer')
Out[29]:
  key   value_x   value_y
0   A -0.857326       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
```

32.5 UNION

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

```
In [30]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'],
   ....:                      'rank': range(1, 4)})
   ....:

In [31]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'],
   ....:                      'rank': [1, 4, 5]})
   ....:
```

```
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
      Chicago     1
       Boston     4
  Los Angeles     5
*/
```

```
In [32]: pd.concat([df1, df2])
Out[32]:
            city  rank
0        Chicago     1
1  San Francisco     2
2  New York City     3
0        Chicago     1
1         Boston     4
2    Los Angeles     5
```

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

```
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
       Boston     4
  Los Angeles     5
*/
```

In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

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

```
2    Los Angeles     5
```

32.6 UPDATE

32.7 DELETE

CHAPTER

THIRTYTHREE

API REFERENCE

33.1 Input/Output

33.1.1 Pickling

read_pickle(path)	Load pickled pandas object (or any other pickled object) from the specified

pandas.read_pickle

pandas.**read_pickle**(*path*)

Load pickled pandas object (or any other pickled object) from the specified file path

Warning: Loading pickled data received from untrusted sources can be unsafe. See: http://docs.python.org/2.7/library/pickle.html

Parameters **path** : string

File path

Returns **unpickled** : type of object stored in file

33.1.2 Flat File

read_table(filepath_or_buffer[, sep, ...])	Read general delimited file into DataFrame
read_csv(filepath_or_buffer[, sep, dialect, ...])	Read CSV (comma-separated) file into DataFrame
read_fwf(filepath_or_buffer[, colspecs, widths])	Read a table of fixed-width formatted lines into DataFrame

pandas.read_table

`pandas.read_table`(*filepath_or_buffer, sep='\t', dialect=None, compression='infer', doublequote=True, escapechar=None, quotechar='"', quoting=0, skipinitialspace=False, lineterminator=None, header='infer', index_col=None, names=None, prefix=None, skiprows=None, skipfooter=None, skip_footer=0, na_values=None, na_fvalues=None, true_values=None, false_values=None, delimiter=None, converters=None, dtype=None, usecols=None, engine=None, delim_whitespace=False, as_recarray=False, na_filter=True, compact_ints=False, use_unsigned=False, low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True, keep_default_na=True, thousands=None, comment=None, decimal='.', parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None, memory_map=False, float_precision=None, nrows=None, iterator=False, chunksize=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True, tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True*)

Read general delimited file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters **filepath_or_buffer** : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

sep : string, default t (tab-stop)

Delimiter to use. Regular expressions are accepted.

engine : {'c', 'python'}

Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (Unsupported with engine='python')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer', then use gzip or bz2 if filepath_or_buffer is a string ending in '.gz' or '.bz2', respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no `names` passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so header=0 denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo' A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and parse_dates specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. Pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if comment='#', parsing '#emptyna,b,cn1,2,3' with *header=0* will result in 'a,b,c' being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return TextFileReader object

chunksize : int, default None

Return TextFileReader object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for sep. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8'). List of Python standard encodings

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns **result** : DataFrame or TextParser

pandas.read_csv

`pandas.`**`read_csv`**(*filepath_or_buffer, sep=', ', dialect=None, compression='infer', doublequote=True, escapechar=None, quotechar='"', quoting=0, skipinitialspace=False, lineterminator=None, header='infer', index_col=None, names=None, prefix=None, skiprows=None, skipfooter=None, skip_footer=0, na_values=None, na_fvalues=None, true_values=None, false_values=None, delimiter=None, converters=None, dtype=None, usecols=None, engine=None, delim_whitespace=False, as_recarray=False, na_filter=True, compact_ints=False, use_unsigned=False, low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True, keep_default_na=True, thousands=None, comment=None, decimal='.', parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None, memory_map=False, float_precision=None, nrows=None, iterator=False, chunksize=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True, tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True*)

Read CSV (comma-separated) file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters **filepath_or_buffer** : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

sep : string, default ','

Delimiter to use. If sep is None, will try to automatically determine this. Regular expressions are accepted.

engine : {'c', 'python'}

Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (Unsupported with engine='python')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer', then use gzip or bz2 if filepath_or_buffer is a string ending in '.gz' or '.bz2', respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no `names` passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so header=0 denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo' A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and parse_dates specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. Pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if comment='#', parsing '#emptyna,b,cn1,2,3' with *header=0* will result in 'a,b,c' being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return TextFileReader object

chunksize : int, default None

Return TextFileReader object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for sep. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8'). List of Python standard encodings

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns result : DataFrame or TextParser

pandas.read_fwf

`pandas.`**`read_fwf`**(*filepath_or_buffer*, *colspecs='infer'*, *widths=None*, ***kwds*)

Read a table of fixed-width formatted lines into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters filepath_or_buffer : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

colspecs : list of pairs (int, int) or 'infer'. optional

A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value 'infer' can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data (default='infer').

widths : list of ints. optional

A list of field widths which can be used instead of 'colspecs' if the intervals are contiguous.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (Unsupported with engine='python')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer', then use gzip or bz2 if filepath_or_buffer is a string ending in '.gz' or '.bz2', respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no `names` passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so header=0 denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo' A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and parse_dates specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. Pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if comment='#', parsing '#emptyna,b,cn1,2,3' with *header=0* will result in 'a,b,c' being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return TextFileReader object

chunksize : int, default None

Return TextFileReader object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for sep. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8'). List of Python standard encodings

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns **result** : DataFrame or TextParser

Also, 'delimiter' is used to specify the filler character of the

fields if it is not spaces (e.g., '~').

33.1.3 Clipboard

`read_clipboard`(**kwargs)	Read text from clipboard and pass to read_table.

pandas.read_clipboard

`pandas.read_clipboard(**kwargs)`

Read text from clipboard and pass to read_table. See read_table for the full argument list

If unspecified, *sep* defaults to 's+'

Returns parsed : DataFrame

33.1.4 Excel

`read_excel`(io[, sheetname])	Read an Excel table into a pandas DataFrame
`ExcelFile.parse`([sheetname, header, ...])	Read an Excel table into DataFrame

pandas.read_excel

`pandas.read_excel(io, sheetname=0, **kwds)`

Read an Excel table into a pandas DataFrame

Parameters io : string, file-like object, or xlrd workbook.

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file://localhost/path/to/workbook.xlsx

sheetname : string, int, mixed list of strings/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

header : int, default 0

Row to use for the column labels of the parsed DataFrame

skiprows : list-like

Rows to skip at the beginning (0-indexed)

skip_footer : int, default 0

Rows at the end to skip (0-indexed)

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.

index_col : int, default None

Column to use as the row labels of the DataFrame. Pass None if there is no such column

parse_cols : int or list, default None

- If None then parse all columns,
- If int then indicates last column to be parsed
- If list of ints then indicates list of column numbers to be parsed
- If string then indicates comma separated list of column names and column ranges (e.g. "A:E" or "A,C,E:F")

na_values : list-like, default None

List of additional strings to recognize as NA/NaN

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

engine: string, default None

If io is not a buffer or path, this must be set to identify io. Acceptable values are None or xlrd

convert_float : boolean, default True

convert integral floats to int (i.e., 1.0 –> 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally

has_index_names : boolean, default False

True if the cols defined in index_col have an index name and are not in the header. Index name will be placed on a separate line below the header.

Returns parsed : DataFrame or Dict of DataFrames

DataFrame from the passed in Excel file. See notes in sheetname argument for more information on when a Dict of Dataframes is returned.

pandas.ExcelFile.parse

`ExcelFile.`**`parse`**(*sheetname=0*, *header=0*, *skiprows=None*, *skip_footer=0*, *index_col=None*, *parse_cols=None*, *parse_dates=False*, *date_parser=None*, *na_values=None*, *thousands=None*, *chunksize=None*, *convert_float=True*, *has_index_names=False*, *converters=None*, ***kwds*)

Read an Excel table into DataFrame

Parameters **sheetname** : 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

header : int, default 0

Row to use for the column labels of the parsed DataFrame

skiprows : list-like

Rows to skip at the beginning (0-indexed)

skip_footer : int, default 0

Rows at the end to skip (0-indexed)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

index_col : int, default None

Column to use as the row labels of the DataFrame. Pass None if there is no such column

parse_cols : int or list, default None

- If None then parse all columns
- If int then indicates last column to be parsed
- If list of ints then indicates list of column numbers to be parsed
- If string then indicates comma separated list of column names and column ranges (e.g. "A:E" or "A,C,E:F")

parse_dates : boolean, default False

Parse date Excel values,

date_parser : function default None

Date parsing function

na_values : list-like, default None

List of additional strings to recognize as NA/NaN

thousands : str, default None

Thousands separator

chunksize : int, default None

Size of file chunk to read for lazy evaluation.

convert_float : boolean, default True

convert integral floats to int (i.e., 1.0 –> 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally.

has_index_names : boolean, default False

True if the cols defined in index_col have an index name and are not in the header

verbose : boolean, default False

Set to True to print a single statement when reading each excel sheet.

Returns parsed : DataFrame or Dict of DataFrames

DataFrame from the passed in Excel file. See notes in sheetname argument for more information on when a Dict of Dataframes is returned.

33.1.5 JSON

`read_json`([path_or_buf, orient, typ, dtype, ...])	Convert a JSON string to pandas object

pandas.read_json

pandas.**read_json**(*path_or_buf=None*, *orient=None*, *typ='frame'*, *dtype=True*, *convert_axes=True*, *convert_dates=True*, *keep_default_dates=True*, *numpy=False*, *precise_float=False*, *date_unit=None*)

Convert a JSON string to pandas object

Parameters filepath_or_buffer : a valid JSON string or file-like

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

- *Series*
  - default is `'index'`
  - allowed values are: `{'split','records','index'}`
  - The Series index must be unique for orient `'index'`.
- *DataFrame*
  - default is `'columns'`
  - allowed values are: {'split','records','index','columns','values'}
  - The DataFrame index must be unique for orients 'index' and 'columns'.
  - The DataFrame columns must be unique for orients 'index', 'columns', and 'records'.
- The format of the JSON string
  - split : dict like `{index -> [index], columns -> [columns], data -> [values]}`

- records : list like `[{column -> value}, ... , {column -> value}]`
- index : dict like `{index -> {column -> value}}`
- columns : dict like `{column -> {index -> value}}`
- values : just the values array

typ : type of object to recover (series or frame), default 'frame'

dtype : boolean or dict, default True

If True, infer dtypes, if a dict of column to dtype, then use those, if False, then don't infer dtypes at all, applies only to the data.

convert_axes : boolean, default True

Try to convert the axes to the proper dtypes.

convert_dates : boolean, default True

List of columns to parse for dates; If True, then try to parse datelike columns default is True

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 builtin 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.

Returns result : Series or DataFrame

`json_normalize`(data[, record_path, meta, ...])	"Normalize" semi-structured JSON data into a flat table

pandas.io.json.json_normalize

`pandas.io.json.`**`json_normalize`**(*data*, *record_path=None*, *meta=None*, *meta_prefix=None*, *record_prefix=None*)

"Normalize" semi-structured JSON data into a flat table

Parameters data : dict or list of dicts

Unserialized JSON objects

record_path : string or list of strings, default None

Path in each object to list of records. If not passed, data will be assumed to be an array of records

meta : list of paths (string or list of strings)

Fields to use as metadata for each record in resulting table

record_prefix : string, default None

If True, prefix records with dotted (?) path, e.g. foo.bar.field if path to records is ['foo', 'bar']

meta_prefix : string, default None

Returns frame : DataFrame

Examples

```
>>> data = [{'state': 'Florida',
...          'shortname': 'FL',
...          'info': {
...               'governor': 'Rick Scott'
...          },
...          'counties': [{'name': 'Dade', 'population': 12345},
...                      {'name': 'Broward', 'population': 40000},
...                      {'name': 'Palm Beach', 'population': 60000}]},
...         {'state': 'Ohio',
...          'shortname': 'OH',
...          'info': {
...               'governor': 'John Kasich'
...          },
...          'counties': [{'name': 'Summit', 'population': 1234},
...                       {'name': 'Cuyahoga', 'population': 1337}]}]
>>> from pandas.io.json import json_normalize
>>> result = json_normalize(data, 'counties', ['state', 'shortname',
...                                           ['info', 'governor']])
>>> result
         name  population info.governor    state shortname
0        Dade       12345    Rick Scott  Florida        FL
1     Broward       40000    Rick Scott  Florida        FL
2  Palm Beach       60000    Rick Scott  Florida        FL
3      Summit        1234   John Kasich     Ohio        OH
4    Cuyahoga        1337   John Kasich     Ohio        OH
```

33.1.6 HTML

`read_html`(io[, match, flavor, header, ...])	Read HTML tables into a `list` of `DataFrame` objects.

pandas.read_html

`pandas.read_html`(*io*, *match='.+'*, *flavor=None*, *header=None*, *index_col=None*, *skiprows=None*, *infer_types=None*, *attrs=None*, *parse_dates=False*, *tupleize_cols=False*, *thousands=','*, *encoding=None*)

Read HTML tables into a `list` of `DataFrame` objects.

Parameters io : str or file-like

A URL, a file-like object, or a raw string containing HTML. Note that lxml only accepts the http, ftp and file url protocols. If you have a URL that starts with `'https'` you might try removing the `'s'`.

match : str or compiled regular expression, optional

The set of tables containing text matching this regex or string will be returned. Unless the HTML is extremely simple you will probably need to pass a non-empty string here. Defaults to '.+' (match any non-empty string). The default value will return all tables contained on a page. This value is converted to a regular expression so that there is consistent behavior between Beautiful Soup and lxml.

flavor : str or None, container of strings

The parsing engine to use. 'bs4' and 'html5lib' are synonymous with each other, they are both there for backwards compatibility. The default of `None` tries to use `lxml` to parse and if that fails it falls back on `bs4` + `html5lib`.

header : int or list-like or None, optional

The row (or list of rows for a `MultiIndex`) to use to make the columns headers.

index_col : int or list-like or None, optional

The column (or list of columns) to use to create the index.

skiprows : int or list-like or slice or None, optional

0-based. Number of rows to skip after parsing the column integer. If a sequence of integers or a slice is given, will skip the rows indexed by that sequence. Note that a single element sequence means 'skip the nth row' whereas an integer means 'skip n rows'.

infer_types : None, optional

This has no effect since 0.15.0. It is here for backwards compatibility.

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,

```
attrs = {'id': 'table'}
```

is a valid attribute dictionary because the 'id' HTML tag attribute is a valid HTML attribute for *any* HTML tag as per this document.

```
attrs = {'asdf': 'table'}
```

is *not* a valid attribute dictionary because 'asdf' is not a valid HTML attribute even if it is a valid XML attribute. Valid HTML 4.01 table attributes can be found here. A working draft of the HTML 5 spec can be found here. It contains the latest information on table attributes for the modern web.

parse_dates : bool, optional

See `read_csv()` for more details.

tupleize_cols : bool, optional

If `False` try to parse multiple header rows into a `MultiIndex`, otherwise return raw tuples. Defaults to `False`.

thousands : str, optional

Separator to use to parse thousands. Defaults to `','`.

encoding : str or None, optional

The encoding used to decode the web page. Defaults to `None`.``None`` preserves the previous encoding behavior, which depends on the underlying parser library (e.g., the parser library will try to use the encoding provided by the document).

Returns dfs : list of DataFrames

See also:

`pandas.read_csv`

Notes

Before using this function you should read the *gotchas about the HTML parsing libraries*.

Expect to do some cleanup after you call this function. For example, you might need to manually assign column names if the column names are converted to NaN when you pass the *header=0* argument. We try to assume as little as possible about the structure of the table and push the idiosyncrasies of the HTML contained in the table to the user.

This function searches for `<table>` elements and only for `<tr>` and `<th>` rows and `<td>` elements within each `<tr>` or `<th>` element in the table. `<td>` stands for "table data".

Similar to `read_csv()` the *header* argument is applied **after** *skiprows* is applied.

This function will *always* return a list of `DataFrame` *or* it will fail, e.g., it will *not* return an empty list.

Examples

See the *read_html documentation in the IO section of the docs* for some examples of reading in HTML tables.

33.1.7 HDFStore: PyTables (HDF5)

`read_hdf`(path_or_buf, key, **kwargs)	read from the store, close it if we opened it
`HDFStore.put`(key, value[, format, append])	Store object in HDFStore
`HDFStore.append`(key, value[, format, ...])	Append to Table in file.
`HDFStore.get`(key)	Retrieve pandas object stored in file
`HDFStore.select`(key[, where, start, stop, ...])	Retrieve pandas object stored in file, optionally based on where

pandas.read_hdf

`pandas.`**`read_hdf`**(*path_or_buf*, *key*, ***kwargs*)

read from the store, close it if we opened it

Retrieve pandas object stored in file, optionally based on where criteria

Parameters path_or_buf : path (string), or buffer to read from

key : group identifier in the store

where : list of Term (or convertable) objects, optional

start : optional, integer (defaults to None), row number to start

selection

stop : optional, integer (defaults to None), row number to stop

selection

columns : optional, a list of columns that if not None, will limit the

return columns

iterator : optional, boolean, return an iterator, default False

chunksize : optional, nrows to include in iteration, return an iterator

Returns The selected object

pandas.HDFStore.put

`HDFStore.put` (*key*, *value*, *format=None*, *append=False*, ***kwargs*)

Store object in HDFStore

Parameters **key** : object

value : {Series, DataFrame, Panel}

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

This will force Table format, append the input data to the existing.

encoding : default None, provide an encoding for strings

dropna : boolean, default True, do not write an ALL nan row to

the store settable by the option 'io.hdf.dropna_table'

pandas.HDFStore.append

`HDFStore.append` (*key*, *value*, *format=None*, *append=True*, *columns=None*, *dropna=None*, ***kwargs*)

Append to Table in file. Node must already exist and be Table format.

Parameters **key** : object

value : {Series, DataFrame, Panel, Panel4D}

format: 'table' is the default

table(t) [table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default True, append the input data to the

existing

data_columns : list of columns to create as data columns, or True to

use all columns

min_itemsize : dict of columns that specify minimum string sizes

nan_rep : string to use as string nan represenation

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 True, do not write an ALL nan row to

the store settable by the option 'io.hdf.dropna_table'

Notes

—–

Does *not* check if data being appended overlaps with existing

data in the table, so be careful

pandas.HDFStore.get

`HDFStore.get(key)`

Retrieve pandas object stored in file

Parameters key : object

Returns obj : type of object stored in file

pandas.HDFStore.select

`HDFStore.select(key, where=None, start=None, stop=None, columns=None, iterator=False, chunksize=None, auto_close=False, **kwargs)`

Retrieve pandas object stored in file, optionally based on where criteria

Parameters key : object

where : list of Term (or convertable) objects, optional

start : integer (defaults to None), row number to start selection

stop : integer (defaults to None), row number to stop selection

columns : a list of columns that if not None, will limit the return

columns

iterator : boolean, return an iterator, default False

chunksize : nrows to include in iteration, return an iterator

auto_close : boolean, should automatically close the store when

finished, default is False

Returns The selected object

Continued on next page

Table 33.9 – continued from previous page

33.1.8 SQL

read_sql_table(table_name, con[, schema, ...])	Read SQL database table into a DataFrame.
read_sql_query(sql, con[, index_col, ...])	Read SQL query into a DataFrame.
read_sql(sql, con[, index_col, ...])	Read SQL query or database table into a DataFrame.

pandas.read_sql_table

pandas.**read_sql_table**(*table_name*, *con*, *schema=None*, *index_col=None*, *coerce_float=True*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy engine, returns a DataFrame. This function does not support DBAPI connections.

Parameters **table_name** : string

Name of SQL table in database

con : SQLAlchemy engine

Sqlite DBAPI connection mode not supported

schema : string, default None

Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

index_col : string, optional

Column to set as index

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

parse_dates : list or dict

- 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

List of column names to select from sql table

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

`read_sql_query` Read SQL query into a DataFrame.

`read_sql`

Notes

Any datetime values with time zone information will be converted to UTC

pandas.read_sql_query

`pandas.read_sql_query`(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *chunksize=None*)

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

Parameters sql : string

SQL query to be executed

con : SQLAlchemy engine or sqlite3 DBAPI2 connection

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

Column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

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

- 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

read_sql

Notes

Any datetime values with time zone information parsed via the *parse_dates* parameter will be converted to UTC

pandas.read_sql

pandas.**read_sql**(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL query or database table into a DataFrame.

Parameters **sql** : string

SQL query to be executed or database table name.

con : SQLAlchemy engine or DBAPI2 connection (fallback mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

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

- 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

List of column names to select from sql table (only used when reading a table).

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

read_sql_table Read SQL database table into a DataFrame

read_sql_query Read SQL query into a DataFrame

Notes

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

33.1.9 Google BigQuery

`read_gbq`(query[, project_id, index_col, ...])	Load data from Google BigQuery.
`to_gbq`(dataframe, destination_table[, ...])	Write a DataFrame to a Google BigQuery table.

pandas.io.gbq.read_gbq

pandas.io.gbq.**read_gbq**(*query*, *project_id=None*, *index_col=None*, *col_order=None*, *reauth=False*)

Load data from Google BigQuery.

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The main method a user calls to execute a Query in Google BigQuery and read results into a pandas DataFrame using the v2 Google API client for Python. Documentation for the API is available at https://developers.google.com/api-client-library/python/. Authentication to the Google BigQuery service is via OAuth 2.0 using the product name 'pandas GBQ'.

Parameters **query** : str

SQL-Like Query to return data values

project_id : str

Google BigQuery Account project ID.

index_col : str (optional)

Name of result column to use for index in results DataFrame

col_order : list(str) (optional)

List of BigQuery column names in the desired order for results DataFrame

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

Returns df: DataFrame

DataFrame representing results of query

pandas.io.gbq.to_gbq

pandas.io.gbq.**to_gbq**(*dataframe*, *destination_table*, *project_id=None*, *chunksize=10000*, *verbose=True*, *reauth=False*)

Write a DataFrame to a Google BigQuery table.

THIS IS AN EXPERIMENTAL LIBRARY

If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The to_gbq method chunks data into a default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: https://developers.google.com/bigquery/streaming-data-into-bigquery.

Parameters **dataframe** : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

33.1.10 STATA

read_stata(filepath_or_buffer[, ...])	Read Stata file into DataFrame

pandas.read_stata

pandas.**read_stata**(*filepath_or_buffer*, *convert_dates=True*, *convert_categoricals=True*, *encoding=None*, *index=None*, *convert_missing=False*, *preserve_dtypes=True*, *columns=None*, *order_categoricals=True*, *chunksize=None*, *iterator=False*)

Read Stata file into DataFrame

Parameters **filepath_or_buffer** : string or file-like object

Path to .dta file or object implementing a binary read() functions

convert_dates : boolean, defaults to True

Convert date variables to DataFrame time values

convert_categoricals : boolean, defaults to True

Read value labels and convert columns to Categorical/Factor variables

encoding : string, None or encoding

Encoding used to parse the files. Note that Stata doesn't support unicode. None defaults to iso-8859-1.

index : identifier of index column

identifier of column that should be used as index of the DataFrame

convert_missing : boolean, defaults to False

Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by 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

Examples

Read a Stata dta file: >> df = pandas.read_stata('filename.dta')

Read a Stata dta file in 10,000 line chunks: >> itr = pandas.read_stata('filename.dta', chunksize=10000) >> for chunk in itr: >> do_something(chunk)

`StataReader.data`(**kwargs)	DEPRECATED: Reads observations from Stata file, converting them into a dataframe
`StataReader.data_label`()	Returns data label of Stata file
`StataReader.value_labels`()	Returns a dict, associating each variable name a dict, associating
`StataReader.variable_labels`()	Returns variable labels as a dict, associating each variable name
`StataWriter.write_file`()	

pandas.io.stata.StataReader.data

`StataReader.`**`data`**(***kwargs*)

DEPRECATED: Reads observations from Stata file, converting them into a dataframe

This is a legacy method. Use *read* in new code.

Parameters **convert_dates** : boolean, defaults to True

Convert date variables to DataFrame time values

convert_categoricals : boolean, defaults to True

Read value labels and convert columns to Categorical/Factor variables

index : identifier of index column

identifier of column that should be used as index of the DataFrame

convert_missing : boolean, defaults to False

Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by 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

pandas.io.stata.StataReader.data_label

`StataReader.data_label()`

Returns data label of Stata file

pandas.io.stata.StataReader.value_labels

`StataReader.value_labels()`

Returns a dict, associating each variable name a dict, associating each value its corresponding label

pandas.io.stata.StataReader.variable_labels

`StataReader.variable_labels()`

Returns variable labels as a dict, associating each variable name with corresponding label

pandas.io.stata.StataWriter.write_file

`StataWriter.write_file()`

33.2 General functions

33.2.1 Data manipulations

melt(frame[, id_vars, value_vars, var_name, ...])	"Unpivots" a DataFrame from wide format to long format, optionally leaving
pivot(index, columns, values)	Produce 'pivot' table based on 3 columns of this DataFrame.
pivot_table(data[, values, index, columns, ...])	Create a spreadsheet-style pivot table as a DataFrame.
crosstab(index, columns[, values, rownames, ...])	Compute a simple cross-tabulation of two (or more) factors.
cut(x, bins[, right, labels, retbins, ...])	Return indices of half-open bins to which each value of *x* belongs.
qcut(x, q[, labels, retbins, precision])	Quantile-based discretization function.
merge(left, right[, how, on, left_on, ...])	Merge DataFrame objects by performing a database-style join operation by co
concat(objs[, axis, join, join_axes, ...])	Concatenate pandas objects along a particular axis with optional set logic alon
get_dummies(data[, prefix, prefix_sep, ...])	Convert categorical variable into dummy/indicator variables
factorize(values[, sort, order, ...])	Encode input values as an enumerated type or categorical variable

pandas.melt

`pandas.melt`(*frame*, *id_vars=None*, *value_vars=None*, *var_name=None*, *value_name='value'*, *col_level=None*)

"Unpivots" a DataFrame from wide format to long format, optionally leaving identifier variables set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (*id_vars*), while all other columns, considered measured variables (*value_vars*), are "unpivoted" to the row axis, leaving just two non-identifier columns, 'variable' and 'value'.

Parameters **frame** : DataFrame

id_vars : tuple, list, or ndarray, optional

Column(s) to use as identifier variables.

value_vars : tuple, list, or ndarray, optional

Column(s) to unpivot. If not specified, uses all columns that are not set as *id_vars*.

var_name : scalar

Name to use for the 'variable' column. If None it uses `frame.columns.name` or 'variable'.

value_name : scalar, default 'value'

Name to use for the 'value' column.

col_level : int or string, optional

If columns are a MultiIndex then use this level to melt.

See also:

pivot_table, DataFrame.pivot

Examples

```
>>> import pandas as pd
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                    'B': {0: 1, 1: 3, 2: 5},
...                    'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5

>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
3  a        C      2
4  b        C      4
5  c        C      6
```

The names of 'variable' and 'value' columns can be customized:

```
>>> 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:

```
>>> 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

>>> 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

>>> pd.melt(df, id_vars=[('A', 'D')], value_vars=[('B', 'E')])
  (A, D) variable_0 variable_1  value
0      a          B          E      1
1      b          B          E      3
2      c          B          E      5
```

pandas.pivot

pandas.**pivot**(*index*, *columns*, *values*)

Produce 'pivot' table based on 3 columns of this DataFrame. Uses unique values from index / columns and fills with values.

Parameters **index** : ndarray

Labels to use to make new frame's index

columns : ndarray

Labels to use to make new frame's columns

values : ndarray

Values to use for populating new frame's values

Returns DataFrame

Notes

Obviously, all 3 of the input arguments must have the same length

pandas.pivot_table

`pandas.pivot_table`(*data*, *values=None*, *index=None*, *columns=None*, *aggfunc='mean'*, *fill_value=None*, *margins=False*, *dropna=True*)

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame

Parameters **data** : DataFrame

values : column to aggregate, optional

index : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, default numpy.mean, or list of functions

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves)

fill_value : scalar, default None

Value to replace missing values with

margins : boolean, default False

Add all row / columns (e.g. for subtotal / grand totals)

dropna : boolean, default True

Do not include columns whose entries are all NaN

Returns **table** : DataFrame

Examples

```
>>> df
   A    B    C      D
0  foo one small  1
1  foo one large  2
2  foo one large  2
3  foo two small  3
4  foo two small  3
5  bar one large  4
```

```
6  bar one small  5
7  bar two small  6
8  bar two large  7

>>> table = pivot_table(df, values='D', index=['A', 'B'],
...                     columns=['C'], aggfunc=np.sum)
>>> table
          small  large
foo  one  1      4
     two  6      NaN
bar  one  5      4
     two  6      7
```

pandas.crosstab

pandas.**crosstab**(*index*, *columns*, *values=None*, *rownames=None*, *colnames=None*, *aggfunc=None*, *margins=False*, *dropna=True*)

Compute a simple cross-tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed

Parameters **index** : array-like, Series, or list of arrays/Series

Values to group by in the rows

columns : array-like, Series, or list of arrays/Series

Values to group by in the columns

values : array-like, optional

Array of values to aggregate according to the factors

aggfunc : function, optional

If no values array is passed, computes a frequency table

rownames : sequence, default None

If passed, must match number of row arrays passed

colnames : sequence, default None

If passed, must match number of column arrays passed

margins : boolean, default False

Add row/column margins (subtotals)

dropna : boolean, default True

Do not include columns whose entries are all NaN

Returns **crosstab** : DataFrame

Notes

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

Examples

```
>>> a
array([foo, foo, foo, foo, bar, bar,
       bar, bar, foo, foo, foo], dtype=object)
>>> b
array([one, one, one, two, one, one,
       one, two, two, two, one], dtype=object)
>>> c
array([dull, dull, shiny, dull, dull, shiny,
       shiny, dull, shiny, shiny, shiny], dtype=object)
```

```
>>> crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
b    one          two
c    dull  shiny  dull  shiny
a
bar  1     2      1     0
foo  2     2      1     2
```

pandas.cut

`pandas.cut`(*x*, *bins*, *right=True*, *labels=None*, *retbins=False*, *precision=3*, *include_lowest=False*)

Return indices of half-open bins to which each value of *x* belongs.

Parameters **x** : array-like

Input array to be binned. It has to be 1-dimensional.

bins : int or sequence of scalars

If *bins* is an int, it defines the number of equal-width bins in the range of *x*. However, in this case, the range of *x* is extended by .1% on each side to include the min or max values of *x*. If *bins* is a sequence it defines the bin edges allowing for non-uniform bin width. No extension of the range of *x* is done in this case.

right : bool, optional

Indicates whether the bins include the rightmost edge or not. If right == True (the default), then the bins [1,2,3,4] indicate (1,2], (2,3], (3,4].

labels : array or boolean, default None

Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins.

retbins : bool, optional

Whether to return the bins or not. Can be useful if bins is given as a scalar.

precision : int

The precision at which to store and display the bins labels

include_lowest : bool

Whether the first interval should be left-inclusive or not.

Returns **out** : Categorical or Series or array of integers if labels is False

The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.

bins : ndarray of floats

Returned only if *retbins* is True.

Notes

The *cut* function can be useful for going from a continuous variable to a categorical variable. For example, *cut* could convert ages to groups of age ranges.

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Categorical object

Examples

```
>>> pd.cut(np.array([.2, 1.4, 2.5, 6.2, 9.7, 2.1]), 3, retbins=True)
([(0.191, 3.367], (0.191, 3.367], (0.191, 3.367], (3.367, 6.533], (6.533, 9.7], (0.191, 3.367]]
Categories (3, object): [(0.191, 3.367] < (3.367, 6.533] < (6.533, 9.7]],
array([ 0.1905    ,  3.36666667,  6.53333333,  9.7       ]))
>>> pd.cut(np.array([.2, 1.4, 2.5, 6.2, 9.7, 2.1]), 3, labels=["good","medium","bad"])
[good, good, good, medium, bad, good]
Categories (3, object): [good < medium < bad]
>>> pd.cut(np.ones(5), 4, labels=False)
array([1, 1, 1, 1, 1], dtype=int64)
```

pandas.qcut

pandas.**qcut**(*x*, *q*, *labels=None*, *retbins=False*, *precision=3*)

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 : 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 or not. Can be useful if bins is given as a scalar.

precision : int

The precision at which to store and display the bins labels

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

```
>>> pd.qcut(range(5), 4)
[[0, 1], [0, 1], (1, 2], (2, 3], (3, 4]]
Categories (4, object): [[0, 1] < (1, 2] < (2, 3] < (3, 4]]
>>> pd.qcut(range(5), 3, labels=["good","medium","bad"])
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]
>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3], dtype=int64)
```

pandas.merge

pandas.**merge**(*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*)

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters **left** : DataFrame

right : DataFrame

how : {'left', 'right', 'outer', 'inner'}, default 'inner'

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

left_on : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

right_on : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per left_on docs

left_index : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

right_index : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns merged : DataFrame

The output type will the be same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A              >>> B
    lkey value         rkey value
0   foo  1         0   foo  5
1   bar  2         1   bar  6
2   baz  3         2   qux  7
3   foo  4         3   bar  8
```

```
>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  foo   1        foo   5
1  foo   4        foo   5
2  bar   2        bar   6
3  bar   2        bar   8
4  baz   3        NaN   NaN
5  NaN   NaN      qux   7
```

pandas.concat

`pandas.concat`(*objs*, *axis=0*, *join='outer'*, *join_axes=None*, *ignore_index=False*, *keys=None*, *levels=None*, *names=None*, *verify_integrity=False*, *copy=True*)

Concatenate pandas objects along a particular axis with optional set logic along the other axes. Can also add a layer of hierarchical indexing on the concatenation axis, which may be useful if the labels are the same (or overlapping) on the passed axis number

Parameters objs : a sequence or mapping of Series, DataFrame, or Panel objects

If a dict is passed, the sorted keys will be used as the *keys* argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised

axis : {0, 1, ...}, default 0

The axis to concatenate along

join : {'inner', 'outer'}, default 'outer'

How to handle indexes on other axis(es)

join_axes : list of Index objects

Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic

verify_integrity : boolean, default False

Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation

keys : sequence, default None

If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level

levels : list of sequences, default None

Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys

names : list, default None

Names for the levels in the resulting hierarchical index

ignore_index : boolean, default False

If True, do not use the index values along the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the the index values on the other axes are still respected in the join.

copy : boolean, default True

If False, do not copy data unnecessarily

Returns concatenated : type of objects

Notes

The keys, levels, and names arguments are all optional

pandas.get_dummies

pandas.**get_dummies**(*data*, *prefix=None*, *prefix_sep='_'*, *dummy_na=False*, *columns=None*, *sparse=False*)

Convert categorical variable into dummy/indicator variables

Parameters data : array-like, Series, or DataFrame

prefix : string, list of strings, or dict of strings, default None

String to append DataFrame column names Pass a list with length equal to the number of columns when calling get_dummies on a DataFrame. Alternativly, *prefix* can be a dictionary mapping column names to prefixes.

prefix_sep : string, default '_'

If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with *prefix.*

dummy_na : bool, default False

Add a column to indicate NaNs, if False NaNs are ignored.

columns : list-like, default None

Column names in the DataFrame to be encoded. If *columns* is None then all the columns with *object* or *category* dtype will be converted.

sparse : bool, default False

Whether the returned DataFrame should be sparse or not.

New in version 0.16.1.

Returns dummies : DataFrame

Examples

```
>>> import pandas as pd
>>> s = pd.Series(list('abca'))

>>> get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0

>>> s1 = ['a', 'b', np.nan]

>>> get_dummies(s1)
   a  b
0  1  0
1  0  1
2  0  0

>>> get_dummies(s1, dummy_na=True)
   a  b  NaN
0  1  0    0
1  0  1    0
2  0  0    1

>>> df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'],
                    'C': [1, 2, 3]})

>>> get_dummies(df, prefix=['col1', 'col2']):
   C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1       1       0       0       1       0
1  2       0       1       1       0       0
2  3       1       0       0       0       1
```

See also `Series.str.get_dummies`.

pandas.factorize

`pandas.factorize`(*values*, *sort=False*, *order=None*, *na_sentinel=-1*, *size_hint=None*)

Encode input values as an enumerated type or categorical variable

Parameters values : ndarray (1-d)

Sequence

sort : boolean, default False

Sort by values

order : deprecated

na_sentinel : int, default -1

Value to mark "not found"

size_hint : hint to the hashtable sizer

Returns labels : the indexer to the original array

uniques : ndarray (1-d) or Index

the unique values. Index is returned when passed values is Index or Series

note: an array of Periods will ignore sort as it returns an always sorted PeriodIndex

33.2.2 Top-level missing data

`isnull`(obj)	Detect missing values (NaN in numeric arrays, None/NaN in object arrays)
`notnull`(obj)	Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays.

pandas.isnull

`pandas.isnull(obj)`

Detect missing values (NaN in numeric arrays, None/NaN in object arrays)

Parameters arr : ndarray or object value

Object to check for null-ness

Returns isnulled : array-like of bool or bool

Array or bool indicating whether an object is null or if an array is given which of the element is null.

See also:

`pandas.notnull` boolean inverse of pandas.isnull

pandas.notnull

`pandas.notnull(obj)`

Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays.

Parameters arr : ndarray or object value

Object to check for *not*-null-ness

Returns isnulled : array-like of bool or bool

Array or bool indicating whether an object is *not* null or if an array is given which of the element is *not* null.

See also:

`pandas.isnull` boolean inverse of pandas.notnull

33.2.3 Top-level dealing with datetimelike

to_datetime(arg[, errors, dayfirst, utc, ...])	Convert argument to datetime.
to_timedelta(arg[, unit, box, coerce])	Convert argument to timedelta
date_range([start, end, periods, freq, tz, ...])	Return a fixed frequency datetime index, with day (calendar) as the default
bdate_range([start, end, periods, freq, tz, ...])	Return a fixed frequency datetime index, with business day as the default
period_range([start, end, periods, freq, name])	Return a fixed frequency datetime index, with day (calendar) as the default
timedelta_range([start, end, periods, freq, ...])	Return a fixed frequency timedelta index, with day as the default
infer_freq(index[, warn])	Infer the most likely frequency given the input index.

pandas.to_datetime

pandas.**to_datetime**(*arg*, *errors='ignore'*, *dayfirst=False*, *utc=None*, *box=True*, *format=None*, *exact=True*, *coerce=False*, *unit='ns'*, *infer_datetime_format=False*)

Convert argument to datetime.

Parameters arg : string, datetime, array of strings (with possible NAs)

errors : {'ignore', 'raise'}, default 'ignore'

Errors are ignored by default (values left untouched)

dayfirst : boolean, default False

If True parses dates with the day first, eg 20/01/2005 Warning: dayfirst=True is not strict, but will prefer to parse with day first (this is a known bug).

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.

coerce : force errors to NaT (False by default)

Timestamps outside the interval between Timestamp.min and Timestamp.max (approximately 1677-09-22 to 2262-04-11) will be also forced to NaT.

unit : unit of the arg (D,s,ms,us,ns) denote the unit in epoch

(e.g. a unix timestamp), which is an integer/float number

infer_datetime_format : boolean, default False

If no *format* is given, try to infer the format based on the first datetime string. Provides a large speed-up in many cases.

Returns ret : datetime if parsing succeeded.

Return type depends on input:

- list-like: DatetimeIndex

- Series: Series of datetime64 dtype
- scalar: Timestamp

In case when it is not possible to return designated types (e.g. when any element of input is before Timestamp.min or after Timestamp.max) return will have datetime.datetime type (or correspoding array/Series).

Examples

Take separate series and convert to datetime

```
>>> import pandas as pd
>>> i = pd.date_range('20000101',periods=100)
>>> df = pd.DataFrame(dict(year = i.year, month = i.month, day = i.day))
>>> pd.to_datetime(df.year*10000 + df.month*100 + df.day, format='%Y%m%d')
0    2000-01-01
1    2000-01-02
...
98   2000-04-08
99   2000-04-09
Length: 100, dtype: datetime64[ns]
```

Or from strings

```
>>> df = df.astype(str)
>>> pd.to_datetime(df.day + df.month + df.year, format="%d%m%Y")
0    2000-01-01
1    2000-01-02
...
98   2000-04-08
99   2000-04-09
Length: 100, dtype: datetime64[ns]
```

Date that does not meet timestamp limitations:

```
>>> pd.to_datetime('13000101', format='%Y%m%d')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', coerce=True)
NaT
```

pandas.to_timedelta

pandas.**to_timedelta**(*arg*, *unit='ns'*, *box=True*, *coerce=False*)

Convert argument to timedelta

Parameters **arg** : string, timedelta, array of strings (with possible NAs)

unit : unit of the arg (D,h,m,s,ms,us,ns) denote the unit, which is an integer/float number

box : boolean, default True

If True returns a Timedelta/TimedeltaIndex of the results if False returns a np.timedelta64 or ndarray of values of dtype timedelta64[ns]

coerce : force errors to NaT (False by default)

Returns **ret** : timedelta64/arrays of timedelta64 if parsing succeeded

pandas.date_range

`pandas.date_range`(*start=None*, *end=None*, *periods=None*, *freq='D'*, *tz=None*, *normalize=False*, *name=None*, *closed=None*)

Return a fixed frequency datetime index, with day (calendar) as the default frequency

Parameters **start** : string or datetime-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'D' (calendar daily)

Frequency strings can have multiples, e.g. '5H'

tz : string or None

Time zone name for returning localized DatetimeIndex, for example

Asia/Hong_Kong

normalize : bool, default False

Normalize start/end dates to midnight before generating date range

name : str, default None

Name of the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns **rng** : DatetimeIndex

Notes

2 of start, end, or periods must be specified

pandas.bdate_range

`pandas.bdate_range`(*start=None*, *end=None*, *periods=None*, *freq='B'*, *tz=None*, *normalize=True*, *name=None*, *closed=None*)

Return a fixed frequency datetime index, with business day as the default frequency

Parameters **start** : string or datetime-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'B' (business daily)

Frequency strings can have multiples, e.g. '5H'

tz : string or None

Time zone name for returning localized DatetimeIndex, for example Asia/Beijing

normalize : bool, default False

Normalize start/end dates to midnight before generating date range

name : str, default None

Name for the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns rng : DatetimeIndex

Notes

2 of start, end, or periods must be specified

pandas.period_range

`pandas.`**`period_range`**(*start=None*, *end=None*, *periods=None*, *freq='D'*, *name=None*)

Return a fixed frequency datetime index, with day (calendar) as the default frequency

Parameters start : starting value, period-like, optional

end : ending value, period-like, optional

periods : int, default None

Number of periods in the index

freq : str/DateOffset, default 'D'

Frequency alias

name : str, default None

Name for the resulting PeriodIndex

Returns prng : PeriodIndex

pandas.timedelta_range

`pandas.`**`timedelta_range`**(*start=None*, *end=None*, *periods=None*, *freq='D'*, *name=None*, *closed=None*)

Return a fixed frequency timedelta index, with day as the default frequency

Parameters start : string or timedelta-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'D' (calendar daily)

Frequency strings can have multiples, e.g. '5H'

name : str, default None

Name of the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns rng : TimedeltaIndex

Notes

2 of start, end, or periods must be specified

pandas.infer_freq

`pandas.infer_freq(index, warn=True)`

Infer the most likely frequency given the input index. If the frequency is uncertain, a warning will be printed.

Parameters index : DatetimeIndex or TimedeltaIndex

if passed a Series will use the values of the series (NOT THE INDEX)

warn : boolean, default True

Returns freq : string or None

None if no discernible frequency TypeError if the index is not datetime-like ValueError if there are less than three values.

33.2.4 Top-level evaluation

`eval`(expr[, parser, engine, truediv, ...])	Evaluate a Python expression as a string using various backends.

pandas.eval

`pandas.eval(expr, parser='pandas', engine='numexpr', truediv=True, local_dict=None, global_dict=None, resolvers=(), level=0, target=None)`

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: `+`, `-`, `*`, `/`, `**`, `%`, `//` (python engine only) along with the following boolean operations: `|` (or), `&` (and), and `~` (not). Additionally, the `'pandas'` parser allows the use of `and`, `or`, and `not` with the same semantics as the corresponding bitwise operators. `Series` and `DataFrame` objects are supported and behave as they would with plain ol' Python evaluation.

Parameters expr : str or unicode

The expression to evaluate. This string cannot contain any Python statements, only Python expressions.

parser : string, default 'pandas', {'pandas', 'python'}

The parser to use to construct the syntax tree from the expression. The default of `'pandas'` parses code slightly different than standard Python. Alternatively, you can parse an expression using the `'python'` parser to retain strict Python semantics. See the *enhancing performance* documentation for more details.

engine : string, default 'numexpr', {'python', 'numexpr'}

The engine used to evaluate the expression. Supported engines are

- **`'numexpr'`: This default engine evaluates pandas objects using** numexpr for large speed ups in complex expressions with large frames.
- **`'python'`: Performs operations as if you had `eval`'d in top** level python. This engine is generally not that useful.

More backends may be available in the future.

truediv : bool, optional

Whether to use true division, like in Python >= 3

local_dict : dict or None, optional

A dictionary of local variables, taken from locals() by default.

global_dict : dict or None, optional

A dictionary of global variables, taken from globals() by default.

resolvers : list of dict-like or None, optional

A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the `query()` method to inject the `index` and `columns` variables that refer to their respective `DataFrame` instance attributes.

level : int, optional

The number of prior stack frames to traverse and add to the current scope. Most users will **not** need to change this parameter.

target : a target object for assignment, optional, default is None

essentially this is a passed in resolver

Returns ndarray, numeric scalar, DataFrame, Series

See also:

`pandas.DataFrame.query`, `pandas.DataFrame.eval`

Notes

The `dtype` of any objects involved in an arithmetic `%` operation are recursively cast to `float64`.

See the *enhancing performance* documentation for more details.

Continued on next

Table 33.17 – continued from previous page

33.2.5 Standard moving window functions

`rolling_count`(arg, window[, freq, center, how])	Rolling count of number of non-NaN observations inside provided window.
`rolling_sum`(arg, window[, min_periods, ...])	Moving sum.
`rolling_mean`(arg, window[, min_periods, ...])	Moving mean.
`rolling_median`(arg, window[, min_periods, ...])	O(N log(window)) implementation using skip list
`rolling_var`(arg, window[, min_periods, ...])	Numerically stable implementation using Welford's method.
`rolling_std`(arg, window[, min_periods, ...])	Moving standard deviation.
`rolling_min`(arg, window[, min_periods, ...])	Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs.
`rolling_max`(arg, window[, min_periods, ...])	Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs.
`rolling_corr`(arg1[, arg2, window, ...])	Moving sample correlation.
`rolling_corr_pairwise`(df1[, df2, window, ...])	Deprecated.
`rolling_cov`(arg1[, arg2, window, ...])	Unbiased moving covariance.
`rolling_skew`(arg, window[, min_periods, ...])	Unbiased moving skewness.
`rolling_kurt`(arg, window[, min_periods, ...])	Unbiased moving kurtosis.
`rolling_apply`(arg, window, func[, ...])	Generic moving function application.
`rolling_quantile`(arg, window, quantile[, ...])	Moving quantile.
`rolling_window`(arg[, window, win_type, ...])	Applies a moving window of type `window_type` and size `window` on the

pandas.rolling_count

pandas.**rolling_count**(*arg*, *window*, *freq=None*, *center=False*, *how=None*)

Rolling count of number of non-NaN observations inside provided window.

Parameters arg : DataFrame or numpy ndarray-like

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

how : string, default 'mean'

Method for down- or re-sampling

Returns rolling_count : type of caller

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_sum

pandas.**rolling_sum**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*, ***kwargs*)

Moving sum.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_mean

pandas.**rolling_mean**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*, ***kwargs*)

Moving mean.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_median

`pandas.`**`rolling_median`**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how='median'*, ***kwargs*)

O(N log(window)) implementation using skip list

Moving median.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default ''median'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_var

`pandas.rolling_var(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)`

Numerically stable implementation using Welford's method.

Moving variance.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_std

`pandas.rolling_std(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)`

Moving standard deviation.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_min

`pandas.`**`rolling_min`**`(`*arg, window, min_periods=None, freq=None, center=False, how='min', **kwargs*`)`

Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving minimum.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default ''min'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_max

pandas.**rolling_max**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how='max'*, ***kwargs*)

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving maximum.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default ''max'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_corr

pandas.**rolling_corr**(*arg1*, *arg2=None*, *window=None*, *min_periods=None*, *freq=None*, *center=False*, *pairwise=None*, *how=None*)

Moving sample correlation.

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns y : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise) DataFrame / Series -> Computes result for each column Series / Series -> Series

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_corr_pairwise

`pandas.`**`rolling_corr_pairwise`**(*df1*, *df2=None*, *window=None*, *min_periods=None*, *freq=None*, *center=False*)

Deprecated. Use rolling_corr(..., pairwise=True) instead.

Pairwise moving sample correlation

Parameters df1 : DataFrame

df2 : DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : Panel whose items are df1.index values

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_cov

pandas.**rolling_cov**(*arg1*, *arg2=None*, *window=None*, *min_periods=None*, *freq=None*, *center=False*, *pairwise=None*, *how=None*, *ddof=1*)

Unbiased moving covariance.

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise) DataFrame / Series -> Computes result for each column Series / Series -> Series

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_skew

pandas.**rolling_skew**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*, ***kwargs*)

Unbiased moving skewness.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_kurt

`pandas.rolling_kurt(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)`

Unbiased moving kurtosis.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_apply

`pandas.rolling_apply(arg, window, func, min_periods=None, freq=None, center=False, args=(), kwargs={})`

Generic moving function application.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

func : function

Must produce a single value from an ndarray input

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

args : tuple

Passed on to func

kwargs : dict

Passed on to func

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_quantile

`pandas.`**`rolling_quantile`**(*arg*, *window*, *quantile*, *min_periods=None*, *freq=None*, *center=False*)

Moving quantile.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

quantile : float

0 <= quantile <= 1

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_window

pandas.**rolling_window**(*arg*, *window=None*, *win_type=None*, *min_periods=None*, *freq=None*, *center=False*, *mean=True*, *axis=0*, *how=None*, ***kwargs*)

Applies a moving window of type `window_type` and size `window` on the data.

Parameters **arg** : Series, DataFrame

window : int or ndarray

Weighting window specification. If the window is an integer, then it is treated as the window length and win_type is required

win_type : str, default None

Window type (see Notes)

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

mean : boolean, default True

If True computes weighted mean, else weighted sum

axis : {0, 1}, default 0

how : string, default 'mean'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

The recognized window types are:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`

- parzen
- bohman
- blackmanharris
- nuttall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general_gaussian (needs power, width)
- slepian (needs width).

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting center=True.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the *mean*).

33.2.6 Standard expanding window functions

expanding_count(arg[, freq])	Expanding count of number of non-NaN observations.
expanding_sum(arg[, min_periods, freq])	Expanding sum.
expanding_mean(arg[, min_periods, freq])	Expanding mean.
expanding_median(arg[, min_periods, freq])	O(N log(window)) implementation using skip list
expanding_var(arg[, min_periods, freq])	Numerically stable implementation using Welford's method.
expanding_std(arg[, min_periods, freq])	Expanding standard deviation.
expanding_min(arg[, min_periods, freq])	Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs.
expanding_max(arg[, min_periods, freq])	Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs.
expanding_corr(arg1[, arg2, min_periods, ...])	Expanding sample correlation.
expanding_corr_pairwise(df1[, df2, ...])	Deprecated.
expanding_cov(arg1[, arg2, min_periods, ...])	Unbiased expanding covariance.
expanding_skew(arg[, min_periods, freq])	Unbiased expanding skewness.
expanding_kurt(arg[, min_periods, freq])	Unbiased expanding kurtosis.
expanding_apply(arg, func[, min_periods, ...])	Generic expanding function application.
expanding_quantile(arg, quantile[, ...])	Expanding quantile.

pandas.expanding_count

pandas.**expanding_count**(*arg*, *freq=None*)

Expanding count of number of non-NaN observations.

Parameters **arg** : DataFrame or numpy ndarray-like

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **expanding_count** : type of caller

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.expanding_sum

`pandas.`**`expanding_sum`**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Expanding sum.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_mean

`pandas.`**`expanding_mean`**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Expanding mean.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_median

`pandas.`**`expanding_median`**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

O(N log(window)) implementation using skip list

Expanding median.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns y : type of input argument

pandas.expanding_var

`pandas.expanding_var(arg, min_periods=1, freq=None, **kwargs)`

Numerically stable implementation using Welford's method.

Expanding variance.

Parameters arg : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns y : type of input argument

pandas.expanding_std

`pandas.expanding_std(arg, min_periods=1, freq=None, **kwargs)`

Expanding standard deviation.

Parameters arg : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns y : type of input argument

pandas.expanding_min

`pandas.expanding_min(arg, min_periods=1, freq=None, **kwargs)`

Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding minimum.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_max

pandas.**expanding_max**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding maximum.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_corr

pandas.**expanding_corr**(*arg1*, *arg2=None*, *min_periods=1*, *freq=None*, *pairwise=None*)

Expanding sample correlation.

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise) DataFrame / Series -> Computes result for each column Series / Series -> Series

pandas.expanding_corr_pairwise

pandas.**expanding_corr_pairwise**(*df1*, *df2=None*, *min_periods=1*, *freq=None*)

Deprecated. Use expanding_corr(..., pairwise=True) instead.

Pairwise expanding sample correlation

Parameters **df1** : DataFrame

df2 : DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : Panel whose items are df1.index values

pandas.expanding_cov

pandas.**expanding_cov**(*arg1*, *arg2=None*, *min_periods=1*, *freq=None*, *pairwise=None*, *ddof=1*)

Unbiased expanding covariance.

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

Returns **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise) DataFrame / Series -> Computes result for each column Series / Series -> Series

pandas.expanding_skew

pandas.**expanding_skew**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)
Unbiased expanding skewness.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_kurt

pandas.**expanding_kurt**(*arg*, *min_periods=1*, *freq=None*, ***kwargs*)
Unbiased expanding kurtosis.

Parameters **arg** : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y** : type of input argument

pandas.expanding_apply

pandas.**expanding_apply**(*arg*, *func*, *min_periods=1*, *freq=None*, *args=()*, *kwargs={}*)
Generic expanding function application.

Parameters **arg** : Series, DataFrame

func : function

Must produce a single value from an ndarray input

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

args : tuple

Passed on to func

kwargs : dict

Passed on to func

Returns y : type of input argument

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.expanding_quantile

pandas.**expanding_quantile**(*arg*, *quantile*, *min_periods=1*, *freq=None*)

Expanding quantile.

Parameters arg : Series, DataFrame

quantile : float

0 <= quantile <= 1

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns y : type of input argument

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

33.2.7 Exponentially-weighted moving window functions

`ewma`(arg[, com, span, halflife, ...])	Exponentially-weighted moving average
`ewmstd`(arg[, com, span, halflife, ...])	Exponentially-weighted moving std
`ewmvar`(arg[, com, span, halflife, ...])	Exponentially-weighted moving variance
`ewmcorr`(arg1[, arg2, com, span, halflife, ...])	Exponentially-weighted moving correlation
`ewmcov`(arg1[, arg2, com, span, halflife, ...])	Exponentially-weighted moving covariance

pandas.ewma

pandas.**ewma**(*arg*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *freq=None*, *adjust=True*, *how=None*, *ignore_na=False*)

Exponentially-weighted moving average

Parameters arg : Series, DataFrame

com : float. optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a "20-day EWMA" would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights (1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

When adjust is False, weighted averages are calculated recursively as: weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

pandas.ewmstd

`pandas.ewmstd`(*arg*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *bias=False*, *ignore_na=False*, *adjust=True*)

Exponentially-weighted moving std

Parameters arg : Series, DataFrame

com : float. optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

bias : boolean, default False

Use a standard estimation bias correction

Returns y : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a "20-day EWMA" would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights (1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

When adjust is False, weighted averages are calculated recursively as: weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

pandas.ewmvar

pandas.**ewmvar**(*arg*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *bias=False*, *freq=None*, *how=None*, *ignore_na=False*, *adjust=True*)

Exponentially-weighted moving variance

Parameters **arg** : Series, DataFrame

com : float. optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

bias : boolean, default False

Use a standard estimation bias correction

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a "20-day EWMA" would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights (1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

When adjust is False, weighted averages are calculated recursively as: weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

pandas.ewmcorr

pandas.**ewmcorr**(*arg1*, *arg2=None*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *freq=None*, *pairwise=None*, *how=None*, *ignore_na=False*, *adjust=True*)

Exponentially-weighted moving correlation

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

com : float. optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have that the decay parameter α is related to the span as $\alpha = 2/(s+1) = 1/(1+c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s-1)/2$

So a "20-day EWMA" would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights (1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

When adjust is False, weighted averages are calculated recursively as: weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

pandas.ewmcov

`pandas.`**`ewmcov`**(*arg1*, *arg2=None*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *bias=False*, *freq=None*, *pairwise=None*, *how=None*, *ignore_na=False*, *adjust=True*)

Exponentially-weighted moving covariance

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

com : float. optional

Center of mass: $\alpha = 1/(1+com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span+1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have that the decay parameter α is related to the span as $\alpha = 2/(s+1) = 1/(1+c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s-1)/2$

So a "20-day EWMA" would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights (1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

When adjust is False, weighted averages are calculated recursively as: weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

33.3 Series

33.3.1 Constructor

`Series`([data, index, dtype, name, copy, ...])	One-dimensional ndarray with axis labels (including time series).

pandas.Series

class `pandas.Series`(*data=None*, *index=None*, *dtype=None*, *name=None*, *copy=False*, *fastpath=False*)

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be any hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN)

Operations between Series (+, -, /, , *) align values based on their associated index values– they need not be the same length. The result index will be the sorted union of the two indexes.

Parameters **data** : array-like, dict, or scalar value

Contains data stored in Series

index : array-like or Index (1d)

Values must be unique and hashable, same length as data. Index object (or other iterable of same length as data) Will default to np.arange(len(data)) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

dtype : numpy.dtype or None

If None, dtype will be inferred

copy : boolean, default False

Copy input data

Attributes

`T`	return the transpose, which is by definition self
`at`	Fast label-based scalar accessor
`axes`	
`base`	return the base object if the memory of the underlying data is shared
`blocks`	Internal property, property synonym for as_blocks()
`data`	return the data pointer of the underlying data
`dtype`	return the dtype object of the underlying data
`dtypes`	return the dtype object of the underlying data
`empty`	True if NDFrame is entirely empty [no items]
`flags`	
`ftype`	return if the data is sparseldense
`ftypes`	return if the data is sparseldense
`iat`	Fast integer location scalar accessor.
`iloc`	Purely integer-location based indexing for selection by position.
`imag`	
`is_time_series`	
`itemsize`	return the size of the dtype of the item of the underlying data
`ix`	A primarily label-location based indexer, with integer position fallback.
`loc`	Purely label-location based indexer for selection by label.
`nbytes`	return the number of bytes in the underlying data
`ndim`	return the number of dimensions of the underlying data, by definition 1
`real`	
`shape`	return a tuple of the shape of the underlying data
`size`	return the number of elements in the underlying data

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`strides`	return the strides of the underlying data
`values`	Return Series as ndarray

pandas.Series.T

`Series.T`

return the transpose, which is by definition self

pandas.Series.at

`Series.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Series.axes

`Series.axes`

pandas.Series.base

`Series.base`

return the base object if the memory of the underlying data is shared

pandas.Series.blocks

`Series.blocks`

Internal property, property synonym for as_blocks()

pandas.Series.data

`Series.data`

return the data pointer of the underlying data

pandas.Series.dtype

`Series.dtype`

return the dtype object of the underlying data

pandas.Series.dtypes

`Series.dtypes`

return the dtype object of the underlying data

pandas.Series.empty

`Series.empty`
True if NDFrame is entirely empty [no items]

pandas.Series.flags

`Series.flags`

pandas.Series.ftype

`Series.ftype`
return if the data is sparse|dense

pandas.Series.ftypes

`Series.ftypes`
return if the data is sparse|dense

pandas.Series.iat

`Series.iat`
Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Series.iloc

`Series.iloc`
Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.Series.imag

`Series.imag`

pandas.Series.is_time_series

`Series.is_time_series`

pandas.Series.itemsize

`Series.itemsize`

return the size of the dtype of the item of the underlying data

pandas.Series.ix

`Series.ix`

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.Series.loc

`Series.loc`

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.Series.nbytes

`Series.nbytes`

return the number of bytes in the underlying data

pandas.Series.ndim

`Series.ndim`
return the number of dimensions of the underlying data, by definition 1

pandas.Series.real

`Series.real`

pandas.Series.shape

`Series.shape`
return a tuple of the shape of the underlying data

pandas.Series.size

`Series.size`
return the number of elements in the underlying data

pandas.Series.strides

`Series.strides`
return the strides of the underlying data

pandas.Series.values

`Series.values`
Return Series as ndarray

Returns arr : numpy.ndarray

is_copy	

Methods

abs()	Return an object with absolute value taken.
add(other[, level, fill_value, axis])	Addition of series and other, element-wise (binary operator *add*).
add_prefix(prefix)	Concatenate prefix string with panel items names.
add_suffix(suffix)	Concatenate suffix string with panel items names
align(other[, join, axis, level, copy, ...])	Align two object on their axes with the
all([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
any([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
append(to_append[, verify_integrity])	Concatenate two or more Series.
apply(func[, convert_dtype, args])	Invoke function on values of Series.
argmax([axis, out, skipna])	Index of first occurrence of maximum of values.
argmin([axis, out, skipna])	Index of first occurrence of minimum of values.
argsort([axis, kind, order])	Overrides ndarray.argsort.
as_blocks()	Convert the frame to a dict of dtype -> Constructor Types that each has a homog

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as_matrix([columns])	Convert the frame to its Numpy-array representation.
asfreq(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
asof(where)	Return last good (non-NaN) value in TimeSeries if value is NaN for requested da
astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
at_time(time[, asof])	Select values at particular time of day (e.g.
autocorr([lag])	Lag-N autocorrelation
between(left, right[, inclusive])	Return boolean Series equivalent to left <= series <= right.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM)
bfill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='bfill')
bool()	Return the bool of a single element PandasObject
cat	alias of CategoricalAccessor
clip([lower, upper, out, axis])	Trim values at input threshold(s)
clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
combine(other, func[, fill_value])	Perform elementwise binary operation on two Series using given function
combine_first(other)	Combine Series values, choosing the calling Series's values first.
compound([axis, skipna, level])	Return the compound percentage of the values for the requested axis
compress(condition[, axis, out])	Return selected slices of an array along given axis as a Series
consolidate([inplace])	Compute NDFrame with "consolidated" internals (data of each dtype grouped to
convert_objects([convert_dates, ...])	Attempt to infer better dtype for object columns
copy([deep])	Make a copy of this object
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, dtype, out, skipna])	Return cumulative max over requested axis.
cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.
describe([percentile_width, percentiles, ...])	Generate various summary statistics, excluding NaN values.
diff([periods])	1st discrete difference of object
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*).
dot(other)	Matrix multiplication with DataFrame or inner-product with Series
drop(labels[, axis, level, inplace, errors])	Return new object with labels in requested axis removed
drop_duplicates([take_last, inplace])	Return Series with duplicate values removed
dropna([axis, inplace])	Return Series without null values
dt	alias of CombinedDatetimelikeProperties
duplicated([take_last])	Return boolean Series denoting duplicate values
eq(other[, axis])	
equals(other)	Determines if two NDFrame objects contain the same elements.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
ffill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='ffill')
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method
filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
first(offset)	Convenience method for subsetting initial periods of time series data
first_valid_index()	Return label for first non-NA/null value
floordiv(other[, level, fill_value, axis])	Integer division of series and other, element-wise (binary operator *floordiv*).
from_array(arr[, index, name, dtype, copy, ...])	
from_csv(path[, sep, parse_dates, header, ...])	Read delimited file into Series
ge(other[, axis])	
get(key[, default])	Get item from object for given key (DataFrame column, Panel slice, etc.).
get_dtype_counts()	Return the counts of dtypes in this object

Table 33.22 – continued from previous page

get_ftype_counts()	Return the counts of ftypes in this object
get_value(label[, takeable])	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
gt(other[, axis])	
hasnans()	return if I have any nans; enables various perf speedups
head([n])	Returns first n rows
hist([by, ax, grid, xlabelsize, xrot, ...])	Draw histogram of the input series using matplotlib
idxmax([axis, out, skipna])	Index of first occurrence of maximum of values.
idxmin([axis, out, skipna])	Index of first occurrence of minimum of values.
iget(i[, axis])	Return the i-th value or values in the Series by location
iget_value(i[, axis])	Return the i-th value or values in the Series by location
interpolate([method, axis, limit, inplace, ...])	Interpolate values according to different methods.
irow(i[, axis])	Return the i-th value or values in the Series by location
isin(values)	Return a boolean Series showing whether each element in the Series is exa
isnull()	Return a boolean same-sized object indicating if the values are null
item()	return the first element of the underlying data as a python scalar
iteritems()	Lazily iterate over (index, value) tuples
iterkv(*args, **kwargs)	iteritems alias used to get around 2to3. Deprecated
keys()	Alias for index
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
last(offset)	Convenience method for subsetting final periods of time series data
last_valid_index()	Return label for last non-NA/null value
le(other[, axis])	
load(path)	Deprecated.
lt(other[, axis])	
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 (which can be
mask(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from
max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
median([axis, skipna, level, numeric_only])	Return the median of the values for the requested axis
min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
mod(other[, level, fill_value, axis])	Modulo of series and other, element-wise (binary operator *mod*).
mode()	Returns the mode(s) of the dataset.
mul(other[, level, fill_value, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
multiply(other[, level, fill_value, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
ne(other[, axis])	
nlargest([n, take_last])	Return the largest *n* elements.
nonzero()	Return the indices of the elements that are non-zero
notnull()	Return a boolean same-sized object indicating if the values are
nsmallest([n, take_last])	Return the smallest *n* elements.
nunique([dropna])	Return number of unique elements in the object.
order([na_last, ascending, kind, ...])	Sorts Series object, by value, maintaining index-value link.
pct_change([periods, fill_method, limit, freq])	Percent change over given number of periods.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs)
plot(data[, kind, ax, figsize, use_index, ...])	Make plots of Series using matplotlib / pylab.
pop(item)	Return item and drop from frame.
pow(other[, level, fill_value, axis])	Exponential power of series 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

Table 33.22 – continued from previous page

ptp([axis, out])	
put(*args, **kwargs)	return a ndarray with the values put
quantile([q])	Return value at the given quantile, a la numpy.percentile.
radd(other[, level, fill_value, axis])	Addition of series and other, element-wise (binary operator *radd*).
rank([method, na_option, ascending, pct])	Compute data ranks (1 through n).
ravel([order])	Return the flattened underlying data as an ndarray
rdiv(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
reindex([index])	Conform Series to new index with optional filling logic, placing NA/NaN in loca
reindex_axis(labels[, axis])	for compatibility with higher dims
reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
rename([index])	Alter axes input function or functions.
rename_axis(mapper[, axis, copy, inplace])	Alter index and / or columns using input function or functions.
reorder_levels(order)	Rearrange index levels using input order.
repeat(reps)	return a new Series with the values repeated reps times
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 regular time-se
reset_index([level, drop, name, inplace])	Analogous to the pandas.DataFrame.reset_index() function, see doc
reshape(*args, **kwargs)	return an ndarray with the values shape
rfloordiv(other[, level, fill_value, axis])	Integer division of series and other, element-wise (binary operator *rfloordiv*).
rmod(other[, level, fill_value, axis])	Modulo of series and other, element-wise (binary operator *rmod*).
rmul(other[, level, fill_value, axis])	Multiplication of series and other, element-wise (binary operator *rmul*).
round([decimals, out])	Return *a* with each element rounded to the given number of decimals.
rpow(other[, level, fill_value, axis])	Exponential power of series and other, element-wise (binary operator *rpow*).
rsub(other[, level, fill_value, axis])	Subtraction of series and other, element-wise (binary operator *rsub*).
rtruediv(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
save(path)	Deprecated.
searchsorted(v[, side, sorter])	Find indices where elements should be inserted to maintain order.
select(crit[, axis])	Return data corresponding to axis labels matching criteria
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.
set_axis(axis, labels)	public verson of axis assignment
set_value(label, value[, takeable])	Quickly set single value at passed label.
shift([periods, freq, axis])	Shift index by desired number of periods with an optional time freq
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
slice_shift([periods, axis])	Equivalent to *shift* without copying data.
sort([axis, ascending, kind, na_position, ...])	Sort values and index labels by value.
sort_index([ascending])	Sort object by labels (along an axis)
sortlevel([level, ascending, sort_remaining])	Sort Series with MultiIndex by chosen level.
squeeze()	squeeze length 1 dimensions
std([axis, skipna, level, ddof, numeric_only])	Return unbiased standard deviation over requested axis.
str	alias of StringMethods
sub(other[, level, fill_value, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
subtract(other[, level, fill_value, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately
swaplevel(i, j[, copy])	Swap levels i and j in a MultiIndex
tail([n])	Returns last n rows
take(indices[, axis, convert, is_copy])	return Series corresponding to requested indices
to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This can b
to_csv(path[, index, sep, na_rep, ...])	Write Series to a comma-separated values (csv) file
to_dense()	Return dense representation of NDFrame (as opposed to sparse)
to_dict()	Convert Series to {label -> value} dict

Table 33.22 – continued from previous page

to_frame([name])	Convert Series to DataFrame
to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_msgpack([path_or_buf])	msgpack (serialize) object to input file path
to_period([freq, copy])	Convert TimeSeries from DatetimeIndex to PeriodIndex with desired
to_pickle(path)	Pickle (serialize) object to input file path
to_sparse([kind, fill_value])	Convert Series to SparseSeries
to_sql(name, con[, flavor, schema, ...])	Write records stored in a DataFrame to a SQL database.
to_string([buf, na_rep, float_format, ...])	Render a string representation of the Series
to_timestamp([freq, how, copy])	Cast to datetimeindex of timestamps, at *beginning* of period
tolist()	Convert Series to a nested list
transpose()	return the transpose, which is by definition self
truediv(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.
tshift([periods, freq, axis])	Shift the time index, using the index's frequency if available
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone
unique()	Return array of unique values in the object.
unstack([level])	Unstack, a.k.a.
update(other)	Modify Series in place using non-NA values from passed Series.
valid([inplace])	
value_counts([normalize, sort, ascending, ...])	Returns object containing counts of unique values.
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
view([dtype])	
where(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from
xs(key[, axis, level, copy, drop_level])	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

pandas.Series.abs

`Series.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Series.add

`Series.add(`*other*, *level=None*, *fill_value=None*, *axis=0*`)`

Addition of series and other, element-wise (binary operator *add*).

Equivalent to `series + other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.radd`

pandas.Series.add_prefix

`Series.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters prefix : string

Returns with_prefix : type of caller

pandas.Series.add_suffix

`Series.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters suffix : string

Returns with_suffix : type of caller

pandas.Series.align

`Series.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters other : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (left, right) : (type of input, 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 requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns all : scalar or Series (if level specified)

pandas.Series.any

`Series.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns any : scalar or Series (if level specified)

pandas.Series.append

`Series.append(to_append, verify_integrity=False)`

Concatenate two or more Series.

Parameters to_append : Series or list/tuple of Series

verify_integrity : boolean, default False

If True, raise Exception on creating index with duplicates

Returns appended : Series

pandas.Series.apply

`Series.apply(func, convert_dtype=True, args=(), **kwds)`

Invoke function on values of Series. Can be ufunc (a NumPy function that applies to the entire Series) or a Python function that only works on single values

Parameters **func** : function

convert_dtype : boolean, default True

Try to find better dtype for elementwise function results. If False, leave as dtype=object

args : tuple

Positional arguments to pass to function in addition to the value

Additional keyword arguments will be passed as keywords to the function

Returns **y** : Series or DataFrame if func returns a Series

See also:

`Series.map` For element-wise operations

pandas.Series.argmax

`Series.argmax(axis=None, out=None, skipna=True)`

Index of first occurrence of maximum of values.

Parameters **skipna** : boolean, default True

Exclude NA/null values

Returns **idxmax** : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.argmin

`Series.argmin(axis=None, out=None, skipna=True)`

Index of first occurrence of minimum of values.

Parameters **skipna** : boolean, default True

Exclude NA/null values

Returns **idxmin** : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmin`.

pandas.Series.argsort

`Series.argsort(axis=0, kind='quicksort', order=None)`

Overrides ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values

Parameters axis : int (can only be zero)

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

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()`

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Returns values : a dict of dtype -> Constructor Types

pandas.Series.as_matrix

`Series.as_matrix(columns=None)`

Convert the frame to its Numpy-array representation.

Parameters columns: list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

Returns values : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

`pandas.DataFrame.values`

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use '.values'.

pandas.Series.asfreq

`Series.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.Series.asof

`Series.asof(where)`

Return last good (non-NaN) value in TimeSeries if value is NaN for requested date.

If there is no good value, NaN is returned.

Parameters **where** : date or array of dates

Returns value or NaN

Notes

Dates are assumed to be sorted

pandas.Series.astype

`Series.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Series.at_time

`Series.at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : type of caller

pandas.Series.autocorr

`Series.autocorr(lag=1)`

Lag-N autocorrelation

Parameters **lag** : int, default 1

Number of lags to apply before performing autocorrelation.

Returns **autocorr** : float

pandas.Series.between

`Series.between(left, right, inclusive=True)`

Return boolean Series equivalent to left <= series <= right. NA values will be treated as False

Parameters **left** : scalar

Left boundary

right : scalar

Right boundary

Returns **is_between** : Series

pandas.Series.between_time

`Series.between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns **values_between_time** : type of caller

pandas.Series.bfill

`Series.bfill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for NDFrame.fillna(method='bfill')

pandas.Series.bool

`Series.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.Series.cat

`Series.cat()`

Accessor object for categorical properties of the Series values.

Be aware that assigning to *categories* is a inplace operation, while all methods return new categorical data per default (but can be called with *inplace=True*).

Examples

```
>>> s.cat.categories
>>> s.cat.categories = list('abc')
>>> s.cat.rename_categories(list('cab'))
>>> s.cat.reorder_categories(list('cab'))
>>> s.cat.add_categories(['d','e'])
>>> s.cat.remove_categories(['d'])
>>> s.cat.remove_unused_categories()
>>> s.cat.set_categories(list('abcde'))
>>> s.cat.as_ordered()
>>> s.cat.as_unordered()
```

pandas.Series.clip

`Series.clip(`*lower=None*, *upper=None*, *out=None*, *axis=None*`)`

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
```

```
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Series.clip_lower

Series.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Series.clip_upper

Series.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Series.combine

Series.**combine**(*other*, *func*, *fill_value=nan*)

Perform elementwise binary operation on two Series using given function with optional fill value when an index is missing from one Series or the other

Parameters **other** : Series or scalar value

func : function

fill_value : scalar value

Returns **result** : Series

pandas.Series.combine_first

`Series.combine_first(other)`

Combine Series values, choosing the calling Series's values first. Result index will be the union of the two indexes

Parameters **other** : Series

Returns **y** : Series

pandas.Series.compound

`Series.compound(axis=None, skipna=None, level=None)`

Return the compound percentage of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **compounded** : scalar or Series (if level specified)

pandas.Series.compress

`Series.compress(condition, axis=0, out=None, **kwargs)`

Return selected slices of an array along given axis as a Series

See also:

`numpy.ndarray.compress`

pandas.Series.consolidate

`Series.consolidate(inplace=False)`

Compute NDFrame with "consolidated" internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters **inplace** : boolean, default False

If False return new object, otherwise modify existing object

Returns consolidated : type of caller

pandas.Series.convert_objects

Series.**convert_objects**(*convert_dates=True*, *convert_numeric=False*, *convert_timedeltas=True*, *copy=True*)

Attempt to infer better dtype for object columns

Parameters convert_dates : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.Series.copy

Series.**copy**(*deep=True*)

Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.Series.corr

Series.**corr**(*other*, *method='pearson'*, *min_periods=None*)

Compute correlation with *other* Series, excluding missing values

Parameters other : Series

method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns correlation : float

pandas.Series.count

`Series.count(level=None)`
Return number of non-NA/null observations in the Series

Parameters level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

Returns nobs : int or Series (if level specified)

pandas.Series.cov

`Series.cov(other, min_periods=None)`
Compute covariance with Series, excluding missing values

Parameters other : Series

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns covariance : float

Normalized by N-1 (unbiased estimator).

pandas.Series.cummax

`Series.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative max over requested axis.

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : scalar

pandas.Series.cummin

`Series.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative min over requested axis.

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : scalar

pandas.Series.cumprod

`Series.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative prod over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : scalar

pandas.Series.cumsum

`Series.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative sum over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : scalar

pandas.Series.describe

`Series.describe(percentile_width=None, percentiles=None, include=None, exclude=None)`
Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Series.diff

`Series.diff(periods=1)`

1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

Returns **diffed** : Series

pandas.Series.div

`Series.div(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rtruediv`

pandas.Series.divide

`Series.divide(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rtruediv`

pandas.Series.dot

`Series.dot(other)`

Matrix multiplication with DataFrame or inner-product with Series objects

Parameters **other** : Series or DataFrame

Returns **dot_product** : scalar or Series

pandas.Series.drop

`Series.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.Series.drop_duplicates

`Series.drop_duplicates(take_last=False, inplace=False)`

Return Series with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

inplace : boolean, default False

If True, performs operation inplace and returns None.

Returns deduplicated : Series

pandas.Series.dropna

`Series.dropna(axis=0, inplace=False, **kwargs)`

Return Series without null values

Returns valid : Series

inplace : boolean, default False

Do operation in place.

pandas.Series.dt

`Series.dt()`

Accessor object for datetimelike properties of the Series values.

Examples

```
>>> 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(take_last=False)`

Return boolean Series denoting duplicate values

Parameters take_last : boolean, default False

Take the last observed index in a group. Default first

Returns duplicated : Series

pandas.Series.eq

`Series.eq(other, axis=None)`

pandas.Series.equals

`Series.equals(other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Series.factorize

`Series.factorize(sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.Series.ffill

`Series.ffill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for NDFrame.fillna(method='ffill')

pandas.Series.fillna

`Series.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)`

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 'index'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : Series

See also:

`reindex`, `asfreq`

pandas.Series.filter

`Series.filter(items=None, like=None, regex=None, axis=None)`

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]]}); df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Series.first

`Series.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Series.first_valid_index

`Series.first_valid_index()`

Return label for first non-NA/null value

pandas.Series.floordiv

`Series.floordiv(other, level=None, fill_value=None, axis=0)`

Integer division of series and other, element-wise (binary operator *floordiv*).

Equivalent to `series // other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rfloordiv`

pandas.Series.from_array

classmethod `Series.from_array(arr, index=None, name=None, dtype=None, copy=False, fastpath=False)`

pandas.Series.from_csv

classmethod `Series.from_csv(path, sep=', ', parse_dates=True, header=None, index_col=0, encoding=None, infer_datetime_format=False)`

Read delimited file into Series

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 0

Row to use at header (skip prior rows)

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

infer_datetime_format: boolean, default False

If True and *parse_dates* is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns y : Series

pandas.Series.ge

`Series.ge(other, axis=None)`

pandas.Series.get

`Series.get(key, default=None)`

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters key : object

Returns value : type of items contained in object

pandas.Series.get_dtype_counts

`Series.get_dtype_counts()`

Return the counts of dtypes in this object

pandas.Series.get_ftype_counts

`Series.get_ftype_counts()`

Return the counts of ftypes in this object

pandas.Series.get_value

`Series.get_value(label, takeable=False)`

Quickly retrieve single value at passed index label

Parameters index : label

takeable : interpret the index as indexers, default False

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)`

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively "SQL-style" grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionaility of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

pandas.Series.gt

`Series.gt(other, axis=None)`

pandas.Series.hasnans

`Series.hasnans()`

return if I have any nans; enables various perf speedups

pandas.Series.head

`Series.head(n=5)`
Returns first n rows

pandas.Series.hist

`Series.hist(by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, **kwds)`
Draw histogram of the input series using matplotlib

Parameters **by** : object, optional

If passed, then used to form histograms for separate groups

ax : matplotlib axis object

If not passed, uses gca()

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

figsize : tuple, default None

figure size in inches by default

bins: integer, default 10

Number of histogram bins to be used

kwds : keywords

To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this

pandas.Series.idxmax

`Series.idxmax(axis=None, out=None, skipna=True)`
Index of first occurrence of maximum of values.

Parameters **skipna** : boolean, default True

Exclude NA/null values

Returns idxmax : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.idxmin

`Series.idxmin(axis=None, out=None, skipna=True)`

Index of first occurrence of minimum of values.

Parameters skipna : boolean, default True

Exclude NA/null values

Returns idxmin : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmin`.

pandas.Series.iget

`Series.iget(i, axis=0)`

Return the i-th value or values in the Series by location

Parameters i : int, slice, or sequence of integers

Returns value : scalar (int) or Series (slice, sequence)

pandas.Series.iget_value

`Series.iget_value(i, axis=0)`

Return the i-th value or values in the Series by location

Parameters i : int, slice, or sequence of integers

Returns value : scalar (int) or Series (slice, sequence)

pandas.Series.interpolate

`Series.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`

Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. 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* with the order given both 'polynomial' and 'spline' requre that you also specify and order (int) e.g. df.interpolate(method='polynomial', order=4)
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html

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.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.Series.irow

`Series.irow(i, axis=0)`

Return the i-th value or values in the Series by location

Parameters **i** : int, slice, or sequence of integers

Returns **value** : scalar (int) or Series (slice, sequence)

pandas.Series.isin

`Series.isin(values)`

Return a boolean `Series` showing whether each element in the `Series` is exactly contained in the passed sequence of `values`.

Parameters **values** : list-like

The sequence of values to test. Passing in a single string will raise a `TypeError`. Instead, turn a single string into a `list` of one element.

Returns **isin** : Series (bool dtype)

Raises **TypeError**

- If `values` is a string

See also:

`pandas.DataFrame.isin`

Examples

```
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0     True
1    False
2     True
dtype: bool
```

Passing a single string as `s.isin('a')` will raise an error. Use a list of one element instead:

```
>>> s.isin(['a'])
0     True
1    False
2    False
dtype: bool
```

pandas.Series.isnull

`Series.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.Series.item

Series.**item**()
return the first element of the underlying data as a python scalar

pandas.Series.iteritems

Series.**iteritems**()
Lazily iterate over (index, value) tuples

pandas.Series.iterkv

Series.**iterkv**(**args*, ***kwargs*)
iteritems alias used to get around 2to3. Deprecated

pandas.Series.keys

Series.**keys**()
Alias for index

pandas.Series.kurt

Series.**kurt**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : scalar or Series (if level specified)

pandas.Series.kurtosis

Series.**kurtosis**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : scalar or Series (if level specified)

pandas.Series.last

`Series.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Series.last_valid_index

`Series.last_valid_index()`

Return label for last non-NA/null value

pandas.Series.le

`Series.le(other, axis=None)`

pandas.Series.load

`Series.load(path)`

Deprecated. Use read_pickle instead.

pandas.Series.lt

`Series.lt(other, axis=None)`

pandas.Series.mad

`Series.mad(axis=None, skipna=None, level=None)`

Return the mean absolute deviation of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mad : scalar or Series (if level specified)

pandas.Series.map

Series.**map**(*arg*, *na_action=None*)

Map values of Series using input correspondence (which can be a dict, Series, or function)

Parameters arg : function, dict, or Series

na_action : {None, 'ignore'}

If 'ignore', propagate NA values

Returns y : Series

same index as caller

Examples

```
>>> x
one   1
two   2
three 3
```

```
>>> y
1  foo
2  bar
3  baz
```

```
>>> x.map(y)
one   foo
two   bar
three baz
```

pandas.Series.mask

Series.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.Series.max

`Series.max`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : scalar or Series (if level specified)

pandas.Series.mean

`Series.mean`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mean : scalar or Series (if level specified)

pandas.Series.median

`Series.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the median of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : scalar or Series (if level specified)

pandas.Series.min

`Series.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : scalar or Series (if level specified)

pandas.Series.mod

`Series.mod(other, level=None, fill_value=None, axis=0)`

Modulo of series and other, element-wise (binary operator *mod*).

Equivalent to `series % other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rmod`

pandas.Series.mode

`Series.mode()`

Returns the mode(s) of the dataset.

Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters sort : bool, default True

If True, will lexicographically sort values, if False skips sorting. Result ordering when `sort=False` is not defined.

Returns modes : Series (sorted)

pandas.Series.mul

`Series.mul(`*other*, *level=None*, *fill_value=None*, *axis=0*`)`

Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rmul`

pandas.Series.multiply

`Series.multiply(`*other*, *level=None*, *fill_value=None*, *axis=0*`)`

Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rmul`

pandas.Series.ne

`Series.ne(other, axis=None)`

pandas.Series.nlargest

`Series.nlargest(n=5, take_last=False)`

Return the largest *n* elements.

Parameters **n** : int

Return this many descending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns **top_n** : Series

The n largest values in the Series, in sorted order

See also:

`Series.nsmallest`

Notes

Faster than `.order(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

pandas.Series.nonzero

`Series.nonzero()`

Return the indices of the elements that are non-zero

This method is equivalent to calling *numpy.nonzero* on the series data. For compatability 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

```
>>> s = pd.Series([0, 3, 0, 4])
>>> s.nonzero()
(array([1, 3]),)
>>> s.iloc[s.nonzero()[0]]
1    3
3    4
dtype: int64
```

pandas.Series.notnull

`Series.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

pandas.Series.nsmallest

`Series.nsmallest(n=5, take_last=False)`

Return the smallest *n* elements.

Parameters n : int

Return this many ascending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns bottom_n : Series

The n smallest values in the Series, in sorted order

See also:

`Series.nlargest`

Notes

Faster than `.order().head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

pandas.Series.nunique

`Series.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters **dropna** : boolean, default True

Don't include NaN in the count.

Returns **nunique** : int

pandas.Series.order

`Series.order(na_last=None, ascending=True, kind='quicksort', na_position='last', inplace=False)`

Sorts Series object, by value, maintaining index-value link. This will return a new Series by default. Series.sort is the equivalent but as an inplace method.

Parameters **na_last** : boolean (optional, default=True) (DEPRECATED; use na_position)

Put NaN's at beginning or end

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default False

Do operation in place.

Returns **y** : Series

See also:

`Series.sort`

pandas.Series.pct_change

`Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.Series.pipe

`Series.`**`pipe`**(*func*, **args*, ***kwargs*)

Apply func(self, *args, **kwargs)

New in version 0.16.2.

Parameters func : function

function to apply to the NDFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the NDFrame.

args : positional arguments passed into `func`.

kwargs : a dictionary of keyword arguments passed into `func`.

Returns object : the return type of `func`.

See also:

`pandas.DataFrame.apply`, `pandas.DataFrame.applymap`, `pandas.Series.map`

Notes

Use `.pipe` when chaining together functions that expect on Series or DataFrames. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (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`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((f, 'arg2'), arg1=a, arg3=c)
...   )
```

pandas.Series.plot

`Series.plot`(*data*, *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.

Parameters **data** : Series

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot

ax : matplotlib axes object

If not passed, uses gca()

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

label : label argument to provide to plot

secondary_y : boolean or sequence of ints, default False

If True then y-axis will be on the right

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

pandas.Series.pop

`Series.pop(item)`

Return item and drop from frame. Raise KeyError if not found.

pandas.Series.pow

`Series.pow(other, level=None, fill_value=None, axis=0)`

Exponential power of series and other, element-wise (binary operator *pow*).

Equivalent to `series ** other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rpow`

pandas.Series.prod

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : scalar or Series (if level specified)

pandas.Series.product

`Series.product` (*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : scalar or Series (if level specified)

pandas.Series.ptp

`Series.ptp` (*axis=None*, *out=None*)

pandas.Series.put

`Series.put` (**args*, ***kwargs*)

return a ndarray with the values put

See also:

`numpy.ndarray.put`

pandas.Series.quantile

`Series.quantile` (*q=0.5*)

Return value at the given quantile, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

Returns **quantile** : float or Series

if `q` is an array, a Series will be returned where the index is `q` and the values are the quantiles.

Examples

```
>>> s = Series([1, 2, 3, 4])
>>> s.quantile(.5)
    2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

pandas.Series.radd

`Series.radd`(*other*, *level=None*, *fill_value=None*, *axis=0*)

Addition of series and other, element-wise (binary operator *radd*).

Equivalent to `other + series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.add`

pandas.Series.rank

`Series.rank`(*method='average'*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

Parameters **method** : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep'}

keep: leave NA values where they are

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : Series

pandas.Series.ravel

`Series.ravel(order='C')`

Return the flattened underlying data as an ndarray

See also:

`numpy.ndarray.ravel`

pandas.Series.rdiv

`Series.rdiv(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.truediv`

pandas.Series.reindex

`Series.reindex(index=None, **kwargs)`

Conform Series to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **index** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : Series

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Series.reindex_axis

`Series.`**`reindex_axis`**(*labels*, *axis=0*, ***kwargs*)

for compatibility with higher dims

pandas.Series.reindex_like

`Series.`**`reindex_like`**(*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Series.rename

`Series.`**`rename`**(*index=None*, ***kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters index : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Series. If True then value of copy is ignored.

Returns **renamed** : Series (new object)

pandas.Series.rename_axis

Series.**rename_axis**(*mapper*, *axis=0*, *copy=True*, *inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **mapper** : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns **renamed** : type of caller

pandas.Series.reorder_levels

Series.**reorder_levels**(*order*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters **order: list of int representing new level order.**

(reference level by number or key)

axis: where to reorder levels

Returns type of caller (new object)

pandas.Series.repeat

Series.**repeat**(*reps*)

return a new Series with the values repeated reps times

See also:

`numpy.ndarray.repeat`

pandas.Series.replace

Series.**replace**(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*, *axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters **to_replace** : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*

- regex: regexs matching *to_replace* will be replaced with *value*

- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.
- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Series.resample

`Series.`**`resample`**(*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Series.reset_index

`Series.reset_index(level=None, drop=False, name=None, inplace=False)`

Analogous to the `pandas.DataFrame.reset_index()` function, see docstring there.

Parameters **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns

name : object, default None

The name of the column corresponding to the Series values

inplace : boolean, default False

Modify the Series in place (do not create a new object)

Returns **resetted** : DataFrame, or Series if drop == True

pandas.Series.reshape

`Series.reshape(*args, **kwargs)`

return an ndarray with the values shape if the specified shape matches exactly the current shape, then return self (for compat)

See also:

`numpy.ndarray.take`

pandas.Series.rfloordiv

`Series.rfloordiv(other, level=None, fill_value=None, axis=0)`

Integer division of series and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.floordiv`

pandas.Series.rmod

`Series.`**`rmod`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Modulo of series and other, element-wise (binary operator *rmod*).

Equivalent to `other % series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.mod`

pandas.Series.rmul

`Series.`**`rmul`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Multiplication of series and other, element-wise (binary operator *rmul*).

Equivalent to `other * series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.mul`

pandas.Series.round

`Series.`**`round`**(*decimals=0*, *out=None*)

Return *a* with each element rounded to the given number of decimals.

Refer to *numpy.around* for full documentation.

See also:

`numpy.around` equivalent function

pandas.Series.rpow

`Series.rpow(other, level=None, fill_value=None, axis=0)`

Exponential power of series and other, element-wise (binary operator *rpow*).

Equivalent to `other ** series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.pow`

pandas.Series.rsub

`Series.rsub(other, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator *rsub*).

Equivalent to `other - series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.sub`

pandas.Series.rtruediv

`Series.rtruediv(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.truediv`

pandas.Series.sample

`Series.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.Series.save

`Series.save(path)`

Deprecated. Use to_pickle instead

pandas.Series.searchsorted

Series.**searchsorted**(*v*, *side='left'*, *sorter=None*)

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series *self* such that, if the corresponding elements in *v* were inserted before the indices, the order of *self* would be preserved.

Parameters **v** : array_like

Values to insert into *a*.

side : {'left', 'right'}, optional

If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *a*).

sorter : 1-D array_like, optional

Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns **indices** : array of ints

Array of insertion points with the same shape as *v*.

See also:

`Series.sort`, `Series.order`, `numpy.searchsorted`

Notes

Binary search is used to find the required insertion points.

Examples

```
>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3
dtype: int64
>>> x.searchsorted(4)
array([3])
>>> x.searchsorted([0, 4])
array([0, 3])
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```

pandas.Series.select

`Series.select(crit, axis=0)`
Return data corresponding to axis labels matching criteria

Parameters crit : function

To be called on each index (label). Should return True or False

axis : int

Returns selection : type of caller

pandas.Series.sem

`Series.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`
Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sem : scalar or Series (if level specified)

pandas.Series.set_axis

`Series.set_axis(axis, labels)`
public verson of axis assignment

pandas.Series.set_value

`Series.set_value(label, value, takeable=False)`
Quickly set single value at passed label. If label is not contained, a new object is created with the label placed at the end of the result index

Parameters label : object

Partial indexing with MultiIndex not allowed

value : object

Scalar value

takeable : interpret the index as indexers, default False

Returns series : Series

If label is contained, will be reference to calling Series, otherwise a new object

pandas.Series.shift

`Series.shift(periods=1, freq=None, axis=0, **kwargs)`

Shift index by desired number of periods with an optional time freq

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 'index'}

Returns **shifted** : Series

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.Series.skew

`Series.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : scalar or Series (if level specified)

pandas.Series.slice_shift

`Series.slice_shift(periods=1, axis=0)`

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Series.sort

Series.**sort**(*axis=0*, *ascending=True*, *kind='quicksort'*, *na_position='last'*, *inplace=True*)

Sort values and index labels by value. This is an inplace sort by default. Series.order is the equivalent but returns a new Series.

Parameters **axis** : int (can only be zero)

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default True

Do operation in place.

See also:

Series.order

pandas.Series.sort_index

Series.**sort_index**(*ascending=True*)

Sort object by labels (along an axis)

Parameters **ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

Returns **sorted_obj** : Series

Examples

```
>>> result1 = s.sort_index(ascending=False)
>>> result2 = s.sort_index(ascending=[1, 0])
```

pandas.Series.sortlevel

Series.**sortlevel**(*level=0*, *ascending=True*, *sort_remaining=True*)

Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters **level** : int or level name, default None

ascending : bool, default True

Returns sorted : Series

pandas.Series.squeeze

`Series.squeeze()`

squeeze length 1 dimensions

pandas.Series.std

`Series.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns std : scalar or Series (if level specified)

pandas.Series.str

`Series.str()`

Vectorized string functions for Series and Index. NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

Examples

```
>>> s.str.split('_')
>>> s.str.replace('_', '')
```

pandas.Series.sub

`Series.sub(other, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rsub`

pandas.Series.subtract

`Series.subtract(other, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rsub`

pandas.Series.sum

`Series.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sum : scalar or Series (if level specified)

pandas.Series.swapaxes

`Series.swapaxes(axis1, axis2, copy=True)`

Interchange axes and swap values axes appropriately

Returns y : same as input

pandas.Series.swaplevel

`Series.swaplevel(i, j, copy=True)`

Swap levels i and j in a MultiIndex

Parameters i, j : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns swapped : Series

pandas.Series.tail

`Series.tail(n=5)`

Returns last n rows

pandas.Series.take

`Series.take(indices, axis=0, convert=True, is_copy=False)`

return Series corresponding to requested indices

Parameters indices : list / array of ints

convert : translate negative to positive indices (default)

Returns taken : Series

See also:

`numpy.ndarray.take`

pandas.Series.to_clipboard

`Series.to_clipboard(excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.Series.to_csv

`Series.to_csv`(*path*, *index=True*, *sep=',', '*, *na_rep=''*, *float_format=None*, *header=False*, *index_label=None*, *mode='w'*, *nanRep=None*, *encoding=None*, *date_format=None*, *decimal='.'*)

Write Series to a comma-separated values (csv) file

Parameters **path** : string file path or file handle / StringIO. If None is provided

the result is returned as a string.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

header : boolean, default False

Write out series name

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

mode : Python write mode, default 'w'

sep : character, default ","

Field delimiter for the output file.

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

date_format: string, default None

Format string for datetime objects.

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

pandas.Series.to_dense

`Series.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.Series.to_dict

`Series.to_dict()`

Convert Series to {label -> value} dict

Returns value_dict : dict

pandas.Series.to_frame

`Series.to_frame(name=None)`

Convert Series to DataFrame

Parameters name : object, default None

The passed name should substitute for the series name (if it has one).

Returns data_frame : DataFrame

pandas.Series.to_hdf

`Series.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

Parameters path_or_buf : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Series.to_json

Series.**to_json**(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}
  - columns : dict like {column -> {index -> value}}
  - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso*' = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Series.to_msgpack

`Series.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.Series.to_period

`Series.to_period(freq=None, copy=True)`

Convert TimeSeries from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters **freq** : string, default

Returns **ts** : TimeSeries with PeriodIndex

pandas.Series.to_pickle

`Series.to_pickle(path)`

Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Series.to_sparse

`Series.to_sparse(kind='block', fill_value=None)`

Convert Series to SparseSeries

Parameters **kind** : {'block', 'integer'}

fill_value : float, defaults to NaN (missing)

Returns **sp** : SparseSeries

pandas.Series.to_sql

`Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters name : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Series.to_string

`Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, length=False, dtype=False, name=False, max_rows=None)`

Render a string representation of the Series

Parameters buf : StringIO-like, optional

buffer to write to

na_rep : string, optional

string representation of NAN to use, default 'NaN'

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats default None

header: boolean, default True

Add the Series header (index name)

length : boolean, default False

Add the Series length

dtype : boolean, default False

Add the Series dtype

name : boolean, default False

Add the Series name if not None

max_rows : int, optional

Maximum number of rows to show before truncating. If None, show all.

Returns formatted : string (if not buffer passed)

pandas.Series.to_timestamp

`Series.`**`to_timestamp`**(*freq=None*, *how='start'*, *copy=True*)

Cast to datetimeindex of timestamps, at *beginning* of period

Parameters freq : string, default frequency of PeriodIndex

Desired frequency

how : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

Returns ts : TimeSeries with DatetimeIndex

pandas.Series.tolist

`Series.`**`tolist`**()

Convert Series to a nested list

pandas.Series.transpose

`Series.`**`transpose`**()

return the transpose, which is by definition self

pandas.Series.truediv

`Series.`**`truediv`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.rtruediv`

pandas.Series.truncate

`Series.truncate`(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters before : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns truncated : type of caller

pandas.Series.tshift

`Series.tshift`(*periods=1*, *freq=None*, *axis=0*, ***kwargs*)

Shift the time index, using the index's frequency if available

Parameters periods : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, default None

Increment to use from datetools module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns shifted : NDFrame

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.Series.tz_convert

`Series.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.Series.tz_localize

`Series.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

pandas.Series.unique

`Series.unique()`

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns **uniques** : ndarray

pandas.Series.unstack

`Series.unstack(level=-1)`

Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default last level

Level(s) to unstack, can pass level name

Returns **unstacked** : DataFrame

Examples

```
>>> s
one  a   1.
one  b   2.
two  a   3.
two  b   4.

>>> s.unstack(level=-1)
     a   b
one  1.  2.
two  3.  4.

>>> s.unstack(level=0)
   one  two
a  1.   2.
b  3.   4.
```

pandas.Series.update

`Series.update(other)`

Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters **other** : Series

pandas.Series.valid

`Series.valid(inplace=False, **kwargs)`

pandas.Series.value_counts

`Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters **normalize** : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns counts : Series

pandas.Series.var

`Series.var`(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns var : scalar or Series (if level specified)

pandas.Series.view

`Series.view`(*dtype=None*)

pandas.Series.where

`Series.where`(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Series.xs

`Series.xs(key, axis=0, level=None, copy=None, drop_level=True)`

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters **key** : object

Some label contained in the index, or partially in a MultiIndex

axis : int, default 0

Axis to retrieve cross-section on

level : object, defaults to first n levels (n=1 or len(key))

In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

copy : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns **xs** : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultiIndex Slicers*

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
```

```
Name: a
>>> df.xs('C', axis=1)
a    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
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
```

33.3.2 Attributes

Axes

- **index**: axis labels

Series.values	Return Series as ndarray
Series.dtype	return the dtype object of the underlying data
Series.ftype	return if the data is sparse|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

pandas.Series.values

Series.**values**

Return Series as ndarray

Returns arr : numpy.ndarray

pandas.Series.dtype

Series.**dtype**
return the dtype object of the underlying data

pandas.Series.ftype

Series.**ftype**
return if the data is sparse|dense

pandas.Series.shape

Series.**shape**
return a tuple of the shape of the underlying data

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.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.itemsize

Series.**itemsize**
return the size of the dtype of the item of the underlying data

pandas.Series.base

Series.**base**
return the base object if the memory of the underlying data is shared

pandas.Series.T

`Series.T`
return the transpose, which is by definition self

33.3.3 Conversion

`Series.astype`(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
`Series.copy`([deep])	Make a copy of this object
`Series.isnull`()	Return a boolean same-sized object indicating if the values are null
`Series.notnull`()	Return a boolean same-sized object indicating if the values are

pandas.Series.astype

`Series.astype`(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Series.copy

`Series.copy`(*deep=True*)
Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Series.isnull

`Series.isnull`()
Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.Series.notnull

`Series.notnull`()
Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

33.3.4 Indexing, iteration

`Series.get`(key[, default])	Get item from object for given key (DataFrame column, Panel slice, etc.).
`Series.at`	Fast label-based scalar accessor
`Series.iat`	Fast integer location scalar accessor.
`Series.ix`	A primarily label-location based indexer, with integer position fallback.
`Series.loc`	Purely label-location based indexer for selection by label.
`Series.iloc`	Purely integer-location based indexing for selection by position.
`Series.__iter__`()	
`Series.iteritems`()	Lazily iterate over (index, value) tuples

pandas.Series.get

`Series.get`(*key*, *default=None*)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters **key** : object

Returns **value** : type of items contained in object

pandas.Series.at

`Series.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Series.iat

`Series.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Series.ix

`Series.ix`

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.Series.loc

`Series.loc`
Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.Series.iloc

`Series.iloc`
Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.Series.__iter__

`Series.__iter__()`

pandas.Series.iteritems

`Series.iteritems()`
Lazily iterate over (index, value) tuples

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the *indexing documentation*.

33.3.5 Binary operator functions

`Series.add`(other[, level, fill_value, axis])	Addition of series and other, element-wise (binary operator *add*).
`Series.sub`(other[, level, fill_value, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
`Series.mul`(other[, level, fill_value, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
`Series.div`(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
`Series.truediv`(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
`Series.floordiv`(other[, level, fill_value, axis])	Integer division of series and other, element-wise (binary operator *floordiv*).
`Series.mod`(other[, level, fill_value, axis])	Modulo of series and other, element-wise (binary operator *mod*).
`Series.pow`(other[, level, fill_value, axis])	Exponential power of series and other, element-wise (binary operator *pow*).
`Series.radd`(other[, level, fill_value, axis])	Addition of series and other, element-wise (binary operator *radd*).
`Series.rsub`(other[, level, fill_value, axis])	Subtraction of series and other, element-wise (binary operator *rsub*).
`Series.rmul`(other[, level, fill_value, axis])	Multiplication of series and other, element-wise (binary operator *rmul*).
`Series.rdiv`(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
`Series.rtruediv`(other[, level, fill_value, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
`Series.rfloordiv`(other[, level, fill_value, ...])	Integer division of series and other, element-wise (binary operator *rfloordiv*).
`Series.rmod`(other[, level, fill_value, axis])	Modulo of series and other, element-wise (binary operator *rmod*).
`Series.rpow`(other[, level, fill_value, axis])	Exponential power of series and other, element-wise (binary operator *rpow*).
`Series.combine`(other, func[, fill_value])	Perform elementwise binary operation on two Series using given function
`Series.combine_first`(other)	Combine Series values, choosing the calling Series's values first.
`Series.round`([decimals, out])	Return *a* with each element rounded to the given number of decimals.
`Series.lt`(other[, axis])	
`Series.gt`(other[, axis])	
`Series.le`(other[, axis])	
`Series.ge`(other[, axis])	
`Series.ne`(other[, axis])	
`Series.eq`(other[, axis])	

pandas.Series.add

`Series.add(other, level=None, fill_value=None, axis=0)`

Addition of series and other, element-wise (binary operator *add*).

Equivalent to `series + other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.radd`

pandas.Series.sub

`Series.sub(other, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rsub`

pandas.Series.mul

`Series.mul(other, level=None, fill_value=None, axis=0)`

Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rmul`

pandas.Series.div

`Series.div(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rtruediv`

pandas.Series.truediv

`Series.`**`truediv`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rtruediv`

pandas.Series.floordiv

`Series.`**`floordiv`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Integer division of series and other, element-wise (binary operator *floordiv*).

Equivalent to `series // other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rfloordiv`

pandas.Series.mod

`Series.`**`mod`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Modulo of series and other, element-wise (binary operator *mod*).

Equivalent to `series % other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rmod`

pandas.Series.pow

`Series.pow(other, level=None, fill_value=None, axis=0)`

Exponential power of series and other, element-wise (binary operator *pow*).

Equivalent to `series ** other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.rpow`

pandas.Series.radd

`Series.radd(other, level=None, fill_value=None, axis=0)`

Addition of series and other, element-wise (binary operator *radd*).

Equivalent to `other + series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.add`

pandas.Series.rsub

`Series.rsub(other, level=None, fill_value=None, axis=0)`

Subtraction of series and other, element-wise (binary operator *rsub*).

Equivalent to `other - series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.sub`

pandas.Series.rmul

`Series.rmul(other, level=None, fill_value=None, axis=0)`

Multiplication of series and other, element-wise (binary operator *rmul*).

Equivalent to `other * series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.mul`

pandas.Series.rdiv

`Series.rdiv(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.truediv`

pandas.Series.rtruediv

`Series.rtruediv(other, level=None, fill_value=None, axis=0)`

Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

See also:

`Series.truediv`

pandas.Series.rfloordiv

`Series.rfloordiv(other, level=None, fill_value=None, axis=0)`

Integer division of series and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.floordiv`

pandas.Series.rmod

`Series.rmod(other, level=None, fill_value=None, axis=0)`

Modulo of series and other, element-wise (binary operator *rmod*).

Equivalent to `other % series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.mod`

pandas.Series.rpow

`Series.rpow(other, level=None, fill_value=None, axis=0)`

Exponential power of series and other, element-wise (binary operator *rpow*).

Equivalent to `other ** series`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:

`Series.pow`

pandas.Series.combine

`Series.combine(other, func, fill_value=nan)`

Perform elementwise binary operation on two Series using given function with optional fill value when an index is missing from one Series or the other

Parameters **other** : Series or scalar value

func : function

fill_value : scalar value

Returns **result** : Series

pandas.Series.combine_first

`Series.combine_first(other)`

Combine Series values, choosing the calling Series's values first. Result index will be the union of the two indexes

Parameters **other** : Series

Returns **y** : Series

pandas.Series.round

`Series.round(decimals=0, out=None)`

Return *a* with each element rounded to the given number of decimals.

Refer to *numpy.around* for full documentation.

See also:

`numpy.around` equivalent function

pandas.Series.lt

`Series.lt(other, axis=None)`

pandas.Series.gt

`Series.gt(other, axis=None)`

pandas.Series.le

`Series.le(other, axis=None)`

pandas.Series.ge

`Series.ge(other, axis=None)`

pandas.Series.ne

`Series.ne(other, axis=None)`

pandas.Series.eq

`Series.eq(other, axis=None)`

33.3.6 Function application, GroupBy

`Series.apply`(func[, convert_dtype, args])	Invoke function on values of Series.
`Series.map`(arg[, na_action])	Map values of Series using input correspondence (which can be
`Series.groupby`([by, axis, level, as_index, ...])	Group series using mapper (dict or key function, apply given function

pandas.Series.apply

`Series.apply`(*func*, *convert_dtype=True*, *args=()*, ***kwds*)

Invoke function on values of Series. Can be ufunc (a NumPy function that applies to the entire Series) or a Python function that only works on single values

Parameters **func** : function

convert_dtype : boolean, default True

Try to find better dtype for elementwise function results. If False, leave as dtype=object

args : tuple

Positional arguments to pass to function in addition to the value

Additional keyword arguments will be passed as keywords to the function

Returns **y** : Series or DataFrame if func returns a Series

See also:

Series.map For element-wise operations

pandas.Series.map

`Series.map`(*arg*, *na_action=None*)

Map values of Series using input correspondence (which can be a dict, Series, or function)

Parameters **arg** : function, dict, or Series

na_action : {None, 'ignore'}

If 'ignore', propagate NA values

Returns **y** : Series

same index as caller

Examples

```
>>> x
one   1
two   2
three 3
```

```
>>> y
1  foo
2  bar
3  baz
```

```
>>> x.map(y)
one   foo
two   bar
three baz
```

pandas.Series.groupby

Series.**groupby**(*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*, *squeeze=False*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively "SQL-style" grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionaility of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

33.3.7 Computations / Descriptive Stats

Series.abs()	Return an object with absolute value taken.

Table 33.28 – continued from previous page

Series.all([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
Series.any([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
Series.autocorr([lag])	Lag-N autocorrelation
Series.between(left, right[, inclusive])	Return boolean Series equivalent to left <= series <= right.
Series.clip([lower, upper, out, axis])	Trim values at input threshold(s)
Series.clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
Series.clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
Series.corr(other[, method, min_periods])	Compute correlation with *other* Series, excluding missing values
Series.count([level])	Return number of non-NA/null observations in the Series
Series.cov(other[, min_periods])	Compute covariance with Series, excluding missing values
Series.cummax([axis, dtype, out, skipna])	Return cumulative max over requested axis.
Series.cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
Series.cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
Series.cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.
Series.describe([percentile_width, ...])	Generate various summary statistics, excluding NaN values.
Series.diff([periods])	1st discrete difference of object
Series.factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
Series.kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurto
Series.mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
Series.max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
Series.mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
Series.median([axis, skipna, level, ...])	Return the median of the values for the requested axis
Series.min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
Series.mode()	Returns the mode(s) of the dataset.
Series.nlargest([n, take_last])	Return the largest *n* elements.
Series.nsmallest([n, take_last])	Return the smallest *n* elements.
Series.pct_change([periods, fill_method, ...])	Percent change over given number of periods.
Series.prod([axis, skipna, level, numeric_only])	Return the product of the values for the requested axis
Series.quantile([q])	Return value at the given quantile, a la numpy.percentile.
Series.rank([method, na_option, ascending, pct])	Compute data ranks (1 through n).
Series.sem([axis, skipna, level, ddof, ...])	Return unbiased standard error of the mean over requested axis.
Series.skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
Series.std([axis, skipna, level, ddof, ...])	Return unbiased standard deviation over requested axis.
Series.sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
Series.var([axis, skipna, level, ddof, ...])	Return unbiased variance over requested axis.
Series.unique()	Return array of unique values in the object.
Series.nunique([dropna])	Return number of unique elements in the object.
Series.value_counts([normalize, sort, ...])	Returns object containing counts of unique values.

pandas.Series.abs

`Series.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Series.all

`Series.all(`*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*`)`

Return whether all elements are True over requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns all : scalar or Series (if level specified)

pandas.Series.any

`Series.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns any : scalar or Series (if level specified)

pandas.Series.autocorr

`Series.autocorr(lag=1)`

Lag-N autocorrelation

Parameters lag : int, default 1

Number of lags to apply before performing autocorrelation.

Returns autocorr : float

pandas.Series.between

`Series.between(left, right, inclusive=True)`

Return boolean Series equivalent to left <= series <= right. NA values will be treated as False

Parameters left : scalar

Left boundary

right : scalar

Right boundary

Returns **is_between** : Series

pandas.Series.clip

`Series.`**`clip`**(*lower=None*, *upper=None*, *out=None*, *axis=None*)

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Series.clip_lower

`Series.`**`clip_lower`**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

`clip`

pandas.Series.clip_upper

`Series.`**`clip_upper`**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

`clip`

pandas.Series.corr

`Series.`**`corr`**(*other*, *method='pearson'*, *min_periods=None*)

Compute correlation with *other* Series, excluding missing values

Parameters **other** : Series

method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns **correlation** : float

pandas.Series.count

`Series.`**`count`**(*level=None*)

Return number of non-NA/null observations in the Series

Parameters **level** : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

Returns **nobs** : int or Series (if level specified)

pandas.Series.cov

`Series.cov(other, min_periods=None)`
Compute covariance with Series, excluding missing values

Parameters **other** : Series

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns **covariance** : float

Normalized by N-1 (unbiased estimator).

pandas.Series.cummax

`Series.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative max over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : scalar

pandas.Series.cummin

`Series.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative min over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : scalar

pandas.Series.cumprod

`Series.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative prod over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : scalar

pandas.Series.cumsum

`Series.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative sum over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : scalar

pandas.Series.describe

`Series.describe`(*percentile_width=None*, *percentiles=None*, *include=None*, *exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Series.diff

`Series.diff(periods=1)`
1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

Returns **diffed** : Series

pandas.Series.factorize

`Series.factorize(sort=False, na_sentinel=-1)`
Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.Series.kurt

`Series.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : scalar or Series (if level specified)

pandas.Series.mad

`Series.mad(axis=None, skipna=None, level=None)`
Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mad : scalar or Series (if level specified)

pandas.Series.max

`Series.max`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : scalar or Series (if level specified)

pandas.Series.mean

`Series.mean`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mean : scalar or Series (if level specified)

pandas.Series.median

`Series.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the median of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : scalar or Series (if level specified)

pandas.Series.min

`Series.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : scalar or Series (if level specified)

pandas.Series.mode

`Series.mode()`

Returns the mode(s) of the dataset.

Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters sort : bool, default True

If True, will lexicographically sort values, if False skips sorting. Result ordering when `sort=False` is not defined.

Returns modes : Series (sorted)

pandas.Series.nlargest

`Series.nlargest(n=5, take_last=False)`

Return the largest *n* elements.

Parameters **n** : int

Return this many descending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns **top_n** : Series

The n largest values in the Series, in sorted order

See also:

`Series.nsmallest`

Notes

Faster than `.order(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

pandas.Series.nsmallest

`Series.nsmallest(n=5, take_last=False)`

Return the smallest *n* elements.

Parameters **n** : int

Return this many ascending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns **bottom_n** : Series

The n smallest values in the Series, in sorted order

See also:

`Series.nlargest`

Notes

Faster than `.order().head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

pandas.Series.pct_change

`Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`
Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.Series.prod

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return the product of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : scalar or Series (if level specified)

pandas.Series.quantile

Series.**quantile**(*q=0.5*)
Return value at the given quantile, a la numpy.percentile.

Parameters q : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

Returns quantile : float or Series

if q is an array, a Series will be returned where the index is q and the values are the quantiles.

Examples

```
>>> s = Series([1, 2, 3, 4])
>>> s.quantile(.5)
    2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

pandas.Series.rank

Series.**rank**(*method='average'*, *na_option='keep'*, *ascending=True*, *pct=False*)
Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

Parameters method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep'}

keep: leave NA values where they are

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns ranks : Series

pandas.Series.sem

`Series.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sem** : scalar or Series (if level specified)

pandas.Series.skew

`Series.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : scalar or Series (if level specified)

pandas.Series.std

`Series.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : scalar or Series (if level specified)

pandas.Series.sum

`Series.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : scalar or Series (if level specified)

pandas.Series.var

`Series.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : scalar or Series (if level specified)

pandas.Series.unique

`Series.unique()`

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.Series.nunique

`Series.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters dropna : boolean, default True

Don't include NaN in the count.

Returns nunique : int

pandas.Series.value_counts

`Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns counts : Series

33.3.8 Reindexing / Selection / Label manipulation

Series.align(other[, join, axis, level, ...])	Align two object on their axes with the
Series.drop(labels[, axis, level, inplace, ...])	Return new object with labels in requested axis removed
Series.drop_duplicates([take_last, inplace])	Return Series with duplicate values removed
Series.duplicated([take_last])	Return boolean Series denoting duplicate values

Table 33.29 – continued from previous page

Series.equals(other)	Determines if two NDFrame objects contain the same elements.
Series.first(offset)	Convenience method for subsetting initial periods of time series data
Series.head([n])	Returns first n rows
Series.idxmax([axis, out, skipna])	Index of first occurrence of maximum of values.
Series.idxmin([axis, out, skipna])	Index of first occurrence of minimum of values.
Series.isin(values)	Return a boolean Series showing whether each element in the Series
Series.last(offset)	Convenience method for subsetting final periods of time series data
Series.reindex([index])	Conform Series to new index with optional filling logic, placing NA/NaN
Series.reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
Series.rename([index])	Alter axes input function or functions.
Series.reset_index([level, drop, name, inplace])	Analogous to the pandas.DataFrame.reset_index() function, s
Series.sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
Series.select(crit[, axis])	Return data corresponding to axis labels matching criteria
Series.take(indices[, axis, convert, is_copy])	return Series corresponding to requested indices
Series.tail([n])	Returns last n rows
Series.truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.
Series.where(cond[, other, inplace, axis, ...])	Return an object of same shape as self and whose corresponding entries a
Series.mask(cond[, other, inplace, axis, ...])	Return an object of same shape as self and whose corresponding entries a

pandas.Series.align

Series.**align**(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*, *fill_axis=0*)

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns **(left, right)** : (type of input, type of other)

Aligned objects

pandas.Series.drop

`Series.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.Series.drop_duplicates

`Series.drop_duplicates(take_last=False, inplace=False)`

Return Series with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

inplace : boolean, default False

If True, performs operation inplace and returns None.

Returns **deduplicated** : Series

pandas.Series.duplicated

`Series.duplicated(take_last=False)`

Return boolean Series denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : Series

pandas.Series.equals

`Series.equals(other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Series.first

`Series.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Series.head

`Series.head(n=5)`

Returns first n rows

pandas.Series.idxmax

`Series.idxmax(axis=None, out=None, skipna=True)`

Index of first occurrence of maximum of values.

Parameters skipna : boolean, default True

Exclude NA/null values

Returns idxmax : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.idxmin

`Series.idxmin(axis=None, out=None, skipna=True)`

Index of first occurrence of minimum of values.

Parameters skipna : boolean, default True

Exclude NA/null values

Returns idxmin : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmin`.

pandas.Series.isin

Series.**isin**(*values*)

Return a boolean Series showing whether each element in the Series is exactly contained in the passed sequence of values.

Parameters **values** : list-like

The sequence of values to test. Passing in a single string will raise a TypeError. Instead, turn a single string into a list of one element.

Returns **isin** : Series (bool dtype)

Raises **TypeError**

- If values is a string

See also:

pandas.DataFrame.isin

Examples

```
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0     True
1    False
2     True
dtype: bool
```

Passing a single string as s.isin('a') will raise an error. Use a list of one element instead:

```
>>> s.isin(['a'])
0     True
1    False
2    False
dtype: bool
```

pandas.Series.last

Series.**last**(*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Series.reindex

Series.**reindex**(*index=None*, ***kwargs*)

Conform Series to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **index** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Series

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Series.reindex_like

`Series.`**`reindex_like`**(*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Series.rename

`Series.rename(index=None, **kwargs)`

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **index** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Series. If True then value of copy is ignored.

Returns **renamed** : Series (new object)

pandas.Series.reset_index

`Series.reset_index(level=None, drop=False, name=None, inplace=False)`

Analogous to the `pandas.DataFrame.reset_index()` function, see docstring there.

Parameters **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns

name : object, default None

The name of the column corresponding to the Series values

inplace : boolean, default False

Modify the Series in place (do not create a new object)

Returns **resetted** : DataFrame, or Series if drop == True

pandas.Series.sample

`Series.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.Series.select

`Series.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.Series.take

`Series.take(indices, axis=0, convert=True, is_copy=False)`

return Series corresponding to requested indices

Parameters **indices** : list / array of ints

convert : translate negative to positive indices (default)

Returns **taken** : Series

See also:

`numpy.ndarray.take`

pandas.Series.tail

`Series.tail(n=5)`

Returns last n rows

pandas.Series.truncate

`Series.truncate(before=None, after=None, axis=None, copy=True)`

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

pandas.Series.where

`Series.where`(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Series.mask

`Series.mask`(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

33.3.9 Missing data handling

`Series.dropna`([axis, inplace])	Return Series without null values
`Series.fillna`([value, method, axis, ...])	Fill NA/NaN values using the specified method
`Series.interpolate`([method, axis, limit, ...])	Interpolate values according to different methods.

pandas.Series.dropna

`Series.`**`dropna`**(*axis=0*, *inplace=False*, ***kwargs*)

Return Series without null values

Returns **valid** : Series

inplace : boolean, default False

Do operation in place.

pandas.Series.fillna

`Series.`**`fillna`**(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*, ***kwargs*)

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 'index'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : Series

See also:

`reindex`, `asfreq`

pandas.Series.interpolate

`Series.`**`interpolate`**(*method='linear'*, *axis=0*, *limit=None*, *inplace=False*, *downcast=None*, ***kwargs*)

Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. 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* with the order given both 'polynomial' and 'spline' requre that you also specify and order (int) e.g. df.interpolate(method='polynomial', order=4)
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html

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.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

33.3.10 Reshaping, sorting

`Series.argsort`([axis, kind, order])	Overrides ndarray.argsort.
`Series.order`([na_last, ascending, kind, ...])	Sorts Series object, by value, maintaining index-value link.
`Series.reorder_levels`(order)	Rearrange index levels using input order.
`Series.sort`([axis, ascending, kind, ...])	Sort values and index labels by value.
`Series.sort_index`([ascending])	Sort object by labels (along an axis)
`Series.sortlevel`([level, ascending, ...])	Sort Series with MultiIndex by chosen level.
`Series.swaplevel`(i, j[, copy])	Swap levels i and j in a MultiIndex
`Series.unstack`([level])	Unstack, a.k.a.
`Series.searchsorted`(v[, side, sorter])	Find indices where elements should be inserted to maintain order.

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.order

`Series.`**`order`**(*na_last=None*, *ascending=True*, *kind='quicksort'*, *na_position='last'*, *inplace=False*)

Sorts Series object, by value, maintaining index-value link. This will return a new Series by default. Series.sort is the equivalent but as an inplace method.

Parameters **na_last** : boolean (optional, default=True) (DEPRECATED; use na_position)

Put NaN's at beginning or end

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default False

Do operation in place.

Returns y : Series

See also:

Series.sort

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.sort

`Series.sort(axis=0, ascending=True, kind='quicksort', na_position='last', inplace=True)`

Sort values and index labels by value. This is an inplace sort by default. Series.order is the equivalent but returns a new Series.

Parameters axis : int (can only be zero)

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default True

Do operation in place.

See also:

Series.order

pandas.Series.sort_index

Series.**sort_index**(*ascending=True*)
Sort object by labels (along an axis)

Parameters **ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

Returns **sorted_obj** : Series

Examples

```
>>> result1 = s.sort_index(ascending=False)
>>> result2 = s.sort_index(ascending=[1, 0])
```

pandas.Series.sortlevel

Series.**sortlevel**(*level=0*, *ascending=True*, *sort_remaining=True*)
Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters **level** : int or level name, default None

ascending : bool, default True

Returns **sorted** : Series

pandas.Series.swaplevel

Series.**swaplevel**(*i*, *j*, *copy=True*)
Swap levels i and j in a MultiIndex

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : Series

pandas.Series.unstack

Series.**unstack**(*level=-1*)
Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default last level

Level(s) to unstack, can pass level name

Returns **unstacked** : DataFrame

Examples

```
>>> s
one  a   1.
one  b   2.
two  a   3.
two  b   4.

>>> s.unstack(level=-1)
     a   b
one  1.  2.
two  3.  4.

>>> s.unstack(level=0)
   one  two
a  1.   2.
b  3.   4.
```

pandas.Series.searchsorted

`Series.`**`searchsorted`**`(`*v*, *side='left'*, *sorter=None*`)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series *self* such that, if the corresponding elements in *v* were inserted before the indices, the order of *self* would be preserved.

Parameters **v** : array_like

Values to insert into *a*.

side : {'left', 'right'}, optional

If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *a*).

sorter : 1-D array_like, optional

Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns **indices** : array of ints

Array of insertion points with the same shape as *v*.

See also:

`Series.sort`, `Series.order`, `numpy.searchsorted`

Notes

Binary search is used to find the required insertion points.

Examples

```
>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3
```

```
dtype: int64
>>> x.searchsorted(4)
array([3])
>>> x.searchsorted([0, 4])
array([0, 3])
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```

33.3.11 Combining / joining / merging

`Series.append`(to_append[, verify_integrity])	Concatenate two or more Series.
`Series.replace`([to_replace, value, inplace, ...])	Replace values given in 'to_replace' with 'value'.
`Series.update`(other)	Modify Series in place using non-NA values from passed Series.

pandas.Series.append

`Series.append(to_append, verify_integrity=False)`

Concatenate two or more Series.

Parameters **to_append** : Series or list/tuple of Series

verify_integrity : boolean, default False

If True, raise Exception on creating index with duplicates

Returns **appended** : Series

pandas.Series.replace

`Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)`

Replace values given in 'to_replace' with 'value'.

Parameters **to_replace** : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.
- dict:

  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Series.update

`Series.`**`update`**(*other*)

Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters other : Series

33.3.12 Time series-related

`Series.asfreq`(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
`Series.asof`(where)	Return last good (non-NaN) value in TimeSeries if value is NaN for requested
`Series.shift`([periods, freq, axis])	Shift index by desired number of periods with an optional time freq
`Series.first_valid_index`()	Return label for first non-NA/null value
`Series.last_valid_index`()	Return label for last non-NA/null value
`Series.resample`(rule[, how, axis, ...])	Convenience method for frequency conversion and resampling of regular time-
`Series.tz_convert`(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
`Series.tz_localize`(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone

pandas.Series.asfreq

`Series.`**`asfreq`**(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.Series.asof

`Series.`**`asof`**(*where*)

Return last good (non-NaN) value in TimeSeries if value is NaN for requested date.

If there is no good value, NaN is returned.

Parameters where : date or array of dates

Returns value or NaN

Notes

Dates are assumed to be sorted

pandas.Series.shift

`Series.`**`shift`**(*periods=1*, *freq=None*, *axis=0*, ***kwargs*)

Shift index by desired number of periods with an optional time freq

Parameters periods : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 'index'}

Returns shifted : Series

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.Series.first_valid_index

`Series.`**`first_valid_index`**()

Return label for first non-NA/null value

pandas.Series.last_valid_index

`Series.`**`last_valid_index`**()

Return label for last non-NA/null value

pandas.Series.resample

`Series.`**`resample`**(*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Series.tz_convert

`Series.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters tz : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises TypeError

If the axis is tz-naive.

pandas.Series.tz_localize

`Series.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

33.3.13 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

`Series.dt.date`	Returns numpy array of datetime.date.
`Series.dt.time`	Returns numpy array of datetime.time.
`Series.dt.year`	The year of the datetime
`Series.dt.month`	The month as January=1, December=12
`Series.dt.day`	The days of the datetime
`Series.dt.hour`	The hours of the datetime
`Series.dt.minute`	The minutes of the datetime
`Series.dt.second`	The seconds of the datetime
`Series.dt.microsecond`	The microseconds of the datetime
`Series.dt.nanosecond`	The nanoseconds of the datetime
`Series.dt.second`	The seconds of the datetime
`Series.dt.week`	The week ordinal of the year
`Series.dt.weekofyear`	The week ordinal of the year
`Series.dt.dayofweek`	The day of the week with Monday=0, Sunday=6
`Series.dt.weekday`	The day of the week with Monday=0, Sunday=6
`Series.dt.dayofyear`	The ordinal day of the year
`Series.dt.quarter`	The quarter of the date
`Series.dt.is_month_start`	Logical indicating if first day of month (defined by frequency)
`Series.dt.is_month_end`	Logical indicating if last day of month (defined by frequency)
`Series.dt.is_quarter_start`	Logical indicating if first day of quarter (defined by frequency)
`Series.dt.is_quarter_end`	Logical indicating if last day of quarter (defined by frequency)
`Series.dt.is_year_start`	Logical indicating if first day of year (defined by frequency)

Continued on next page

Table 33.34 – continued from previous page

Series.dt.is_year_end	Logical indicating if last day of year (defined by frequency)
Series.dt.daysinmonth	The number of days in the month
Series.dt.days_in_month	The number of days in the month
Series.dt.tz	
Series.dt.freq	get/set the frequncy of the Index

pandas.Series.dt.date

Series.dt.**date**
Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.Series.dt.time

Series.dt.**time**
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.Series.dt.year

Series.dt.**year**
The year of the datetime

pandas.Series.dt.month

Series.dt.**month**
The month as January=1, December=12

pandas.Series.dt.day

Series.dt.**day**
The days of the datetime

pandas.Series.dt.hour

Series.dt.**hour**
The hours of the datetime

pandas.Series.dt.minute

Series.dt.**minute**
The minutes of the datetime

pandas.Series.dt.second

Series.dt.**second**
The seconds of the datetime

pandas.Series.dt.microsecond

`Series.dt.microsecond`
The microseconds of the datetime

pandas.Series.dt.nanosecond

`Series.dt.nanosecond`
The nanoseconds of the datetime

pandas.Series.dt.second

`Series.dt.second`
The seconds of the datetime

pandas.Series.dt.week

`Series.dt.week`
The week ordinal of the year

pandas.Series.dt.weekofyear

`Series.dt.weekofyear`
The week ordinal of the year

pandas.Series.dt.dayofweek

`Series.dt.dayofweek`
The day of the week with Monday=0, Sunday=6

pandas.Series.dt.weekday

`Series.dt.weekday`
The day of the week with Monday=0, Sunday=6

pandas.Series.dt.dayofyear

`Series.dt.dayofyear`
The ordinal day of the year

pandas.Series.dt.quarter

`Series.dt.quarter`
The quarter of the date

pandas.Series.dt.is_month_start

`Series.dt.is_month_start`
Logical indicating if first day of month (defined by frequency)

pandas.Series.dt.is_month_end

`Series.dt.is_month_end`
Logical indicating if last day of month (defined by frequency)

pandas.Series.dt.is_quarter_start

`Series.dt.is_quarter_start`
Logical indicating if first day of quarter (defined by frequency)

pandas.Series.dt.is_quarter_end

`Series.dt.is_quarter_end`
Logical indicating if last day of quarter (defined by frequency)

pandas.Series.dt.is_year_start

`Series.dt.is_year_start`
Logical indicating if first day of year (defined by frequency)

pandas.Series.dt.is_year_end

`Series.dt.is_year_end`
Logical indicating if last day of year (defined by frequency)

pandas.Series.dt.daysinmonth

`Series.dt.daysinmonth`
The number of days in the month

New in version 0.16.0.

pandas.Series.dt.days_in_month

`Series.dt.days_in_month`
The number of days in the month

New in version 0.16.0.

pandas.Series.dt.tz

`Series.dt.tz`

pandas.Series.dt.freq

`Series.dt.freq`
get/set the frequncy of the Index

Datetime Methods

Series.dt.to_period(*args, **kwargs)	Cast to PeriodIndex at a particular frequency
Series.dt.to_pydatetime()	
Series.dt.tz_localize(*args, **kwargs)	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),
Series.dt.tz_convert(*args, **kwargs)	Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateut
Series.dt.normalize(*args, **kwargs)	Return DatetimeIndex with times to midnight.

pandas.Series.dt.to_period

`Series.dt.to_period(*args, **kwargs)`
Cast to PeriodIndex at a particular frequency

pandas.Series.dt.to_pydatetime

`Series.dt.to_pydatetime()`

pandas.Series.dt.tz_localize

`Series.dt.tz_localize(*args, **kwargs)`
Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns **localized** : DatetimeIndex

Raises **TypeError**

If the DatetimeIndex is tz-aware and tz is not None.

pandas.Series.dt.tz_convert

`Series.dt.tz_convert(*args, **kwargs)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns **normalized** : DatetimeIndex

Raises **TypeError**

If DatetimeIndex is tz-naive.

pandas.Series.dt.normalize

`Series.dt.normalize(*args, **kwargs)`

Return DatetimeIndex with times to midnight. Length is unaltered

Returns **normalized** : DatetimeIndex

Timedelta Properties

`Series.dt.days`	Number of days for each element.
`Series.dt.seconds`	Number of seconds (>= 0 and less than 1 day) for each element.
`Series.dt.microseconds`	Number of microseconds (>= 0 and less than 1 second) for each element.
`Series.dt.nanoseconds`	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
`Series.dt.components`	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds

pandas.Series.dt.days

`Series.dt.days`

Number of days for each element.

pandas.Series.dt.seconds

`Series.dt.seconds`

Number of seconds (>= 0 and less than 1 day) for each element.

pandas.Series.dt.microseconds

`Series.dt.microseconds`

Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.Series.dt.nanoseconds

`Series.dt.nanoseconds`

Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.Series.dt.components

Series.dt.**components**

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

Timedelta Methods

Series.dt.to_pytimedelta()

pandas.Series.dt.to_pytimedelta

Series.dt.**to_pytimedelta**()

33.3.14 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 acccessed like Series.str.<function/property>.

Series.str.capitalize()	Convert strings in the Series/Index to be capitalized.
Series.str.cat([others, sep, na_rep])	Concatenate strings in the Series/Index with given separator.
Series.str.center(width[, fillchar])	Filling left and right side of strings in the Series/Index with an additional cha
Series.str.contains(pat[, case, flags, na, ...])	Return boolean Series/array whether given pattern/regex is contained in ea
Series.str.count(pat[, flags])	Count occurrences of pattern in each string of the Series/Index.
Series.str.decode(encoding[, errors])	Decode character string in the Series/Index to unicode using indicated encod
Series.str.encode(encoding[, errors])	Encode character string in the Series/Index to some other encoding using ind
Series.str.endswith(pat[, na])	Return boolean Series indicating whether each string in the Series/Index ends
Series.str.extract(pat[, flags])	Find groups in each string in the Series using passed regular expression.
Series.str.find(sub[, start, end])	Return lowest indexes in each strings in the Series/Index where the substring
Series.str.findall(pat[, flags])	Find all occurrences of pattern or regular expression in the Series/Index.
Series.str.get(i)	Extract element from lists, tuples, or strings in each element in the Series/Ind
Series.str.index(sub[, start, end])	Return lowest indexes in each strings where the substring is fully contained b
Series.str.join(sep)	Join lists contained as elements in the Series/Index with passed delimiter.
Series.str.len()	Compute length of each string in the Series/Index.
Series.str.ljust(width[, fillchar])	Filling right side of strings in the Series/Index with an additional character.
Series.str.lower()	Convert strings in the Series/Index to lowercase.
Series.str.lstrip([to_strip])	Strip whitespace (including newlines) from each string in the Series/Index fro
Series.str.match(pat[, case, flags, na, ...])	Deprecated: Find groups in each string in the Series/Index using passed regu
Series.str.normalize(form)	Return the Unicode normal form for the strings in the Series/Index.
Series.str.pad(width[, side, fillchar])	Pad strings in the Series/Index with an additional character to specified side.
Series.str.partition([pat, expand])	Split the string at the first occurrence of *sep*, and return 3 elements containin
Series.str.repeat(repeats)	Duplicate each string in the Series/Index by indicated number of times.
Series.str.replace(pat, repl[, n, case, flags])	Replace occurrences of pattern/regex in the Series/Index with some other stri
Series.str.rfind(sub[, start, end])	Return highest indexes in each strings in the Series/Index where the substring
Series.str.rindex(sub[, start, end])	Return highest indexes in each strings where the substring is fully contained
Series.str.rjust(width[, fillchar])	Filling left side of strings in the Series/Index with an additional character.
Series.str.rpartition([pat, expand])	Split the string at the last occurrence of *sep*, and return 3 elements containing
Series.str.rstrip([to_strip])	Strip whitespace (including newlines) from each string in the Series/Index fro
Series.str.slice([start, stop, step])	Slice substrings from each element in the Series/Index
Series.str.slice_replace([start, stop, repl])	Replace a slice of each string in the Series/Index with another string.

Table 33.38 – continued from previous page

Series.str.split(*args, **kwargs)	Split each string (a la re.split) in the Series/Index by given pattern, propagati
Series.str.rsplit([pat, n, expand])	Split each string in the Series/Index by the given delimiter string, starting at t
Series.str.startswith(pat[, na])	Return boolean Series/array indicating whether each string in the Series/In
Series.str.strip([to_strip])	Strip whitespace (including newlines) from each string in the Series/Index fr
Series.str.swapcase()	Convert strings in the Series/Index to be swapcased.
Series.str.title()	Convert strings in the Series/Index to titlecase.
Series.str.translate(table[, deletechars])	Map all characters in the string through the given mapping table.
Series.str.upper()	Convert strings in the Series/Index to uppercase.
Series.str.wrap(width, **kwargs)	Wrap long strings in the Series/Index to be formatted in paragraphs with leng
Series.str.zfill(width)	“
Series.str.isalnum()	Check whether all characters in each string in the Series/Index are alphanum
Series.str.isalpha()	Check whether all characters in each string in the Series/Index are alphabetic
Series.str.isdigit()	Check whether all characters in each string in the Series/Index are digits.
Series.str.isspace()	Check whether all characters in each string in the Series/Index are whitespac
Series.str.islower()	Check whether all characters in each string in the Series/Index are lowercase
Series.str.isupper()	Check whether all characters in each string in the Series/Index are uppercase
Series.str.istitle()	Check whether all characters in each string in the Series/Index are titlecase.
Series.str.isnumeric()	Check whether all characters in each string in the Series/Index are numeric.
Series.str.isdecimal()	Check whether all characters in each string in the Series/Index are decimal.
Series.str.get_dummies([sep])	Split each string in the Series by sep and return a frame of dummy/indicator

pandas.Series.str.capitalize

`Series.str.capitalize()`

Convert strings in the Series/Index to be capitalized. Equivalent to `str.capitalize()`.

Returns converted : Series/Index of objects

pandas.Series.str.cat

`Series.str.cat(others=None, sep=None, na_rep=None)`

Concatenate strings in the Series/Index with given separator.

Parameters others : list-like, or list of list-likes

If None, returns str concatenating strings of the Series

sep : string or None, default None

na_rep : string or None, default None

If None, an NA in any array will propagate

Returns concat : Series/Index of objects or str

Examples

If `others` is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```
>>> Series(['a', 'b', 'c']).str.cat(['A', 'B', 'C'], sep=',')
0    a,A
1    b,B
2    c,C
dtype: object
```

Otherwise, strings in the Series are concatenated. Result will be a string.

```
>>> Series(['a', 'b', 'c']).str.cat(sep=',')
'a,b,c'
```

Also, you can pass a list of list-likes.

```
>>> Series(['a', 'b']).str.cat([['x', 'y'], ['1', '2']], sep=',')
0    a,x,1
1    b,y,2
dtype: object
```

pandas.Series.str.center

`Series.str.center(width, fillchar=' ')`

Filling left and right side of strings in the Series/Index with an additional character. Equivalent to `str.center()`.

Parameters **width** : int

Minimum width of resulting string; additional characters will be filled with `fillchar`

fillchar : str

Additional character for filling, default is whitespace

Returns **filled** : Series/Index of objects

pandas.Series.str.contains

`Series.str.contains(pat, case=True, flags=0, na=nan, regex=True)`

Return boolean Series/`array` whether given pattern/regex is contained in each string in the Series/Index.

Parameters **pat** : string

Character sequence or regular expression

case : boolean, default True

If True, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

na : default NaN, fill value for missing values.

regex : bool, default True

If True use re.search, otherwise use Python in operator

Returns **contained** : Series/array of boolean values

See also:

`match` analagous, but stricter, relying on re.match instead of re.search

pandas.Series.str.count

`Series.str.count(pat, flags=0, **kwargs)`

Count occurrences of pattern in each string of the Series/Index.

Parameters **pat** : string, valid regular expression

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

Returns **counts** : Series/Index of integer values

pandas.Series.str.decode

`Series.str.decode(encoding, errors='strict')`

Decode character string in the Series/Index to unicode using indicated encoding. Equivalent to `str.decode()`.

Parameters **encoding** : string

errors : string

Returns **decoded** : Series/Index of objects

pandas.Series.str.encode

`Series.str.encode(encoding, errors='strict')`

Encode character string in the Series/Index to some other encoding using indicated encoding. Equivalent to `str.encode()`.

Parameters **encoding** : string

errors : string

Returns **encoded** : Series/Index of objects

pandas.Series.str.endswith

`Series.str.endswith(pat, na=nan)`

Return boolean Series indicating whether each string in the Series/Index ends with passed pattern. Equivalent to `str.endswith()`.

Parameters **pat** : string

Character sequence

na : bool, default NaN

Returns **endswith** : Series/array of boolean values

pandas.Series.str.extract

`Series.str.extract(pat, flags=0)`

Find groups in each string in the Series using passed regular expression.

Parameters **pat** : string

Pattern or regular expression

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

Returns **extracted groups** : Series (one group) or DataFrame (multiple groups)

Note that dtype of the result is always object, even when no match is found and the result is a Series or DataFrame containing only NaN values.

Examples

A pattern with one group will return a Series. Non-matches will be NaN.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
0      1
1      2
2    NaN
dtype: object
```

A pattern with more than one group will return a DataFrame.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
     0    1
0    a    1
1    b    2
2  NaN  NaN
```

A pattern may contain optional groups.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])?(\d)')
     0  1
0    a  1
1    b  2
2  NaN  3
```

Named groups will become column names in the result.

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

pandas.Series.str.find

`Series.str.find(sub, start=0, end=None)`

Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.find()`.

Parameters **sub** : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns **found** : Series/Index of integer values

See also:

rfind Return highest indexes in each strings

pandas.Series.str.findall

`Series.str.findall(pat, flags=0, **kwargs)`

Find all occurrences of pattern or regular expression in the Series/Index. Equivalent to `re.findall()`.

Parameters **pat** : string

Pattern or regular expression

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

Returns **matches** : Series/Index of lists

pandas.Series.str.get

`Series.str.get(i)`

Extract element from lists, tuples, or strings in each element in the Series/Index.

Parameters **i** : int

Integer index (location)

Returns **items** : Series/Index of objects

pandas.Series.str.index

`Series.str.index(sub, start=0, end=None)`

Return lowest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.find` except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard `str.index`.

Parameters **sub** : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns **found** : Series/Index of objects

See also:

rindex Return highest indexes in each strings

pandas.Series.str.join

`Series.str.join(sep)`
Join lists contained as elements in the Series/Index with passed delimiter. Equivalent to `str.join()`.

Parameters **sep** : string

Delimiter

Returns **joined** : Series/Index of objects

pandas.Series.str.len

`Series.str.len()`
Compute length of each string in the Series/Index.

Returns **lengths** : Series/Index of integer values

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.right()`.

Parameters **width** : int

Minimum width of resulting string; additional characters will be filled with `fillchar`

fillchar : str

Additional character for filling, default is whitespace

Returns **filled** : Series/Index of objects

pandas.Series.str.lower

`Series.str.lower()`
Convert strings in the Series/Index to lowercase. Equivalent to `str.lower()`.

Returns **converted** : Series/Index of objects

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

pandas.Series.str.match

`Series.str.match(pat, case=True, flags=0, na=nan, as_indexer=False)`
Deprecated: Find groups in each string in the Series/Index using passed regular expression. If as_indexer=True, determine if each string matches a regular expression.

Parameters **pat** : string

Character sequence or regular expression

case : boolean, default True

If True, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

na : default NaN, fill value for missing values.

as_indexer : False, by default, gives deprecated behavior better achieved

using str_extract. True return boolean indexer.

Returns Series/array of boolean values

if as_indexer=True

Series/Index of tuples

if as_indexer=False, default but deprecated

See also:

`contains` analagous, but less strict, relying on re.search instead of re.match

`extract` now preferred to the deprecated usage of match (as_indexer=False)

Notes

To extract matched groups, which is the deprecated behavior of match, use str.extract.

pandas.Series.str.normalize

`Series.str.normalize(`*form*`)`

Return the Unicode normal form for the strings in the Series/Index. For more information on the forms, see the `unicodedata.normalize()`.

Parameters **form** : {'NFC', 'NFKC', 'NFD', 'NFKD'}

Unicode form

Returns **normalized** : Series/Index of objects

pandas.Series.str.pad

`Series.str.pad(`*width, side='left', fillchar=' '*`)`

Pad strings in the Series/Index with an additional character to specified side.

Parameters **width** : int

Minimum width of resulting string; additional characters will be filled with spaces

side : {'left', 'right', 'both'}, default 'left'

fillchar : str

Additional character for filling, default is whitespace

Returns **padded** : Series/Index of objects

pandas.Series.str.partition

`Series.str.partition(pat=' ', expand=True)`

Split the string at the first occurrence of *sep*, and return 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing the string itself, followed by two empty strings.

Parameters **pat** : string, default whitespace

String to split on.

expand : bool, default True

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

Returns **split** : DataFrame/MultiIndex or Series/Index of objects

See also:

rpartition Split the string at the last occurrence of *sep*

Examples

```
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
0    A_B_C
1    D_E_F
2        X
dtype: object

>>> s.str.partition('_')
   0  1    2
0  A  _  B_C
1  D  _  E_F
2  X

>>> s.str.rpartition('_')
     0  1  2
0  A_B  _  C
1  D_E  _  F
2          X
```

pandas.Series.str.repeat

`Series.str.repeat(repeats)`

Duplicate each string in the Series/Index by indicated number of times.

Parameters **repeats** : int or array

Same value for all (int) or different value per (array)

Returns **repeated** : Series/Index of objects

pandas.Series.str.replace

`Series.str.replace(pat, repl, n=-1, case=True, flags=0)`

Replace occurrences of pattern/regex in the Series/Index with some other string. Equivalent to `str.replace()` or `re.sub()`.

Parameters **pat** : string

Character sequence or regular expression

repl : string

Replacement sequence

n : int, default -1 (all)

Number of replacements to make from start

case : boolean, default True

If True, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

Returns **replaced** : Series/Index of objects

pandas.Series.str.rfind

`Series.str.rfind(sub, start=0, end=None)`

Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.rfind()`.

Parameters **sub** : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns **found** : Series/Index of integer values

See also:

`find` Return lowest indexes in each strings

pandas.Series.str.rindex

`Series.str.rindex(sub, start=0, end=None)`

Return highest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.rfind` except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard `str.rindex`.

Parameters **sub** : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns **found** : Series/Index of objects

See also:

`index` Return lowest indexes in each strings

pandas.Series.str.rjust

`Series.str.rjust(`*width*, *fillchar=' '*`)`

Filling left side of strings in the Series/Index with an additional character. Equivalent to `str.left()`.

Parameters **width** : int

Minimum width of resulting string; additional characters will be filled with `fillchar`

fillchar : str

Additional character for filling, default is whitespace

Returns **filled** : Series/Index of objects

pandas.Series.str.rpartition

`Series.str.rpartition(`*pat=' '*, *expand=True*`)`

Split the string at the last occurrence of *sep*, and return 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing two empty strings, followed by the string itself.

Parameters **pat** : string, default whitespace

String to split on.

expand : bool, default True

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

Returns **split** : DataFrame/MultiIndex or Series/Index of objects

See also:

`partition` Split the string at the first occurrence of *sep*

Examples

```
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
0    A_B_C
1    D_E_F
2        X
dtype: object
```

```
>>> s.str.partition('_')
   0  1    2
0  A  _  B_C
1  D  _  E_F
2  X

>>> s.str.rpartition('_')
     0  1  2
0  A_B  _  C
1  D_E  _  F
2          X
```

pandas.Series.str.rstrip

`Series.str.rstrip(to_strip=None)`

Strip whitespace (including newlines) from each string in the Series/Index from right side. Equivalent to `str.rstrip()`.

Returns **stripped** : Series/Index of objects

pandas.Series.str.slice

`Series.str.slice(start=None, stop=None, step=None)`

Slice substrings from each element in the Series/Index

Parameters **start** : int or None

stop : int or None

step : int or None

Returns **sliced** : Series/Index of objects

pandas.Series.str.slice_replace

`Series.str.slice_replace(start=None, stop=None, repl=None)`

Replace a slice of each string in the Series/Index with another string.

Parameters **start** : int or None

stop : int or None

repl : str or None

String for replacement

Returns **replaced** : Series/Index of objects

pandas.Series.str.split

`Series.str.split(*args, **kwargs)`

Split each string (a la re.split) in the Series/Index by given pattern, propagating NA values. Equivalent to `str.split()`.

Parameters **pat** : string, default None

String or regular expression to split on. If None, splits on whitespace

n : int, default -1 (all)

None, 0 and -1 will be interpreted as return all splits

expand : bool, default False

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

New in version 0.16.1.

return_type : deprecated, use *expand*

Returns split : Series/Index or DataFrame/MultiIndex of objects

pandas.Series.str.rsplit

`Series.str.rsplit(pat=None, n=-1, expand=False)`

Split each string in the Series/Index by the given delimiter string, starting at the end of the string and working to the front. Equivalent to `str.rsplit()`.

New in version 0.16.2.

Parameters pat : string, default None

Separator to split on. If None, splits on whitespace

n : int, default -1 (all)

None, 0 and -1 will be interpreted as return all splits

expand : bool, default False

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

Returns split : Series/Index or DataFrame/MultiIndex of objects

pandas.Series.str.startswith

`Series.str.startswith(pat, na=nan)`

Return boolean Series/`array` indicating whether each string in the Series/Index starts with passed pattern. Equivalent to `str.startswith()`.

Parameters pat : string

Character sequence

na : bool, default NaN

Returns startswith : Series/array of boolean values

pandas.Series.str.strip

`Series.str.strip(to_strip=None)`

Strip whitespace (including newlines) from each string in the Series/Index from left and right sides. Equivalent to `str.strip()`.

Returns stripped : Series/Index of objects

pandas.Series.str.swapcase

`Series.str.swapcase()`

Convert strings in the Series/Index to be swapcased. Equivalent to `str.swapcase()`.

Returns converted : Series/Index of objects

pandas.Series.str.title

`Series.str.title()`

Convert strings in the Series/Index to titlecase. Equivalent to `str.title()`.

Returns converted : Series/Index of objects

pandas.Series.str.translate

`Series.str.translate(table, deletechars=None)`

Map all characters in the string through the given mapping table. Equivalent to standard `str.translate()`. Note that the optional argument deletechars is only valid if you are using python 2. For python 3, character deletion should be specified via the table argument.

Parameters table : dict (python 3), str or None (python 2)

In python 3, table is a mapping of Unicode ordinals to Unicode ordinals, strings, or None. Unmapped characters are left untouched. Characters mapped to None are deleted. `str.maketrans()` is a helper function for making translation tables. In python 2, table is either a string of length 256 or None. If the table argument is None, no translation is applied and the operation simply removes the characters in deletechars. `string.maketrans()` is a helper function for making translation tables.

deletechars : str, optional (python 2)

A string of characters to delete. This argument is only valid in python 2.

Returns translated : Series/Index of objects

pandas.Series.str.upper

`Series.str.upper()`

Convert strings in the Series/Index to uppercase. Equivalent to `str.upper()`.

Returns converted : Series/Index of objects

pandas.Series.str.wrap

`Series.str.wrap(width, **kwargs)`

Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given width.

This method has the same keyword parameters and defaults as `textwrap.TextWrapper`.

Parameters width : int

Maximum line-width

expand_tabs : bool, optional

If true, tab characters will be expanded to spaces (default: True)

replace_whitespace : bool, optional

If true, each whitespace character (as defined by string.whitespace) remaining after tab expansion will be replaced by a single space (default: True)

drop_whitespace : bool, optional

If true, whitespace that, after wrapping, happens to end up at the beginning or end of a line is dropped (default: True)

break_long_words : bool, optional

If true, then words longer than width will be broken in order to ensure that no lines are longer than width. If it is false, long words will not be broken, and some lines may be longer than width. (default: True)

break_on_hyphens : bool, optional

If true, wrapping will occur preferably on whitespace and right after hyphens in compound words, as it is customary in English. If false, only whitespaces will be considered as potentially good places for line breaks, but you need to set break_long_words to false if you want truly insecable 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

```
>>> s = pd.Series(['line to be wrapped', 'another line to be wrapped'])
>>> s.str.wrap(12)
0             line to be\nwrapped
1    another line\nto be\nwrapped
```

pandas.Series.str.zfill

`Series.str.`**`zfill`**(*width*)

" Filling left side of strings in the Series/Index with 0. Equivalent to `str.zfill()`.

Parameters width : int

Minimum width of resulting string; additional characters will be filled with 0

Returns filled : Series/Index of objects

pandas.Series.str.isalnum

`Series.str.isalnum()`
Check whether all characters in each string in the Series/Index are alphanumeric. Equivalent to `str.isalnum()`.

Returns is : Series/array of boolean values

pandas.Series.str.isalpha

`Series.str.isalpha()`
Check whether all characters in each string in the Series/Index are alphabetic. Equivalent to `str.isalpha()`.

Returns is : Series/array of boolean values

pandas.Series.str.isdigit

`Series.str.isdigit()`
Check whether all characters in each string in the Series/Index are digits. Equivalent to `str.isdigit()`.

Returns is : Series/array of boolean values

pandas.Series.str.isspace

`Series.str.isspace()`
Check whether all characters in each string in the Series/Index are whitespace. Equivalent to `str.isspace()`.

Returns is : Series/array of boolean values

pandas.Series.str.islower

`Series.str.islower()`
Check whether all characters in each string in the Series/Index are lowercase. Equivalent to `str.islower()`.

Returns is : Series/array of boolean values

pandas.Series.str.isupper

`Series.str.isupper()`
Check whether all characters in each string in the Series/Index are uppercase. Equivalent to `str.isupper()`.

Returns is : Series/array of boolean values

pandas.Series.str.istitle

`Series.str.istitle()`
Check whether all characters in each string in the Series/Index are titlecase. Equivalent to `str.istitle()`.

Returns is : Series/array of boolean values

pandas.Series.str.isnumeric

`Series.str.isnumeric()`

Check whether all characters in each string in the Series/Index are numeric. Equivalent to `str.isnumeric()`.

Returns is : Series/array of boolean values

pandas.Series.str.isdecimal

`Series.str.isdecimal()`

Check whether all characters in each string in the Series/Index are decimal. Equivalent to `str.isdecimal()`.

Returns is : Series/array of boolean values

pandas.Series.str.get_dummies

`Series.str.get_dummies(sep='|')`

Split each string in the Series by sep and return a frame of dummy/indicator variables.

Parameters sep : string, default "|"

String to split on.

Returns dummies : DataFrame

See also:

`pandas.get_dummies`

Examples

```
>>> Series(['a|b', 'a', 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  1  0  0
2  1  0  1
```

```
>>> 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
```

33.3.15 Categorical

If the Series is of dtype `category`, `Series.cat` can be used to change the the categorical data. This accessor is similar to the `Series.dt` or `Series.str` and has the following usable methods and properties:

`Series.cat.categories`	The categories of this categorical.
`Series.cat.ordered`	Gets the ordered attribute
`Series.cat.codes`	

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 a inplace operation!

Raises ValueError

If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.ordered

`Series.cat.ordered`
Gets the ordered attribute

pandas.Series.cat.codes

`Series.cat.codes`

Series.cat.rename_categories(*args, **kwargs)	Renames categories.
Series.cat.reorder_categories(*args, **kwargs)	Reorders categories as specified in new_categories.
Series.cat.add_categories(*args, **kwargs)	Add new categories.
Series.cat.remove_categories(*args, **kwargs)	Removes the specified categories.
Series.cat.remove_unused_categories(*args, ...)	Removes categories which are not used.
Series.cat.set_categories(*args, **kwargs)	Sets the categories to the specified new_categories.
Series.cat.as_ordered(*args, **kwargs)	Sets the Categorical to be ordered
Series.cat.as_unordered(*args, **kwargs)	Sets the Categorical to be unordered

pandas.Series.cat.rename_categories

`Series.cat.rename_categories(*args, **kwargs)`
Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters new_categories : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns cat : Categorical with renamed categories added or None if inplace.

Raises ValueError

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.reorder_categories

`Series.cat.reorder_categories(*args, **kwargs)`

Reorders categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

Parameters new_categories : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns cat : Categorical with reordered categories or None if inplace.

Raises ValueError

If the new categories do not contain all old category items or any new ones

See also:

rename_categories, add_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.add_categories

`Series.cat.add_categories(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters new_categories : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns cat : Categorical with new categories added or None if inplace.

Raises ValueError

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.Series.cat.remove_categories

`Series.cat.remove_categories(*args, **kwargs)`

Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters removals : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns cat : Categorical with removed categories or None if inplace.

Raises ValueError

If the removals are not contained in the categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_unused_categories`, `set_categories`

pandas.Series.cat.remove_unused_categories

`Series.cat.remove_unused_categories(*args, **kwargs)`

Removes categories which are not used.

Parameters inplace : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns cat : Categorical with unused categories dropped or None if inplace.

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `set_categories`

pandas.Series.cat.set_categories

`Series.cat.set_categories(*args, **kwargs)`

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters **new_categories** : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns **cat** : Categorical with reordered categories or None if inplace.

Raises **ValueError**

If new_categories does not validate as categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`

pandas.Series.cat.as_ordered

`Series.cat.as_ordered(*args, **kwargs)`

Sets the Categorical to be ordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.Series.cat.as_unordered

`Series.cat.as_unordered(*args, **kwargs)`

Sets the Categorical to be unordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

To create a Series of dtype `category`, use `cat = s.astype("category")`.

The following two `Categorical` constructors are considered API but should only be used when adding ordering information or special categories is need at creation time of the categorical data:

`Categorical`(values[, categories, ordered, ...])	Represents a categorical variable in classic R / S-plus fashion

pandas.Categorical

class `pandas.Categorical`(*values*, *categories=None*, *ordered=False*, *name=None*, *fastpath=False*, *levels=None*)

Represents a categorical variable in classic R / S-plus fashion

Categoricals can only take on only a limited, and usually fixed, number of possible values (*categories*). In contrast to statistical categorical variables, a *Categorical* might have an order, but numerical operations (additions, divisions, ...) are not possible.

All values of the *Categorical* are either in *categories* or *np.nan*. Assigning values outside of *categories* will raise a *ValueError*. Order is defined by the order of the *categories*, not lexical order of the values.

Parameters values : list-like

The values of the categorical. If categories are given, values not in categories will be replaced with NaN.

categories : Index-like (unique), optional

The unique categories for this categorical. If not given, the categories are assumed to be the unique values of values.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will not be ordered.

name : str, optional

Name for the Categorical variable. If name is None, will attempt to infer from values.

Raises ValueError

If the categories do not validate.

TypeError

If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

Examples

```
>>> from pandas import Categorical
>>> Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1 < 2 < 3]

>>> Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
[a, b, c, a, b, c]
Categories (3, object): [a < b < c]

>>> a = Categorical(['a','b','c','a','b','c'], ['c', 'b', 'a'])
>>> a.min()
'c'
```

Attributes

`categories`	The categories of this categorical.

Continued on next page

Table 33.42 – continued from previous page

codes	The category codes of this categorical.
ordered	Gets the ordered attribute

name	(string) The name of this Categorical.

Methods

add_categories(new_categories[, inplace])	Add new categories.
argsort([ascending])	Implements ndarray.argsort.
as_ordered([inplace])	Sets the Categorical to be ordered
as_unordered([inplace])	Sets the Categorical to be unordered
astype(dtype)	coerce this type to another dtype
check_for_ordered(op)	assert that we are ordered
copy()	Copy constructor.
describe()	Describes this Categorical
dropna()	Return the Categorical without null values.
equals(other)	Returns True if categorical arrays are equal.
fillna(*args, **kwargs)	Fill NA/NaN values using the specified method.
from_array(data, **kwargs)	Make a Categorical type from a single array-like object.
from_codes(codes, categories[, ordered, name])	Make a Categorical type from codes and categories arrays.
get_values()	Return the values.
is_dtype_equal(other)	Returns True if categoricals are the same dtype
isnull()	Detect missing values
max([numeric_only])	The maximum value of the object.
min([numeric_only])	The minimum value of the object.
mode()	Returns the mode(s) of the Categorical.
notnull()	Reverse of isnull
order([inplace, ascending, na_position])	Sorts the Category by category value returning a new Categorical by default.
ravel([order])	Return a flattened (numpy) array.
remove_categories(removals[, inplace])	Removes the specified categories.
remove_unused_categories([inplace])	Removes categories which are not used.
rename_categories(new_categories[, inplace])	Renames categories.
reorder_categories(new_categories[, ...])	Reorders categories as specified in new_categories.
repeat(repeats)	Repeat elements of a Categorical.
reshape(new_shape, **kwargs)	compat with .reshape
searchsorted(v[, side, sorter])	Find indices where elements should be inserted to maintain order.
set_categories(new_categories[, ordered, ...])	Sets the categories to the specified new_categories.
set_ordered(value[, inplace])	Sets the ordered attribute to the boolean value
sort([inplace, ascending, na_position])	Sorts the Category inplace by category value.
take(indexer[, allow_fill, fill_value])	Take the codes by the indexer, fill with the fill_value.
take_nd(indexer[, allow_fill, fill_value])	Take the codes by the indexer, fill with the fill_value.
to_dense()	Return my 'dense' representation
unique()	Return the unique values.
value_counts([dropna])	Returns a Series containing counts of each category.
view()	Return a view of myself.

pandas.Categorical.from_codes

classmethod Categorical.**from_codes**(*codes*, *categories*, *ordered=False*, *name=None*)

Make a Categorical type from codes and categories arrays.

This constructor is useful if you already have codes and categories and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

Parameters **codes** : array-like, integers

An integer array, where each integer points to a category in categories or -1 for NaN

categories : index-like

The categories for the categorical. Items need to be unique.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will be unordered.

name : str, optional

Name for the Categorical variable.

`Categorical.from_codes`(codes, categories[, ...])	Make a Categorical type from codes and categories arrays.

pandas.Categorical.from_codes

classmethod `Categorical.`**`from_codes`**(*codes*, *categories*, *ordered=False*, *name=None*)

Make a Categorical type from codes and categories arrays.

This constructor is useful if you already have codes and categories and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

Parameters **codes** : array-like, integers

An integer array, where each integer points to a category in categories or -1 for NaN

categories : index-like

The categories for the categorical. Items need to be unique.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will be unordered.

name : str, optional

Name for the Categorical variable.

`np.asarray(categorical)` works by implementing the array interface. Be aware, that this converts the Categorical back to a numpy array, so levels and order information is not preserved!

`Categorical.__array__`([dtype])	The numpy array interface.

pandas.Categorical.__array__

`Categorical.`**`__array__`**(*dtype=None*)

The numpy array interface.

Returns **values** : numpy array

A numpy array of either the specified dtype or, if dtype==None (default), the same dtype as categorical.categories.dtype

33.3.16 Plotting

`Series.hist`([by, ax, grid, xlabelsize, ...])	Draw histogram of the input series using matplotlib
`Series.plot`(data[, kind, ax, figsize, ...])	Make plots of Series using matplotlib / pylab.

pandas.Series.hist

`Series.hist` (*by=None*, *ax=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *figsize=None*, *bins=10*, ***kwds*)

Draw histogram of the input series using matplotlib

Parameters **by** : object, optional

If passed, then used to form histograms for separate groups

ax : matplotlib axis object

If not passed, uses gca()

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

figsize : tuple, default None

figure size in inches by default

bins: integer, default 10

Number of histogram bins to be used

kwds : keywords

To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this

pandas.Series.plot

`Series.plot`(*data*, *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.

Parameters **data** : Series

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot

ax : matplotlib axes object

If not passed, uses gca()

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

label : label argument to provide to plot

secondary_y : boolean or sequence of ints, default False

If True then y-axis will be on the right

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

33.3.17 Serialization / IO / Conversion

Series.from_csv(path[, sep, parse_dates, ...])	Read delimited file into Series
Series.to_pickle(path)	Pickle (serialize) object to input file path
Series.to_csv(path[, index, sep, na_rep, ...])	Write Series to a comma-separated values (csv) file
Series.to_dict()	Convert Series to {label -> value} dict
Series.to_frame([name])	Convert Series to DataFrame
Series.to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
Series.to_sql(name, con[, flavor, schema, ...])	Write records stored in a DataFrame to a SQL database.
Series.to_msgpack([path_or_buf])	msgpack (serialize) object to input file path
Series.to_json([path_or_buf, orient, ...])	Convert the object to a JSON string.
Series.to_sparse([kind, fill_value])	Convert Series to SparseSeries
Series.to_dense()	Return dense representation of NDFrame (as opposed to sparse)
Series.to_string([buf, na_rep, ...])	Render a string representation of the Series
Series.to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This can l

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 delimited file into Series

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 0

Row to use at header (skip prior rows)

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

infer_datetime_format: boolean, default False

If True and *parse_dates* is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns **y** : Series

pandas.Series.to_pickle

`Series.to_pickle`(*path*)

Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Series.to_csv

`Series.to_csv`(*path*, *index=True*, *sep='*, *'*, *na_rep=''*, *float_format=None*, *header=False*, *index_label=None*, *mode='w'*, *nanRep=None*, *encoding=None*, *date_format=None*, *decimal='.'*)

Write Series to a comma-separated values (csv) file

Parameters **path** : string file path or file handle / StringIO. If None is provided

the result is returned as a string.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

header : boolean, default False

Write out series name

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

mode : Python write mode, default 'w'

sep : character, default ","

Field delimiter for the output file.

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

date_format: string, default None

Format string for datetime objects.

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

pandas.Series.to_dict

`Series.to_dict()`
Convert Series to {label -> value} dict

Returns value_dict : dict

pandas.Series.to_frame

`Series.to_frame(name=None)`
Convert Series to DataFrame

Parameters name : object, default None

The passed name should substitute for the series name (if it has one).

Returns data_frame : DataFrame

pandas.Series.to_hdf

`Series.to_hdf(path_or_buf, key, **kwargs)`
activate the HDFStore

Parameters path_or_buf : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Series.to_sql

`Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Series.to_msgpack

`Series.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.Series.to_json

`Series.`**`to_json`**(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}
  - columns : dict like {column -> {index -> value}}
  - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso*' = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Series.to_sparse

`Series.to_sparse`(*kind='block'*, *fill_value=None*)

Convert Series to SparseSeries

Parameters **kind** : {'block', 'integer'}

fill_value : float, defaults to NaN (missing)

Returns **sp** : SparseSeries

pandas.Series.to_dense

`Series.to_dense`()

Return dense representation of NDFrame (as opposed to sparse)

pandas.Series.to_string

`Series.to_string`(*buf=None*, *na_rep='NaN'*, *float_format=None*, *header=True*, *length=False*, *dtype=False*, *name=False*, *max_rows=None*)

Render a string representation of the Series

Parameters **buf** : StringIO-like, optional

buffer to write to

na_rep : string, optional

string representation of NAN to use, default 'NaN'

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats default None

header: boolean, default True

Add the Series header (index name)

length : boolean, default False

Add the Series length

dtype : boolean, default False

Add the Series dtype

name : boolean, default False

Add the Series name if not None

max_rows : int, optional

Maximum number of rows to show before truncating. If None, show all.

Returns **formatted** : string (if not buffer passed)

pandas.Series.to_clipboard

Series.**to_clipboard**(*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.3.18 Sparse methods

SparseSeries.to_coo([row_levels, ...])	Create a scipy.sparse.coo_matrix from a SparseSeries with MultiIndex.
SparseSeries.from_coo(A[, dense_index])	Create a SparseSeries from a scipy.sparse.coo_matrix.

pandas.SparseSeries.to_coo

SparseSeries.**to_coo**(*row_levels=(0,)*, *column_levels=(1,)*, *sort_labels=False*)

Create a scipy.sparse.coo_matrix from a SparseSeries with MultiIndex.

Use row_levels and column_levels to determine the row and column coordinates respectively. row_levels and column_levels are the names (labels) or numbers of the levels. {row_levels, column_levels} must be a partition of the MultiIndex level names (or numbers).

New in version 0.16.0.

Parameters **row_levels** : tuple/list

column_levels : tuple/list

sort_labels : bool, default False

Sort the row and column labels before forming the sparse matrix.

Returns **y** : scipy.sparse.coo_matrix

rows : list (row labels)

columns : list (column labels)

Examples

```
>>> 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)]
```

pandas.SparseSeries.from_coo

classmethod `SparseSeries.from_coo`(*A*, *dense_index=False*)

Create a SparseSeries from a scipy.sparse.coo_matrix.

New in version 0.16.0.

Parameters **A** : scipy.sparse.coo_matrix

dense_index : bool, default False

If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original coo_matrix. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the coo_matrix.

Returns **s** : SparseSeries

Examples

```
>>> from scipy import sparse
>>> A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
                          shape=(3, 4))
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>
>>> A.todense()
matrix([[ 0.,  0.,  1.,  2.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])
>>> ss = SparseSeries.from_coo(A)
>>> ss
0  2    1
```

```
   3    2
1  0    3
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([3], dtype=int32)
```

33.4 DataFrame

33.4.1 Constructor

DataFrame([data, index, columns, dtype, copy])	Two-dimensional size-mutable, potentially heterogeneous tabular data structure v

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

index : Index or array-like

Index to use for resulting frame. Will default to np.arange(n) if no indexing information part of input data and no index provided

columns : Index or array-like

Column labels to use for resulting frame. Will default to np.arange(n) if no column labels are provided

dtype : dtype, default None

Data type to force, otherwise infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

See also:

DataFrame.from_records constructor from tuples, also record arrays

DataFrame.from_dict from dicts of Series, arrays, or dicts

DataFrame.from_csv from CSV files

DataFrame.from_items from sequence of (key, value) pairs

pandas.read_csv, pandas.read_table, pandas.read_clipboard

Examples

```
>>> d = {'col1': ts1, 'col2': ts2}
>>> df = DataFrame(data=d, index=index)
>>> df2 = DataFrame(np.random.randn(10, 5))
>>> df3 = DataFrame(np.random.randn(10, 5),
...                 columns=['a', 'b', 'c', 'd', 'e'])
```

Attributes

T	Transpose index and columns
at	Fast label-based scalar accessor
axes	
blocks	Internal property, property synonym for as_blocks()
dtypes	Return the dtypes in this object
empty	True if NDFrame is entirely empty [no items]
ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
iat	Fast integer location scalar accessor.
iloc	Purely integer-location based indexing for selection by position.
ix	A primarily label-location based indexer, with integer position fallback.
loc	Purely label-location based indexer for selection by label.
ndim	Number of axes / array dimensions
shape	
size	number of elements in the NDFrame
values	Numpy representation of NDFrame

pandas.DataFrame.T

DataFrame.**T**

Transpose index and columns

pandas.DataFrame.at

DataFrame.**at**

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.DataFrame.axes

DataFrame.**axes**

pandas.DataFrame.blocks

DataFrame.**blocks**

Internal property, property synonym for as_blocks()

pandas.DataFrame.dtypes

`DataFrame.dtypes`
Return the dtypes in this object

pandas.DataFrame.empty

`DataFrame.empty`
True if NDFrame is entirely empty [no items]

pandas.DataFrame.ftypes

`DataFrame.ftypes`
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.iat

`DataFrame.iat`
Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.DataFrame.iloc

`DataFrame.iloc`
Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.DataFrame.ix

`DataFrame.ix`
A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.DataFrame.loc

`DataFrame.`**`loc`**

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.DataFrame.ndim

`DataFrame.`**`ndim`**

Number of axes / array dimensions

pandas.DataFrame.shape

`DataFrame.`**`shape`**

pandas.DataFrame.size

`DataFrame.`**`size`**

number of elements in the NDFrame

pandas.DataFrame.values

`DataFrame.`**`values`**

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	

Methods

abs()	Return an object with absolute value taken.
add(other[, axis, level, fill_value])	Addition of dataframe and other, element-wise (binary operator *add*).
add_prefix(prefix)	Concatenate prefix string with panel items names.
add_suffix(suffix)	Concatenate suffix string with panel items names
align(other[, join, axis, level, copy, ...])	Align two object on their axes with the
all([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
any([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
append(other[, ignore_index, verify_integrity])	Append rows of *other* to the end of this frame, returning a new object.
apply(func[, axis, broadcast, raw, reduce, args])	Applies function along input axis of DataFrame.
applymap(func)	Apply a function to a DataFrame that is intended to operate elementwise, i.e.
as_blocks()	Convert the frame to a dict of dtype -> Constructor Types that each has a homo
as_matrix([columns])	Convert the frame to its Numpy-array representation.
asfreq(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
assign(**kwargs)	Assign new columns to a DataFrame, returning a new object (a copy) with all t
astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
at_time(time[, asof])	Select values at particular time of day (e.g.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM)
bfill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='bfill')
bool()	Return the bool of a single element PandasObject
boxplot([column, by, ax, fontsize, rot, ...])	Make a box plot from DataFrame column optionally grouped by some columns
clip([lower, upper, out, axis])	Trim values at input threshold(s)
clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
combine(other, func[, fill_value, overwrite])	Add two DataFrame objects and do not propagate NaN values, so if for a
combineAdd(other)	Add two DataFrame objects and do not propagate
combineMult(other)	Multiply two DataFrame objects and do not propagate NaN values, so if
combine_first(other)	Combine two DataFrame objects and default to non-null values in frame calling
compound([axis, skipna, level])	Return the compound percentage of the values for the requested axis
consolidate([inplace])	Compute NDFrame with "consolidated" internals (data of each dtype grouped t
convert_objects([convert_dates, ...])	Attempt to infer better dtype for object columns
copy([deep])	Make a copy of this object
corr([method, min_periods])	Compute pairwise correlation of columns, excluding NA/null values
corrwith(other[, axis, drop])	Compute pairwise correlation between rows or columns of two DataFrame obje
count([axis, level, numeric_only])	Return Series with number of non-NA/null observations over requested axis.
cov([min_periods])	Compute pairwise covariance of columns, excluding NA/null values
cummax([axis, dtype, out, skipna])	Return cumulative max over requested axis.
cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.

Table 33.51 – cont

describe([percentile_width, percentiles, ...])	Generate various summary statistics, excluding NaN values.
diff([periods, axis])	1st discrete difference of object
div(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *truediv*
divide(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *truediv*
dot(other)	Matrix multiplication with DataFrame or Series objects
drop(labels[, axis, level, inplace, errors])	Return new object with labels in requested axis removed
drop_duplicates(*args, **kwargs)	Return DataFrame with duplicate rows removed, optionally only
dropna([axis, how, thresh, subset, inplace])	Return object with labels on given axis omitted where alternately any
duplicated(*args, **kwargs)	Return boolean Series denoting duplicate rows, optionally only
eq(other[, axis, level])	Wrapper for flexible comparison methods eq
equals(other)	Determines if two NDFrame objects contain the same elements.
eval(expr, **kwargs)	Evaluate an expression in the context of the calling DataFrame instance.
ffill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='ffill')
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method
filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
first(offset)	Convenience method for subsetting initial periods of time series data
first_valid_index()	Return label for first non-NA/null value
floordiv(other[, axis, level, fill_value])	Integer division of dataframe and other, element-wise (binary operator *floordiv*)
from_csv(path[, header, sep, index_col, ...])	Read delimited file into DataFrame
from_dict(data[, orient, dtype])	Construct DataFrame from dict of array-like or dicts
from_items(items[, columns, orient])	Convert (key, value) pairs to DataFrame.
from_records(data[, index, exclude, ...])	Convert structured or record ndarray to DataFrame
ge(other[, axis, level])	Wrapper for flexible comparison methods ge
get(key[, default])	Get item from object for given key (DataFrame column, Panel slice, etc.).
get_dtype_counts()	Return the counts of dtypes in this object
get_ftype_counts()	Return the counts of ftypes in this object
get_value(index, col[, takeable])	Quickly retrieve single value at passed column and index
get_values()	same as values (but handles sparseness conversions)
groupby([by, axis, level, as_index, sort, ...])	Group series using mapper (dict or key function, apply given function
gt(other[, axis, level])	Wrapper for flexible comparison methods gt
head([n])	Returns first n rows
hist(data[, column, by, grid, xlabelsize, ...])	Draw histogram of the DataFrame's series using matplotlib / pylab.
icol(i)	
idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
iget_value(i, j)	
info([verbose, buf, max_cols, memory_usage, ...])	Concise summary of a DataFrame.
insert(loc, column, value[, allow_duplicates])	Insert column into DataFrame at specified location.
interpolate([method, axis, limit, inplace, ...])	Interpolate values according to different methods.
irow(i[, copy])	
isin(values)	Return boolean DataFrame showing whether each element in the DataFrame is
isnull()	Return a boolean same-sized object indicating if the values are null
iteritems()	Iterator over (column, series) pairs
iterkv(*args, **kwargs)	iteritems alias used to get around 2to3. Deprecated
iterrows()	Iterate over rows of DataFrame as (index, Series) pairs.
itertuples([index])	Iterate over rows of DataFrame as tuples, with index value
join(other[, on, how, lsuffix, rsuffix, sort])	Join columns with other DataFrame either on index or on a key column.
keys()	Get the 'info axis' (see Indexing for more)
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosi
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosi
last(offset)	Convenience method for subsetting final periods of time series data
last_valid_index()	Return label for last non-NA/null value

Table 33.51 – cont

le(other[, axis, level])	Wrapper for flexible comparison methods le
load(path)	Deprecated.
lookup(row_labels, col_labels)	Label-based “fancy indexing” function for DataFrame.
lt(other[, axis, level])	Wrapper for flexible comparison methods lt
mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
mask(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are fro
max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
median([axis, skipna, level, numeric_only])	Return the median of the values for the requested axis
memory_usage([index])	Memory usage of DataFrame columns.
merge(right[, how, on, left_on, right_on, ...])	Merge DataFrame objects by performing a database-style join operation by col
min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
mod(other[, axis, level, fill_value])	Modulo of dataframe and other, element-wise (binary operator *mod*).
mode([axis, numeric_only])	Gets the mode(s) of each element along the axis selected.
mul(other[, axis, level, fill_value])	Multiplication of dataframe and other, element-wise (binary operator *mul*).
multiply(other[, axis, level, fill_value])	Multiplication of dataframe and other, element-wise (binary operator *mul*).
ne(other[, axis, level])	Wrapper for flexible comparison methods ne
notnull()	Return a boolean same-sized object indicating if the values are
pct_change([periods, fill_method, limit, freq])	Percent change over given number of periods.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs)
pivot([index, columns, values])	Reshape data (produce a “pivot” table) based on column values.
pivot_table(data[, values, index, columns, ...])	Create a spreadsheet-style pivot table as a DataFrame.
plot(data[, x, y, kind, ax, subplots, ...])	Make plots of DataFrame using matplotlib / pylab.
pop(item)	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])	Return values at the given quantile over requested axis, a la numpy.percentile.
query(expr, **kwargs)	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, numeric_only, method, ...])	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 *rtruedi*
reindex([index, columns])	Conform DataFrame to new index with optional filling logic, placing NA/NaN
reindex_axis(labels[, axis, method, level, ...])	Conform input object to new index with optional filling logic, placing NA/NaN
reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
rename([index, columns])	Alter axes input function or functions.
rename_axis(mapper[, axis, copy, inplace])	Alter index and / or columns using input function or functions.
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 regular time-
reset_index([level, drop, inplace, ...])	For DataFrame with multi-level index, return new DataFrame with labeling inf
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*).
rpow(other[, axis, level, fill_value])	Exponential power of dataframe and other, element-wise (binary operator *rpow*
rsub(other[, axis, level, fill_value])	Subtraction of dataframe and other, element-wise (binary operator *rsub*).
rtruediv(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *rtruedi*
sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
save(path)	Deprecated.
select(crit[, axis])	Return data corresponding to axis labels matching criteria
select_dtypes([include, exclude])	Return a subset of a DataFrame including/excluding columns based on their dt
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.

Table 33.51 – cont

set_axis(axis, labels)	public verson of axis assignment
set_index(keys[, drop, append, inplace, ...])	Set the DataFrame index (row labels) using one or more existing columns.
set_value(index, col, value[, takeable])	Put single value at passed column and index
shift([periods, freq, axis])	Shift index by desired number of periods with an optional time freq
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
slice_shift([periods, axis])	Equivalent to *shift* without copying data.
sort([columns, axis, ascending, inplace, ...])	Sort DataFrame either by labels (along either axis) or by the values in
sort_index([axis, by, ascending, inplace, ...])	Sort DataFrame either by labels (along either axis) or by the values in
sortlevel([level, axis, ascending, inplace, ...])	Sort multilevel index by chosen axis and primary level.
squeeze()	squeeze length 1 dimensions
stack([level, dropna])	Pivot a level of the (possibly hierarchical) column labels, returning a DataFram
std([axis, skipna, level, ddof, numeric_only])	Return unbiased standard deviation over requested axis.
sub(other[, axis, level, fill_value])	Subtraction of dataframe and other, element-wise (binary operator *sub*).
subtract(other[, axis, level, fill_value])	Subtraction of dataframe and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately
swaplevel(i, j[, axis])	Swap levels i and j in a MultiIndex on a particular axis
tail([n])	Returns last n rows
take(indices[, axis, convert, is_copy])	Analogous to ndarray.take
to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This can
to_csv([path_or_buf, sep, na_rep, ...])	Write DataFrame to a comma-separated values (csv) file
to_dense()	Return dense representation of NDFrame (as opposed to sparse)
to_dict(*args, **kwargs)	Convert DataFrame to dictionary.
to_excel(excel_writer[, sheet_name, na_rep, ...])	Write DataFrame to a excel sheet
to_gbq(destination_table[, project_id, ...])	Write a DataFrame to a Google BigQuery table.
to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
to_html([buf, columns, col_space, colSpace, ...])	Render a DataFrame as an HTML table.
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_latex([buf, columns, col_space, ...])	Render a DataFrame to a tabular environment table.
to_msgpack([path_or_buf])	msgpack (serialize) object to input file path
to_panel()	Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
to_period([freq, axis, copy])	Convert DataFrame from DatetimeIndex to PeriodIndex with desired
to_pickle(path)	Pickle (serialize) object to input file path
to_records([index, convert_datetime64])	Convert DataFrame to record array.
to_sparse([fill_value, kind])	Convert to SparseDataFrame
to_sql(name, con[, flavor, schema, ...])	Write records stored in a DataFrame to a SQL database.
to_stata(fname[, convert_dates, ...])	A class for writing Stata binary dta files from array-like objects
to_string([buf, columns, col_space, ...])	Render a DataFrame to a console-friendly tabular output.
to_timestamp([freq, how, axis, copy])	Cast to DatetimeIndex of timestamps, at *beginning* of period
to_wide(*args, **kwargs)	
transpose()	Transpose index and columns
truediv(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *truediv*
truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.
tshift([periods, freq, axis])	Shift the time index, using the index's frequency if available
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone
unstack([level])	Pivot a level of the (necessarily hierarchical) index labels, returning a DataFran
update(other[, join, overwrite, ...])	Modify DataFrame in place using non-NA values from passed DataFrame.
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
where(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are fro
xs(key[, axis, level, copy, drop_level])	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

pandas.DataFrame.abs

`DataFrame.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.DataFrame.add

`DataFrame.add(other, axis='columns', level=None, fill_value=None)`

Addition of dataframe and other, element-wise (binary operator *add*).

Equivalent to `dataframe + other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.radd`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.add_prefix

`DataFrame.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.DataFrame.add_suffix

`DataFrame.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.DataFrame.align

DataFrame.**align**(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*, *fill_axis=0*)

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns **(left, right)** : (type of input, type of other)

Aligned objects

pandas.DataFrame.all

DataFrame.**all**(*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether all elements are True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : Series or DataFrame (if level specified)

pandas.DataFrame.any

`DataFrame.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : Series or DataFrame (if level specified)

pandas.DataFrame.append

`DataFrame.append(other, ignore_index=False, verify_integrity=False)`

Append rows of *other* to the end of this frame, returning a new object. Columns not in this frame are added as new columns.

Parameters **other** : DataFrame or Series/dict-like object, or list of these

The data to append.

ignore_index : boolean, default False

If True, do not use the index labels.

verify_integrity : boolean, default False

If True, raise ValueError on creating index with duplicates.

Returns **appended** : DataFrame

See also:

`pandas.concat` General function to concatenate DataFrame, Series or Panel objects

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Examples

```
>>> 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:

```
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

pandas.DataFrame.apply

`DataFrame.apply`(*func*, *axis=0*, *broadcast=False*, *raw=False*, *reduce=None*, *args=()*, ***kwds*)

Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame's index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates, or the reduce argument if the DataFrame is empty.

Parameters func : function

Function to apply to each column/row

axis : {0 or 'index', 1 or 'columns'}, default 0

- 0 or 'index': apply function to each column
- 1 or 'columns': apply function to each row

broadcast : boolean, default False

For aggregation functions, return object of same size with values propagated

reduce : boolean or None, default None

Try to apply reduction procedures. If the DataFrame is empty, apply will use reduce to determine whether the result should be a Series or a DataFrame. If reduce is None (the default), apply's return value will be guessed by calling func an empty Series (note: while guessing, exceptions raised by func will be ignored). If reduce is True a Series will always be returned, and if False a DataFrame will always be returned.

raw : boolean, default False

If False, convert each row or column into a Series. If raw=True the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

args : tuple

Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

Returns applied : Series or DataFrame

See also:

`DataFrame.applymap` For elementwise operations

Notes

In the current implementation apply calls func twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first column/row.

Examples

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

pandas.DataFrame.applymap

`DataFrame.applymap(func)`

Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing map(func, series) for each series in the DataFrame

Parameters **func** : function

Python function, returns a single value from a single value

Returns **applied** : DataFrame

See also:

`DataFrame.apply` For operations on rows/columns

pandas.DataFrame.as_blocks

`DataFrame.as_blocks()`

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Returns **values** : a dict of dtype -> Constructor Types

pandas.DataFrame.as_matrix

`DataFrame.as_matrix(columns=None)`

Convert the frame to its Numpy-array representation.

Parameters **columns: list, optional, default:None**

If None, return all columns, otherwise, returns specified columns.

Returns **values** : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

`pandas.DataFrame.values`

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use '.values'.

pandas.DataFrame.asfreq

`DataFrame.`**`asfreq`**`(`*freq*, *method=None*, *how=None*, *normalize=False*`)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.DataFrame.assign

`DataFrame.`**`assign`**`(`***kwargs*`)`

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition to the new ones.

New in version 0.16.0.

Parameters **kwargs** : keyword, value pairs

keywords are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns **df** : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Since kwargs is a dictionary, the order of your arguments may not be preserved. The make things predicatable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within the same assign is possible, but you cannot reference other columns created within the same assign call.

Examples

```
>>> df = DataFrame({'A': range(1, 11), 'B': np.random.randn(10)})
```

Where the value is a callable, evaluated on *df*:

```
>>> df.assign(ln_A = lambda x: np.log(x.A))
    A         B      ln_A
0   1  0.426905  0.000000
1   2 -0.780949  0.693147
2   3 -0.418711  1.098612
3   4 -0.269708  1.386294
4   5 -0.274002  1.609438
5   6 -0.500792  1.791759
6   7  1.649697  1.945910
7   8 -1.495604  2.079442
8   9  0.549296  2.197225
9  10 -0.758542  2.302585
```

Where the value already exists and is inserted:

```
>>> newcol = np.log(df['A'])
>>> df.assign(ln_A=newcol)
    A         B      ln_A
0   1  0.426905  0.000000
1   2 -0.780949  0.693147
2   3 -0.418711  1.098612
3   4 -0.269708  1.386294
4   5 -0.274002  1.609438
5   6 -0.500792  1.791759
6   7  1.649697  1.945910
7   8 -1.495604  2.079442
8   9  0.549296  2.197225
9  10 -0.758542  2.302585
```

pandas.DataFrame.astype

DataFrame.**astype**(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.DataFrame.at_time

`DataFrame.at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : type of caller

pandas.DataFrame.between_time

`DataFrame.between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns **values_between_time** : type of caller

pandas.DataFrame.bfill

`DataFrame.bfill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for NDFrame.fillna(method='bfill')

pandas.DataFrame.bool

`DataFrame.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.DataFrame.boxplot

`DataFrame.boxplot(column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwds)`

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters **data** : the pandas object holding the data

column : column name or list of names, or vector

Can be any valid input to groupby

by : string or sequence

Column in the DataFrame to group by

ax : Matplotlib axes object, optional

fontsize : int or string

rot : label rotation angle

figsize : A tuple (width, height) in inches

grid : Setting this to True will show the grid

layout : tuple (optional)

(rows, columns) for the layout of the plot

return_type : {'axes', 'dict', 'both'}, default 'dict'

The kind of object to return. 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot; 'axes' returns the matplotlib axes the boxplot is drawn on; 'both' returns a namedtuple with the axes and dict.

When grouping with `by`, a dict mapping columns to `return_type` is returned.

kwds : other plotting keyword arguments to be passed to matplotlib boxplot

function

Returns lines : dict

ax : matplotlib Axes

(ax, lines): namedtuple

Notes

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

pandas.DataFrame.clip

`DataFrame.`**`clip`**(*lower=None*, *upper=None*, *out=None*, *axis=None*)

Trim values at input threshold(s)

Parameters lower : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns clipped : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
```

```
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.DataFrame.clip_lower

DataFrame.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.DataFrame.clip_upper

DataFrame.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.DataFrame.combine

DataFrame.**combine**(*other*, *func*, *fill_value=None*, *overwrite=True*)

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters other : DataFrame

func : function

fill_value : scalar value

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

Returns result : DataFrame

pandas.DataFrame.combineAdd

`DataFrame.combineAdd(other)`

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters other : DataFrame

Returns DataFrame

pandas.DataFrame.combineMult

`DataFrame.combineMult(other)`

Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters other : DataFrame

Returns DataFrame

pandas.DataFrame.combine_first

`DataFrame.combine_first(other)`

Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

Parameters other : DataFrame

Returns combined : DataFrame

Examples

a's values prioritized, use values from b to fill holes:

```
>>> a.combine_first(b)
```

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. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns compounded : Series or DataFrame (if level specified)

pandas.DataFrame.consolidate

DataFrame.**consolidate**(*inplace=False*)

Compute NDFrame with "consolidated" internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters inplace : boolean, default False

If False return new object, otherwise modify existing object

Returns consolidated : type of caller

pandas.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

Parameters convert_dates : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.DataFrame.copy

DataFrame.**copy**(*deep=True*)

Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.DataFrame.corr

`DataFrame.corr(method='pearson', min_periods=1)`
Compute pairwise correlation of columns, excluding NA/null values

Parameters method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result. Currently only available for pearson and spearman correlation

Returns y : DataFrame

pandas.DataFrame.corrwith

`DataFrame.corrwith(other, axis=0, drop=False)`
Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters other : DataFrame

axis : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' to compute column-wise, 1 or 'columns' for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns correls : Series

pandas.DataFrame.count

`DataFrame.count(axis=0, level=None, numeric_only=False)`
Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

Parameters axis : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default False

Include only float, int, boolean data

Returns count : Series (or DataFrame if level specified)

pandas.DataFrame.cov

`DataFrame.cov(min_periods=None)`

Compute pairwise covariance of columns, excluding NA/null values

Parameters **min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns **y** : DataFrame

Notes

y contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.DataFrame.cummax

`DataFrame.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : Series

pandas.DataFrame.cummin

`DataFrame.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : Series

pandas.DataFrame.cumprod

`DataFrame.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative prod over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : Series

pandas.DataFrame.cumsum

`DataFrame.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)`
Return cumulative sum over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Series

pandas.DataFrame.describe

`DataFrame.describe(percentile_width=None, percentiles=None, include=None, exclude=None)`
Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.DataFrame.diff

`DataFrame.diff(periods=1, axis=0)`
1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

axis : {0 or 'index', 1 or 'columns'}, default 0

Take difference over rows (0) or columns (1).

Returns **diffed** : DataFrame

pandas.DataFrame.div

`DataFrame.div(other, axis='columns', level=None, fill_value=None)`
Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rtruediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.divide

`DataFrame.divide(other, axis='columns', level=None, fill_value=None)`
Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rtruediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.dot

`DataFrame.`**`dot`**(*other*)

Matrix multiplication with DataFrame or Series objects

Parameters **other** : DataFrame or Series

Returns **dot_product** : DataFrame or Series

pandas.DataFrame.drop

`DataFrame.`**`drop`**(*labels*, *axis=0*, *level=None*, *inplace=False*, *errors='raise'*)

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.DataFrame.drop_duplicates

`DataFrame.`**`drop_duplicates`**`(`**args*, ***kwargs*`)`

Return DataFrame with duplicate rows removed, optionally only considering certain columns

Parameters subset : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

Take the last observed row in a row. Defaults to the first row

inplace : boolean, default False

Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns deduplicated : DataFrame

pandas.DataFrame.dropna

`DataFrame.`**`dropna`**`(`*axis=0*, *how='any'*, *thresh=None*, *subset=None*, *inplace=False*`)`

Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters axis : {0 or 'index', 1 or 'columns'}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

how : {'any', 'all'}

- any : if any NA values are present, drop that label
- all : if all values are NA, drop that label

thresh : int, default None

int value : require that many non-NA values

subset : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

inplace : boolean, defalt False

If True, do operation inplace and return None.

Returns dropped : DataFrame

pandas.DataFrame.duplicated

`DataFrame.`**`duplicated`**`(`**args*, ***kwargs*`)`

Return boolean Series denoting duplicate rows, optionally only considering certain columns

Parameters subset : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

For a set of distinct duplicate rows, flag all but the last row as duplicated. Default is for all but the first row to be flagged

cols : kwargs only argument of subset [deprecated]

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*, ***kwargs*)

Evaluate an expression in the context of the calling DataFrame instance.

Parameters expr : string

The expression string to evaluate.

kwargs : dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

Returns ret : ndarray, scalar, or pandas object

See also:

`pandas.DataFrame.query`, `pandas.eval`

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

pandas.DataFrame.ffill

`DataFrame.ffill(axis=None, inplace=False, limit=None, downcast=None)`
Synonym for NDFrame.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, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : DataFrame

See also:

`reindex`, `asfreq`

pandas.DataFrame.filter

`DataFrame.filter(items=None, like=None, regex=None, axis=None)`
Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]]}); df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

`DataFrame.first(offset)`
Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.DataFrame.first_valid_index

`DataFrame.first_valid_index()`
Return label for first non-NA/null value

pandas.DataFrame.floordiv

`DataFrame.floordiv(other, axis='columns', level=None, fill_value=None)`
Integer division of dataframe and other, element-wise (binary operator *floordiv*).

Equivalent to `dataframe // other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rfloordiv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.from_csv

classmethod `DataFrame.from_csv`(*path*, *header=0*, *sep=','*, *index_col=0*, *parse_dates=True*, *encoding=None*, *tupleize_cols=False*, *infer_datetime_format=False*)

Read delimited file into DataFrame

Parameters **path** : string file path or file handle / StringIO

header : int, default 0

Row to use at 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

Notes

Preferable to use read_table for most general purposes but from_csv makes for an easy roundtrip to and from file, especially with a DataFrame of time series data

pandas.DataFrame.from_dict

classmethod `DataFrame.from_dict`(*data*, *orient='columns'*, *dtype=None*)

Construct DataFrame from dict of array-like or dicts

Parameters **data** : dict

{field : array-like} or {field : dict}

orient : {'columns', 'index'}, default 'columns'

The "orientation" of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass 'columns' (default). Otherwise if the keys should be rows, pass 'index'.

dtype : dtype, default None

Data type to force, otherwise infer

Returns DataFrame

pandas.DataFrame.from_items

classmethod `DataFrame.from_items`(*items*, *columns=None*, *orient='columns'*)

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

Parameters **items** : sequence of (key, value) pairs

Values should be arrays or Series.

columns : sequence of column labels, optional

Must be passed if orient='index'.

orient : {'columns', 'index'}, default 'columns'

The "orientation" of the data. If the keys of the input correspond to column labels, pass 'columns' (default). Otherwise if the keys correspond to the index, pass 'index'.

Returns **frame** : DataFrame

pandas.DataFrame.from_records

classmethod `DataFrame.from_records`(*data*, *index=None*, *exclude=None*, *columns=None*, *coerce_float=False*, *nrows=None*)

Convert structured or record ndarray to DataFrame

Parameters **data** : ndarray (structured dtype), list of tuples, dict, or DataFrame

index : string, list of fields, array-like

Field of array to use as the index, alternately a specific set of input labels to use

exclude : sequence, default None

Columns or fields to exclude

columns : sequence, default None

Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns)

coerce_float : boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

Returns df : DataFrame

pandas.DataFrame.ge

`DataFrame.ge(other, axis='columns', level=None)`

Wrapper for flexible comparison methods ge

pandas.DataFrame.get

`DataFrame.get(key, default=None)`

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters key : object

Returns value : type of items contained in object

pandas.DataFrame.get_dtype_counts

`DataFrame.get_dtype_counts()`

Return the counts of dtypes in this object

pandas.DataFrame.get_ftype_counts

`DataFrame.get_ftype_counts()`

Return the counts of ftypes in this object

pandas.DataFrame.get_value

`DataFrame.get_value(index, col, takeable=False)`

Quickly retrieve single value at passed column and index

Parameters index : row label

col : column label

takeable : interpret the index/col as indexers, default False

Returns value : scalar value

pandas.DataFrame.get_values

`DataFrame.get_values()`

same as values (but handles sparseness conversions)

pandas.DataFrame.groupby

`DataFrame.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False)`

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

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

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionaility of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

pandas.DataFrame.gt

`DataFrame.gt(other, axis='columns', level=None)`

Wrapper for flexible comparison methods gt

pandas.DataFrame.head

`DataFrame.head(n=5)`

Returns first n rows

pandas.DataFrame.hist

`DataFrame.hist(data, column=None, by=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, ax=None, sharex=False, sharey=False, figsize=None, layout=None, bins=10, **kwds)`

Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters data : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.DataFrame.icol

DataFrame.**icol**(*i*)

pandas.DataFrame.idxmax

DataFrame.**idxmax**(*axis=0*, *skipna=True*)

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns **idxmax** : Series

See also:

`Series.idxmax`

Notes

This method is the DataFrame version of `ndarray.argmax`.

pandas.DataFrame.idxmin

DataFrame.**idxmin**(*axis=0*, *skipna=True*)

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **idxmin** : Series

See also:

`Series.idxmin`

Notes

This method is the DataFrame version of `ndarray.argmin`.

pandas.DataFrame.iget_value

DataFrame.**iget_value**(*i*, *j*)

pandas.DataFrame.info

`DataFrame.info`(*verbose=None*, *buf=None*, *max_cols=None*, *memory_usage=None*, *null_counts=None*)

Concise summary of a DataFrame.

Parameters **verbose** : {None, True, False}, optional

Whether to print the full summary. None follows the *display.max_info_columns* setting. True or False overrides the *display.max_info_columns* setting.

buf : writable buffer, defaults to sys.stdout

max_cols : int, default None

Determines whether full summary or short summary is printed. None follows the *display.max_info_columns* setting.

memory_usage : boolean, default None

Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the *display.memory_usage* setting. True or False overrides the *display.memory_usage* setting. Memory usage is shown in human-readable units (base-2 representation).

null_counts : boolean, default None

Whether to show the non-null counts If None, then only show if the frame is smaller than max_info_rows and max_info_columns. If True, always show counts. If False, never show counts.

pandas.DataFrame.insert

`DataFrame.insert`(*loc*, *column*, *value*, *allow_duplicates=False*)

Insert column into DataFrame at specified location.

If *allow_duplicates* is False, raises Exception if column is already contained in the DataFrame.

Parameters **loc** : int

Must have 0 <= loc <= len(columns)

column : object

value : int, Series, or array-like

pandas.DataFrame.interpolate

`DataFrame.interpolate`(*method='linear'*, *axis=0*, *limit=None*, *inplace=False*, *downcast=None*, ***kwargs*)

Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. 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* with the order given both 'polynomial' and 'spline' requre that you also specify and order (int) e.g. df.interpolate(method='polynomial', order=4)
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html

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.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.DataFrame.irow

`DataFrame.irow(i, copy=False)`

pandas.DataFrame.isin

`DataFrame.isin(values)`

Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters **values** : iterable, Series, DataFrame or dictionary

The result will only be true at a location if all the labels match. If *values* is a Series, that's the index. If *values* is a dictionary, the keys must be the column names, which must match. If *values* is a DataFrame, then both the index and column labels must match.

Returns DataFrame of booleans

Examples

When `values` is a list:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
       A      B
0   True   True
1  False  False
2   True  False
```

When `values` is a dict:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
       A      B
0   True  False  # Note that B didn't match the 1 here.
1  False   True
2   True   True
```

When `values` is a Series or DataFrame:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
       A      B
0   True  False
1  False  False  # Column A in `other` has a 3, but not at index 1.
2   True   True
```

pandas.DataFrame.isnull

`DataFrame.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.DataFrame.iteritems

`DataFrame.iteritems()`

Iterator over (column, series) pairs

pandas.DataFrame.iterkv

`DataFrame.iterkv(*args, **kwargs)`

iteritems alias used to get around 2to3. Deprecated

pandas.DataFrame.iterrows

`DataFrame.iterrows()`

Iterate over rows of DataFrame as (index, Series) pairs.

Returns it : generator

A generator that iterates over the rows of the frame.

Notes

- `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = DataFrame([[1, 1.0]], columns=['x', 'y'])
>>> row = next(df.iterrows())[1]
>>> print(row['x'].dtype)
float64
>>> print(df['x'].dtype)
int64
```

pandas.DataFrame.itertuples

`DataFrame.itertuples(`*index=True*`)`

Iterate over rows of DataFrame as tuples, with index value as first element of the tuple

pandas.DataFrame.join

`DataFrame.join(`*other*, *on=None*, *how='left'*, *lsuffix='‘*, *rsuffix='‘*, *sort=False*`)`

Join columns with other DataFrame either on index or on a key column. Efficiently Join multiple DataFrame objects by index at once by passing a list.

Parameters other : DataFrame, Series with name field set, or list of DataFrame

Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame

on : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation

how : {‘left’, ‘right’, ‘outer’, ‘inner’}

How to handle indexes of the two objects. Default: ‘left’ for joining on index, None otherwise

- left: use calling frame’s index
- right: use input frame’s index
- outer: form union of indexes
- inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

sort : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

Returns **joined** : DataFrame

Notes

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

pandas.DataFrame.keys

`DataFrame.keys()`

Get the 'info axis' (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.DataFrame.kurt

`DataFrame.kurt`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Series or DataFrame (if level specified)

pandas.DataFrame.kurtosis

`DataFrame.kurtosis`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Series or DataFrame (if level specified)

pandas.DataFrame.last

`DataFrame.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.DataFrame.last_valid_index

`DataFrame.last_valid_index()`

Return label for last non-NA/null value

pandas.DataFrame.le

`DataFrame.le(other, axis='columns', level=None)`

Wrapper for flexible comparison methods le

pandas.DataFrame.load

`DataFrame.load(path)`

Deprecated. Use read_pickle instead.

pandas.DataFrame.lookup

`DataFrame.lookup(row_labels, col_labels)`

Label-based "fancy indexing" function for DataFrame. Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

Parameters **row_labels** : sequence

The row labels to use for lookup

col_labels : sequence

The column labels to use for lookup

Notes

Akin to:

```
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))
```

Examples

values [ndarray] The found values

pandas.DataFrame.lt

DataFrame.**lt**(*other*, *axis='columns'*, *level=None*)
Wrapper for flexible comparison methods lt

pandas.DataFrame.mad

DataFrame.**mad**(*axis=None*, *skipna=None*, *level=None*)
Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Series or DataFrame (if level specified)

pandas.DataFrame.mask

DataFrame.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)
Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.DataFrame.max

`DataFrame.`**`max`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : Series or DataFrame (if level specified)

pandas.DataFrame.mean

`DataFrame.`**`mean`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values for the requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mean : Series or DataFrame (if level specified)

pandas.DataFrame.median

`DataFrame.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the median of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : Series or DataFrame (if level specified)

pandas.DataFrame.memory_usage

`DataFrame.memory_usage(index=False)`

Memory usage of DataFrame columns.

Parameters **index** : bool

Specifies whether to include memory usage of DataFrame's index in returned Series. If *index=True* (default is False) the first index of the Series is *Index*.

Returns **sizes** : Series

A series with column names as index and memory usage of columns with units of bytes.

See also:

`numpy.ndarray.nbytes`

Notes

Memory usage does not include memory consumed by elements that are not components of the array.

pandas.DataFrame.merge

`DataFrame.merge(right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True)`

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters **right** : DataFrame

how : {'left', 'right', 'outer', 'inner'}, default 'inner'

- left: use only keys from left frame (SQL: left outer join)

- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

left_on : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

right_on : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per left_on docs

left_index : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

right_index : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns merged : DataFrame

The output type will the be same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A              >>> B
    lkey value         rkey value
0   foo  1         0   foo  5
1   bar  2         1   bar  6
2   baz  3         2   qux  7
3   foo  4         3   bar  8

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  foo   1        foo   5
1  foo   4        foo   5
2  bar   2        bar   6
3  bar   2        bar   8
```

```
4   baz    3         NaN   NaN
5   NaN    NaN       qux   7
```

pandas.DataFrame.min

`DataFrame.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : Series or DataFrame (if level specified)

pandas.DataFrame.mod

`DataFrame.mod(other, axis='columns', level=None, fill_value=None)`

Modulo of dataframe and other, element-wise (binary operator *mod*).

Equivalent to `dataframe % other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rmod`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mode

`DataFrame.mode(axis=0, numeric_only=False)`

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe `df`, you can just do this: `df.fillna(df.mode().iloc[0])`

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

- 0 or 'index' : get mode of each column
- 1 or 'columns' : get mode of each row

numeric_only : boolean, default False

if True, only apply to numeric columns

Returns **modes** : DataFrame (sorted)

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
   A
0  1
1  2
```

pandas.DataFrame.mul

`DataFrame.mul(other, axis='columns', level=None, fill_value=None)`

Multiplication of dataframe and other, element-wise (binary operator *mul*).

Equivalent to `dataframe * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rmul`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.multiply

`DataFrame.multiply(other, axis='columns', level=None, fill_value=None)`
Multiplication of dataframe and other, element-wise (binary operator *mul*).

Equivalent to `dataframe * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rmul`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.ne

`DataFrame.ne(other, axis='columns', level=None)`
Wrapper for flexible comparison methods ne

pandas.DataFrame.notnull

`DataFrame.notnull()`
Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

pandas.DataFrame.pct_change

`DataFrame.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.DataFrame.pipe

`DataFrame.pipe(func, *args, **kwargs)`

Apply func(self, *args, **kwargs)

New in version 0.16.2.

Parameters **func** : function

function to apply to the NDFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the NDFrame.

args : positional arguments passed into `func`.

kwargs : a dictionary of keyword arguments passed into `func`.

Returns **object** : the return type of `func`.

See also:

`pandas.DataFrame.apply`, `pandas.DataFrame.applymap`, `pandas.Series.map`

Notes

Use `.pipe` when chaining together functions that expect on Series or DataFrames. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (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`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((f, 'arg2'), arg1=a, arg3=c)
...  )
```

pandas.DataFrame.pivot

`DataFrame.pivot`(*index=None*, *columns=None*, *values=None*)

Reshape data (produce a "pivot" table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

Parameters **index** : string or object

Column name to use to make new frame's index

columns : string or object

Column name to use to make new frame's columns

values : string or object, optional

Column name to use for populating new frame's values

Returns **pivoted** : DataFrame

If no values column specified, will have hierarchically indexed columns

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

Examples

```
>>> df
    foo   bar  baz
0   one   A    1.
1   one   B    2.
2   one   C    3.
3   two   A    4.
4   two   B    5.
5   two   C    6.

>>> df.pivot('foo', 'bar', 'baz')
     A   B   C
one  1   2   3
two  4   5   6
```

```
>>> df.pivot('foo', 'bar')['baz']
     A   B   C
one  1   2   3
two  4   5   6
```

pandas.DataFrame.pivot_table

DataFrame.**pivot_table**(*data*, *values=None*, *index=None*, *columns=None*, *aggfunc='mean'*, *fill_value=None*, *margins=False*, *dropna=True*)

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame

Parameters **data** : DataFrame

values : column to aggregate, optional

index : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, default numpy.mean, or list of functions

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves)

fill_value : scalar, default None

Value to replace missing values with

margins : boolean, default False

Add all row / columns (e.g. for subtotal / grand totals)

dropna : boolean, default True

Do not include columns whose entries are all NaN

Returns **table** : DataFrame

Examples

```
>>> df
   A   B   C      D
0  foo one small  1
1  foo one large  2
2  foo one large  2
3  foo two small  3
4  foo two small  3
5  bar one large  4
6  bar one small  5
7  bar two small  6
8  bar two large  7
```

```
>>> table = pivot_table(df, values='D', index=['A', 'B'],
...                     columns=['C'], aggfunc=np.sum)
>>> table
          small  large
foo  one  1      4
     two  6      NaN
bar  one  5      4
     two  6      7
```

pandas.DataFrame.plot

`DataFrame.plot`(*data, 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.

Parameters **data** : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns **axes** : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)
- If *kind* = 'scatter' and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = 'hexbin', you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each *(x, y)* point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each *(x, y)* point and *reduce_C_function* is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

pandas.DataFrame.pop

`DataFrame.pop(item)`

Return item and drop from frame. Raise KeyError if not found.

pandas.DataFrame.pow

`DataFrame.pow`(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Exponential power of dataframe and other, element-wise (binary operator *pow*).

Equivalent to `dataframe ** other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rpow`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.prod

`DataFrame.prod`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Series or DataFrame (if level specified)

pandas.DataFrame.product

`DataFrame.product`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Series or DataFrame (if level specified)

pandas.DataFrame.quantile

DataFrame.**quantile**(*q=0.5*, *axis=0*, *numeric_only=True*)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

axis : {0, 1, 'index', 'columns'} (default 0)

0 or 'index' for row-wise, 1 or 'columns' for column-wise

Returns **quantiles** : Series or DataFrame

If `q` is an array, a DataFrame will be returned where the index is `q`, the columns are the columns of self, and the values are the quantiles. If `q` is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                  columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
       a     b
0.1  1.3   3.7
0.5  2.5  55.0
```

pandas.DataFrame.query

DataFrame.**query**(*expr*, ***kwargs*)

Query the columns of a frame with a boolean expression.

New in version 0.13.

Parameters **expr** : string

The query string to evaluate. You can refer to variables in the environment by prefixing them with an '@' character like `@a + b`.

kwargs : dict

See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

Returns q : DataFrame

See also:

`pandas.eval`, `DataFrame.eval`

Notes

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `pandas.eval()` function to evaluate the passed query.

The `query()` method uses a slightly modified Python syntax by default. For example, the `&` and `|` (bitwise) operators have the precedence of their boolean cousins, `and` and `or`. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The `DataFrame.index` and `DataFrame.columns` attributes of the `DataFrame` instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query.

For further details and examples see the `query` documentation in *indexing*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = 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

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.add`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rank

`DataFrame.`**`rank`**(*axis=0*, *numeric_only=None*, *method='average'*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep', 'top', 'bottom'}

- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : DataFrame

pandas.DataFrame.rdiv

`DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)`

Floating division of dataframe and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.truediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.reindex

`DataFrame.reindex(index=None, columns=None, **kwargs)`

Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **index, columns** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : DataFrame

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.DataFrame.reindex_axis

DataFrame.**reindex_axis**(*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters labels : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 'index', 'columns'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : DataFrame

See also:

reindex, reindex_like

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.DataFrame.reindex_like

`DataFrame.reindex_like(other, method=None, copy=True, limit=None)`

return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.DataFrame.rename

`DataFrame.rename(index=None, columns=None, **kwargs)`

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **index, columns** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new DataFrame. If True then value of copy is ignored.

Returns **renamed** : DataFrame (new object)

pandas.DataFrame.rename_axis

`DataFrame.rename_axis(mapper, axis=0, copy=True, inplace=False)`

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **mapper** : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns **renamed** : type of caller

pandas.DataFrame.reorder_levels

`DataFrame.reorder_levels(order, axis=0)`

Rearrange index levels using input order. May not drop or duplicate levels

Parameters **order** : list of int or list of str

List representing new level order. Reference level by number (position) or by key (label).

axis : int

Where to reorder levels.

Returns type of caller (new object)

pandas.DataFrame.replace

`DataFrame.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)`

Replace values given in 'to_replace' with 'value'.

Parameters **to_replace** : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.
- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.DataFrame.resample

`DataFrame.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.DataFrame.reset_index

`DataFrame.reset_index(level=None, drop=False, inplace=False, col_level=0, col_fill='')`

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

Parameters **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns. This resets the index to the default integer index.

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

col_level : int or str, default 0

If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

col_fill : object, default ‘’

If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

Returns resetted : DataFrame

pandas.DataFrame.rfloordiv

`DataFrame.rfloordiv(other, axis='columns', level=None, fill_value=None)`

Integer division of dataframe and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.floordiv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmod

`DataFrame.rmod(other, axis='columns', level=None, fill_value=None)`

Modulo of dataframe and other, element-wise (binary operator *rmod*).

Equivalent to `other % dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.mod`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

`DataFrame.`**`rmul`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Multiplication of dataframe and other, element-wise (binary operator *rmul*).

Equivalent to `other * dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.mul`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rpow

`DataFrame.`**`rpow`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Exponential power of dataframe and other, element-wise (binary operator *rpow*).

Equivalent to `other ** dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.pow`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rsub

`DataFrame.`**`rsub`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Subtraction of dataframe and other, element-wise (binary operator *rsub*).

Equivalent to `other - dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.sub`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.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

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.truediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.sample

`DataFrame.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.DataFrame.save

`DataFrame.save(path)`

Deprecated. Use to_pickle instead

pandas.DataFrame.select

`DataFrame.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.DataFrame.select_dtypes

`DataFrame.select_dtypes(include=None, exclude=None)`

Return a subset of a DataFrame including/excluding columns based on their `dtype`.

Parameters **include, exclude** : list-like

A list of dtypes or strings to be included/excluded. You must pass in a non-empty sequence for at least one of these.

Returns **subset** : DataFrame

The subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.

Raises **ValueError**

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

TypeError

- If either of `include` or `exclude` is not a sequence

Notes

- To select all *numeric* types use the numpy dtype `numpy.number`

- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the numpy dtype hierarchy
- To select Pandas categorical dtypes, use 'category'

Examples

```
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
        a      b  c
0  0.3962   True  1
1  0.1459  False  2
2  0.2623   True  1
3  0.0764  False  2
4 -0.9703   True  1
5 -1.2094  False  2
>>> df.select_dtypes(include=['float64'])
   c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
       b
0   True
1  False
2   True
3  False
4   True
5  False
```

pandas.DataFrame.sem

`DataFrame.`**`sem`**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sem** : Series or DataFrame (if level specified)

pandas.DataFrame.set_axis

`DataFrame.set_axis(axis, labels)`
public verson of axis assignment

pandas.DataFrame.set_index

`DataFrame.set_index(keys, drop=True, append=False, inplace=False, verify_integrity=False)`
Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

Parameters **keys** : column label or list of column labels / arrays

drop : boolean, default True

Delete columns to be used as the new index

append : boolean, default False

Whether to append columns to existing index

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

verify_integrity : boolean, default False

Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method

Returns **dataframe** : DataFrame

Examples

```
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

pandas.DataFrame.set_value

`DataFrame.set_value(index, col, value, takeable=False)`
Put single value at passed column and index

Parameters **index** : row label

col : column label

value : scalar value

takeable : interpret the index/col as indexers, default False

Returns **frame** : DataFrame

If label pair is contained, will be reference to calling DataFrame, otherwise a new object

pandas.DataFrame.shift

`DataFrame.shift(periods=1, freq=None, axis=0, **kwargs)`

Shift index by desired number of periods with an optional time freq

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns **shifted** : DataFrame

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.DataFrame.skew

`DataFrame.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Series or DataFrame (if level specified)

pandas.DataFrame.slice_shift

`DataFrame.slice_shift(periods=1, axis=0)`

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.DataFrame.sort

DataFrame.**sort**(*columns=None*, *axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in column(s)

Parameters **columns** : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

axis : {0 or 'index', 1 or 'columns'}, default 0

Sort index/rows versus columns

inplace : boolean, default False

Sort the DataFrame without creating a new instance

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

pandas.DataFrame.sort_index

DataFrame.**sort_index**(*axis=0*, *by=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in a column

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

Sort index/rows versus columns

by : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

inplace : boolean, default False

Sort the DataFrame without creating a new instance

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort_index(by=['A', 'B'], ascending=[True, False])
```

pandas.DataFrame.sortlevel

DataFrame.**sortlevel**(*level=0, axis=0, ascending=True, inplace=False, sort_remaining=True*)

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters **level** : int

axis : {0 or 'index', 1 or 'columns'}, default 0

ascending : boolean, default True

inplace : boolean, default False

Sort the DataFrame without creating a new instance

sort_remaining : boolean, default True

Sort by the other levels too.

Returns **sorted** : DataFrame

pandas.DataFrame.squeeze

DataFrame.**squeeze**()

squeeze length 1 dimensions

pandas.DataFrame.stack

DataFrame.**stack**(*level=-1, dropna=True*)

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default last level

Level(s) to stack, can pass level name

dropna : boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

Returns **stacked** : DataFrame or Series

Examples

```
>>> s
     a   b
one  1.  2.
two  3.  4.

>>> s.stack()
one a    1
    b    2
two a    3
    b    4
```

pandas.DataFrame.std

`DataFrame.std`(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : Series or DataFrame (if level specified)

pandas.DataFrame.sub

`DataFrame.sub`(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Subtraction of dataframe and other, element-wise (binary operator *sub*).

Equivalent to `dataframe - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rsub`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.subtract

`DataFrame.`**`subtract`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Subtraction of dataframe and other, element-wise (binary operator *sub*).

Equivalent to `dataframe - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rsub`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.sum

`DataFrame.`**`sum`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : Series or DataFrame (if level specified)

pandas.DataFrame.swapaxes

`DataFrame.`**`swapaxes`**(*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns **y** : same as input

pandas.DataFrame.swaplevel

`DataFrame.`**`swaplevel`**(*i*, *j*, *axis=0*)

Swap levels i and j in a MultiIndex on a particular axis

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)

pandas.DataFrame.tail

`DataFrame.`**`tail`**(*n=5*)

Returns last n rows

pandas.DataFrame.take

`DataFrame.`**`take`**(*indices*, *axis=0*, *convert=True*, *is_copy=True*)

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.DataFrame.to_clipboard

`DataFrame.`**`to_clipboard`**(*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.DataFrame.to_csv

DataFrame.**to_csv**(*path_or_buf=None*, *sep=', '*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *mode='w'*, *encoding=None*, *quoting=None*, *quotechar='"'*, *line_terminator='\n'*, *chunksize=None*, *tupleize_cols=False*, *date_format=None*, *doublequote=True*, *escapechar=None*, *decimal='.'*, ***kwds*)

Write DataFrame to a comma-separated values (csv) file

Parameters path_or_buf : string or file handle, default None

File path or object, if None is provided the result is returned as a string.

sep : character, default ","

Field delimiter for the output file.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, or False, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R

nanRep : None

deprecated, use na_rep

mode : str

Python write mode, default 'w'

encoding : string, optional

A string representing the encoding to use in the output file, defaults to 'ascii' on Python 2 and 'utf-8' on Python 3.

line_terminator : string, default '\n'

The newline character or character sequence to use in the output file

quoting : optional constant from csv module

defaults to csv.QUOTE_MINIMAL

quotechar : string (length 1), default '"'

character used to quote fields

doublequote : boolean, default True

Control quoting of *quotechar* inside a field

escapechar : string (length 1), default None

character used to escape *sep* and *quotechar* when appropriate

chunksize : int or None

rows to write at a time

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False)

date_format : string, default None

Format string for datetime objects

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

New in version 0.16.0.

pandas.DataFrame.to_dense

`DataFrame.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.DataFrame.to_dict

`DataFrame.to_dict(*args, **kwargs)`

Convert DataFrame to dictionary.

Parameters **orient** : str {'dict', 'list', 'series', 'split', 'records'}

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}]

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

Returns **result** : dict like {column -> {index -> value}}

pandas.DataFrame.to_excel

`DataFrame.to_excel`(*excel_writer*, *sheet_name='Sheet1'*, *na_rep='‘*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *startrow=0*, *startcol=0*, *engine=None*, *merge_cells=True*, *encoding=None*, *inf_rep='inf'*)

Write DataFrame to a excel sheet

Parameters **excel_writer** : string or ExcelWriter object

File path or existing ExcelWriter

sheet_name : string, default ‘Sheet1’

Name of sheet which will contain DataFrame

na_rep : string, default ‘’

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow :

upper left cell row to dump data frame

startcol :

upper left cell column to dump data frame

engine : string, default None

write engine to use - you can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

merge_cells : boolean, default True

Write MultiIndex and Hierarchical Rows as merged cells.

encoding: string, default None

encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep : string, default 'inf'

Representation for infinity (there is no native representation for infinity in Excel)

Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook:

```
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer,'Sheet1')
>>> df2.to_excel(writer,'Sheet2')
>>> writer.save()
```

pandas.DataFrame.to_gbq

DataFrame.**to_gbq**(*destination_table*, *project_id=None*, *chunksize=10000*, *verbose=True*, *reauth=False*)

Write a DataFrame to a Google BigQuery table.

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If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The to_gbq method chunks data into a default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: https://developers.google.com/bigquery/streaming-data-into-bigquery.

Parameters **dataframe** : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

pandas.DataFrame.to_hdf

`DataFrame.to_hdf`(*path_or_buf*, *key*, ***kwargs*)
activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.DataFrame.to_html

`DataFrame.to_html`(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *bold_rows=True*, *classes=None*, *escape=True*, *max_rows=None*, *max_cols=None*, *show_dimensions=False*, *notebook=False*)
Render a DataFrame as an HTML table.

to_html-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table

escape [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences.=

max_rows [int, optional] Maximum number of rows to show before truncating. If None, show all.

max_cols [int, optional] Maximum number of columns to show before truncating. If None, show all.

Parameters frame : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_json

DataFrame.**to_json**(*path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}
  - columns : dict like {column -> {index -> value}}
  - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso*' = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.DataFrame.to_latex

`DataFrame.to_latex`(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *bold_rows=True*, *longtable=False*, *escape=True*)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires usepackage{booktabs}.

to_latex-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

longtable [boolean, default False] Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.

escape [boolean, default True] When set to False prevents from escaping latex special characters in column names.

Parameters **frame** : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_msgpack

`DataFrame.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.DataFrame.to_panel

`DataFrame.to_panel()`

Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns panel : Panel

pandas.DataFrame.to_period

`DataFrame.to_period(freq=None, axis=0, copy=True)`

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters freq : string, default

axis : {0 or 'index', 1 or 'columns'}, default 0

The axis to convert (the index by default)

copy : boolean, default True

If False then underlying input data is not copied

Returns ts : TimeSeries with PeriodIndex

pandas.DataFrame.to_pickle

DataFrame.**to_pickle**(*path*)

Pickle (serialize) object to input file path

Parameters path : string

File path

pandas.DataFrame.to_records

DataFrame.**to_records**(*index=True*, *convert_datetime64=True*)

Convert DataFrame to record array. Index will be put in the 'index' field of the record array if requested

Parameters index : boolean, default True

Include index in resulting record array, stored in 'index' field

convert_datetime64 : boolean, default True

Whether to convert the index to datetime.datetime if it is a DatetimeIndex

Returns y : recarray

pandas.DataFrame.to_sparse

DataFrame.**to_sparse**(*fill_value=None*, *kind='block'*)

Convert to SparseDataFrame

Parameters fill_value : float, default NaN

kind : {'block', 'integer'}

Returns y : SparseDataFrame

pandas.DataFrame.to_sql

DataFrame.**to_sql**(*name*, *con*, *flavor='sqlite'*, *schema=None*, *if_exists='fail'*, *index=True*, *index_label=None*, *chunksize=None*, *dtype=None*)

Write records stored in a DataFrame to a SQL database.

Parameters name : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.DataFrame.to_stata

DataFrame.**to_stata**(*fname*, *convert_dates=None*, *write_index=True*, *encoding='latin-1'*, *byteorder=None*, *time_stamp=None*, *data_label=None*)

A class for writing Stata binary dta files from array-like objects

Parameters **fname** : file path or buffer

Where to save the dta file.

convert_dates : dict

Dictionary mapping column of datetime types to the stata internal format that you want to use for the dates. Options are 'tc', 'td', 'tm', 'tw', 'th', 'tq', 'ty'. Column can be either a number or a name.

encoding : str

Default is latin-1. Note that Stata does not support unicode.

byteorder : str

Can be ">", "<", "little", or "big". The default is None which uses *sys.byteorder*

Examples

```
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

Or with dates

```
>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```

pandas.DataFrame.to_string

DataFrame.**to_string**(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *line_width=None*, *max_rows=None*, *max_cols=None*, *show_dimensions=False*)

Render a DataFrame to a console-friendly tabular output.

Parameters **frame** : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_timestamp

`DataFrame.`**`to_timestamp`**(*freq=None*, *how='start'*, *axis=0*, *copy=True*)

Cast to DatetimeIndex of timestamps, at *beginning* of period

Parameters freq : string, default frequency of PeriodIndex

Desired frequency

how : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

axis : {0 or 'index', 1 or 'columns'}, default 0

The axis to convert (the index by default)

copy : boolean, default True

If false then underlying input data is not copied

Returns df : DataFrame with DatetimeIndex

pandas.DataFrame.to_wide

`DataFrame.`**`to_wide`**(**args*, ***kwargs*)

pandas.DataFrame.transpose

`DataFrame.`**`transpose`**()

Transpose index and columns

pandas.DataFrame.truediv

`DataFrame.`**`truediv`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.rtruediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.truncate

`DataFrame.`**`truncate`**(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

pandas.DataFrame.tshift

`DataFrame.`**`tshift`**(*periods=1*, *freq=None*, *axis=0*, ***kwargs*)

Shift the time index, using the index's frequency if available

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, default None

Increment to use from datetools module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns **shifted** : NDFrame

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.DataFrame.tz_convert

`DataFrame.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.DataFrame.tz_localize

`DataFrame.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

pandas.DataFrame.unstack

`DataFrame.unstack(level=-1)`

Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels. If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex). The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default -1 (last level)

Level(s) of index to unstack, can pass level name

Returns **unstacked** : DataFrame or Series

See also:

DataFrame.pivot Pivot a table based on column values.

DataFrame.stack Pivot a level of the column labels (inverse operation from *unstack*).

Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                    ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one  a   1
     b   2
two  a   3
     b   4
dtype: float64
```

```
>>> s.unstack(level=-1)
     a   b
one  1  2
two  3  4
```

```
>>> s.unstack(level=0)
   one  two
a  1   3
b  2   4
```

```
>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.
     b  3.
two  a  2.
     b  4.
```

pandas.DataFrame.update

DataFrame.**update**(*other*, *join='left'*, *overwrite=True*, *filter_func=None*, *raise_conflict=False*)

Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

Parameters **other** : DataFrame, or object coercible into a DataFrame

join : {'left'}, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : boolean

If True, will raise an error if the DataFrame and other both contain data in the same place.

pandas.DataFrame.var

`DataFrame.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Series or DataFrame (if level specified)

pandas.DataFrame.where

`DataFrame.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.DataFrame.xs

DataFrame.**xs**(*key*, *axis=0*, *level=None*, *copy=None*, *drop_level=True*)

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters key : object

Some label contained in the index, or partially in a MultiIndex

axis : int, default 0

Axis to retrieve cross-section on

level : object, defaults to first n levels (n=1 or len(key))

In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

copy : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns xs : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultiIndex Slicers*

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
Name: a
>>> df.xs('C', axis=1)
a    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
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
```

33.4.2 Attributes and underlying data

Axes

- **index**: row labels
- **columns**: column labels

DataFrame.as_matrix([columns])	Convert the frame to its Numpy-array representation.
DataFrame.dtypes	Return the dtypes in this object
DataFrame.ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
DataFrame.get_dtype_counts()	Return the counts of dtypes in this object
DataFrame.get_ftype_counts()	Return the counts of ftypes in this object
DataFrame.select_dtypes([include, exclude])	Return a subset of a DataFrame including/excluding columns based on their
DataFrame.values	Numpy representation of NDFrame
DataFrame.axes	
DataFrame.ndim	Number of axes / array dimensions
DataFrame.size	number of elements in the NDFrame
DataFrame.shape	

pandas.DataFrame.as_matrix

DataFrame.**as_matrix**(*columns=None*)

Convert the frame to its Numpy-array representation.

Parameters columns: list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

Returns values : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

pandas.DataFrame.values

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use '.values'.

pandas.DataFrame.dtypes

`DataFrame.`**`dtypes`**

Return the dtypes in this object

pandas.DataFrame.ftypes

`DataFrame.`**`ftypes`**

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.get_dtype_counts

`DataFrame.`**`get_dtype_counts`**`()`

Return the counts of dtypes in this object

pandas.DataFrame.get_ftype_counts

`DataFrame.`**`get_ftype_counts`**`()`

Return the counts of ftypes in this object

pandas.DataFrame.select_dtypes

`DataFrame.`**`select_dtypes`**`(`*include=None*, *exclude=None*`)`

Return a subset of a DataFrame including/excluding columns based on their `dtype`.

Parameters **include, exclude** : list-like

A list of dtypes or strings to be included/excluded. You must pass in a non-empty sequence for at least one of these.

Returns **subset** : DataFrame

The subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.

Raises **ValueError**

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

TypeError

- If either of `include` or `exclude` is not a sequence

Notes

- To select all *numeric* types use the numpy dtype `numpy.number`
- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the numpy dtype hierarchy
- To select Pandas categorical dtypes, use 'category'

Examples

```
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
        a      b  c
0  0.3962   True  1
1  0.1459  False  2
2  0.2623   True  1
3  0.0764  False  2
4 -0.9703   True  1
5 -1.2094  False  2
>>> df.select_dtypes(include=['float64'])
   c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
       b
0   True
1  False
2   True
3  False
4   True
5  False
```

pandas.DataFrame.values

`DataFrame.`**`values`**

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.DataFrame.axes

`DataFrame.axes`

pandas.DataFrame.ndim

`DataFrame.ndim`
Number of axes / array dimensions

pandas.DataFrame.size

`DataFrame.size`
number of elements in the NDFrame

pandas.DataFrame.shape

`DataFrame.shape`

33.4.3 Conversion

`DataFrame.astype`(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
`DataFrame.convert_objects`([convert_dates, ...])	Attempt to infer better dtype for object columns
`DataFrame.copy`([deep])	Make a copy of this object
`DataFrame.isnull`()	Return a boolean same-sized object indicating if the values are null
`DataFrame.notnull`()	Return a boolean same-sized object indicating if the values are

pandas.DataFrame.astype

`DataFrame.astype`(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

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

Parameters **convert_dates** : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.DataFrame.copy

`DataFrame.copy(deep=True)`

Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.DataFrame.isnull

`DataFrame.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.DataFrame.notnull

`DataFrame.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

33.4.4 Indexing, iteration

`DataFrame.head([n])`	Returns first n rows
`DataFrame.at`	Fast label-based scalar accessor
`DataFrame.iat`	Fast integer location scalar accessor.
`DataFrame.ix`	A primarily label-location based indexer, with integer position fallback.

Table 33.54 – continued from previous page

DataFrame.loc	Purely label-location based indexer for selection by label.
DataFrame.iloc	Purely integer-location based indexing for selection by position.
DataFrame.insert(loc, column, value[, ...])	Insert column into DataFrame at specified location.
DataFrame.__iter__()	Iterate over infor axis
DataFrame.iteritems()	Iterator over (column, series) pairs
DataFrame.iterrows()	Iterate over rows of DataFrame as (index, Series) pairs.
DataFrame.itertuples([index])	Iterate over rows of DataFrame as tuples, with index value
DataFrame.lookup(row_labels, col_labels)	Label-based "fancy indexing" function for DataFrame.
DataFrame.pop(item)	Return item and drop from frame.
DataFrame.tail([n])	Returns last n rows
DataFrame.xs(key[, axis, level, copy, ...])	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
DataFrame.isin(values)	Return boolean DataFrame showing whether each element in the DataFrame is
DataFrame.where(cond[, other, inplace, ...])	Return an object of same shape as self and whose corresponding entries are fro
DataFrame.mask(cond[, other, inplace, axis, ...])	Return an object of same shape as self and whose corresponding entries are fro
DataFrame.query(expr, **kwargs)	Query the columns of a frame with a boolean expression.

pandas.DataFrame.head

DataFrame.**head**(*n=5*)

Returns first n rows

pandas.DataFrame.at

DataFrame.**at**

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.DataFrame.iat

DataFrame.**iat**

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.DataFrame.ix

DataFrame.**ix**

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.DataFrame.loc

`DataFrame.loc`

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.DataFrame.iloc

`DataFrame.iloc`

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.DataFrame.insert

`DataFrame.insert(loc, column, value, allow_duplicates=False)`

Insert column into DataFrame at specified location.

If *allow_duplicates* is False, raises Exception if column is already contained in the DataFrame.

Parameters **loc** : int

Must have 0 <= loc <= len(columns)

column : object

value : int, Series, or array-like

pandas.DataFrame.__iter__

`DataFrame.__iter__()`

Iterate over infor axis

pandas.DataFrame.iteritems

`DataFrame.iteritems()`

Iterator over (column, series) pairs

pandas.DataFrame.iterrows

`DataFrame.iterrows()`

Iterate over rows of DataFrame as (index, Series) pairs.

Returns it : generator

A generator that iterates over the rows of the frame.

Notes

- `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = DataFrame([[1, 1.0]], columns=['x', 'y'])
>>> row = next(df.iterrows())[1]
>>> print(row['x'].dtype)
float64
>>> print(df['x'].dtype)
int64
```

pandas.DataFrame.itertuples

`DataFrame.itertuples(`*index=True*`)`

Iterate over rows of DataFrame as tuples, with index value as first element of the tuple

pandas.DataFrame.lookup

`DataFrame.lookup(`*row_labels*, *col_labels*`)`

Label-based "fancy indexing" function for DataFrame. Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

Parameters row_labels : sequence

The row labels to use for lookup

col_labels : sequence

The column labels to use for lookup

Notes

Akin to:

```
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))
```

Examples

values [ndarray] The found values

pandas.DataFrame.pop

DataFrame.**pop**(*item*)
Return item and drop from frame. Raise KeyError if not found.

pandas.DataFrame.tail

DataFrame.**tail**(*n=5*)
Returns last n rows

pandas.DataFrame.xs

DataFrame.**xs**(*key*, *axis=0*, *level=None*, *copy=None*, *drop_level=True*)
Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters **key** : object

Some label contained in the index, or partially in a MultiIndex

axis : int, default 0

Axis to retrieve cross-section on

level : object, defaults to first n levels (n=1 or len(key))

In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

copy : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns **xs** : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultiIndex Slicers*

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
Name: a
>>> df.xs('C', axis=1)
a    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
first third
bar   1      4  1  8  9
baz   1      6  6  8  0
>>> df.xs(('baz', 2), level=[0, 'third'])
        A  B  C  D
second
three   5  3  5  3
```

pandas.DataFrame.isin

`DataFrame.isin(values)`

Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters **values** : iterable, Series, DataFrame or dictionary

The result will only be true at a location if all the labels match. If *values* is a Series, that's the index. If *values* is a dictionary, the keys must be the column names, which must match. If *values* is a DataFrame, then both the index and column labels must match.

Returns DataFrame of booleans

Examples

When `values` is a list:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
       A      B
0   True   True
1  False  False
2   True  False
```

When `values` is a dict:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
       A      B
0   True  False  # Note that B didn't match the 1 here.
1  False   True
2   True   True
```

When `values` is a Series or DataFrame:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
       A      B
0   True  False
1  False  False  # Column A in `other` has a 3, but not at index 1.
2   True   True
```

pandas.DataFrame.where

`DataFrame.`**`where`**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.DataFrame.mask

`DataFrame.mask(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.DataFrame.query

`DataFrame.query(expr, **kwargs)`

Query the columns of a frame with a boolean expression.

New in version 0.13.

Parameters expr : string

The query string to evaluate. You can refer to variables in the environment by prefixing them with an '@' character like `@a + b`.

kwargs : dict

See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

Returns q : DataFrame

See also:

`pandas.eval`, `DataFrame.eval`

Notes

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `pandas.eval()` function to evaluate the passed query.

The query() method uses a slightly modified Python syntax by default. For example, the & and | (bitwise) operators have the precedence of their boolean cousins, and and or. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument parser='python'. This enforces the same semantics as evaluation in Python space. Likewise, you can pass engine='python' to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using numexpr as the engine.

The DataFrame.index and DataFrame.columns attributes of the DataFrame instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier index is used for the frame index; you can also use the name of the index to identify it in a query.

For further details and examples see the query documentation in *indexing*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.query('a > b')
>>> df[df.a > df.b]  # same result as the previous expression
```

For more information on .at, .iat, .ix, .loc, and .iloc, see the *indexing documentation*.

33.4.5 Binary operator functions

DataFrame.add(other[, axis, level, fill_value])	Addition of dataframe and other, element-wise (binary operator *add*).
DataFrame.sub(other[, axis, level, fill_value])	Subtraction of dataframe and other, element-wise (binary operator *sub*).
DataFrame.mul(other[, axis, level, fill_value])	Multiplication of dataframe and other, element-wise (binary operator *mul*).
DataFrame.div(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *trued*
DataFrame.truediv(other[, axis, level, ...])	Floating division of dataframe and other, element-wise (binary operator *trued*
DataFrame.floordiv(other[, axis, level, ...])	Integer division of dataframe and other, element-wise (binary operator *floordi*
DataFrame.mod(other[, axis, level, fill_value])	Modulo of dataframe and other, element-wise (binary operator *mod*).
DataFrame.pow(other[, axis, level, fill_value])	Exponential power of dataframe and other, element-wise (binary operator *pow*
DataFrame.radd(other[, axis, level, fill_value])	Addition of dataframe and other, element-wise (binary operator *radd*).
DataFrame.rsub(other[, axis, level, fill_value])	Subtraction of dataframe and other, element-wise (binary operator *rsub*).
DataFrame.rmul(other[, axis, level, fill_value])	Multiplication of dataframe and other, element-wise (binary operator *rmul*).
DataFrame.rdiv(other[, axis, level, fill_value])	Floating division of dataframe and other, element-wise (binary operator *rtrued*
DataFrame.rtruediv(other[, axis, level, ...])	Floating division of dataframe and other, element-wise (binary operator *rtrued*
DataFrame.rfloordiv(other[, axis, level, ...])	Integer division of dataframe and other, element-wise (binary operator *rfloord*
DataFrame.rmod(other[, axis, level, fill_value])	Modulo of dataframe and other, element-wise (binary operator *rmod*).
DataFrame.rpow(other[, axis, level, fill_value])	Exponential power of dataframe and other, element-wise (binary operator *rpo*
DataFrame.lt(other[, axis, level])	Wrapper for flexible comparison methods lt
DataFrame.gt(other[, axis, level])	Wrapper for flexible comparison methods gt
DataFrame.le(other[, axis, level])	Wrapper for flexible comparison methods le
DataFrame.ge(other[, axis, level])	Wrapper for flexible comparison methods ge
DataFrame.ne(other[, axis, level])	Wrapper for flexible comparison methods ne
DataFrame.eq(other[, axis, level])	Wrapper for flexible comparison methods eq
DataFrame.combine(other, func[, fill_value, ...])	Add two DataFrame objects and do not propagate NaN values, so if for a
DataFrame.combineAdd(other)	Add two DataFrame objects and do not propagate
DataFrame.combine_first(other)	Combine two DataFrame objects and default to non-null values in frame callin

Continued

Table 33.55 – continued from previous page

DataFrame.combineMult(other)	Multiply two DataFrame objects and do not propagate NaN values, so if

pandas.DataFrame.add

DataFrame.**add**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Addition of dataframe and other, element-wise (binary operator *add*).

Equivalent to `dataframe + other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

DataFrame.radd

Notes

Mismatched indices will be unioned together

pandas.DataFrame.sub

DataFrame.**sub**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Subtraction of dataframe and other, element-wise (binary operator *sub*).

Equivalent to `dataframe - other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rsub`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mul

`DataFrame.`**`mul`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Multiplication of dataframe and other, element-wise (binary operator *mul*).

Equivalent to `dataframe * other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.rmul`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.div

`DataFrame.`**`div`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

DataFrame.rtruediv

Notes

Mismatched indices will be unioned together

pandas.DataFrame.truediv

`DataFrame.truediv(other, axis='columns', level=None, fill_value=None)`

Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

DataFrame.rtruediv

Notes

Mismatched indices will be unioned together

pandas.DataFrame.floordiv

`DataFrame.floordiv(other, axis='columns', level=None, fill_value=None)`

Integer division of dataframe and other, element-wise (binary operator *floordiv*).

Equivalent to `dataframe // other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rfloordiv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mod

`DataFrame.`**`mod`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Modulo of dataframe and other, element-wise (binary operator *mod*).

Equivalent to `dataframe % other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rmod`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.pow

`DataFrame.`**`pow`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Exponential power of dataframe and other, element-wise (binary operator *pow*).

Equivalent to `dataframe ** other`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.rpow`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.radd

`DataFrame.`**`radd`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Addition of dataframe and other, element-wise (binary operator *radd*).

Equivalent to `other + dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.add`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rsub

`DataFrame.rsub(other, axis='columns', level=None, fill_value=None)`

Subtraction of dataframe and other, element-wise (binary operator *rsub*).

Equivalent to `other - dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.sub`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

`DataFrame.rmul(other, axis='columns', level=None, fill_value=None)`

Multiplication of dataframe and other, element-wise (binary operator *rmul*).

Equivalent to `other * dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.mul`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rdiv

`DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)`

Floating division of dataframe and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.truediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.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

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.truediv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rfloordiv

`DataFrame.`**`rfloordiv`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Integer division of dataframe and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

See also:

`DataFrame.floordiv`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmod

`DataFrame.`**`rmod`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Modulo of dataframe and other, element-wise (binary operator *rmod*).

Equivalent to `other % dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.mod`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rpow

`DataFrame.`**`rpow`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Exponential power of dataframe and other, element-wise (binary operator *rpow*).

Equivalent to `other ** dataframe`, but with support to substitute a fill_value for missing data in one of the inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

`DataFrame.pow`

Notes

Mismatched indices will be unioned together

pandas.DataFrame.lt

`DataFrame.`**`lt`**(*other*, *axis='columns'*, *level=None*)

Wrapper for flexible comparison methods lt

pandas.DataFrame.gt

`DataFrame.`**`gt`**(*other*, *axis='columns'*, *level=None*)

Wrapper for flexible comparison methods gt

pandas.DataFrame.le

`DataFrame.le(other, axis='columns', level=None)`
Wrapper for flexible comparison methods le

pandas.DataFrame.ge

`DataFrame.ge(other, axis='columns', level=None)`
Wrapper for flexible comparison methods ge

pandas.DataFrame.ne

`DataFrame.ne(other, axis='columns', level=None)`
Wrapper for flexible comparison methods ne

pandas.DataFrame.eq

`DataFrame.eq(other, axis='columns', level=None)`
Wrapper for flexible comparison methods eq

pandas.DataFrame.combine

`DataFrame.combine(other, func, fill_value=None, overwrite=True)`
Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

func : function

fill_value : scalar value

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

Returns **result** : DataFrame

pandas.DataFrame.combineAdd

`DataFrame.combineAdd(other)`
Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

Returns DataFrame

pandas.DataFrame.combine_first

`DataFrame.combine_first(other)`
Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

Parameters **other** : DataFrame

Returns **combined** : DataFrame

Examples

a's values prioritized, use values from b to fill holes:

```
>>> a.combine_first(b)
```

pandas.DataFrame.combineMult

DataFrame.**combineMult**(*other*)

Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

Returns DataFrame

33.4.6 Function application, GroupBy

DataFrame.apply(func[, axis, broadcast, ...])	Applies function along input axis of DataFrame.
DataFrame.applymap(func)	Apply a function to a DataFrame that is intended to operate elementwise, i.e.
DataFrame.groupby([by, axis, level, ...])	Group series using mapper (dict or key function, apply given function

pandas.DataFrame.apply

DataFrame.**apply**(*func*, *axis=0*, *broadcast=False*, *raw=False*, *reduce=None*, *args=()*, ***kwds*)

Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame's index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates, or the reduce argument if the DataFrame is empty.

Parameters **func** : function

Function to apply to each column/row

axis : {0 or 'index', 1 or 'columns'}, default 0

- 0 or 'index': apply function to each column
- 1 or 'columns': apply function to each row

broadcast : boolean, default False

For aggregation functions, return object of same size with values propagated

reduce : boolean or None, default None

Try to apply reduction procedures. If the DataFrame is empty, apply will use reduce to determine whether the result should be a Series or a DataFrame. If reduce is None (the default), apply's return value will be guessed by calling func an empty Series (note: while guessing, exceptions raised by func will be ignored). If reduce is True a Series will always be returned, and if False a DataFrame will always be returned.

raw : boolean, default False

If False, convert each row or column into a Series. If raw=True the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

args : tuple

Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

Returns applied : Series or DataFrame

See also:

`DataFrame.applymap` For elementwise operations

Notes

In the current implementation apply calls func twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first column/row.

Examples

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

pandas.DataFrame.applymap

DataFrame.**applymap**(*func*)

Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing map(func, series) for each series in the DataFrame

Parameters func : function

Python function, returns a single value from a single value

Returns applied : DataFrame

See also:

`DataFrame.apply` For operations on rows/columns

pandas.DataFrame.groupby

DataFrame.**groupby**(*by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters by : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively "SQL-style" grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionaility of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

33.4.7 Computations / Descriptive Stats

`DataFrame.abs`()	Return an object with absolute value taken.
`DataFrame.all`([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
`DataFrame.any`([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
`DataFrame.clip`([lower, upper, out, axis])	Trim values at input threshold(s)
`DataFrame.clip_lower`(threshold[, axis])	Return copy of the input with values below given value(s) truncated
`DataFrame.clip_upper`(threshold[, axis])	Return copy of input with values above given value(s) truncated
`DataFrame.corr`([method, min_periods])	Compute pairwise correlation of columns, excluding NA/null values
`DataFrame.corrwith`(other[, axis, drop])	Compute pairwise correlation between rows or columns of two DataFrame
`DataFrame.count`([axis, level, numeric_only])	Return Series with number of non-NA/null observations over requested ax
`DataFrame.cov`([min_periods])	Compute pairwise covariance of columns, excluding NA/null values
`DataFrame.cummax`([axis, dtype, out, skipna])	Return cumulative max over requested axis.
`DataFrame.cummin`([axis, dtype, out, skipna])	Return cumulative min over requested axis.
`DataFrame.cumprod`([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
`DataFrame.cumsum`([axis, dtype, out, skipna])	Return cumulative sum over requested axis.

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DataFrame.describe([percentile_width, ...])	Generate various summary statistics, excluding NaN values.
DataFrame.diff([periods, axis])	1st discrete difference of object
DataFrame.eval(expr, **kwargs)	Evaluate an expression in the context of the calling DataFrame instance.
DataFrame.kurt([axis, skipna, level, ...])	Return unbiased kurtosis over requested axis using Fishers definition of ku
DataFrame.mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
DataFrame.max([axis, skipna, level, ...])	This method returns the maximum of the values in the object.
DataFrame.mean([axis, skipna, level, ...])	Return the mean 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, ...])	Percent change over given number of periods.
DataFrame.prod([axis, skipna, level, ...])	Return the product of the values for the requested axis
DataFrame.quantile([q, axis, numeric_only])	Return values at the given quantile over requested axis, a la numpy.percent
DataFrame.rank([axis, numeric_only, method, ...])	Compute numerical data ranks (1 through n) along axis.
DataFrame.sem([axis, skipna, level, ddof, ...])	Return unbiased standard error of the mean over requested axis.
DataFrame.skew([axis, skipna, level, ...])	Return unbiased skew over requested axis
DataFrame.sum([axis, skipna, level, ...])	Return the sum of the values for the requested axis
DataFrame.std([axis, skipna, level, ddof, ...])	Return unbiased standard deviation over requested axis.
DataFrame.var([axis, skipna, level, ddof, ...])	Return unbiased variance over requested axis.

pandas.DataFrame.abs

`DataFrame.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.DataFrame.all

`DataFrame.all(`*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*`)`

Return whether all elements are True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : Series or DataFrame (if level specified)

pandas.DataFrame.any

`DataFrame.any(`*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*`)`

Return whether any element is True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : Series or DataFrame (if level specified)

pandas.DataFrame.clip

DataFrame.**clip**(*lower=None*, *upper=None*, *out=None*, *axis=None*)

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
```

```
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.DataFrame.clip_lower

DataFrame.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.DataFrame.clip_upper

DataFrame.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.DataFrame.corr

DataFrame.**corr**(*method='pearson'*, *min_periods=1*)

Compute pairwise correlation of columns, excluding NA/null values

Parameters **method** : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result. Currently only available for pearson and spearman correlation

Returns **y** : DataFrame

pandas.DataFrame.corrwith

`DataFrame.`**`corrwith`**`(`*other*, *axis=0*, *drop=False*`)`

Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters **other** : DataFrame

axis : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' to compute column-wise, 1 or 'columns' for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns **correls** : Series

pandas.DataFrame.count

`DataFrame.`**`count`**`(`*axis=0*, *level=None*, *numeric_only=False*`)`

Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default False

Include only float, int, boolean data

Returns **count** : Series (or DataFrame if level specified)

pandas.DataFrame.cov

`DataFrame.`**`cov`**`(`*min_periods=None*`)`

Compute pairwise covariance of columns, excluding NA/null values

Parameters **min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns **y** : DataFrame

Notes

y contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.DataFrame.cummax

`DataFrame.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : Series

pandas.DataFrame.cummin

`DataFrame.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : Series

pandas.DataFrame.cumprod

`DataFrame.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative prod over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : Series

pandas.DataFrame.cumsum

`DataFrame.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative sum over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Series

pandas.DataFrame.describe

`DataFrame.describe(percentile_width=None, percentiles=None, include=None, exclude=None)`

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.DataFrame.diff

`DataFrame.`**`diff`**(*periods=1*, *axis=0*)

1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

axis : {0 or 'index', 1 or 'columns'}, default 0

Take difference over rows (0) or columns (1).

Returns **diffed** : DataFrame

pandas.DataFrame.eval

DataFrame.**eval**(*expr*, ***kwargs*)

Evaluate an expression in the context of the calling DataFrame instance.

Parameters **expr** : string

The expression string to evaluate.

kwargs : dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

Returns **ret** : ndarray, scalar, or pandas object

See also:

`pandas.DataFrame.query`, `pandas.eval`

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

pandas.DataFrame.kurt

DataFrame.**kurt**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Series or DataFrame (if level specified)

pandas.DataFrame.mad

`DataFrame.mad(axis=None, skipna=None, level=None)`
Return the mean absolute deviation of the values for the requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mad : Series or DataFrame (if level specified)

pandas.DataFrame.max

`DataFrame.max(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : Series or DataFrame (if level specified)

pandas.DataFrame.mean

`DataFrame.mean(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return the mean of the values for the requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mean : Series or DataFrame (if level specified)

pandas.DataFrame.median

`DataFrame.`**`median`**`(`*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*`)`

Return the median of the values for the requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : Series or DataFrame (if level specified)

pandas.DataFrame.min

`DataFrame.`**`min`**`(`*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*`)`

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : Series or DataFrame (if level specified)

pandas.DataFrame.mode

`DataFrame.`**`mode`**`(`*axis=0*, *numeric_only=False*`)`

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe `df`, you can just do this: `df.fillna(df.mode().iloc[0])`

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

- 0 or 'index' : get mode of each column
- 1 or 'columns' : get mode of each row

numeric_only : boolean, default False

if True, only apply to numeric columns

Returns **modes** : DataFrame (sorted)

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
   A
0  1
1  2
```

pandas.DataFrame.pct_change

`DataFrame.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.DataFrame.prod

`DataFrame.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Series or DataFrame (if level specified)

pandas.DataFrame.quantile

DataFrame.**quantile**(*q=0.5*, *axis=0*, *numeric_only=True*)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

axis : {0, 1, 'index', 'columns'} (default 0)

0 or 'index' for row-wise, 1 or 'columns' for column-wise

Returns **quantiles** : Series or DataFrame

If `q` is an array, a DataFrame will be returned where the index is `q`, the columns are the columns of self, and the values are the quantiles. If `q` is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                   columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
       a     b
0.1  1.3   3.7
0.5  2.5  55.0
```

pandas.DataFrame.rank

DataFrame.**rank**(*axis=0*, *numeric_only=None*, *method='average'*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep', 'top', 'bottom'}

- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns ranks : DataFrame

pandas.DataFrame.sem

`DataFrame.`**`sem`**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sem : Series or DataFrame (if level specified)

pandas.DataFrame.skew

`DataFrame.`**`skew`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Series or DataFrame (if level specified)

pandas.DataFrame.sum

`DataFrame.`**`sum`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : Series or DataFrame (if level specified)

pandas.DataFrame.std

`DataFrame.`**`std`**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : Series or DataFrame (if level specified)

pandas.DataFrame.var

DataFrame.**var**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)
Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Series or DataFrame (if level specified)

33.4.8 Reindexing / Selection / Label manipulation

DataFrame.add_prefix(prefix)	Concatenate prefix string with panel items names.
DataFrame.add_suffix(suffix)	Concatenate suffix string with panel items names
DataFrame.align(other[, join, axis, level, ...])	Align two object on their axes with the
DataFrame.drop(labels[, axis, level, ...])	Return new object with labels in requested axis removed
DataFrame.drop_duplicates(*args, **kwargs)	Return DataFrame with duplicate rows removed, optionally only
DataFrame.duplicated(*args, **kwargs)	Return boolean Series denoting duplicate rows, optionally only
DataFrame.equals(other)	Determines if two NDFrame objects contain the same elements.
DataFrame.filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
DataFrame.first(offset)	Convenience method for subsetting initial periods of time series data
DataFrame.head([n])	Returns first n rows
DataFrame.idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
DataFrame.idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
DataFrame.last(offset)	Convenience method for subsetting final periods of time series data
DataFrame.reindex([index, columns])	Conform DataFrame to new index with optional filling logic, placing NA/N
DataFrame.reindex_axis(labels[, axis, ...])	Conform input object to new index with optional filling logic, placing NA/N
DataFrame.reindex_like(other[, method, ...])	return an object with matching indicies to myself
DataFrame.rename([index, columns])	Alter axes input function or functions.
DataFrame.reset_index([level, drop, ...])	For DataFrame with multi-level index, return new DataFrame with labeling
DataFrame.sample([n, frac, replace, ...])	Returns a random sample of items from an axis of object.
DataFrame.select(crit[, axis])	Return data corresponding to axis labels matching criteria
DataFrame.set_index(keys[, drop, append, ...])	Set the DataFrame index (row labels) using one or more existing columns.
DataFrame.tail([n])	Returns last n rows
DataFrame.take(indices[, axis, convert, is_copy])	Analogous to ndarray.take
DataFrame.truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.

pandas.DataFrame.add_prefix

`DataFrame.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.DataFrame.add_suffix

`DataFrame.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.DataFrame.align

`DataFrame.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns **(left, right)** : (type of input, type of other)

Aligned objects

pandas.DataFrame.drop

`DataFrame.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.DataFrame.drop_duplicates

`DataFrame.drop_duplicates(*args, **kwargs)`

Return DataFrame with duplicate rows removed, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

Take the last observed row in a row. Defaults to the first row

inplace : boolean, default False

Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns **deduplicated** : DataFrame

pandas.DataFrame.duplicated

`DataFrame.duplicated(*args, **kwargs)`

Return boolean Series denoting duplicate rows, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

For a set of distinct duplicate rows, flag all but the last row as duplicated. Default is for all but the first row to be flagged

cols : kwargs only argument of subset [deprecated]

Returns **duplicated** : Series

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.filter

`DataFrame.filter(items=None, like=None, regex=None, axis=None)`

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]]}); df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

`DataFrame.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.DataFrame.head

`DataFrame.head(n=5)`

Returns first n rows

pandas.DataFrame.idxmax

`DataFrame.idxmax(axis=0, skipna=True)`

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns **idxmax** : Series

See also:

`Series.idxmax`

Notes

This method is the DataFrame version of `ndarray.argmax`.

pandas.DataFrame.idxmin

`DataFrame.idxmin(axis=0, skipna=True)`

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **idxmin** : Series

See also:

`Series.idxmin`

Notes

This method is the DataFrame version of `ndarray.argmin`.

pandas.DataFrame.last

`DataFrame.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.DataFrame.reindex

`DataFrame.reindex(index=None, columns=None, **kwargs)`

Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **index, columns** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : DataFrame

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.DataFrame.reindex_axis

`DataFrame.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan)`

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **labels** : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 'index', 'columns'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : DataFrame

See also:

`reindex`, `reindex_like`

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.DataFrame.reindex_like

`DataFrame.`**`reindex_like`**(*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.DataFrame.rename

`DataFrame.`**`rename`**(*index=None*, *columns=None*, ***kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters index, columns : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new DataFrame. If True then value of copy is ignored.

Returns **renamed** : DataFrame (new object)

pandas.DataFrame.reset_index

DataFrame.**reset_index**(*level=None*, *drop=False*, *inplace=False*, *col_level=0*, *col_fill=''*)

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

Parameters **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns. This resets the index to the default integer index.

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

col_level : int or str, default 0

If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

col_fill : object, default ''

If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

Returns **resetted** : DataFrame

pandas.DataFrame.sample

DataFrame.**sample**(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*, *axis=None*)

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.DataFrame.select

`DataFrame.`**`select`**(*crit*, *axis=0*)

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.DataFrame.set_index

`DataFrame.`**`set_index`**(*keys*, *drop=True*, *append=False*, *inplace=False*, *verify_integrity=False*)

Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

Parameters **keys** : column label or list of column labels / arrays

drop : boolean, default True

Delete columns to be used as the new index

append : boolean, default False

Whether to append columns to existing index

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

verify_integrity : boolean, default False

Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method

Returns **dataframe** : DataFrame

Examples

```
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

pandas.DataFrame.tail

DataFrame.**tail**(*n=5*)
Returns last n rows

pandas.DataFrame.take

DataFrame.**take**(*indices*, *axis=0*, *convert=True*, *is_copy=True*)
Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.DataFrame.truncate

DataFrame.**truncate**(*before=None*, *after=None*, *axis=None*, *copy=True*)
Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

33.4.9 Missing data handling

DataFrame.dropna([axis, how, thresh, ...])	Return object with labels on given axis omitted where alternately any
DataFrame.fillna([value, method, axis, ...])	Fill NA/NaN values using the specified method
DataFrame.replace([to_replace, value, ...])	Replace values given in 'to_replace' with 'value'.

pandas.DataFrame.dropna

`DataFrame.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)`

Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters **axis** : {0 or 'index', 1 or 'columns'}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

how : {'any', 'all'}

- any : if any NA values are present, drop that label
- all : if all values are NA, drop that label

thresh : int, default None

int value : require that many non-NA values

subset : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

inplace : boolean, defalt False

If True, do operation inplace and return None.

Returns **dropped** : DataFrame

pandas.DataFrame.fillna

`DataFrame.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)`

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : DataFrame

See also:

`reindex`, `asfreq`

pandas.DataFrame.replace

`DataFrame.replace`(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*, *axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.
- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

33.4.10 Reshaping, sorting, transposing

`DataFrame.pivot`([index, columns, values])	Reshape data (produce a "pivot" table) based on column values.
`DataFrame.reorder_levels`(order[, axis])	Rearrange index levels using input order.
`DataFrame.sort`([columns, axis, ascending, ...])	Sort DataFrame either by labels (along either axis) or by the values in
`DataFrame.sort_index`([axis, by, ascending, ...])	Sort DataFrame either by labels (along either axis) or by the values in
`DataFrame.sortlevel`([level, axis, ...])	Sort multilevel index by chosen axis and primary level.
`DataFrame.swaplevel`(i, j[, axis])	Swap levels i and j in a MultiIndex on a particular axis
`DataFrame.stack`([level, dropna])	Pivot a level of the (possibly hierarchical) column labels, returning a DataFr
`DataFrame.unstack`([level])	Pivot a level of the (necessarily hierarchical) index labels, returning a DataF
`DataFrame.T`	Transpose index and columns
`DataFrame.to_panel`()	Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
`DataFrame.transpose`()	Transpose index and columns

pandas.DataFrame.pivot

DataFrame.**pivot**(*index=None*, *columns=None*, *values=None*)

Reshape data (produce a "pivot" table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

Parameters **index** : string or object

Column name to use to make new frame's index

columns : string or object

Column name to use to make new frame's columns

values : string or object, optional

Column name to use for populating new frame's values

Returns **pivoted** : DataFrame

If no values column specified, will have hierarchically indexed columns

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

Examples

```
>>> df
    foo   bar  baz
0   one   A    1.
1   one   B    2.
2   one   C    3.
3   two   A    4.
4   two   B    5.
5   two   C    6.
```

```
>>> df.pivot('foo', 'bar', 'baz')
     A   B   C
one  1   2   3
two  4   5   6
```

```
>>> df.pivot('foo', 'bar')['baz']
     A   B   C
one  1   2   3
two  4   5   6
```

pandas.DataFrame.reorder_levels

DataFrame.**reorder_levels**(*order*, *axis=0*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters **order** : list of int or list of str

List representing new level order. Reference level by number (position) or by key (label).

axis : int

Where to reorder levels.

Returns type of caller (new object)

pandas.DataFrame.sort

DataFrame.**sort**(*columns=None*, *axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in column(s)

Parameters **columns** : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

axis : {0 or 'index', 1 or 'columns'}, default 0

Sort index/rows versus columns

inplace : boolean, default False

Sort the DataFrame without creating a new instance

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

pandas.DataFrame.sort_index

DataFrame.**sort_index**(*axis=0*, *by=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in a column

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

Sort index/rows versus columns

by : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

inplace : boolean, default False

Sort the DataFrame without creating a new instance

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort_index(by=['A', 'B'], ascending=[True, False])
```

pandas.DataFrame.sortlevel

`DataFrame.sortlevel(`*level=0, axis=0, ascending=True, inplace=False, sort_remaining=True*`)`

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters **level** : int

axis : {0 or 'index', 1 or 'columns'}, default 0

ascending : boolean, default True

inplace : boolean, default False

Sort the DataFrame without creating a new instance

sort_remaining : boolean, default True

Sort by the other levels too.

Returns **sorted** : DataFrame

pandas.DataFrame.swaplevel

`DataFrame.swaplevel(`*i, j, axis=0*`)`

Swap levels i and j in a MultiIndex on a particular axis

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)

pandas.DataFrame.stack

`DataFrame.stack(`*level=-1, dropna=True*`)`

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default last level

Level(s) to stack, can pass level name

dropna : boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

Returns **stacked** : DataFrame or Series

Examples

```
>>> s
     a    b
one  1.   2.
two  3.   4.

>>> s.stack()
one a     1
    b     2
two a     3
    b     4
```

pandas.DataFrame.unstack

DataFrame.**unstack**(*level=-1*)

Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels. If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex). The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default -1 (last level)

Level(s) of index to unstack, can pass level name

Returns **unstacked** : DataFrame or Series

See also:

DataFrame.pivot Pivot a table based on column values.

DataFrame.stack Pivot a level of the column labels (inverse operation from *unstack*).

Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                    ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one  a   1
     b   2
two  a   3
     b   4
dtype: float64

>>> s.unstack(level=-1)
     a   b
one  1  2
two  3  4
```

```
>>> s.unstack(level=0)
   one  two
a  1    3
b  2    4

>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.
     b  3.
two  a  2.
     b  4.
```

pandas.DataFrame.T

DataFrame.**T**
Transpose index and columns

pandas.DataFrame.to_panel

DataFrame.**to_panel**()
Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns panel : Panel

pandas.DataFrame.transpose

DataFrame.**transpose**()
Transpose index and columns

33.4.11 Combining / joining / merging

DataFrame.append(other[, ignore_index, ...])	Append rows of *other* to the end of this frame, returning a new object.
DataFrame.assign(**kwargs)	Assign new columns to a DataFrame, returning a new object (a copy) with all th
DataFrame.join(other[, on, how, lsuffix, ...])	Join columns with other DataFrame either on index or on a key column.
DataFrame.merge(right[, how, on, left_on, ...])	Merge DataFrame objects by performing a database-style join operation by colu
DataFrame.update(other[, join, overwrite, ...])	Modify DataFrame in place using non-NA values from passed DataFrame.

pandas.DataFrame.append

DataFrame.**append**(*other*, *ignore_index=False*, *verify_integrity=False*)
Append rows of *other* to the end of this frame, returning a new object. Columns not in this frame are added as new columns.

Parameters other : DataFrame or Series/dict-like object, or list of these

The data to append.

ignore_index : boolean, default False

If True, do not use the index labels.

verify_integrity : boolean, default False

If True, raise ValueError on creating index with duplicates.

Returns appended : DataFrame

See also:

`pandas.concat` General function to concatenate DataFrame, Series or Panel objects

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Examples

```
>>> 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:

```
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

pandas.DataFrame.assign

`DataFrame.assign(**kwargs)`

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition to the new ones.

New in version 0.16.0.

Parameters kwargs : keyword, value pairs

keywords are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns df : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Since `kwargs` is a dictionary, the order of your arguments may not be preserved. The make things predicatable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within the same `assign` is possible, but you cannot reference other columns created within the same `assign` call.

Examples

```
>>> df = DataFrame({'A': range(1, 11), 'B': np.random.randn(10)})
```

Where the value is a callable, evaluated on *df*:

```
>>> df.assign(ln_A = lambda x: np.log(x.A))
    A         B      ln_A
0   1  0.426905  0.000000
1   2 -0.780949  0.693147
2   3 -0.418711  1.098612
3   4 -0.269708  1.386294
4   5 -0.274002  1.609438
5   6 -0.500792  1.791759
6   7  1.649697  1.945910
7   8 -1.495604  2.079442
8   9  0.549296  2.197225
9  10 -0.758542  2.302585
```

Where the value already exists and is inserted:

```
>>> newcol = np.log(df['A'])
>>> df.assign(ln_A=newcol)
    A         B      ln_A
0   1  0.426905  0.000000
1   2 -0.780949  0.693147
2   3 -0.418711  1.098612
3   4 -0.269708  1.386294
4   5 -0.274002  1.609438
5   6 -0.500792  1.791759
6   7  1.649697  1.945910
7   8 -1.495604  2.079442
8   9  0.549296  2.197225
9  10 -0.758542  2.302585
```

pandas.DataFrame.join

`DataFrame.`**`join`**(*other*, *on=None*, *how='left'*, *lsuffix=''*, *rsuffix=''*, *sort=False*)

Join columns with other DataFrame either on index or on a key column. Efficiently Join multiple DataFrame objects by index at once by passing a list.

Parameters **other** : DataFrame, Series with name field set, or list of DataFrame

Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame

on : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation

how : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise

- left: use calling frame's index
- right: use input frame's index
- outer: form union of indexes
- inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

sort : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

Returns **joined** : DataFrame

Notes

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

pandas.DataFrame.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*)

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters **right** : DataFrame

how : {'left', 'right', 'outer', 'inner'}, default 'inner'

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

left_on : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

right_on : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per left_on docs

left_index : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

right_index : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns merged : DataFrame

The output type will the be same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A              >>> B
    lkey value         rkey value
0   foo  1         0   foo  5
1   bar  2         1   bar  6
2   baz  3         2   qux  7
3   foo  4         3   bar  8
```

```
>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  foo   1        foo   5
1  foo   4        foo   5
2  bar   2        bar   6
3  bar   2        bar   8
4  baz   3        NaN   NaN
5  NaN   NaN      qux   7
```

pandas.DataFrame.update

`DataFrame.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)`

Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

Parameters other : DataFrame, or object coercible into a DataFrame

join : {'left'}, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : boolean

If True, will raise an error if the DataFrame and other both contain data in the same place.

33.4.12 Time series-related

DataFrame.asfreq(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset obj
DataFrame.shift([periods, freq, axis])	Shift index by desired number of periods with an optional time freq
DataFrame.first_valid_index()	Return label for first non-NA/null value
DataFrame.last_valid_index()	Return label for last non-NA/null value
DataFrame.resample(rule[, how, axis, ...])	Convenience method for frequency conversion and resampling of regular t
DataFrame.to_period([freq, axis, copy])	Convert DataFrame from DatetimeIndex to PeriodIndex with desired
DataFrame.to_timestamp([freq, how, axis, copy])	Cast to DatetimeIndex of timestamps, at *beginning* of period
DataFrame.tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
DataFrame.tz_localize(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone

pandas.DataFrame.asfreq

DataFrame.**asfreq**(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.DataFrame.shift

DataFrame.**shift**(*periods=1*, *freq=None*, *axis=0*, ***kwargs*)

Shift index by desired number of periods with an optional time freq

Parameters periods : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns shifted : DataFrame

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.DataFrame.first_valid_index

`DataFrame.`**`first_valid_index`**`()`

Return label for first non-NA/null value

pandas.DataFrame.last_valid_index

`DataFrame.`**`last_valid_index`**`()`

Return label for last non-NA/null value

pandas.DataFrame.resample

`DataFrame.`**`resample`**`(`*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*`)`

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.DataFrame.to_period

`DataFrame.to_period(freq=None, axis=0, copy=True)`

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters **freq** : string, default

axis : {0 or 'index', 1 or 'columns'}, default 0

The axis to convert (the index by default)

copy : boolean, default True

If False then underlying input data is not copied

Returns **ts** : TimeSeries with PeriodIndex

pandas.DataFrame.to_timestamp

`DataFrame.to_timestamp(freq=None, how='start', axis=0, copy=True)`

Cast to DatetimeIndex of timestamps, at *beginning* of period

Parameters **freq** : string, default frequency of PeriodIndex

Desired frequency

how : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

axis : {0 or 'index', 1 or 'columns'}, default 0

The axis to convert (the index by default)

copy : boolean, default True

If false then underlying input data is not copied

Returns **df** : DataFrame with DatetimeIndex

pandas.DataFrame.tz_convert

`DataFrame.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises TypeError

If the axis is tz-naive.

pandas.DataFrame.tz_localize

DataFrame.**tz_localize**(**args*, ***kwargs*)

Localize tz-naive TimeSeries to target time zone

Parameters tz : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises TypeError

If the TimeSeries is tz-aware and tz is not None.

33.4.13 Plotting

DataFrame.boxplot([column, by, ax, ...])	Make a box plot from DataFrame column optionally grouped by some columns or
DataFrame.hist(data[, column, by, grid, ...])	Draw histogram of the DataFrame's series using matplotlib / pylab.
DataFrame.plot(data[, x, y, kind, ax, ...])	Make plots of DataFrame using matplotlib / pylab.

pandas.DataFrame.boxplot

DataFrame.**boxplot**(*column=None*, *by=None*, *ax=None*, *fontsize=None*, *rot=0*, *grid=True*, *figsize=None*, *layout=None*, *return_type=None*, ***kwds*)

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters data : the pandas object holding the data

column : column name or list of names, or vector

Can be any valid input to groupby

by : string or sequence

Column in the DataFrame to group by

ax : Matplotlib axes object, optional

fontsize : int or string

rot : label rotation angle

figsize : A tuple (width, height) in inches

grid : Setting this to True will show the grid

layout : tuple (optional)

(rows, columns) for the layout of the plot

return_type : {'axes', 'dict', 'both'}, default 'dict'

The kind of object to return. 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot; 'axes' returns the matplotlib axes the boxplot is drawn on; 'both' returns a namedtuple with the axes and dict.

When grouping with `by`, a dict mapping columns to `return_type` is returned.

kwds : other plotting keyword arguments to be passed to matplotlib boxplot

function

Returns **lines** : dict

ax : matplotlib Axes

(ax, lines): namedtuple

Notes

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

pandas.DataFrame.hist

`DataFrame.hist`(*data*, *column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, *figsize=None*, *layout=None*, *bins=10*, ***kwds*)

Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters **data** : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.DataFrame.plot

`DataFrame.`**`plot`**(*data*, *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.

Parameters **data** : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'

- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)
- If *kind* = 'scatter' and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = 'hexbin', you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each *(x, y)* point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each *(x, y)* point and *reduce_C_function* is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

33.4.14 Serialization / IO / Conversion

`DataFrame.from_csv`(path[, header, sep, ...])	Read delimited file into DataFrame
`DataFrame.from_dict`(data[, orient, dtype])	Construct DataFrame from dict of array-like or dicts
`DataFrame.from_items`(items[, columns, orient])	Convert (key, value) pairs to DataFrame.
`DataFrame.from_records`(data[, index, ...])	Convert structured or record ndarray to DataFrame
`DataFrame.info`([verbose, buf, max_cols, ...])	Concise summary of a DataFrame.
`DataFrame.to_pickle`(path)	Pickle (serialize) object to input file path
`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)	activate the HDFStore
`DataFrame.to_sql`(name, con[, flavor, ...])	Write records stored in a DataFrame to a SQL database.
`DataFrame.to_dict`(*args, **kwargs)	Convert DataFrame to dictionary.
`DataFrame.to_excel`(excel_writer[, ...])	Write DataFrame to a excel sheet
`DataFrame.to_json`([path_or_buf, orient, ...])	Convert the object to a JSON string.
`DataFrame.to_html`([buf, columns, col_space, ...])	Render a DataFrame as an HTML table.
`DataFrame.to_latex`([buf, columns, ...])	Render a DataFrame to a tabular environment table.
`DataFrame.to_stata`(fname[, convert_dates, ...])	A class for writing Stata binary dta files from array-like objects
`DataFrame.to_msgpack`([path_or_buf])	msgpack (serialize) object to input file path
`DataFrame.to_gbq`(destination_table[, ...])	Write a DataFrame to a Google BigQuery table.
`DataFrame.to_records`([index, convert_datetime64])	Convert DataFrame to 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.to_clipboard`([excel, sep])	Attempt to write text representation of object to the system clipboard T

pandas.DataFrame.from_csv

classmethod `DataFrame.from_csv`(*path*, *header=0*, *sep=', '*, *index_col=0*, *parse_dates=True*, *encoding=None*, *tupleize_cols=False*, *infer_datetime_format=False*)

Read delimited file into DataFrame

Parameters path : string file path or file handle / StringIO

header : int, default 0

Row to use at 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

Notes

Preferable to use read_table for most general purposes but from_csv makes for an easy roundtrip to and from file, especially with a DataFrame of time series data

pandas.DataFrame.from_dict

classmethod `DataFrame.from_dict`(*data*, *orient='columns'*, *dtype=None*)

Construct DataFrame from dict of array-like or dicts

Parameters data : dict

{field : array-like} or {field : dict}

orient : {'columns', 'index'}, default 'columns'

The "orientation" of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass 'columns' (default). Otherwise if the keys should be rows, pass 'index'.

dtype : dtype, default None

Data type to force, otherwise infer

Returns DataFrame

pandas.DataFrame.from_items

classmethod `DataFrame.from_items`(*items*, *columns=None*, *orient='columns'*)

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

Parameters items : sequence of (key, value) pairs

Values should be arrays or Series.

columns : sequence of column labels, optional

Must be passed if orient='index'.

orient : {'columns', 'index'}, default 'columns'

The "orientation" of the data. If the keys of the input correspond to column labels, pass 'columns' (default). Otherwise if the keys correspond to the index, pass 'index'.

Returns frame : DataFrame

pandas.DataFrame.from_records

classmethod `DataFrame.from_records`(*data*, *index=None*, *exclude=None*, *columns=None*, *coerce_float=False*, *nrows=None*)

Convert structured or record ndarray to DataFrame

Parameters data : ndarray (structured dtype), list of tuples, dict, or DataFrame

index : string, list of fields, array-like

Field of array to use as the index, alternately a specific set of input labels to use

exclude : sequence, default None

Columns or fields to exclude

columns : sequence, default None

Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns)

coerce_float : boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

Returns df : DataFrame

pandas.DataFrame.info

`DataFrame.info`(*verbose=None*, *buf=None*, *max_cols=None*, *memory_usage=None*, *null_counts=None*)

Concise summary of a DataFrame.

Parameters verbose : {None, True, False}, optional

Whether to print the full summary. None follows the *display.max_info_columns* setting. True or False overrides the *display.max_info_columns* setting.

buf : writable buffer, defaults to sys.stdout

max_cols : int, default None

Determines whether full summary or short summary is printed. None follows the *display.max_info_columns* setting.

memory_usage : boolean, default None

Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the *display.memory_usage* setting. True or False overrides the *display.memory_usage* setting. Memory usage is shown in human-readable units (base-2 representation).

null_counts : boolean, default None

Whether to show the non-null counts If None, then only show if the frame is smaller than max_info_rows and max_info_columns. If True, always show counts. If False, never show counts.

pandas.DataFrame.to_pickle

DataFrame.**to_pickle**(*path*)

Pickle (serialize) object to input file path

Parameters path : string

File path

pandas.DataFrame.to_csv

DataFrame.**to_csv**(*path_or_buf=None, sep=', ', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, mode='w', encoding=None, quoting=None, quotechar='"', line_terminator='\n', chunksize=None, tupleize_cols=False, date_format=None, doublequote=True, escapechar=None, decimal='.', **kwds*)

Write DataFrame to a comma-separated values (csv) file

Parameters path_or_buf : string or file handle, default None

File path or object, if None is provided the result is returned as a string.

sep : character, default ","

Field delimiter for the output file.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, or False, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R

nanRep : None

deprecated, use na_rep

mode : str

Python write mode, default 'w'

encoding : string, optional

A string representing the encoding to use in the output file, defaults to 'ascii' on Python 2 and 'utf-8' on Python 3.

line_terminator : string, default '\n'

The newline character or character sequence to use in the output file

quoting : optional constant from csv module

defaults to csv.QUOTE_MINIMAL

quotechar : string (length 1), default '"'

character used to quote fields

doublequote : boolean, default True

Control quoting of *quotechar* inside a field

escapechar : string (length 1), default None

character used to escape *sep* and *quotechar* when appropriate

chunksize : int or None

rows to write at a time

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False)

date_format : string, default None

Format string for datetime objects

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

New in version 0.16.0.

pandas.DataFrame.to_hdf

`DataFrame.to_hdf(path_or_buf, key, **kwargs)`
activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.DataFrame.to_sql

`DataFrame.to_sql`(*name*, *con*, *flavor='sqlite'*, *schema=None*, *if_exists='fail'*, *index=True*, *index_label=None*, *chunksize=None*, *dtype=None*)

Write records stored in a DataFrame to a SQL database.

Parameters name : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.DataFrame.to_dict

`DataFrame.to_dict(*args, **kwargs)`

Convert DataFrame to dictionary.

Parameters **orient** : str {'dict', 'list', 'series', 'split', 'records'}

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}]

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

Returns **result** : dict like {column -> {index -> value}}

pandas.DataFrame.to_excel

`DataFrame.to_excel(excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf')`

Write DataFrame to a excel sheet

Parameters **excel_writer** : string or ExcelWriter object

File path or existing ExcelWriter

sheet_name : string, default 'Sheet1'

Name of sheet which will contain DataFrame

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow :

upper left cell row to dump data frame

startcol :

upper left cell column to dump data frame

engine : string, default None

write engine to use - you can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

merge_cells : boolean, default True

Write MultiIndex and Hierarchical Rows as merged cells.

encoding: string, default None

encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep : string, default 'inf'

Representation for infinity (there is no native representation for infinity in Excel)

Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook:

```
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer,'Sheet1')
>>> df2.to_excel(writer,'Sheet2')
>>> writer.save()
```

pandas.DataFrame.to_json

`DataFrame.to_json`(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}
  - columns : dict like {column -> {index -> value}}
  - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso'* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.DataFrame.to_html

`DataFrame.to_html`(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *bold_rows=True*, *classes=None*, *escape=True*, *max_rows=None*, *max_cols=None*, *show_dimensions=False*, *notebook=False*)

Render a DataFrame as an HTML table.

to_html-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table

escape [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences.=

max_rows [int, optional] Maximum number of rows to show before truncating. If None, show all.

max_cols [int, optional] Maximum number of columns to show before truncating. If None, show all.

Parameters **frame** : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns **formatted** : string (or unicode, depending on data and options)

pandas.DataFrame.to_latex

`DataFrame.`**`to_latex`**(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *bold_rows=True*, *longtable=False*, *escape=True*)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires usepackage{booktabs}.

to_latex-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

longtable [boolean, default False] Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.

escape [boolean, default True] When set to False prevents from escaping latex special characters in column names.

Parameters **frame** : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_stata

DataFrame.**to_stata**(*fname*, *convert_dates=None*, *write_index=True*, *encoding='latin-1'*, *byteorder=None*, *time_stamp=None*, *data_label=None*)

A class for writing Stata binary dta files from array-like objects

Parameters fname : file path or buffer

Where to save the dta file.

convert_dates : dict

Dictionary mapping column of datetime types to the stata internal format that you want to use for the dates. Options are 'tc', 'td', 'tm', 'tw', 'th', 'tq', 'ty'. Column can be either a number or a name.

encoding : str

Default is latin-1. Note that Stata does not support unicode.

byteorder : str

Can be ">", "<", "little", or "big". The default is None which uses *sys.byteorder*

Examples

```
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

Or with dates

```
>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```

pandas.DataFrame.to_msgpack

DataFrame.**to_msgpack**(*path_or_buf=None*, ***kwargs*)

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.DataFrame.to_gbq

`DataFrame.to_gbq`(*destination_table*, *project_id=None*, *chunksize=10000*, *verbose=True*, *reauth=False*)

Write a DataFrame to a Google BigQuery table.

THIS IS AN EXPERIMENTAL LIBRARY

If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The to_gbq method chunks data into a default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: https://developers.google.com/bigquery/streaming-data-into-bigquery.

Parameters **dataframe** : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

pandas.DataFrame.to_records

`DataFrame.to_records`(*index=True*, *convert_datetime64=True*)

Convert DataFrame to record array. Index will be put in the 'index' field of the record array if requested

Parameters **index** : boolean, default True

Include index in resulting record array, stored in 'index' field

convert_datetime64 : boolean, default True

Whether to convert the index to datetime.datetime if it is a DatetimeIndex

Returns **y** : recarray

pandas.DataFrame.to_sparse

`DataFrame.to_sparse`(*fill_value=None*, *kind='block'*)

Convert to SparseDataFrame

Parameters **fill_value** : float, default NaN

kind : {'block', 'integer'}

Returns **y** : SparseDataFrame

pandas.DataFrame.to_dense

`DataFrame.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.DataFrame.to_string

`DataFrame.to_string(buf=None, columns=None, col_space=None, colSpace=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 frame : DataFrame

object to render

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

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_clipboard

DataFrame.**to_clipboard**(*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.5 Panel

33.5.1 Constructor

Panel([data, items, major_axis, minor_axis, ...])	Represents wide format panel data, stored as 3-dimensional array

pandas.Panel

class pandas.**Panel**(*data=None*, *items=None*, *major_axis=None*, *minor_axis=None*, *copy=False*, *dtype=None*)

Represents wide format panel data, stored as 3-dimensional array

Parameters data : ndarray (items x major x minor), or dict of DataFrames

items : Index or array-like

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

at	Fast label-based scalar accessor
axes	index(es) of the NDFrame
blocks	Internal property, property synonym for as_blocks()
dtypes	Return the dtypes in this object
empty	True if NDFrame is entirely empty [no items]
ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
iat	Fast integer location scalar accessor.
iloc	Purely integer-location based indexing for selection by position.
ix	A primarily label-location based indexer, with integer position fallback.
loc	Purely label-location based indexer for selection by label.
ndim	Number of axes / array dimensions
shape	tuple of axis dimensions
size	number of elements in the NDFrame
values	Numpy representation of NDFrame

pandas.Panel.at

Panel.**at**

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel.axes

Panel.**axes**

index(es) of the NDFrame

pandas.Panel.blocks

Panel.**blocks**

Internal property, property synonym for as_blocks()

pandas.Panel.dtypes

Panel.**dtypes**

Return the dtypes in this object

pandas.Panel.empty

Panel.**empty**

True if NDFrame is entirely empty [no items]

pandas.Panel.ftypes

`Panel.ftypes`
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel.iat

`Panel.iat`
Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel.iloc

`Panel.iloc`
Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.Panel.ix

`Panel.ix`
A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.Panel.loc

`Panel.loc`
Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.Panel.ndim

`Panel.ndim`
Number of axes / array dimensions

pandas.Panel.shape

`Panel.shape`
tuple of axis dimensions

pandas.Panel.size

`Panel.size`
number of elements in the NDFrame

pandas.Panel.values

`Panel.values`
Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	

Table 33.67 – continued from previous

Methods

abs()	Return an object with absolute value taken.
add(other[, axis])	Addition of series and other, element-wise (binary operator *add*).
add_prefix(prefix)	Concatenate prefix string with panel items names.
add_suffix(suffix)	Concatenate suffix string with panel items names
align(other[, join, axis, level, copy, ...])	Align two object on their axes with the
all([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
any([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
apply(func[, axis])	Applies function along input axis of the Panel
as_blocks()	Convert the frame to a dict of dtype -> Constructor Types that each has a homoge
as_matrix()	
asfreq(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
at_time(time[, asof])	Select values at particular time of day (e.g.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM)
bfill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='bfill')
bool()	Return the bool of a single element PandasObject
clip([lower, upper, out, axis])	Trim values at input threshold(s)
clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
compound([axis, skipna, level])	Return the compound percentage of the values for the requested axis
conform(frame[, axis])	Conform input DataFrame to align with chosen axis pair.
consolidate([inplace])	Compute NDFrame with "consolidated" internals (data of each dtype grouped to
convert_objects([convert_dates, ...])	Attempt to infer better dtype for object columns
copy([deep])	Make a copy of this object
count([axis])	Return number of observations over requested axis.
cummax([axis, dtype, out, skipna])	Return cumulative max over requested axis.
cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.
describe([percentile_width, percentiles, ...])	Generate various summary statistics, excluding NaN values.
div(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
divide(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
drop(labels[, axis, level, inplace, errors])	Return new object with labels in requested axis removed
dropna([axis, how, inplace])	Drop 2D from panel, holding passed axis constant
eq(other)	Wrapper for comparison method eq
equals(other)	Determines if two NDFrame objects contain the same elements.
ffill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='ffill')
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method
filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
first(offset)	Convenience method for subsetting initial periods of time series data
floordiv(other[, axis])	Integer division of series and other, element-wise (binary operator *floordiv*).
fromDict(data[, intersect, orient, dtype])	Construct Panel from dict of DataFrame objects
from_dict(data[, intersect, orient, dtype])	Construct Panel from dict of DataFrame objects
ge(other)	Wrapper for comparison method ge
get(key[, default])	Get item from object for given key (DataFrame column, Panel slice, etc.).
get_dtype_counts()	Return the counts of dtypes in this object
get_ftype_counts()	Return the counts of ftypes in this object
get_value(*args, **kwargs)	Quickly retrieve single value at (item, major, minor) location

Table 33.67 – continued from previous

get_values()	same as values (but handles sparseness conversions)
groupby(function[, axis])	Group data on given axis, returning GroupBy object
gt(other)	Wrapper for comparison method gt
head([n])	
interpolate([method, axis, limit, inplace, ...])	Interpolate values according to different methods.
isnull()	Return a boolean same-sized object indicating if the values are null
iteritems()	Iterate over (label, values) on info axis
iterkv(*args, **kwargs)	iteritems alias used to get around 2to3. Deprecated
join(other[, how, lsuffix, rsuffix])	Join items with other Panel either on major and minor axes column
keys()	Get the 'info axis' (see Indexing for more)
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
last(offset)	Convenience method for subsetting final periods of time series data
le(other)	Wrapper for comparison method le
load(path)	Deprecated.
lt(other)	Wrapper for comparison method lt
mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
major_xs(key[, copy])	Return slice of panel along major axis
mask(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from
max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
median([axis, skipna, level, numeric_only])	Return the median of the values for the requested axis
min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
minor_xs(key[, copy])	Return slice of panel along minor axis
mod(other[, axis])	Modulo of series and other, element-wise (binary operator *mod*).
mul(other[, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
multiply(other[, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
ne(other)	Wrapper for comparison method ne
notnull()	Return a boolean same-sized object indicating if the values are
pct_change([periods, fill_method, limit, freq])	Percent change over given number of periods.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs)
pop(item)	Return item and drop from frame.
pow(other[, axis])	Exponential power of series 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
radd(other[, axis])	Addition of series and other, element-wise (binary operator *radd*).
rdiv(other[, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
reindex([items, major_axis, minor_axis])	Conform Panel to new index with optional filling logic, placing NA/NaN in locat
reindex_axis(labels[, axis, method, level, ...])	Conform input object to new index with optional filling logic, placing NA/NaN i
reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
rename([items, major_axis, minor_axis])	Alter axes input function or functions.
rename_axis(mapper[, axis, copy, inplace])	Alter index and / or columns using input function or functions.
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 regular time-se
rfloordiv(other[, axis])	Integer division of series and other, element-wise (binary operator *rfloordiv*).
rmod(other[, axis])	Modulo of series and other, element-wise (binary operator *rmod*).
rmul(other[, axis])	Multiplication of series and other, element-wise (binary operator *rmul*).
rpow(other[, axis])	Exponential power of series and other, element-wise (binary operator *rpow*).
rsub(other[, axis])	Subtraction of series and other, element-wise (binary operator *rsub*).
rtruediv(other[, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
save(path)	Deprecated.

Table 33.67 – continued from previous

select(crit[, axis])	Return data corresponding to axis labels matching criteria
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.
set_axis(axis, labels)	public verson of axis assignment
set_value(*args, **kwargs)	Quickly set single value at (item, major, minor) location
shift(*args, **kwargs)	Shift index by desired number of periods with an optional time freq.
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
slice_shift([periods, axis])	Equivalent to *shift* without copying data.
sort_index([axis, ascending])	Sort object by labels (along an axis)
squeeze()	squeeze length 1 dimensions
std([axis, skipna, level, ddof, numeric_only])	Return unbiased standard deviation over requested axis.
sub(other[, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
subtract(other[, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately
swaplevel(i, j[, axis])	Swap levels i and j in a MultiIndex on a particular axis
tail([n])	
take(indices[, axis, convert, is_copy])	Analogous to ndarray.take
toLong(*args, **kwargs)	
to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This can be
to_dense()	Return dense representation of NDFrame (as opposed to sparse)
to_excel(path[, na_rep, engine])	Write each DataFrame in Panel to a separate excel sheet
to_frame([filter_observations])	Transform wide format into long (stacked) format as DataFrame whose columns
to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_long(*args, **kwargs)	
to_msgpack([path_or_buf])	msgpack (serialize) object to input file path
to_pickle(path)	Pickle (serialize) object to input file path
to_sparse([fill_value, kind])	Convert to SparsePanel
to_sql(name, con[, flavor, schema, ...])	Write records stored in a DataFrame to a SQL database.
transpose(*args, **kwargs)	Permute the dimensions of the Panel
truediv(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.
tshift([periods, freq, axis])	
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone
update(other[, join, overwrite, ...])	Modify Panel in place using non-NA values from passed Panel, or object coercib
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
where(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from
xs(key[, axis, copy])	Return slice of panel along selected axis

pandas.Panel.abs

`Panel.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Panel.add

`Panel.add(other, axis=0)`

Addition of series and other, element-wise (binary operator *add*). Equivalent to `panel + other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.radd`

pandas.Panel.add_prefix

`Panel.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Panel.add_suffix

`Panel.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Panel.align

`Panel.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (left, right) : (type of input, 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 requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns all : DataFrame or Panel (if level specified)

pandas.Panel.any

`Panel.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns any : DataFrame or Panel (if level specified)

pandas.Panel.apply

`Panel.apply(func, axis='major', **kwargs)`

Applies function along input axis of the Panel

Parameters func : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns **result** : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel.as_blocks

Panel.**as_blocks**()

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Returns **values** : a dict of dtype -> Constructor Types

pandas.Panel.as_matrix

Panel.**as_matrix**()

pandas.Panel.asfreq

Panel.**asfreq**(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.Panel.astype

`Panel.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Panel.at_time

`Panel.at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : type of caller

pandas.Panel.between_time

`Panel.between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns **values_between_time** : type of caller

pandas.Panel.bfill

`Panel.bfill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for NDFrame.fillna(method='bfill')

pandas.Panel.bool

`Panel.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.Panel.clip

`Panel.clip(lower=None, upper=None, out=None, axis=None)`

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Panel.clip_lower

Panel.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Panel.clip_upper

Panel.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters threshold : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input

See also:

clip

pandas.Panel.compound

Panel.**compound**(*axis=None*, *skipna=None*, *level=None*)

Return the compound percentage of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns compounded : DataFrame or Panel (if level specified)

pandas.Panel.conform

Panel.**conform**(*frame*, *axis='items'*)

Conform input DataFrame to align with chosen axis pair.

Parameters frame : DataFrame

axis : {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame

pandas.Panel.consolidate

Panel.**consolidate**(*inplace=False*)

Compute NDFrame with "consolidated" internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters **inplace** : boolean, default False

If False return new object, otherwise modify existing object

Returns **consolidated** : type of caller

pandas.Panel.convert_objects

`Panel.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)`

Attempt to infer better dtype for object columns

Parameters **convert_dates** : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns **converted** : same as input object

pandas.Panel.copy

`Panel.copy(deep=True)`

Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Panel.count

`Panel.count(axis='major')`

Return number of observations over requested axis.

Parameters **axis** : {'items', 'major', 'minor'} or {0, 1, 2}

Returns **count** : DataFrame

pandas.Panel.cummax

`Panel.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : DataFrame

pandas.Panel.cummin

`Panel.`**`cummin`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative min over requested axis.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : DataFrame

pandas.Panel.cumprod

`Panel.`**`cumprod`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative prod over requested axis.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : DataFrame

pandas.Panel.cumsum

`Panel.`**`cumsum`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative sum over requested axis.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : DataFrame

pandas.Panel.describe

`Panel.`**`describe`**(*percentile_width=None*, *percentiles=None*, *include=None*, *exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.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.drop

`Panel.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.Panel.dropna

`Panel.dropna(axis=0, how='any', inplace=False)`

Drop 2D from panel, holding passed axis constant

Parameters **axis** : int, default 0

Axis to hold constant. E.g. axis=1 will drop major_axis entries having a certain amount of NA data

how : {'all', 'any'}, default 'any'

'any': one or more values are NA in the DataFrame along the axis. For 'all' they all must be.

inplace : bool, default False

If True, do operation inplace and return None.

Returns **dropped** : Panel

pandas.Panel.eq

`Panel.eq(other)`
Wrapper for comparison method eq

pandas.Panel.equals

`Panel.equals(other)`
Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel.ffill

`Panel.ffill(axis=None, inplace=False, limit=None, downcast=None)`
Synonym for NDFrame.fillna(method='ffill')

pandas.Panel.fillna

`Panel.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)`
Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : Panel

See also:

`reindex`, `asfreq`

pandas.Panel.filter

`Panel.filter(items=None, like=None, regex=None, axis=None)`

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]]}); df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Panel.first

`Panel.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Panel.floordiv

`Panel.floordiv(other, axis=0)`

Integer division of series and other, element-wise (binary operator *floordiv*). Equivalent to `panel // other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rfloordiv`

pandas.Panel.fromDict

classmethod `Panel.`**`fromDict`**(*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters **data** : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'

The "orientation" of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass 'minor'

dtype : dtype, default None

Data type to force, otherwise infer

Returns Panel

pandas.Panel.from_dict

classmethod `Panel.`**`from_dict`**(*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters **data** : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'

The "orientation" of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass 'minor'

dtype : dtype, default None

Data type to force, otherwise infer

Returns Panel

pandas.Panel.ge

`Panel.ge(other)`
Wrapper for comparison method ge

pandas.Panel.get

`Panel.get(key, default=None)`
Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters **key** : object

Returns **value** : type of items contained in object

pandas.Panel.get_dtype_counts

`Panel.get_dtype_counts()`
Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts

`Panel.get_ftype_counts()`
Return the counts of ftypes in this object

pandas.Panel.get_value

`Panel.get_value(*args, **kwargs)`
Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns **value** : scalar value

pandas.Panel.get_values

`Panel.get_values()`
same as values (but handles sparseness conversions)

pandas.Panel.groupby

`Panel.groupby(function, axis='major')`
Group data on given axis, returning GroupBy object

Parameters **function** : callable

Mapping function for chosen access

axis : {'major', 'minor', 'items'}, default 'major'

Returns **grouped** : PanelGroupBy

pandas.Panel.gt

`Panel.gt(other)`
Wrapper for comparison method gt

pandas.Panel.head

`Panel.head(n=5)`

pandas.Panel.interpolate

`Panel.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`
Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. 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* with the order given both 'polynomial' and 'spline' requre that you also specify and order (int) e.g. df.interpolate(method='polynomial', order=4)
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html

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.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

reindex, replace, fillna

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.Panel.isnull

`Panel.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel.iteritems

`Panel.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel.iterkv

`Panel.iterkv(*args, **kwargs)`

iteritems alias used to get around 2to3. Deprecated

pandas.Panel.join

`Panel.join(other, how='left', lsuffix='', rsuffix='')`

Join items with other Panel either on major and minor axes column

Parameters **other** : Panel or list of Panels

Index should be similar to one of the columns in this one

how : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise * left: use calling frame's index * right: use input frame's index * outer: form union of indexes * inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

Returns joined : Panel

pandas.Panel.keys

`Panel.keys()`

Get the 'info axis' (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.Panel.kurt

`Panel.kurt`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : DataFrame or Panel (if level specified)

pandas.Panel.kurtosis

`Panel.kurtosis`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : DataFrame or Panel (if level specified)

pandas.Panel.last

`Panel.last(offset)`
Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel.le

`Panel.le(other)`
Wrapper for comparison method le

pandas.Panel.load

`Panel.load(path)`
Deprecated. Use read_pickle instead.

pandas.Panel.lt

`Panel.lt(other)`
Wrapper for comparison method lt

pandas.Panel.mad

`Panel.mad(axis=None, skipna=None, level=None)`
Return the mean absolute deviation of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mad : DataFrame or Panel (if level specified)

pandas.Panel.major_xs

Panel.**major_xs**(*key*, *copy=None*)

Return slice of panel along major axis

Parameters **key** : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see *MultiIndex Slicers*

pandas.Panel.mask

Panel.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel.max

Panel.**max**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : DataFrame or Panel (if level specified)

pandas.Panel.mean

`Panel.mean(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the mean of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : DataFrame or Panel (if level specified)

pandas.Panel.median

`Panel.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the median of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : DataFrame or Panel (if level specified)

pandas.Panel.min

`Panel.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : DataFrame or Panel (if level specified)

pandas.Panel.minor_xs

`Panel.minor_xs(key, copy=None)`

Return slice of panel along minor axis

Parameters **key** : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see *MultiIndex Slicers*

pandas.Panel.mod

`Panel.mod(other, axis=0)`

Modulo of series and other, element-wise (binary operator *mod*). Equivalent to `panel % other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rmod`

pandas.Panel.mul

`Panel.`**`mul`**`(`*other*, *axis=0*`)`

Multiplication of series and other, element-wise (binary operator *mul*). Equivalent to `panel * other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rmul`

pandas.Panel.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*`)`

Wrapper for comparison method ne

pandas.Panel.notnull

`Panel.`**`notnull`**`()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

pandas.Panel.pct_change

`Panel.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.Panel.pipe

`Panel.pipe(func, *args, **kwargs)`

Apply func(self, *args, **kwargs)

New in version 0.16.2.

Parameters **func** : function

function to apply to the NDFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the NDFrame.

args : positional arguments passed into `func`.

kwargs : a dictionary of keyword arguments passed into `func`.

Returns **object** : the return type of `func`.

See also:

`pandas.DataFrame.apply`, `pandas.DataFrame.applymap`, `pandas.Series.map`

Notes

Use `.pipe` when chaining together functions that expect on Series or DataFrames. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (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`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((f, 'arg2'), arg1=a, arg3=c)
...  )
```

pandas.Panel.pop

`Panel.pop(item)`
Return item and drop from frame. Raise KeyError if not found.

pandas.Panel.pow

`Panel.pow(other, axis=0)`
Exponential power of series and other, element-wise (binary operator *pow*). Equivalent to `panel ** other`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rpow`

pandas.Panel.prod

`Panel.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return the product of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns prod : DataFrame or Panel (if level specified)

pandas.Panel.product

`Panel.product` (*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : DataFrame or Panel (if level specified)

pandas.Panel.radd

`Panel.radd` (*other*, *axis=0*)

Addition of series and other, element-wise (binary operator *radd*). Equivalent to `other + panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.add`

pandas.Panel.rdiv

`Panel.rdiv` (*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to `other / panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.truediv`

pandas.Panel.reindex

`Panel.reindex(items=None, major_axis=None, minor_axis=None, **kwargs)`

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **items, major_axis, minor_axis** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel.reindex_axis

`Panel.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan)`

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **labels** : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : Panel

See also:

reindex, reindex_like

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel.reindex_like

Panel.**reindex_like**(*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Panel.rename

`Panel.rename`(*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **items, major_axis, minor_axis** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns **renamed** : Panel (new object)

pandas.Panel.rename_axis

`Panel.rename_axis`(*mapper*, *axis=0*, *copy=True*, *inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **mapper** : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns **renamed** : type of caller

pandas.Panel.replace

`Panel.replace`(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*, *axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters **to_replace** : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.

- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Panel.resample

`Panel.`**`resample`**(*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

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.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*`)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.Panel.save

`Panel.save(path)`

Deprecated. Use to_pickle instead

pandas.Panel.select

`Panel.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters crit : function

To be called on each index (label). Should return True or False

axis : int

Returns selection : type of caller

pandas.Panel.sem

`Panel.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sem** : DataFrame or Panel (if level specified)

pandas.Panel.set_axis

`Panel.`**`set_axis`**(*axis*, *labels*)

public verson of axis assignment

pandas.Panel.set_value

`Panel.`**`set_value`**(**args*, ***kwargs*)

Quickly set single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns **panel** : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

pandas.Panel.shift

`Panel.`**`shift`**(**args*, ***kwargs*)

Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of DataFrame.shift()

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns **shifted** : Panel

pandas.Panel.skew

`Panel.`**`skew`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : DataFrame or Panel (if level specified)

pandas.Panel.slice_shift

`Panel.slice_shift(periods=1, axis=0)`

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Panel.sort_index

`Panel.sort_index(axis=0, ascending=True)`

Sort object by labels (along an axis)

Parameters **axis** : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns **sorted_obj** : type of caller

pandas.Panel.squeeze

`Panel.squeeze()`

squeeze length 1 dimensions

pandas.Panel.std

`Panel.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : DataFrame or Panel (if level specified)

pandas.Panel.sub

`Panel.sub(other, axis=0)`

Subtraction of series and other, element-wise (binary operator *sub*). Equivalent to `panel - other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rsub`

pandas.Panel.subtract

`Panel.subtract(other, axis=0)`

Subtraction of series and other, element-wise (binary operator *sub*). Equivalent to `panel - other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rsub`

pandas.Panel.sum

`Panel.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sum : DataFrame or Panel (if level specified)

pandas.Panel.swapaxes

`Panel.swapaxes(axis1, axis2, copy=True)`

Interchange axes and swap values axes appropriately

Returns y : same as input

pandas.Panel.swaplevel

`Panel.swaplevel(i, j, axis=0)`

Swap levels i and j in a MultiIndex on a particular axis

Parameters i, j : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns swapped : type of caller (new object)

pandas.Panel.tail

`Panel.tail(n=5)`

pandas.Panel.take

`Panel.take(indices, axis=0, convert=True, is_copy=True)`

Analogous to ndarray.take

Parameters indices : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns taken : type of caller

pandas.Panel.toLong

`Panel.toLong(*args, **kwargs)`

pandas.Panel.to_clipboard

`Panel.to_clipboard(excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.Panel.to_dense

`Panel.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.Panel.to_excel

`Panel.to_excel(path, na_rep='', engine=None, **kwargs)`

Write each DataFrame in Panel to a separate excel sheet

Parameters **path** : string or ExcelWriter object

File path or existing ExcelWriter

na_rep : string, default ''

Missing data representation

engine : 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*)

activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Panel.to_json

Panel.**to_json**(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}
  - columns : dict like {column -> {index -> value}}
  - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso*' = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel.to_long

`Panel.to_long(*args, **kwargs)`

pandas.Panel.to_msgpack

`Panel.to_msgpack(path_or_buf=None, **kwargs)`
msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.Panel.to_pickle

`Panel.to_pickle(path)`
Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Panel.to_sparse

`Panel.to_sparse(fill_value=None, kind='block')`
Convert to SparsePanel

Parameters **fill_value** : float, default NaN

kind : {'block', 'integer'}

Returns **y** : SparseDataFrame

pandas.Panel.to_sql

`Panel.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`
Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Panel.transpose

`Panel.`**`transpose`**`(`**args*, ***kwargs*`)`

Permute the dimensions of the Panel

Parameters **args** : three positional arguments: each oneof

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns **y** : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel.truediv

`Panel.truediv(other, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rtruediv`

pandas.Panel.truncate

`Panel.truncate(before=None, after=None, axis=None, copy=True)`

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

pandas.Panel.tshift

`Panel.tshift(periods=1, freq=None, axis='major', **kwds)`

pandas.Panel.tz_convert

`Panel.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises TypeError

If the axis is tz-naive.

pandas.Panel.tz_localize

Panel.**tz_localize**(**args*, ***kwargs*)

Localize tz-naive TimeSeries to target time zone

Parameters tz : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises TypeError

If the TimeSeries is tz-aware and tz is not None.

pandas.Panel.update

Panel.**update**(*other*, *join='left'*, *overwrite=True*, *filter_func=None*, *raise_conflict=False*)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

Parameters other : Panel, or object coercible to Panel

join : How to join individual DataFrames

{'left', 'right', 'outer', 'inner'}, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling panel

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

pandas.Panel.var

`Panel.`**`var`**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : DataFrame or Panel (if level specified)

pandas.Panel.where

`Panel.`**`where`**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel.xs

Panel.**xs**(*key*, *axis=1*, *copy=None*)
Return slice of panel along selected axis

Parameters **key** : object

Label

axis : {'items', 'major', 'minor}, default 1/'major'

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : ndim(self)-1

Notes

xs is only for getting, not setting values.

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*

33.5.2 Attributes and underlying data

Axes

- **items**: axis 0; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1; the index (rows) of each of the DataFrames
- **minor_axis**: axis 2; the columns of each of the DataFrames

Panel.values	Numpy representation of NDFrame
Panel.axes	index(es) of the NDFrame
Panel.ndim	Number of axes / array dimensions
Panel.size	number of elements in the NDFrame
Panel.shape	tuple of axis dimensions
Panel.dtypes	Return the dtypes in this object
Panel.ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
Panel.get_dtype_counts()	Return the counts of dtypes in this object
Panel.get_ftype_counts()	Return the counts of ftypes in this object

pandas.Panel.values

Panel.**values**
Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.Panel.axes

`Panel.axes`
index(es) of the NDFrame

pandas.Panel.ndim

`Panel.ndim`
Number of axes / array dimensions

pandas.Panel.size

`Panel.size`
number of elements in the NDFrame

pandas.Panel.shape

`Panel.shape`
tuple of axis dimensions

pandas.Panel.dtypes

`Panel.dtypes`
Return the dtypes in this object

pandas.Panel.ftypes

`Panel.ftypes`
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel.get_dtype_counts

`Panel.get_dtype_counts()`
Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts

`Panel.get_ftype_counts()`
Return the counts of ftypes in this object

Continued on next page

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33.5.3 Conversion

Panel.astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
Panel.copy([deep])	Make a copy of this object
Panel.isnull()	Return a boolean same-sized object indicating if the values are null
Panel.notnull()	Return a boolean same-sized object indicating if the values are

pandas.Panel.astype

Panel.**astype**(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Panel.copy

Panel.**copy**(*deep=True*)

Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Panel.isnull

Panel.**isnull**()

Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel.notnull

Panel.**notnull**()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

33.5.4 Getting and setting

Panel.get_value(*args, **kwargs)	Quickly retrieve single value at (item, major, minor) location
Panel.set_value(*args, **kwargs)	Quickly set single value at (item, major, minor) location

pandas.Panel.get_value

Panel.**get_value**(**args*, ***kwargs*)

Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns **value** : scalar value

pandas.Panel.set_value

Panel.**set_value**(**args*, ***kwargs*)

Quickly set single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns **panel** : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

33.5.5 Indexing, iteration, slicing

Panel.at	Fast label-based scalar accessor
Panel.iat	Fast integer location scalar accessor.
Panel.ix	A primarily label-location based indexer, with integer position fallback.
Panel.loc	Purely label-location based indexer for selection by label.
Panel.iloc	Purely integer-location based indexing for selection by position.
Panel.__iter__()	Iterate over infor axis
Panel.iteritems()	Iterate over (label, values) on info axis
Panel.pop(item)	Return item and drop from frame.
Panel.xs(key[, axis, copy])	Return slice of panel along selected axis
Panel.major_xs(key[, copy])	Return slice of panel along major axis
Panel.minor_xs(key[, copy])	Return slice of panel along minor axis

pandas.Panel.at

Panel.**at**

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel.iat

`Panel.`**`iat`**

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel.ix

`Panel.`**`ix`**

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.Panel.loc

`Panel.`**`loc`**

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.Panel.iloc

`Panel.`**`iloc`**

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.Panel.__iter__

`Panel.__iter__()`

Iterate over infor axis

pandas.Panel.iteritems

`Panel.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel.pop

`Panel.pop(item)`

Return item and drop from frame. Raise KeyError if not found.

pandas.Panel.xs

`Panel.xs(key, axis=1, copy=None)`

Return slice of panel along selected axis

Parameters **key** : object

Label

axis : {'items', 'major', 'minor}, default 1/'major'

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : ndim(self)-1

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultiIndex Slicers*

pandas.Panel.major_xs

`Panel.major_xs(key, copy=None)`
Return slice of panel along major axis

Parameters **key** : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see *MultiIndex Slicers*

pandas.Panel.minor_xs

`Panel.minor_xs(key, copy=None)`
Return slice of panel along minor axis

Parameters **key** : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see *MultiIndex Slicers*

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the *indexing documentation*.

33.5.6 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*).

Continued on next page

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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*).
Panel.rpow(other[, axis])	Exponential power of series and other, element-wise (binary operator *rpow*).
Panel.lt(other)	Wrapper for comparison method lt
Panel.gt(other)	Wrapper for comparison method gt
Panel.le(other)	Wrapper for comparison method le
Panel.ge(other)	Wrapper for comparison method ge
Panel.ne(other)	Wrapper for comparison method ne
Panel.eq(other)	Wrapper for comparison method eq

pandas.Panel.add

Panel.**add**(*other*, *axis=0*)

Addition of series and other, element-wise (binary operator *add*). Equivalent to `panel + other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

Panel.radd

pandas.Panel.sub

Panel.**sub**(*other*, *axis=0*)

Subtraction of series and other, element-wise (binary operator *sub*). Equivalent to `panel - other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

Panel.rsub

pandas.Panel.mul

Panel.**mul**(*other*, *axis=0*)

Multiplication of series and other, element-wise (binary operator *mul*). Equivalent to `panel * other`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rmul`

pandas.Panel.div

`Panel.div(other, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rtruediv`

pandas.Panel.truediv

`Panel.truediv(other, axis=0)`

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rtruediv`

pandas.Panel.floordiv

`Panel.floordiv(other, axis=0)`

Integer division of series and other, element-wise (binary operator *floordiv*). Equivalent to `panel // other`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rfloordiv`

pandas.Panel.mod

`Panel.mod(other, axis=0)`

Modulo of series and other, element-wise (binary operator *mod*). Equivalent to `panel % other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rmod`

pandas.Panel.pow

`Panel.pow(other, axis=0)`

Exponential power of series and other, element-wise (binary operator *pow*). Equivalent to `panel ** other`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.rpow`

pandas.Panel.radd

`Panel.radd(other, axis=0)`

Addition of series and other, element-wise (binary operator *radd*). Equivalent to `other + panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.add`

pandas.Panel.rsub

`Panel.rsub(other, axis=0)`

Subtraction of series and other, element-wise (binary operator *rsub*). Equivalent to `other - panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.sub`

pandas.Panel.rmul

`Panel.`**`rmul`**(*other*, *axis=0*)
Multiplication of series and other, element-wise (binary operator *rmul*). Equivalent to `other * panel`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.mul`

pandas.Panel.rdiv

`Panel.`**`rdiv`**(*other*, *axis=0*)
Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to `other / panel`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.truediv`

pandas.Panel.rtruediv

`Panel.`**`rtruediv`**(*other*, *axis=0*)
Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to `other / panel`.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.truediv`

pandas.Panel.rfloordiv

`Panel.`**`rfloordiv`**(*other*, *axis=0*)
Integer division of series and other, element-wise (binary operator *rfloordiv*). Equivalent to `other // panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.floordiv`

pandas.Panel.rmod

`Panel.`**`rmod`**(*other*, *axis=0*)

Modulo of series and other, element-wise (binary operator *rmod*). Equivalent to `other % panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.mod`

pandas.Panel.rpow

`Panel.`**`rpow`**(*other*, *axis=0*)

Exponential power of series and other, element-wise (binary operator *rpow*). Equivalent to `other ** panel`.

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

`Panel.pow`

pandas.Panel.lt

`Panel.`**`lt`**(*other*)

Wrapper for comparison method lt

pandas.Panel.gt

`Panel.`**`gt`**(*other*)

Wrapper for comparison method gt

pandas.Panel.le

Panel.**le**(*other*)
Wrapper for comparison method le

pandas.Panel.ge

Panel.**ge**(*other*)
Wrapper for comparison method ge

pandas.Panel.ne

Panel.**ne**(*other*)
Wrapper for comparison method ne

pandas.Panel.eq

Panel.**eq**(*other*)
Wrapper for comparison method eq

33.5.7 Function application, GroupBy

Panel.apply(func[, axis])	Applies function along input axis of the Panel
Panel.groupby(function[, axis])	Group data on given axis, returning GroupBy object

pandas.Panel.apply

Panel.**apply**(*func*, *axis='major'*, ***kwargs*)
Applies function along input axis of the Panel

Parameters **func** : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns **result** : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel.groupby

Panel.**groupby**(*function*, *axis='major'*)
Group data on given axis, returning GroupBy object

Parameters **function** : callable

Mapping function for chosen access

axis : {'major', 'minor', 'items'}, default 'major'

Returns **grouped** : PanelGroupBy

33.5.8 Computations / Descriptive Stats

Panel.abs()	Return an object with absolute value taken.
Panel.clip([lower, upper, out, axis])	Trim values at input threshold(s)
Panel.clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
Panel.clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
Panel.count([axis])	Return number of observations over requested axis.
Panel.cummax([axis, dtype, out, skipna])	Return cumulative max over requested axis.
Panel.cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
Panel.cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
Panel.cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.
Panel.max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
Panel.mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
Panel.median([axis, skipna, level, numeric_only])	Return the median of the values for the requested axis
Panel.min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
Panel.pct_change([periods, fill_method, ...])	Percent change over given number of periods.
Panel.prod([axis, skipna, level, numeric_only])	Return the product of the values for the requested axis
Panel.sem([axis, skipna, level, ddof, ...])	Return unbiased standard error of the mean over requested axis.
Panel.skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
Panel.sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
Panel.std([axis, skipna, level, ddof, ...])	Return unbiased standard deviation over requested axis.
Panel.var([axis, skipna, level, ddof, ...])	Return unbiased variance over requested axis.

pandas.Panel.abs

Panel.**abs**()
Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Panel.clip

Panel.**clip**(*lower=None*, *upper=None*, *out=None*, *axis=None*)
Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0          1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Panel.clip_lower

Panel.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Panel.clip_upper

Panel.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input

See also:

`clip`

pandas.Panel.count

`Panel.count`(*axis='major'*)

Return number of observations over requested axis.

Parameters axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns count : DataFrame

pandas.Panel.cummax

`Panel.cummax`(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative max over requested axis.

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : DataFrame

pandas.Panel.cummin

`Panel.cummin`(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative min over requested axis.

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : DataFrame

pandas.Panel.cumprod

`Panel.cumprod`(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative prod over requested axis.

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns prod : DataFrame

pandas.Panel.cumsum

`Panel.`**`cumsum`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative sum over requested axis.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : DataFrame

pandas.Panel.max

`Panel.`**`max`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : DataFrame or Panel (if level specified)

pandas.Panel.mean

`Panel.`**`mean`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : DataFrame or Panel (if level specified)

pandas.Panel.median

`Panel.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return the median of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : DataFrame or Panel (if level specified)

pandas.Panel.min

`Panel.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : DataFrame or Panel (if level specified)

pandas.Panel.pct_change

`Panel.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`
Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.Panel.prod

`Panel.`**`prod`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns prod : DataFrame or Panel (if level specified)

pandas.Panel.sem

`Panel.`**`sem`**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sem : DataFrame or Panel (if level specified)

pandas.Panel.skew

`Panel.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns skew : DataFrame or Panel (if level specified)

pandas.Panel.sum

`Panel.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sum : DataFrame or Panel (if level specified)

pandas.Panel.std

`Panel.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : DataFrame or Panel (if level specified)

pandas.Panel.var

Panel.**var**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : DataFrame or Panel (if level specified)

33.5.9 Reindexing / Selection / Label manipulation

Panel.add_prefix(prefix)	Concatenate prefix string with panel items names.
Panel.add_suffix(suffix)	Concatenate suffix string with panel items names
Panel.drop(labels[, axis, level, inplace, ...])	Return new object with labels in requested axis removed
Panel.equals(other)	Determines if two NDFrame objects contain the same elements.
Panel.filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
Panel.first(offset)	Convenience method for subsetting initial periods of time series data
Panel.last(offset)	Convenience method for subsetting final periods of time series data
Panel.reindex([items, major_axis, minor_axis])	Conform Panel to new index with optional filling logic, placing NA/NaN in
Panel.reindex_axis(labels[, axis, method, ...])	Conform input object to new index with optional filling logic, placing NA/
Panel.reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
Panel.rename([items, major_axis, minor_axis])	Alter axes input function or functions.
Panel.sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
Panel.select(crit[, axis])	Return data corresponding to axis labels matching criteria
Panel.take(indices[, axis, convert, is_copy])	Analogous to ndarray.take
Panel.truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.

pandas.Panel.add_prefix

Panel.**add_prefix**(*prefix*)

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Panel.add_suffix

`Panel.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Panel.drop

`Panel.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.Panel.equals

`Panel.equals(other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel.filter

`Panel.filter(items=None, like=None, regex=None, axis=None)`

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]]}); df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Panel.first

`Panel.`**`first`**`(`*offset*`)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Panel.last

`Panel.`**`last`**`(`*offset*`)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel.reindex

`Panel.`**`reindex`**`(`*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*`)`

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters items, major_axis, minor_axis : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap

- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel.reindex_axis

`Panel.`**`reindex_axis`**(*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **labels** : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

See also:

reindex, reindex_like

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel.reindex_like

Panel.**reindex_like**(*other*, *method=None*, *copy=True*, *limit=None*)
return an object with matching indicies to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Panel.rename

Panel.**rename**(*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*)
Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters items, major_axis, minor_axis : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns renamed : Panel (new object)

pandas.Panel.sample

Panel.**sample**(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*, *axis=None*)
Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters n : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.Panel.select

`Panel.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.Panel.take

`Panel.take(indices, axis=0, convert=True, is_copy=True)`

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.Panel.truncate

`Panel.truncate`(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

33.5.10 Missing data handling

`Panel.dropna`([axis, how, inplace])	Drop 2D from panel, holding passed axis constant
`Panel.fillna`([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method

pandas.Panel.dropna

`Panel.dropna`(*axis=0*, *how='any'*, *inplace=False*)

Drop 2D from panel, holding passed axis constant

Parameters **axis** : int, default 0

Axis to hold constant. E.g. axis=1 will drop major_axis entries having a certain amount of NA data

how : {'all', 'any'}, default 'any'

'any': one or more values are NA in the DataFrame along the axis. For 'all' they all must be.

inplace : bool, default False

If True, do operation inplace and return None.

Returns **dropped** : Panel

pandas.Panel.fillna

`Panel.fillna`(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*, ***kwargs*)

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : Panel

See also:

`reindex`, `asfreq`

33.5.11 Reshaping, sorting, transposing

`Panel.sort_index`([axis, ascending])	Sort object by labels (along an axis)
`Panel.swaplevel`(i, j[, axis])	Swap levels i and j in a MultiIndex on a particular axis
`Panel.transpose`(*args, **kwargs)	Permute the dimensions of the Panel
`Panel.swapaxes`(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately
`Panel.conform`(frame[, axis])	Conform input DataFrame to align with chosen axis pair.

pandas.Panel.sort_index

`Panel.sort_index`(*axis=0*, *ascending=True*)

Sort object by labels (along an axis)

Parameters axis : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns sorted_obj : type of caller

pandas.Panel.swaplevel

`Panel.swaplevel`(*i*, *j*, *axis=0*)

Swap levels i and j in a MultiIndex on a particular axis

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)

pandas.Panel.transpose

`Panel.transpose(*args, **kwargs)`

Permute the dimensions of the Panel

Parameters **args** : three positional arguments: each oneof

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns **y** : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel.swapaxes

`Panel.swapaxes(axis1, axis2, copy=True)`

Interchange axes and swap values axes appropriately

Returns **y** : same as input

pandas.Panel.conform

`Panel.conform(frame, axis='items')`

Conform input DataFrame to align with chosen axis pair.

Parameters **frame** : DataFrame

axis : {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame

33.5.12 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

pandas.Panel.join

`Panel.join(other, how='left', lsuffix='', rsuffix='')`

Join items with other Panel either on major and minor axes column

Parameters **other** : Panel or list of Panels

Index should be similar to one of the columns in this one

how : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise * left: use calling frame's index * right: use input frame's index * outer: form union of indexes * inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

Returns **joined** : Panel

pandas.Panel.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.

33.5.13 Time series-related

`Panel.asfreq`(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
`Panel.shift`(*args, **kwargs)	Shift index by desired number of periods with an optional time freq.
`Panel.resample`(rule[, how, axis, ...])	Convenience method for frequency conversion and resampling of regular time-se
`Panel.tz_convert`(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
`Panel.tz_localize`(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone

pandas.Panel.asfreq

`Panel.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.Panel.shift

`Panel.shift(*args, **kwargs)`

Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of DataFrame.shift()

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns **shifted** : Panel

pandas.Panel.resample

`Panel.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Panel.tz_convert

`Panel.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis ia a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.Panel.tz_localize

`Panel.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)

- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises TypeError

If the TimeSeries is tz-aware and tz is not None.

33.5.14 Serialization / IO / Conversion

Panel.from_dict(data[, intersect, orient, dtype])	Construct Panel from dict of DataFrame objects
Panel.to_pickle(path)	Pickle (serialize) object to input file path
Panel.to_excel(path[, na_rep, engine])	Write each DataFrame in Panel to a separate excel sheet
Panel.to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
Panel.to_json([path_or_buf, orient, ...])	Convert the object to a JSON string.
Panel.to_sparse([fill_value, kind])	Convert to SparsePanel
Panel.to_frame([filter_observations])	Transform wide format into long (stacked) format as DataFrame whose colun
Panel.to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This car

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.to_pickle

Panel.**to_pickle**(*path*)

Pickle (serialize) object to input file path

Parameters path : string

File path

pandas.Panel.to_excel

`Panel.to_excel(path, na_rep='', engine=None, **kwargs)`

Write each DataFrame in Panel to a separate excel sheet

Parameters **path** : string or ExcelWriter object

File path or existing ExcelWriter

na_rep : string, default ''

Missing data representation

engine : string, default None

write engine to use - you can also set this via the options `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_hdf

`Panel.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Panel.to_json

`Panel.to_json`(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
  - split : dict like {index -> [index], columns -> [columns], data -> [values]}
  - records : list like [{column -> value}, ... , {column -> value}]
  - index : dict like {index -> {column -> value}}

- columns : dict like {column -> {index -> value}}
- values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso'* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel.to_sparse

Panel.**to_sparse**(*fill_value=None*, *kind='block'*)

Convert to SparsePanel

Parameters **fill_value** : float, default NaN

kind : {'block', 'integer'}

Returns **y** : SparseDataFrame

pandas.Panel.to_frame

Panel.**to_frame**(*filter_observations=True*)

Transform wide format into long (stacked) format as DataFrame whose columns are the Panel's items and whose index is a MultiIndex formed of the Panel's major and minor axes.

Parameters **filter_observations** : boolean, default True

Drop (major, minor) pairs without a complete set of observations across all the items

Returns **y** : DataFrame

pandas.Panel.to_clipboard

Panel.**to_clipboard**(*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.6 Panel4D

33.6.1 Constructor

`Panel4D`([data, labels, items, major_axis, ...])	Represents a 4 dimensional structured

pandas.Panel4D

class `pandas.Panel4D`(*data=None*, *labels=None*, *items=None*, *major_axis=None*, *minor_axis=None*, *copy=False*, *dtype=None*)

Represents a 4 dimensional structured

Parameters **data** : ndarray (labels x items x major x minor), or dict of Panels

labels : Index or array-like

items : Index or array-like

major_axis : Index or array-like: axis=2

minor_axis : Index or array-like: axis=3

dtype : dtype, default None

Data type to force, otherwise infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

Attributes

`at`	Fast label-based scalar accessor
`axes`	index(es) of the NDFrame
`blocks`	Internal property, property synonym for as_blocks()
`dtypes`	Return the dtypes in this object
`empty`	True if NDFrame is entirely empty [no items]
`ftypes`	Return the ftypes (indication of sparse/dense and dtype) in this object.
`iat`	Fast integer location scalar accessor.
`iloc`	Purely integer-location based indexing for selection by position.

Continued on next page

Table 33.82 – continued from previous page

ix	A primarily label-location based indexer, with integer position fallback.
loc	Purely label-location based indexer for selection by label.
ndim	Number of axes / array dimensions
shape	tuple of axis dimensions
size	number of elements in the NDFrame
values	Numpy representation of NDFrame

pandas.Panel4D.at

Panel4D.**at**
Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel4D.axes

Panel4D.**axes**
index(es) of the NDFrame

pandas.Panel4D.blocks

Panel4D.**blocks**
Internal property, property synonym for as_blocks()

pandas.Panel4D.dtypes

Panel4D.**dtypes**
Return the dtypes in this object

pandas.Panel4D.empty

Panel4D.**empty**
True if NDFrame is entirely empty [no items]

pandas.Panel4D.ftypes

Panel4D.**ftypes**
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.iat

Panel4D.**iat**
Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel4D.iloc

`Panel4D.iloc`
Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*

pandas.Panel4D.ix

`Panel4D.ix`
A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at *Advanced Indexing*.

pandas.Panel4D.loc

`Panel4D.loc`
Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at *Selection by Label*

pandas.Panel4D.ndim

`Panel4D.ndim`
Number of axes / array dimensions

pandas.Panel4D.shape

`Panel4D.shape`
tuple of axis dimensions

pandas.Panel4D.size

`Panel4D.size`
number of elements in the NDFrame

pandas.Panel4D.values

`Panel4D.values`
Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	

Methods

abs()	Return an object with absolute value taken.
add(other[, axis])	Addition of series and other, element-wise (binary operator *add*).
add_prefix(prefix)	Concatenate prefix string with panel items names.
add_suffix(suffix)	Concatenate suffix string with panel items names
align(other[, join, axis, level, copy, ...])	Align two object on their axes with the
all([axis, bool_only, skipna, level])	Return whether all elements are True over requested axis
any([axis, bool_only, skipna, level])	Return whether any element is True over requested axis
apply(func[, axis])	Applies function along input axis of the Panel
as_blocks()	Convert the frame to a dict of dtype -> Constructor Types that each has a homoge
as_matrix()	
asfreq(freq[, method, how, normalize])	Convert all TimeSeries inside to specified frequency using DateOffset objects.
astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
at_time(time[, asof])	Select values at particular time of day (e.g.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM)
bfill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='bfill')

Table 33.83 – continued from previous page

bool()	Return the bool of a single element PandasObject
clip([lower, upper, out, axis])	Trim values at input threshold(s)
clip_lower(threshold[, axis])	Return copy of the input with values below given value(s) truncated
clip_upper(threshold[, axis])	Return copy of input with values above given value(s) truncated
compound([axis, skipna, level])	Return the compound percentage of the values for the requested axis
conform(frame[, axis])	Conform input DataFrame to align with chosen axis pair.
consolidate([inplace])	Compute NDFrame with "consolidated" internals (data of each dtype grouped to
convert_objects([convert_dates, ...])	Attempt to infer better dtype for object columns
copy([deep])	Make a copy of this object
count([axis])	Return number of observations over requested axis.
cummax([axis, dtype, out, skipna])	Return cumulative max over requested axis.
cummin([axis, dtype, out, skipna])	Return cumulative min over requested axis.
cumprod([axis, dtype, out, skipna])	Return cumulative prod over requested axis.
cumsum([axis, dtype, out, skipna])	Return cumulative sum over requested axis.
describe([percentile_width, percentiles, ...])	Generate various summary statistics, excluding NaN values.
div(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
divide(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
drop(labels[, axis, level, inplace, errors])	Return new object with labels in requested axis removed
dropna(*args, **kwargs)	
eq(other)	Wrapper for comparison method eq
equals(other)	Determines if two NDFrame objects contain the same elements.
ffill([axis, inplace, limit, downcast])	Synonym for NDFrame.fillna(method='ffill')
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method
filter(*args, **kwargs)	
first(offset)	Convenience method for subsetting initial periods of time series data
floordiv(other[, axis])	Integer division of series and other, element-wise (binary operator *floordiv*).
fromDict(data[, intersect, orient, dtype])	Construct Panel from dict of DataFrame objects
from_dict(data[, intersect, orient, dtype])	Construct Panel from dict of DataFrame objects
ge(other)	Wrapper for comparison method ge
get(key[, default])	Get item from object for given key (DataFrame column, Panel slice, etc.).
get_dtype_counts()	Return the counts of dtypes in this object
get_ftype_counts()	Return the counts of ftypes in this object
get_value(*args, **kwargs)	Quickly retrieve single value at (item, major, minor) location
get_values()	same as values (but handles sparseness conversions)
groupby(*args, **kwargs)	
gt(other)	Wrapper for comparison method gt
head([n])	
interpolate([method, axis, limit, inplace, ...])	Interpolate values according to different methods.
isnull()	Return a boolean same-sized object indicating if the values are null
iteritems()	Iterate over (label, values) on info axis
iterkv(*args, **kwargs)	iteritems alias used to get around 2to3. Deprecated
join(*args, **kwargs)	
keys()	Get the 'info axis' (see Indexing for more)
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
last(offset)	Convenience method for subsetting final periods of time series data
le(other)	Wrapper for comparison method le
load(path)	Deprecated.
lt(other)	Wrapper for comparison method lt
mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
major_xs(key[, copy])	Return slice of panel along major axis
mask(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from

Table 33.83 – continued from previous page

max([axis, skipna, level, numeric_only])	This method returns the maximum of the values in the object.
mean([axis, skipna, level, numeric_only])	Return the mean of the values for the requested axis
median([axis, skipna, level, numeric_only])	Return the median of the values for the requested axis
min([axis, skipna, level, numeric_only])	This method returns the minimum of the values in the object.
minor_xs(key[, copy])	Return slice of panel along minor axis
mod(other[, axis])	Modulo of series and other, element-wise (binary operator *mod*).
mul(other[, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
multiply(other[, axis])	Multiplication of series and other, element-wise (binary operator *mul*).
ne(other)	Wrapper for comparison method ne
notnull()	Return a boolean same-sized object indicating if the values are
pct_change([periods, fill_method, limit, freq])	Percent change over given number of periods.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs)
pop(item)	Return item and drop from frame.
pow(other[, axis])	Exponential power of series 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
radd(other[, axis])	Addition of series and other, element-wise (binary operator *radd*).
rdiv(other[, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
reindex([items, major_axis, minor_axis])	Conform Panel to new index with optional filling logic, placing NA/NaN in locat
reindex_axis(labels[, axis, method, level, ...])	Conform input object to new index with optional filling logic, placing NA/NaN i
reindex_like(other[, method, copy, limit])	return an object with matching indicies to myself
rename([items, major_axis, minor_axis])	Alter axes input function or functions.
rename_axis(mapper[, axis, copy, inplace])	Alter index and / or columns using input function or functions.
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 regular time-se
rfloordiv(other[, axis])	Integer division of series and other, element-wise (binary operator *rfloordiv*).
rmod(other[, axis])	Modulo of series and other, element-wise (binary operator *rmod*).
rmul(other[, axis])	Multiplication of series and other, element-wise (binary operator *rmul*).
rpow(other[, axis])	Exponential power of series and other, element-wise (binary operator *rpow*).
rsub(other[, axis])	Subtraction of series and other, element-wise (binary operator *rsub*).
rtruediv(other[, axis])	Floating division of series and other, element-wise (binary operator *rtruediv*).
sample([n, frac, replace, weights, ...])	Returns a random sample of items from an axis of object.
save(path)	Deprecated.
select(crit[, axis])	Return data corresponding to axis labels matching criteria
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.
set_axis(axis, labels)	public verson of axis assignment
set_value(*args, **kwargs)	Quickly set single value at (item, major, minor) location
shift(*args, **kwargs)	
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis
slice_shift([periods, axis])	Equivalent to *shift* without copying data.
sort_index([axis, ascending])	Sort object by labels (along an axis)
squeeze()	squeeze length 1 dimensions
std([axis, skipna, level, ddof, numeric_only])	Return unbiased standard deviation over requested axis.
sub(other[, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
subtract(other[, axis])	Subtraction of series and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only])	Return the sum of the values for the requested axis
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately
swaplevel(i, j[, axis])	Swap levels i and j in a MultiIndex on a particular axis
tail([n])	
take(indices[, axis, convert, is_copy])	Analogous to ndarray.take
toLong(*args, **kwargs)	
to_clipboard([excel, sep])	Attempt to write text representation of object to the system clipboard This can be

Table 33.83 – continued from previous page

to_dense()	Return dense representation of NDFrame (as opposed to sparse)
to_excel(*args, **kwargs)	
to_frame(*args, **kwargs)	
to_hdf(path_or_buf, key, **kwargs)	activate the HDFStore
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_long(*args, **kwargs)	
to_msgpack([path_or_buf])	msgpack (serialize) object to input file path
to_pickle(path)	Pickle (serialize) object to input file path
to_sparse(*args, **kwargs)	
to_sql(name, con[, flavor, schema, ...])	Write records stored in a DataFrame to a SQL database.
transpose(*args, **kwargs)	Permute the dimensions of the Panel
truediv(other[, axis])	Floating division of series and other, element-wise (binary operator *truediv*).
truncate([before, after, axis, copy])	Truncates a sorted NDFrame before and/or after some particular dates.
tshift([periods, freq, axis])	
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(*args, **kwargs)	Localize tz-naive TimeSeries to target time zone
update(other[, join, overwrite, ...])	Modify Panel in place using non-NA values from passed Panel, or object coercib
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
where(cond[, other, inplace, axis, level, ...])	Return an object of same shape as self and whose corresponding entries are from
xs(key[, axis, copy])	Return slice of panel along selected axis

pandas.Panel4D.abs

Panel4D.**abs**()

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Panel4D.add

Panel4D.**add**(*other*, *axis=0*)

Addition of series and other, element-wise (binary operator *add*). Equivalent to `panel + other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

Panel4D.radd

pandas.Panel4D.add_prefix

Panel4D.**add_prefix**(*prefix*)

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Panel4D.add_suffix

`Panel4D.add_suffix`(*suffix*)

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Panel4D.align

`Panel4D.align`(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*, *fill_axis=0*)

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : {'outer', 'inner', 'left', 'right'}, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns **(left, right)** : (type of input, type of other)

Aligned objects

pandas.Panel4D.all

`Panel4D.all`(*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether all elements are True over requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : Panel or Panel4D (if level specified)

pandas.Panel4D.any

Panel4D.**any**(*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether any element is True over requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : Panel or Panel4D (if level specified)

pandas.Panel4D.apply

Panel4D.**apply**(*func*, *axis='major'*, ***kwargs*)

Applies function along input axis of the Panel

Parameters **func** : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns **result** : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel4D.as_blocks

`Panel4D.as_blocks()`

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Returns values : a dict of dtype -> Constructor Types

pandas.Panel4D.as_matrix

`Panel4D.as_matrix()`

pandas.Panel4D.asfreq

`Panel4D.asfreq`(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.Panel4D.astype

`Panel4D.astype`(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters dtype : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns casted : type of caller

pandas.Panel4D.at_time

`Panel4D.at_time`(*time*, *asof=False*)

Select values at particular time of day (e.g. 9:30AM)

Parameters time : datetime.time or string

Returns **values_at_time** : type of caller

pandas.Panel4D.between_time

`Panel4D.`**`between_time`**(*start_time*, *end_time*, *include_start=True*, *include_end=True*)

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns **values_between_time** : type of caller

pandas.Panel4D.bfill

`Panel4D.`**`bfill`**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for NDFrame.fillna(method='bfill')

pandas.Panel4D.bool

`Panel4D.`**`bool`**()

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.Panel4D.clip

`Panel4D.`**`clip`**(*lower=None*, *upper=None*, *out=None*, *axis=None*)

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
  0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
          0         1
```

```
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
          0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Panel4D.clip_lower

Panel4D.**clip_lower**(*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Panel4D.clip_upper

Panel4D.**clip_upper**(*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

clip

pandas.Panel4D.compound

Panel4D.**compound**(*axis=None*, *skipna=None*, *level=None*)

Return the compound percentage of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **compounded** : Panel or Panel4D (if level specified)

pandas.Panel4D.conform

`Panel4D.`**`conform`**(*frame*, *axis='items'*)

Conform input DataFrame to align with chosen axis pair.

Parameters **frame** : DataFrame

axis : {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame

pandas.Panel4D.consolidate

`Panel4D.`**`consolidate`**(*inplace=False*)

Compute NDFrame with "consolidated" internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters **inplace** : boolean, default False

If False return new object, otherwise modify existing object

Returns **consolidated** : type of caller

pandas.Panel4D.convert_objects

`Panel4D.`**`convert_objects`**(*convert_dates=True*, *convert_numeric=False*, *convert_timedeltas=True*, *copy=True*)

Attempt to infer better dtype for object columns

Parameters **convert_dates** : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.Panel4D.copy

`Panel4D.copy(deep=True)`

Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.Panel4D.count

`Panel4D.count(axis='major')`

Return number of observations over requested axis.

Parameters axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns count : DataFrame

pandas.Panel4D.cummax

`Panel4D.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : Panel

pandas.Panel4D.cummin

`Panel4D.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : Panel

pandas.Panel4D.cumprod

`Panel4D.`**`cumprod`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)
Return cumulative prod over requested axis.

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : Panel

pandas.Panel4D.cumsum

`Panel4D.`**`cumsum`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)
Return cumulative sum over requested axis.

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Panel

pandas.Panel4D.describe

`Panel4D.`**`describe`**(*percentile_width=None*, *percentiles=None*, *include=None*, *exclude=None*)
Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Panel4D.div

`Panel4D.`**`div`**(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rtruediv`

pandas.Panel4D.divide

`Panel4D.`**`divide`**(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rtruediv`

pandas.Panel4D.drop

`Panel4D.`**`drop`**(*labels*, *axis=0*, *level=None*, *inplace=False*, *errors='raise'*)

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

New in version 0.16.1.

Returns **dropped** : type of caller

pandas.Panel4D.dropna

`Panel4D.`**`dropna`**(**args*, ***kwargs*)

pandas.Panel4D.eq

`Panel4D.`**`eq`**(*other*)

Wrapper for comparison method eq

pandas.Panel4D.equals

`Panel4D.`**`equals`**(*other*)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel4D.ffill

`Panel4D.`**`ffill`**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for NDFrame.fillna(method='ffill')

pandas.Panel4D.fillna

`Panel4D.`**`fillna`**(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*, ***kwargs*)

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : Panel

See also:

`reindex`, `asfreq`

pandas.Panel4D.filter

`Panel4D.filter(*args, **kwargs)`

pandas.Panel4D.first

`Panel4D.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Panel4D.floordiv

`Panel4D.floordiv(other, axis=0)`

Integer division of series and other, element-wise (binary operator *floordiv*). Equivalent to `panel // other`.

Parameters other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rfloordiv`

pandas.Panel4D.fromDict

classmethod `Panel4D.fromDict`(*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters **data** : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'

The "orientation" of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass 'minor'

dtype : dtype, default None

Data type to force, otherwise infer

Returns Panel

pandas.Panel4D.from_dict

classmethod `Panel4D.from_dict`(*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters **data** : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'

The "orientation" of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass 'minor'

dtype : dtype, default None

Data type to force, otherwise infer

Returns Panel

pandas.Panel4D.ge

`Panel4D.ge(other)`
Wrapper for comparison method ge

pandas.Panel4D.get

`Panel4D.get(key, default=None)`
Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters **key** : object

Returns **value** : type of items contained in object

pandas.Panel4D.get_dtype_counts

`Panel4D.get_dtype_counts()`
Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts

`Panel4D.get_ftype_counts()`
Return the counts of ftypes in this object

pandas.Panel4D.get_value

`Panel4D.get_value(*args, **kwargs)`
Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns **value** : scalar value

pandas.Panel4D.get_values

`Panel4D.get_values()`
same as values (but handles sparseness conversions)

pandas.Panel4D.groupby

`Panel4D.groupby(*args, **kwargs)`

pandas.Panel4D.gt

`Panel4D.gt(other)`
Wrapper for comparison method gt

pandas.Panel4D.head

`Panel4D.head(n=5)`

pandas.Panel4D.interpolate

`Panel4D.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`
Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. 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* with the order given both 'polynomial' and 'spline' requre that you also specify and order (int) e.g. df.interpolate(method='polynomial', order=4)
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html

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.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.Panel4D.isnull

`Panel4D.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel4D.iteritems

`Panel4D.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel4D.iterkv

`Panel4D.iterkv(*args, **kwargs)`

iteritems alias used to get around 2to3. Deprecated

pandas.Panel4D.join

`Panel4D.join(*args, **kwargs)`

pandas.Panel4D.keys

`Panel4D.keys()`

Get the 'info axis' (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.Panel4D.kurt

`Panel4D.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Panel or Panel4D (if level specified)

pandas.Panel4D.kurtosis

Panel4D.**kurtosis**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Panel or Panel4D (if level specified)

pandas.Panel4D.last

Panel4D.**last**(*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel4D.le

Panel4D.**le**(*other*)

Wrapper for comparison method le

pandas.Panel4D.load

`Panel4D.load(path)`
Deprecated. Use read_pickle instead.

pandas.Panel4D.lt

`Panel4D.lt(other)`
Wrapper for comparison method lt

pandas.Panel4D.mad

`Panel4D.mad(axis=None, skipna=None, level=None)`
Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Panel or Panel4D (if level specified)

pandas.Panel4D.major_xs

`Panel4D.major_xs(key, copy=None)`
Return slice of panel along major axis

Parameters **key** : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see *MultiIndex Slicers*

pandas.Panel4D.mask

Panel4D.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.Panel4D.max

Panel4D.**max**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : Panel or Panel4D (if level specified)

pandas.Panel4D.mean

Panel4D.**mean**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values for the requested axis

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mean : Panel or Panel4D (if level specified)

pandas.Panel4D.median

`Panel4D.`**`median`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the median of the values for the requested axis

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : Panel or Panel4D (if level specified)

pandas.Panel4D.min

`Panel4D.`**`min`**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : Panel or Panel4D (if level specified)

pandas.Panel4D.minor_xs

Panel4D.**minor_xs**(*key*, *copy=None*)
Return slice of panel along minor axis

Parameters **key** : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see *MultiIndex Slicers*

pandas.Panel4D.mod

Panel4D.**mod**(*other*, *axis=0*)
Modulo of series and other, element-wise (binary operator *mod*). Equivalent to `panel % other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rmod`

pandas.Panel4D.mul

Panel4D.**mul**(*other*, *axis=0*)
Multiplication of series and other, element-wise (binary operator *mul*). Equivalent to `panel * other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rmul`

pandas.Panel4D.multiply

`Panel4D.multiply(other, axis=0)`

Multiplication of series and other, element-wise (binary operator *mul*). Equivalent to `panel * other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rmul`

pandas.Panel4D.ne

`Panel4D.ne(other)`

Wrapper for comparison method ne

pandas.Panel4D.notnull

`Panel4D.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

pandas.Panel4D.pct_change

`Panel4D.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.Panel4D.pipe

Panel4D.**pipe**(*func*, **args*, ***kwargs*)

Apply func(self, *args, **kwargs)

New in version 0.16.2.

Parameters **func** : function

function to apply to the NDFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the NDFrame.

args : positional arguments passed into `func`.

kwargs : a dictionary of keyword arguments passed into `func`.

Returns **object** : the return type of `func`.

See also:

`pandas.DataFrame.apply`, `pandas.DataFrame.applymap`, `pandas.Series.map`

Notes

Use `.pipe` when chaining together functions that expect on Series or DataFrames. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (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`:

```
>>> (df.pipe(h)
...    .pipe(g, arg1=a)
...    .pipe((f, 'arg2'), arg1=a, arg3=c)
...  )
```

pandas.Panel4D.pop

Panel4D.**pop**(*item*)

Return item and drop from frame. Raise KeyError if not found.

pandas.Panel4D.pow

Panel4D.**pow**(*other*, *axis=0*)

Exponential power of series and other, element-wise (binary operator *pow*). Equivalent to `panel ** other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rpow`

pandas.Panel4D.prod

`Panel4D.prod`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Panel or Panel4D (if level specified)

pandas.Panel4D.product

`Panel4D.product`(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Panel or Panel4D (if level specified)

pandas.Panel4D.radd

`Panel4D.`**`radd`**(*other*, *axis=0*)

Addition of series and other, element-wise (binary operator *radd*). Equivalent to `other + panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.add`

pandas.Panel4D.rdiv

`Panel4D.`**`rdiv`**(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to `other / panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.truediv`

pandas.Panel4D.reindex

`Panel4D.`**`reindex`**(*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*)

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters **items, major_axis, minor_axis** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel4D.reindex_axis

Panel4D.**reindex_axis**(*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters labels : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : Panel

See also:

reindex, reindex_like

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel4D.reindex_like

Panel4D.**reindex_like**(*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Panel4D.rename

Panel4D.**rename**(*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **items, major_axis, minor_axis** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns **renamed** : Panel (new object)

pandas.Panel4D.rename_axis

Panel4D.**rename_axis**(*mapper*, *axis=0*, *copy=True*, *inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **mapper** : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns **renamed** : type of caller

pandas.Panel4D.replace

Panel4D.**replace**(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*, *axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters **to_replace** : str, regex, list, dict, Series, numeric, or None

- str or regex:
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str and regex rules apply as above.
- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
  - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or `Series`.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Otherwise, *to_replace* must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a `list`.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are `list` s or `ndarray` s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Panel4D.resample

`Panel4D.`**`resample`**(*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Panel4D.rfloordiv

`Panel4D.rfloordiv(other, axis=0)`

Integer division of series and other, element-wise (binary operator *rfloordiv*). Equivalent to `other // panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.floordiv`

pandas.Panel4D.rmod

`Panel4D.rmod(other, axis=0)`

Modulo of series and other, element-wise (binary operator *rmod*). Equivalent to `other % panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.mod`

pandas.Panel4D.rmul

`Panel4D.rmul(other, axis=0)`
Multiplication of series and other, element-wise (binary operator *rmul*). Equivalent to `other * panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.mul`

pandas.Panel4D.rpow

`Panel4D.rpow(other, axis=0)`
Exponential power of series and other, element-wise (binary operator *rpow*). Equivalent to `other ** panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.pow`

pandas.Panel4D.rsub

`Panel4D.rsub(other, axis=0)`
Subtraction of series and other, element-wise (binary operator *rsub*). Equivalent to `other - panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.sub`

pandas.Panel4D.rtruediv

`Panel4D.rtruediv(other, axis=0)`
Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to `other / panel`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.truediv`

pandas.Panel4D.sample

`Panel4D.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

Parameters **n** : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. 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 Same type as caller.

pandas.Panel4D.save

`Panel4D.save(path)`

Deprecated. Use to_pickle instead

pandas.Panel4D.select

`Panel4D.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns selection : type of caller

pandas.Panel4D.sem

Panel4D.**sem**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sem : Panel or Panel4D (if level specified)

pandas.Panel4D.set_axis

Panel4D.**set_axis**(*axis*, *labels*)

public verson of axis assignment

pandas.Panel4D.set_value

Panel4D.**set_value**(**args*, ***kwargs*)

Quickly set single value at (item, major, minor) location

Parameters item : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns panel : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

pandas.Panel4D.shift

Panel4D.**shift**(**args*, ***kwargs*)

pandas.Panel4D.skew

`Panel4D.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Panel or Panel4D (if level specified)

pandas.Panel4D.slice_shift

`Panel4D.slice_shift(periods=1, axis=0)`

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Panel4D.sort_index

`Panel4D.sort_index(axis=0, ascending=True)`

Sort object by labels (along an axis)

Parameters **axis** : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns **sorted_obj** : type of caller

pandas.Panel4D.squeeze

`Panel4D.squeeze()`

squeeze length 1 dimensions

pandas.Panel4D.std

`Panel4D.std`(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)
Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : Panel or Panel4D (if level specified)

pandas.Panel4D.sub

`Panel4D.sub`(*other*, *axis=0*)
Subtraction of series and other, element-wise (binary operator *sub*). Equivalent to `panel - other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rsub`

pandas.Panel4D.subtract

`Panel4D.subtract`(*other*, *axis=0*)
Subtraction of series and other, element-wise (binary operator *sub*). Equivalent to `panel - other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rsub`

pandas.Panel4D.sum

Panel4D.**sum**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : Panel or Panel4D (if level specified)

pandas.Panel4D.swapaxes

Panel4D.**swapaxes**(*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns **y** : same as input

pandas.Panel4D.swaplevel

Panel4D.**swaplevel**(*i*, *j*, *axis=0*)

Swap levels i and j in a MultiIndex on a particular axis

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)

pandas.Panel4D.tail

Panel4D.**tail**(*n=5*)

pandas.Panel4D.take

Panel4D.**take**(*indices*, *axis=0*, *convert=True*, *is_copy=True*)

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.Panel4D.toLong

Panel4D.**toLong**(**args*, ***kwargs*)

pandas.Panel4D.to_clipboard

Panel4D.**to_clipboard**(*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.Panel4D.to_dense

Panel4D.**to_dense**()

Return dense representation of NDFrame (as opposed to sparse)

pandas.Panel4D.to_excel

Panel4D.**to_excel**(**args*, ***kwargs*)

pandas.Panel4D.to_frame

Panel4D.**to_frame**(**args*, ***kwargs*)

pandas.Panel4D.to_hdf

Panel4D.**to_hdf**(*path_or_buf*, *key*, ***kwargs*)

activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to `'a'`, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Panel4D.to_json

`Panel4D.`**`to_json`**(*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters **path_or_buf** : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
  - default is 'index'
  - allowed values are: {'split','records','index'}
- DataFrame
  - default is 'columns'
  - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string

- split : dict like {index -> [index], columns -> [columns], data -> [values]}
- records : list like [{column -> value}, ... , {column -> value}]
- index : dict like {index -> {column -> value}}
- columns : dict like {column -> {index -> value}}
- values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso*' = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel4D.to_long

`Panel4D.to_long(*args, **kwargs)`

pandas.Panel4D.to_msgpack

`Panel4D.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.Panel4D.to_pickle

`Panel4D.to_pickle(path)`

Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Panel4D.to_sparse

`Panel4D.to_sparse(*args, **kwargs)`

pandas.Panel4D.to_sql

`Panel4D.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Panel4D.transpose

Panel4D.**transpose**(**args*, ***kwargs*)

Permute the dimensions of the Panel

Parameters **args** : three positional arguments: each oneof

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns **y** : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel4D.truediv

Panel4D.**truediv**(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator *truediv*). Equivalent to `panel / other`.

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

See also:

`Panel4D.rtruediv`

pandas.Panel4D.truncate

Panel4D.**truncate**(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns truncated : type of caller

pandas.Panel4D.tshift

`Panel4D.tshift`(*periods=1*, *freq=None*, *axis='major'*, ***kwds*)

pandas.Panel4D.tz_convert

`Panel4D.tz_convert`(*tz*, *axis=0*, *level=None*, *copy=True*)

Convert tz-aware axis to target time zone.

Parameters tz : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis 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.Panel4D.tz_localize

`Panel4D.tz_localize`(**args*, ***kwargs*)

Localize tz-naive TimeSeries to target time zone

Parameters tz : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises TypeError

If the TimeSeries is tz-aware and tz is not None.

pandas.Panel4D.update

Panel4D.**update**(*other*, *join='left'*, *overwrite=True*, *filter_func=None*, *raise_conflict=False*)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

Parameters **other** : Panel, or object coercible to Panel

join : How to join individual DataFrames

{'left', 'right', 'outer', 'inner'}, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling panel

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

pandas.Panel4D.var

Panel4D.**var**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Panel or Panel4D (if level specified)

pandas.Panel4D.where

Panel4D.**where**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel4D.xs

`Panel4D.xs(key, axis=1, copy=None)`

Return slice of panel along selected axis

Parameters **key** : object

Label

axis : {'items', 'major', 'minor}, default 1/'major'

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : ndim(self)-1

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultiIndex Slicers*

33.6.2 Attributes and underlying data

Axes

- **labels**: axis 1; each label corresponds to a Panel contained inside
- **items**: axis 2; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 3; the index (rows) of each of the DataFrames
- **minor_axis**: axis 4; the columns of each of the DataFrames

`Panel4D.values`	Numpy representation of NDFrame
`Panel4D.axes`	index(es) of the NDFrame
`Panel4D.ndim`	Number of axes / array dimensions

Continued on next page

Table 33.84 – continued from previous page

Panel4D.size	number of elements in the NDFrame
Panel4D.shape	tuple of axis dimensions
Panel4D.dtypes	Return the dtypes in this object
Panel4D.ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
Panel4D.get_dtype_counts()	Return the counts of dtypes in this object
Panel4D.get_ftype_counts()	Return the counts of ftypes in this object

pandas.Panel4D.values

Panel4D.**values**

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.Panel4D.axes

Panel4D.**axes**

index(es) of the NDFrame

pandas.Panel4D.ndim

Panel4D.**ndim**

Number of axes / array dimensions

pandas.Panel4D.size

Panel4D.**size**

number of elements in the NDFrame

pandas.Panel4D.shape

Panel4D.**shape**

tuple of axis dimensions

pandas.Panel4D.dtypes

Panel4D.**dtypes**

Return the dtypes in this object

pandas.Panel4D.ftypes

Panel4D.**ftypes**
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.get_dtype_counts

Panel4D.**get_dtype_counts**()
Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts

Panel4D.**get_ftype_counts**()
Return the counts of ftypes in this object

33.6.3 Conversion

Panel4D.astype(dtype[, copy, raise_on_error])	Cast object to input numpy.dtype
Panel4D.copy([deep])	Make a copy of this object
Panel4D.isnull()	Return a boolean same-sized object indicating if the values are null
Panel4D.notnull()	Return a boolean same-sized object indicating if the values are

pandas.Panel4D.astype

Panel4D.**astype**(*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Panel4D.copy

Panel4D.**copy**(*deep=True*)
Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Panel4D.isnull

Panel4D.**isnull**()
Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel4D.notnull

`Panel4D.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

33.7 Index

Many of these methods or variants thereof are available on the objects that contain an index (Series/Dataframe) and those should most likely be used before calling these methods directly.

Index	Immutable ndarray implementing an ordered, sliceable set.

33.7.1 pandas.Index

class `pandas.Index`

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects

Parameters data : array-like (1-dimensional)

dtype : NumPy dtype (default: object)

copy : bool

Make a copy of input ndarray

name : object

Name to be stored in the index

tupleize_cols : bool (default: True)

When True, attempt to create a MultiIndex if possible

Notes

An Index instance can **only** contain hashable objects

Attributes

T	return the transpose, which is by definition self
base	return the base object if the memory of the underlying data is shared
data	return the data pointer of the underlying data
flags	
has_duplicates	

Continued on next page

Table 33.87 – continued from previous page

is_monotonic	alias for is_monotonic_increasing (deprecated)
is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
is_monotonic_increasing	return if the index is monotonic increasing (only equal or
itemsize	return the size of the dtype of the item of the underlying data
names	
nbytes	return the number of bytes in the underlying data
ndim	return the number of dimensions of the underlying data, by definition 1
nlevels	
shape	return a tuple of the shape of the underlying data
size	return the number of elements in the underlying data
strides	return the strides of the underlying data
values	return the underlying data as an ndarray

pandas.Index.T

Index.**T**
return the transpose, which is by definition self

pandas.Index.base

Index.**base**
return the base object if the memory of the underlying data is shared

pandas.Index.data

Index.**data**
return the data pointer of the underlying data

pandas.Index.flags

Index.**flags**

pandas.Index.has_duplicates

Index.**has_duplicates**

pandas.Index.is_monotonic

Index.**is_monotonic**
alias for is_monotonic_increasing (deprecated)

pandas.Index.is_monotonic_decreasing

Index.**is_monotonic_decreasing**
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.Index.is_monotonic_increasing

Index.**is_monotonic_increasing**
return if the index is monotonic increasing (only equal or increasing) values.

pandas.Index.itemsize

Index.**itemsize**
return the size of the dtype of the item of the underlying data

pandas.Index.names

Index.**names**

pandas.Index.nbytes

Index.**nbytes**
return the number of bytes in the underlying data

pandas.Index.ndim

Index.**ndim**
return the number of dimensions of the underlying data, by definition 1

pandas.Index.nlevels

Index.**nlevels**

pandas.Index.shape

Index.**shape**
return a tuple of the shape of the underlying data

pandas.Index.size

Index.**size**
return the number of elements in the underlying data

pandas.Index.strides

Index.**strides**
return the strides of the underlying data

pandas.Index.values

Index.**values**
return the underlying data as an ndarray

asi8	
dtype	
inferred_type	
is_all_dates	
is_unique	
name	

Methods

all(*args, **kwargs)	Return whether all elements are True
any(*args, **kwargs)	Return whether any element is True
append(other)	Append a collection of Index options together
argmax([axis])	return a ndarray of the maximum argument indexer
argmin([axis])	return a ndarray of the minimum argument indexer
argsort(*args, **kwargs)	return an ndarray indexer of the underlying data
asof(label)	For a sorted index, return the most recent label up to and including the passed la
asof_locs(where, mask)	where : array of timestamps
astype(dtype)	
copy([names, name, dtype, deep])	Make a copy of this object.
delete(loc)	Make new Index with passed location(-s) deleted
diff(*args, **kwargs)	
difference(other)	Compute sorted set difference of two Index objects
drop(labels[, errors])	Make new Index with passed list of labels deleted
drop_duplicates([take_last])	Return Index with duplicate values removed
duplicated([take_last])	Return boolean np.array denoting duplicate values
equals(other)	Determines if two Index objects contain the same elements.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
format([name, formatter])	Render a string representation of the Index
get_duplicates()	
get_indexer(target[, method, limit])	Compute indexer and mask for new index given the current index.
get_indexer_for(target, **kwargs)	guaranteed return of an indexer even when non-unique
get_indexer_non_unique(target)	return an indexer suitable for taking from a non unique index
get_level_values(level)	Return vector of label values for requested level, equal to the length
get_loc(key[, method])	Get integer location for requested label
get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
get_values()	return the underlying data as an ndarray
groupby(to_groupby)	Group the index labels by a given array of values.
hasnans()	return if I have any nans; enables various perf speedups
holds_integer()	
identical(other)	Similar to equals, but check that other comparable attributes are
insert(loc, item)	Make new Index inserting new item at location.
intersection(other)	Form the intersection of two Index objects.
is_(other)	More flexible, faster check like `is` but that works through views
is_boolean()	
is_categorical()	
is_floating()	

Continued on nex

Table 33.88 – continued from previous page

is_integer()	
is_lexsorted_for_tuple(tup)	
is_mixed()	
is_numeric()	
is_object()	
is_type_compatible(kind)	
isin(values[, level])	Compute boolean array of whether each index value is found in the passed set of
item()	return the first element of the underlying data as a python scalar
join(other[, how, level, return_indexers])	*this is an internal non-public method*
map(mapper)	
max()	The maximum value of the object
min()	The minimum value of the object
nunique([dropna])	Return number of unique elements in the object.
order([return_indexer, ascending])	Return sorted copy of Index
putmask(mask, value)	return a new Index of the values set with the mask
ravel([order])	return an ndarray of the flattened values of the underlying data
reindex(target[, method, level, limit])	Create index with target's values (move/add/delete values as necessary)
rename(name[, inplace])	Set new names on index.
repeat(n)	return a new Index of the values repeated n times
searchsorted(key[, side])	np.ndarray searchsorted compat
set_names(names[, level, inplace])	Set new names on index.
set_value(arr, key, value)	Fast lookup of value from 1-dimensional ndarray.
shift([periods, freq])	Shift Index containing datetime objects by input number of periods and
slice_indexer([start, end, step, kind])	For an ordered Index, compute the slice indexer for input labels and
slice_locs([start, end, step, kind])	Compute slice locations for input labels.
sort(*args, **kwargs)	
str	alias of StringMethods
summary([name])	
sym_diff(other[, result_name])	Compute the sorted symmetric difference of two Index objects.
take(indexer[, axis])	return a new Index of the values selected by the indexer
to_datetime([dayfirst])	For an Index containing strings or datetime.datetime objects, attempt
to_native_types([slicer])	slice and dice then format
to_series(**kwargs)	Create a Series with both index and values equal to the index keys
tolist()	return a list of the Index values
transpose()	return the transpose, which is by definition self
union(other)	Form the union of two Index objects and sorts if possible
unique()	Return array of unique values in the object.
value_counts([normalize, sort, ascending, ...])	Returns object containing counts of unique values.
view([cls])	

pandas.Index.all

Index.**all**(**args*, ***kwargs*)

Return whether all elements are True

Parameters All arguments to numpy.all are accepted.

Returns all : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.any

`Index.any(*args, **kwargs)`

Return whether any element is True

Parameters All arguments to numpy.any are accepted.

Returns any : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.append

`Index.append(other)`

Append a collection of Index options together

Parameters other : Index or list/tuple of indices

Returns appended : Index

pandas.Index.argmax

`Index.argmax(axis=None)`

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.Index.argmin

`Index.argmin(axis=None)`

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.Index.argsort

`Index.argsort(*args, **kwargs)`

return an ndarray indexer of the underlying data

See also:

`numpy.ndarray.argsort`

pandas.Index.asof

`Index.asof(label)`

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` asof is a thin wrapper around get_loc with method='pad'

pandas.Index.asof_locs

`Index.asof_locs(where, mask)`
where : array of timestamps mask : array of booleans where data is not NA

pandas.Index.astype

`Index.astype(dtype)`

pandas.Index.copy

`Index.copy(names=None, name=None, dtype=None, deep=False)`
Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.Index.delete

`Index.delete(loc)`
Make new Index with passed location(-s) deleted

Returns **new_index** : Index

pandas.Index.diff

`Index.diff(*args, **kwargs)`

pandas.Index.difference

`Index.difference(other)`
Compute sorted set difference of two Index objects

Parameters **other** : Index or array-like

Returns **diff** : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.Index.drop

`Index.drop(labels, errors='raise')`
Make new Index with passed list of labels deleted

Parameters **labels** : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : Index

pandas.Index.drop_duplicates

`Index.drop_duplicates(take_last=False)`
Return Index with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **deduplicated** : Index

pandas.Index.duplicated

`Index.duplicated(take_last=False)`
Return boolean np.array denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : np.array

pandas.Index.equals

`Index.equals(other)`
Determines if two Index objects contain the same elements.

pandas.Index.factorize

`Index.factorize(sort=False, na_sentinel=-1)`
Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.Index.format

`Index.format(name=False, formatter=None, **kwargs)`
Render a string representation of the Index

pandas.Index.get_duplicates

`Index.get_duplicates()`

pandas.Index.get_indexer

`Index.get_indexer(target, method=None, limit=None)`
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'}

- 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

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns **indexer** : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.Index.get_indexer_for

`Index.get_indexer_for(target, **kwargs)`
guaranteed return of an indexer even when non-unique

pandas.Index.get_indexer_non_unique

`Index.get_indexer_non_unique(target)`
return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.Index.get_level_values

`Index.get_level_values(level)`

Return vector of label values for requested level, equal to the length of the index

Parameters **level** : int

Returns **values** : ndarray

pandas.Index.get_loc

`Index.get_loc(key, method=None)`

Get integer location for requested label

Parameters **key** : label

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- 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.

Returns **loc** : int if unique index, possibly slice or mask if not

pandas.Index.get_slice_bound

`Index.get_slice_bound(label, side, kind)`

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters **label** : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.Index.get_value

`Index.get_value(series, key)`

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.get_values

`Index.get_values()`

return the underlying data as an ndarray

pandas.Index.groupby

`Index.groupby(to_groupby)`
Group the index labels by a given array of values.

Parameters **to_groupby** : array

Values used to determine the groups.

Returns **groups** : dict

{group name -> group labels}

pandas.Index.hasnans

`Index.hasnans()`
return if I have any nans; enables various perf speedups

pandas.Index.holds_integer

`Index.holds_integer()`

pandas.Index.identical

`Index.identical(other)`
Similar to equals, but check that other comparable attributes are also equal

pandas.Index.insert

`Index.insert(loc, item)`
Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters **loc** : int

item : object

Returns **new_index** : Index

pandas.Index.intersection

`Index.intersection(other)`
Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters **other** : Index or array-like

Returns **intersection** : Index

pandas.Index.is

`Index.is_(other)`
More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters **other** : object

other object to compare against.

Returns **True if both have same underlying data, False otherwise** : bool

pandas.Index.is_boolean

`Index.is_boolean()`

pandas.Index.is_categorical

`Index.is_categorical()`

pandas.Index.is_floating

`Index.is_floating()`

pandas.Index.is_integer

`Index.is_integer()`

pandas.Index.is_lexsorted_for_tuple

`Index.is_lexsorted_for_tuple(tup)`

pandas.Index.is_mixed

`Index.is_mixed()`

pandas.Index.is_numeric

`Index.is_numeric()`

pandas.Index.is_object

`Index.is_object()`

pandas.Index.is_type_compatible

`Index.is_type_compatible(kind)`

pandas.Index.isin

`Index.isin(values, level=None)`
Compute boolean array of whether each index value is found in the passed set of values.

Parameters **values** : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns **is_contained** : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.Index.item

`Index.item()`
return the first element of the underlying data as a python scalar

pandas.Index.join

`Index.join(other, how='left', level=None, return_indexers=False)`
this is an internal non-public method

Compute join_index and indexers to conform data structures to the new index.

Parameters **other** : Index

how : {'left', 'right', 'inner', 'outer'}

level : int or level name, default None

return_indexers : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.Index.map

`Index.map(mapper)`

pandas.Index.max

`Index.max()`
The maximum value of the object

pandas.Index.min

`Index.min()`

The minimum value of the object

pandas.Index.nunique

`Index.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters **dropna** : boolean, default True

Don't include NaN in the count.

Returns **nunique** : int

pandas.Index.order

`Index.order(return_indexer=False, ascending=True)`

Return sorted copy of Index

pandas.Index.putmask

`Index.putmask(mask, value)`

return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.Index.ravel

`Index.ravel(order='C')`

return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.Index.reindex

`Index.reindex(target, method=None, level=None, limit=None)`

Create index with target's values (move/add/delete values as necessary)

Parameters **target** : an iterable

Returns **new_index** : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.Index.rename

Index.**rename**(*name*, *inplace=False*)
Set new names on index. Defaults to returning new index.

Parameters **name** : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.Index.repeat

Index.**repeat**(*n*)
return a new Index of the values repeated n times

See also:

numpy.ndarray.repeat

pandas.Index.searchsorted

Index.**searchsorted**(*key*, *side='left'*)
np.ndarray searchsorted compat

pandas.Index.set_names

Index.**set_names**(*names*, *level=None*, *inplace=False*)
Set new names on index. Defaults to returning new index.

Parameters **names** : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                  (2, u'one'), (2, u'two')],
                                 names=['foo', 'bar'])
```

```
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

pandas.Index.set_value

`Index.`**`set_value`**(*arr*, *key*, *value*)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.shift

`Index.`**`shift`**(*periods=1*, *freq=None*)
Shift Index containing datetime objects by input number of periods and DateOffset

Returns **shifted** : Index

pandas.Index.slice_indexer

`Index.`**`slice_indexer`**(*start=None*, *end=None*, *step=None*, *kind=None*)
For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.Index.slice_locs

`Index.`**`slice_locs`**(*start=None*, *end=None*, *step=None*, *kind=None*)
Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

pandas.Index.sort

`Index.sort(*args, **kwargs)`

pandas.Index.summary

`Index.summary(name=None)`

pandas.Index.sym_diff

`Index.sym_diff(other, result_name=None)`

Compute the sorted symmetric difference of two Index objects.

Parameters **other** : Index or array-like

result_name : str

Returns **sym_diff** : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing `NaN` values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.Index.take

`Index.take(indexer, axis=0)`

return a new Index of the values selected by the indexer

See also:

`numpy.ndarray.take`

pandas.Index.to_datetime

`Index.to_datetime(dayfirst=False)`
For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.Index.to_native_types

`Index.to_native_types(slicer=None, **kwargs)`
slice and dice then format

pandas.Index.to_series

`Index.to_series(**kwargs)`
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.Index.tolist

`Index.tolist()`
return a list of the Index values

pandas.Index.transpose

`Index.transpose()`
return the transpose, which is by definition self

pandas.Index.union

`Index.union(other)`
Form the union of two Index objects and sorts if possible

Parameters other : Index or array-like

Returns union : Index

pandas.Index.unique

`Index.unique()`
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.Index.value_counts

`Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`
Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters **normalize** : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.Index.view

`Index.view(cls=None)`

33.7.2 Attributes

Index.values	return the underlying data as an ndarray
Index.is_monotonic	alias for is_monotonic_increasing (deprecated)
Index.is_monotonic_increasing	return if the index is monotonic increasing (only equal or
Index.is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
Index.is_unique	
Index.has_duplicates	
Index.dtype	
Index.inferred_type	
Index.is_all_dates	
Index.shape	return a tuple of the shape of the underlying data
Index.nbytes	return the number of bytes in the underlying data
Index.ndim	return the number of dimensions of the underlying data, by definition 1
Index.size	return the number of elements in the underlying data
Index.strides	return the strides of the underlying data
Index.itemsize	return the size of the dtype of the item of the underlying data
Index.base	return the base object if the memory of the underlying data is shared
Index.T	return the transpose, which is by definition self

pandas.Index.values

`Index.values`

return the underlying data as an ndarray

pandas.Index.is_monotonic

`Index.is_monotonic`
alias for is_monotonic_increasing (deprecated)

pandas.Index.is_monotonic_increasing

`Index.is_monotonic_increasing`
return if the index is monotonic increasing (only equal or increasing) values.

pandas.Index.is_monotonic_decreasing

`Index.is_monotonic_decreasing`
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.Index.is_unique

`Index.is_unique` = None

pandas.Index.has_duplicates

`Index.has_duplicates`

pandas.Index.dtype

`Index.dtype` = None

pandas.Index.inferred_type

`Index.inferred_type` = None

pandas.Index.is_all_dates

`Index.is_all_dates` = None

pandas.Index.shape

`Index.shape`
return a tuple of the shape of the underlying data

pandas.Index.nbytes

`Index.nbytes`
return the number of bytes in the underlying data

pandas.Index.ndim

`Index.ndim`
return the number of dimensions of the underlying data, by definition 1

pandas.Index.size

`Index.size`
return the number of elements in the underlying data

pandas.Index.strides

`Index.strides`
return the strides of the underlying data

pandas.Index.itemsize

`Index.itemsize`
return the size of the dtype of the item of the underlying data

pandas.Index.base

`Index.base`
return the base object if the memory of the underlying data is shared

pandas.Index.T

`Index.T`
return the transpose, which is by definition self

33.7.3 Modifying and Computations

Index.all(*args, **kwargs)	Return whether all elements are True
Index.any(*args, **kwargs)	Return whether any element is True
Index.argmin([axis])	return a ndarray of the minimum argument indexer
Index.argmax([axis])	return a ndarray of the maximum argument indexer
Index.copy([names, name, dtype, deep])	Make a copy of this object.
Index.delete(loc)	Make new Index with passed location(-s) deleted
Index.drop(labels[, errors])	Make new Index with passed list of labels deleted
Index.drop_duplicates([take_last])	Return Index with duplicate values removed
Index.duplicated([take_last])	Return boolean np.array denoting duplicate values
Index.equals(other)	Determines if two Index objects contain the same elements.
Index.factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
Index.identical(other)	Similar to equals, but check that other comparable attributes are
Index.insert(loc, item)	Make new Index inserting new item at location.
Index.min()	The minimum value of the object
Index.max()	The maximum value of the object
Index.order([return_indexer, ascending])	Return sorted copy of Index

Continued on next page

Table 33.90 – continued from previous page

Index.reindex(target[, method, level, limit])	Create index with target's values (move/add/delete values as necessary)
Index.repeat(n)	return a new Index of the values repeated n times
Index.take(indexer[, axis])	return a new Index of the values selected by the indexer
Index.putmask(mask, value)	return a new Index of the values set with the mask
Index.set_names(names[, level, inplace])	Set new names on index.
Index.unique()	Return array of unique values in the object.
Index.nunique([dropna])	Return number of unique elements in the object.
Index.value_counts([normalize, sort, ...])	Returns object containing counts of unique values.

pandas.Index.all

`Index.all(*args, **kwargs)`

Return whether all elements are True

Parameters All arguments to numpy.all are accepted.

Returns all : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.any

`Index.any(*args, **kwargs)`

Return whether any element is True

Parameters All arguments to numpy.any are accepted.

Returns any : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.argmin

`Index.argmin(axis=None)`

return a ndarray of the minimum argument indexer

See also:

numpy.ndarray.argmin

pandas.Index.argmax

`Index.argmax(axis=None)`

return a ndarray of the maximum argument indexer

See also:

numpy.ndarray.argmax

pandas.Index.copy

`Index.copy(names=None, name=None, dtype=None, deep=False)`

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.Index.delete

`Index.delete(loc)`

Make new Index with passed location(-s) deleted

Returns **new_index** : Index

pandas.Index.drop

`Index.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters **labels** : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : Index

pandas.Index.drop_duplicates

`Index.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **deduplicated** : Index

pandas.Index.duplicated

`Index.duplicated(take_last=False)`

Return boolean np.array denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : np.array

pandas.Index.equals

`Index.equals(other)`
Determines if two Index objects contain the same elements.

pandas.Index.factorize

`Index.factorize(sort=False, na_sentinel=-1)`
Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.Index.identical

`Index.identical(other)`
Similar to equals, but check that other comparable attributes are also equal

pandas.Index.insert

`Index.insert(loc, item)`
Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters **loc** : int

item : object

Returns **new_index** : Index

pandas.Index.min

`Index.min()`
The minimum value of the object

pandas.Index.max

`Index.max()`
The maximum value of the object

pandas.Index.order

`Index.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.Index.reindex

`Index.reindex(target, method=None, level=None, limit=None)`
Create index with target's values (move/add/delete values as necessary)

Parameters **target** : an iterable

Returns **new_index** : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.Index.repeat

`Index.repeat(n)`
return a new Index of the values repeated n times

See also:

`numpy.ndarray.repeat`

pandas.Index.take

`Index.take(indexer, axis=0)`
return a new Index of the values selected by the indexer

See also:

`numpy.ndarray.take`

pandas.Index.putmask

`Index.putmask(mask, value)`
return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.Index.set_names

`Index.set_names(names, level=None, inplace=False)`
Set new names on index. Defaults to returning new index.

Parameters **names** : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                  (2, u'one'), (2, u'two')],
                                 names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

pandas.Index.unique

`Index.`**`unique`**`()`

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.Index.nunique

`Index.`**`nunique`**`(`*dropna=True*`)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters dropna : boolean, default True

Don't include NaN in the count.

Returns nunique : int

pandas.Index.value_counts

`Index.`**`value_counts`**`(`*normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*`)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns counts : Series

33.7.4 Conversion

Index.astype(dtype)	
Index.tolist()	return a list of the Index values
Index.to_datetime([dayfirst])	For an Index containing strings or datetime.datetime objects, attempt
Index.to_series(**kwargs)	Create a Series with both index and values equal to the index keys

pandas.Index.astype

Index.**astype**(*dtype*)

pandas.Index.tolist

Index.**tolist**()

return a list of the Index values

pandas.Index.to_datetime

Index.**to_datetime**(*dayfirst=False*)

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.Index.to_series

Index.**to_series**(***kwargs*)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

33.7.5 Sorting

Index.argsort(*args, **kwargs)	return an ndarray indexer of the underlying data
Index.order([return_indexer, ascending])	Return sorted copy of Index
Index.sort(*args, **kwargs)	

pandas.Index.argsort

`Index.argsort(*args, **kwargs)`
return an ndarray indexer of the underlying data

See also:

numpy.ndarray.argsort

pandas.Index.order

`Index.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.Index.sort

`Index.sort(*args, **kwargs)`

33.7.6 Time-specific operations

Index.shift([periods, freq])	Shift Index containing datetime objects by input number of periods and

pandas.Index.shift

`Index.shift(periods=1, freq=None)`
Shift Index containing datetime objects by input number of periods and DateOffset

Returns shifted : Index

33.7.7 Combining / joining / set operations

Index.append(other)	Append a collection of Index options together
Index.join(other[, how, level, return_indexers])	*this is an internal non-public method*
Index.intersection(other)	Form the intersection of two Index objects.
Index.union(other)	Form the union of two Index objects and sorts if possible
Index.difference(other)	Compute sorted set difference of two Index objects
Index.sym_diff(other[, result_name])	Compute the sorted symmetric difference of two Index objects.

pandas.Index.append

`Index.append(other)`
Append a collection of Index options together

Parameters other : Index or list/tuple of indices

Returns appended : Index

pandas.Index.join

`Index.join(other, how='left', level=None, return_indexers=False)`
this is an internal non-public method

Compute join_index and indexers to conform data structures to the new index.

Parameters **other** : Index

how : {'left', 'right', 'inner', 'outer'}

level : int or level name, default None

return_indexers : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.Index.intersection

`Index.intersection(other)`
Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters **other** : Index or array-like

Returns **intersection** : Index

pandas.Index.union

`Index.union(other)`
Form the union of two Index objects and sorts if possible

Parameters **other** : Index or array-like

Returns **union** : Index

pandas.Index.difference

`Index.difference(other)`
Compute sorted set difference of two Index objects

Parameters **other** : Index or array-like

Returns **diff** : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.Index.sym_diff

`Index.sym_diff(other, result_name=None)`
Compute the sorted symmetric difference of two Index objects.

Parameters other : Index or array-like

result_name : str

Returns sym_diff : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing `NaN` values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

33.7.8 Selecting

`Index.get_indexer`(target[, method, limit])	Compute indexer and mask for new index given the current index.
`Index.get_indexer_non_unique`(target)	return an indexer suitable for taking from a non unique index
`Index.get_level_values`(level)	Return vector of label values for requested level, equal to the length
`Index.get_loc`(key[, method])	Get integer location for requested label
`Index.get_value`(series, key)	Fast lookup of value from 1-dimensional ndarray.
`Index.isin`(values[, level])	Compute boolean array of whether each index value is found in the passed set o
`Index.slice_indexer`([start, end, step, kind])	For an ordered Index, compute the slice indexer for input labels and
`Index.slice_locs`([start, end, step, kind])	Compute slice locations for input labels.

pandas.Index.get_indexer

`Index.`**`get_indexer`**(*target*, *method=None*, *limit=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’}

- 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

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns **indexer** : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.Index.get_indexer_non_unique

`Index.`**`get_indexer_non_unique`**(*target*)

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.Index.get_level_values

`Index.`**`get_level_values`**(*level*)

Return vector of label values for requested level, equal to the length of the index

Parameters **level** : int

Returns **values** : ndarray

pandas.Index.get_loc

`Index.`**`get_loc`**(*key*, *method=None*)

Get integer location for requested label

Parameters **key** : label

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- 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.

Returns **loc** : int if unique index, possibly slice or mask if not

pandas.Index.get_value

`Index.`**`get_value`**(*series*, *key*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.isin

`Index.isin(values, level=None)`

Compute boolean array of whether each index value is found in the passed set of values.

Parameters **values** : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns **is_contained** : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.Index.slice_indexer

`Index.slice_indexer(start=None, end=None, step=None, kind=None)`

For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.Index.slice_locs

`Index.slice_locs(start=None, end=None, step=None, kind=None)`

Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

33.8 CategoricalIndex

CategoricalIndex	Immutable Index implementing an ordered, sliceable set.

33.8.1 pandas.CategoricalIndex

class pandas.**CategoricalIndex**

Immutable Index implementing an ordered, sliceable set. CategoricalIndex represents a sparsely populated Index with an underlying Categorical.

New in version 0.16.1.

Parameters **data** : array-like or Categorical, (1-dimensional)

categories : optional, array-like

categories for the CategoricalIndex

ordered : boolean,

designating if the categories are ordered

copy : bool

Make a copy of input ndarray

name : object

Name to be stored in the index

Attributes

T	return the transpose, which is by definition self
base	return the base object if the memory of the underlying data is shared
categories	
codes	
data	return the data pointer of the underlying data
flags	
has_duplicates	
inferred_type	
is_monotonic	alias for is_monotonic_increasing (deprecated)
is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
is_monotonic_increasing	return if the index is monotonic increasing (only equal or
itemsize	return the size of the dtype of the item of the underlying data
names	
nbytes	return the number of bytes in the underlying data
ndim	return the number of dimensions of the underlying data, by definition 1
nlevels	

Continued on next page

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ordered	
shape	return a tuple of the shape of the underlying data
size	return the number of elements in the underlying data
strides	return the strides of the underlying data
values	return the underlying data, which is a Categorical

pandas.CategoricalIndex.T

CategoricalIndex.**T**
return the transpose, which is by definition self

pandas.CategoricalIndex.base

CategoricalIndex.**base**
return the base object if the memory of the underlying data is shared

pandas.CategoricalIndex.categories

CategoricalIndex.**categories**

pandas.CategoricalIndex.codes

CategoricalIndex.**codes**

pandas.CategoricalIndex.data

CategoricalIndex.**data**
return the data pointer of the underlying data

pandas.CategoricalIndex.flags

CategoricalIndex.**flags**

pandas.CategoricalIndex.has_duplicates

CategoricalIndex.**has_duplicates**

pandas.CategoricalIndex.inferred_type

CategoricalIndex.**inferred_type**

pandas.CategoricalIndex.is_monotonic

CategoricalIndex.**is_monotonic**
alias for is_monotonic_increasing (deprecated)

pandas.CategoricalIndex.is_monotonic_decreasing

CategoricalIndex.**is_monotonic_decreasing**
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.CategoricalIndex.is_monotonic_increasing

CategoricalIndex.**is_monotonic_increasing**
return if the index is monotonic increasing (only equal or increasing) values.

pandas.CategoricalIndex.itemsize

CategoricalIndex.**itemsize**
return the size of the dtype of the item of the underlying data

pandas.CategoricalIndex.names

CategoricalIndex.**names**

pandas.CategoricalIndex.nbytes

CategoricalIndex.**nbytes**
return the number of bytes in the underlying data

pandas.CategoricalIndex.ndim

CategoricalIndex.**ndim**
return the number of dimensions of the underlying data, by definition 1

pandas.CategoricalIndex.nlevels

CategoricalIndex.**nlevels**

pandas.CategoricalIndex.ordered

CategoricalIndex.**ordered**

pandas.CategoricalIndex.shape

CategoricalIndex.**shape**
return a tuple of the shape of the underlying data

pandas.CategoricalIndex.size

CategoricalIndex.**size**
return the number of elements in the underlying data

pandas.CategoricalIndex.strides

CategoricalIndex.**strides**
return the strides of the underlying data

pandas.CategoricalIndex.values

CategoricalIndex.**values**
return the underlying data, which is a Categorical

asi8	
dtype	
is_all_dates	
is_unique	
name	

Methods

add_categories(*args, **kwargs)	Add new categories.
all([other])	
any([other])	
append(other)	Append a collection of CategoricalIndex options together
argmax([axis])	return a ndarray of the maximum argument indexer
argmin([axis])	return a ndarray of the minimum argument indexer
argsort(*args, **kwargs)	
as_ordered(*args, **kwargs)	Sets the Categorical to be ordered
as_unordered(*args, **kwargs)	Sets the Categorical to be unordered
asof(label)	For a sorted index, return the most recent label up to and including the passed
asof_locs(where, mask)	where : array of timestamps
astype(dtype)	
copy([names, name, dtype, deep])	Make a copy of this object.
delete(loc)	Make new Index with passed location(-s) deleted
diff(*args, **kwargs)	
difference(other)	Compute sorted set difference of two Index objects
drop(labels[, errors])	Make new Index with passed list of labels deleted
drop_duplicates([take_last])	Return Index with duplicate values removed
duplicated([take_last])	Return boolean np.array denoting duplicate values
equals(other)	Determines if two CategorialIndex objects contain the same elements.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
format([name, formatter])	Render a string representation of the Index
get_duplicates()	
get_indexer(target[, method, limit])	Compute indexer and mask for new index given the current index.
get_indexer_for(target, **kwargs)	guaranteed return of an indexer even when non-unique
get_indexer_non_unique(target)	this is the same for a CategoricalIndex for get_indexer; the API returns the m
get_level_values(level)	Return vector of label values for requested level, equal to the length
get_loc(key[, method])	Get integer location for requested label
get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
get_values()	return the underlying data as an ndarray
groupby(to_groupby)	Group the index labels by a given array of values.
hasnans()	return if I have any nans; enables various perf speedups

Conti

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holds_integer()	
identical(other)	Similar to equals, but check that other comparable attributes are
insert(loc, item)	Make new Index inserting new item at location.
intersection(other)	Form the intersection of two Index objects.
is_(other)	More flexible, faster check like is but that works through views
is_boolean()	
is_categorical()	
is_floating()	
is_integer()	
is_lexsorted_for_tuple(tup)	
is_mixed()	
is_numeric()	
is_object()	
is_type_compatible(kind)	
isin(values[, level])	Compute boolean array of whether each index value is found in the passed se
item()	return the first element of the underlying data as a python scalar
join(other[, how, level, return_indexers])	*this is an internal non-public method*
map(mapper)	
max(*args, **kwargs)	The maximum value of the object.
min(*args, **kwargs)	The minimum value of the object.
nunique([dropna])	Return number of unique elements in the object.
order([return_indexer, ascending])	Return sorted copy of Index
putmask(mask, value)	return a new Index of the values set with the mask
ravel([order])	return an ndarray of the flattened values of the underlying data
reindex(target[, method, level, limit])	Create index with target's values (move/add/delete values as necessary)
remove_categories(*args, **kwargs)	Removes the specified categories.
remove_unused_categories(*args, **kwargs)	Removes categories which are not used.
rename(name[, inplace])	Set new names on index.
rename_categories(*args, **kwargs)	Renames categories.
reorder_categories(*args, **kwargs)	Reorders categories as specified in new_categories.
repeat(n)	return a new Index of the values repeated n times
searchsorted(key[, side])	np.ndarray searchsorted compat
set_categories(*args, **kwargs)	Sets the categories to the specified new_categories.
set_names(names[, level, inplace])	Set new names on index.
set_value(arr, key, value)	Fast lookup of value from 1-dimensional ndarray.
shift([periods, freq])	Shift Index containing datetime objects by input number of periods and
slice_indexer([start, end, step, kind])	For an ordered Index, compute the slice indexer for input labels and
slice_locs([start, end, step, kind])	Compute slice locations for input labels.
sort(*args, **kwargs)	
str	alias of StringMethods
summary([name])	
sym_diff(other[, result_name])	Compute the sorted symmetric difference of two Index objects.
take(indexer[, axis])	return a new CategoricalIndex of the values selected by the indexer
to_datetime([dayfirst])	For an Index containing strings or datetime.datetime objects, attempt
to_native_types([slicer])	slice and dice then format
to_series(**kwargs)	Create a Series with both index and values equal to the index keys
tolist()	return a list of the Index values
transpose()	return the transpose, which is by definition self
union(other)	Form the union of two Index objects and sorts if possible
unique()	Return array of unique values in the object.
value_counts([normalize, sort, ascending, ...])	Returns object containing counts of unique values.
view([cls])	

pandas.CategoricalIndex.add_categories

`CategoricalIndex.add_categories(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters **new_categories** : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns **cat** : Categorical with new categories added or None if inplace.

Raises **ValueError**

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.all

`CategoricalIndex.all(other=None)`

pandas.CategoricalIndex.any

`CategoricalIndex.any(other=None)`

pandas.CategoricalIndex.append

`CategoricalIndex.append(other)`

Append a collection of CategoricalIndex options together

Parameters **other** : Index or list/tuple of indices

Returns **appended** : Index

Raises **ValueError if other is not in the categories**

pandas.CategoricalIndex.argmax

`CategoricalIndex.argmax(axis=None)`

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.CategoricalIndex.argmin

`CategoricalIndex.argmin(axis=None)`
return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.CategoricalIndex.argsort

`CategoricalIndex.argsort(*args, **kwargs)`

pandas.CategoricalIndex.as_ordered

`CategoricalIndex.as_ordered(*args, **kwargs)`
Sets the Categorical to be ordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.CategoricalIndex.as_unordered

`CategoricalIndex.as_unordered(*args, **kwargs)`
Sets the Categorical to be unordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

pandas.CategoricalIndex.asof

`CategoricalIndex.asof(label)`
For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` asof is a thin wrapper around get_loc with method='pad'

pandas.CategoricalIndex.asof_locs

`CategoricalIndex.asof_locs(where, mask)`
where : array of timestamps mask : array of booleans where data is not NA

pandas.CategoricalIndex.astype

`CategoricalIndex.astype(dtype)`

pandas.CategoricalIndex.copy

`CategoricalIndex.copy(names=None, name=None, dtype=None, deep=False)`

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.CategoricalIndex.delete

`CategoricalIndex.delete(loc)`

Make new Index with passed location(-s) deleted

Returns **new_index** : Index

pandas.CategoricalIndex.diff

`CategoricalIndex.diff(*args, **kwargs)`

pandas.CategoricalIndex.difference

`CategoricalIndex.difference(other)`

Compute sorted set difference of two Index objects

Parameters **other** : Index or array-like

Returns **diff** : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.CategoricalIndex.drop

`CategoricalIndex.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters **labels** : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : Index

pandas.CategoricalIndex.drop_duplicates

`CategoricalIndex.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **deduplicated** : Index

pandas.CategoricalIndex.duplicated

`CategoricalIndex.duplicated(take_last=False)`

Return boolean np.array denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : np.array

pandas.CategoricalIndex.equals

`CategoricalIndex.equals(other)`

Determines if two CategorialIndex objects contain the same elements.

pandas.CategoricalIndex.factorize

`CategoricalIndex.factorize(sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.CategoricalIndex.format

`CategoricalIndex.format(name=False, formatter=None, **kwargs)`

Render a string representation of the Index

pandas.CategoricalIndex.get_duplicates

`CategoricalIndex.get_duplicates()`

pandas.CategoricalIndex.get_indexer

`CategoricalIndex.get_indexer(target, method=None, limit=None)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index. The mask determines whether labels are found or not in the current index

Parameters **target** : MultiIndex or Index (of tuples)

method : {'pad', 'ffill', 'backfill', 'bfill'}

pad / ffill: propagate LAST valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

Returns **(indexer, mask)** : (ndarray, ndarray)

Notes

This is a low-level method and probably should be used at your own risk

Examples

```
>>> indexer, mask = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
>>> new_values[-mask] = np.nan
```

pandas.CategoricalIndex.get_indexer_for

`CategoricalIndex.get_indexer_for(target, **kwargs)`

guaranteed return of an indexer even when non-unique

pandas.CategoricalIndex.get_indexer_non_unique

`CategoricalIndex.get_indexer_non_unique(target)`

this is the same for a CategoricalIndex for get_indexer; the API returns the missing values as well

pandas.CategoricalIndex.get_level_values

`CategoricalIndex.get_level_values(level)`

Return vector of label values for requested level, equal to the length of the index

Parameters **level** : int

Returns **values** : ndarray

pandas.CategoricalIndex.get_loc

`CategoricalIndex.get_loc(key, method=None)`

Get integer location for requested label

Parameters **key** : label

method : {None}

- default: exact matches only.

Returns **loc** : int if unique index, possibly slice or mask if not

pandas.CategoricalIndex.get_slice_bound

`CategoricalIndex.`**`get_slice_bound`**(*label*, *side*, *kind*)

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters **label** : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.CategoricalIndex.get_value

`CategoricalIndex.`**`get_value`**(*series*, *key*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.CategoricalIndex.get_values

`CategoricalIndex.`**`get_values`**()

return the underlying data as an ndarray

pandas.CategoricalIndex.groupby

`CategoricalIndex.`**`groupby`**(*to_groupby*)

Group the index labels by a given array of values.

Parameters **to_groupby** : array

Values used to determine the groups.

Returns **groups** : dict

{group name -> group labels}

pandas.CategoricalIndex.hasnans

`CategoricalIndex.`**`hasnans`**()

return if I have any nans; enables various perf speedups

pandas.CategoricalIndex.holds_integer

`CategoricalIndex.`**`holds_integer`**()

pandas.CategoricalIndex.identical

`CategoricalIndex.`**`identical`**(*other*)

Similar to equals, but check that other comparable attributes are also equal

pandas.CategoricalIndex.insert

`CategoricalIndex.insert(loc, item)`

Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters **loc** : int

item : object

Returns **new_index** : Index

Raises **ValueError if the item is not in the categories**

pandas.CategoricalIndex.intersection

`CategoricalIndex.intersection(other)`

Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters **other** : Index or array-like

Returns **intersection** : Index

pandas.CategoricalIndex.is

`CategoricalIndex.is_(other)`

More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters **other** : object

other object to compare against.

Returns **True if both have same underlying data, False otherwise** : bool

pandas.CategoricalIndex.is_boolean

`CategoricalIndex.is_boolean()`

pandas.CategoricalIndex.is_categorical

`CategoricalIndex.is_categorical()`

pandas.CategoricalIndex.is_floating

`CategoricalIndex.is_floating()`

pandas.CategoricalIndex.is_integer

`CategoricalIndex.is_integer()`

pandas.CategoricalIndex.is_lexsorted_for_tuple

`CategoricalIndex.is_lexsorted_for_tuple(tup)`

pandas.CategoricalIndex.is_mixed

`CategoricalIndex.is_mixed()`

pandas.CategoricalIndex.is_numeric

`CategoricalIndex.is_numeric()`

pandas.CategoricalIndex.is_object

`CategoricalIndex.is_object()`

pandas.CategoricalIndex.is_type_compatible

`CategoricalIndex.is_type_compatible(`*kind*`)`

pandas.CategoricalIndex.isin

`CategoricalIndex.isin(`*values*, *level=None*`)`

Compute boolean array of whether each index value is found in the passed set of values.

Parameters **values** : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns **is_contained** : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.CategoricalIndex.item

`CategoricalIndex.item()`

return the first element of the underlying data as a python scalar

pandas.CategoricalIndex.join

`CategoricalIndex.join(`*other*, *how='left'*, *level=None*, *return_indexers=False*`)`

this is an internal non-public method

Compute join_index and indexers to conform data structures to the new index.

Parameters **other** : Index

how : {'left', 'right', 'inner', 'outer'}

level : int or level name, default None

return_indexers : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.CategoricalIndex.map

`CategoricalIndex.map(mapper)`

pandas.CategoricalIndex.max

`CategoricalIndex.max(*args, **kwargs)`

The maximum value of the object.

Only ordered *Categoricals* have a maximum!

Returns **max** : the maximum of this *Categorical*

Raises **TypeError**

If the *Categorical* is not *ordered*.

pandas.CategoricalIndex.min

`CategoricalIndex.min(*args, **kwargs)`

The minimum value of the object.

Only ordered *Categoricals* have a minimum!

Returns **min** : the minimum of this *Categorical*

Raises **TypeError**

If the *Categorical* is not *ordered*.

pandas.CategoricalIndex.nunique

`CategoricalIndex.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters **dropna** : boolean, default True

Don't include NaN in the count.

Returns **nunique** : int

pandas.CategoricalIndex.order

`CategoricalIndex.order(return_indexer=False, ascending=True)`

Return sorted copy of Index

pandas.CategoricalIndex.putmask

`CategoricalIndex.putmask(mask, value)`
return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.CategoricalIndex.ravel

`CategoricalIndex.ravel(order='C')`
return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.CategoricalIndex.reindex

`CategoricalIndex.reindex(target, method=None, level=None, limit=None)`
Create index with target's values (move/add/delete values as necessary)

Returns **new_index** : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.CategoricalIndex.remove_categories

`CategoricalIndex.remove_categories(*args, **kwargs)`
Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters **removals** : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns **cat** : Categorical with removed categories or None if inplace.

Raises **ValueError**

If the removals are not contained in the categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_unused_categories

`CategoricalIndex.remove_unused_categories(*args, **kwargs)`

Removes categories which are not used.

Parameters **inplace** : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns **cat** : Categorical with unused categories dropped or None if inplace.

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `set_categories`

pandas.CategoricalIndex.rename

`CategoricalIndex.rename(name, inplace=False)`

Set new names on index. Defaults to returning new index.

Parameters **name** : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.CategoricalIndex.rename_categories

`CategoricalIndex.rename_categories(*args, **kwargs)`

Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters **new_categories** : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns **cat** : Categorical with renamed categories added or None if inplace.

Raises **ValueError**

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

`reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.reorder_categories

`CategoricalIndex.reorder_categories(*args, **kwargs)`

Reorders categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

Parameters **new_categories** : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns **cat** : Categorical with reordered categories or None if inplace.

Raises **ValueError**

If the new categories do not contain all old category items or any new ones

See also:

`rename_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.repeat

`CategoricalIndex.repeat(n)`

return a new Index of the values repeated n times

See also:

`numpy.ndarray.repeat`

pandas.CategoricalIndex.searchsorted

`CategoricalIndex.searchsorted(key, side='left')`

np.ndarray searchsorted compat

pandas.CategoricalIndex.set_categories

`CategoricalIndex.set_categories(*args, **kwargs)`

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters **new_categories** : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns **cat** : Categorical with reordered categories or None if inplace.

Raises **ValueError**

If new_categories does not validate as categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`

pandas.CategoricalIndex.set_names

`CategoricalIndex.`**`set_names`**(*names*, *level=None*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters **names** : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                  (2, u'one'), (2, u'two')],
```

```
                                 names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

pandas.CategoricalIndex.set_value

CategoricalIndex.**set_value**(*arr*, *key*, *value*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.CategoricalIndex.shift

CategoricalIndex.**shift**(*periods=1*, *freq=None*)

Shift Index containing datetime objects by input number of periods and DateOffset

Returns **shifted** : Index

pandas.CategoricalIndex.slice_indexer

CategoricalIndex.**slice_indexer**(*start=None*, *end=None*, *step=None*, *kind=None*)

For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.CategoricalIndex.slice_locs

CategoricalIndex.**slice_locs**(*start=None*, *end=None*, *step=None*, *kind=None*)

Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns start, end : int

pandas.CategoricalIndex.sort

`CategoricalIndex.sort(*args, **kwargs)`

pandas.CategoricalIndex.summary

`CategoricalIndex.summary(name=None)`

pandas.CategoricalIndex.sym_diff

`CategoricalIndex.sym_diff(other, result_name=None)`

Compute the sorted symmetric difference of two Index objects.

Parameters other : Index or array-like

result_name : str

Returns sym_diff : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing `NaN` values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.CategoricalIndex.take

`CategoricalIndex.take(indexer, axis=0)`
return a new CategoricalIndex of the values selected by the indexer

See also:

numpy.ndarray.take

pandas.CategoricalIndex.to_datetime

`CategoricalIndex.to_datetime(dayfirst=False)`
For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.CategoricalIndex.to_native_types

`CategoricalIndex.to_native_types(slicer=None, **kwargs)`
slice and dice then format

pandas.CategoricalIndex.to_series

`CategoricalIndex.to_series(**kwargs)`
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.CategoricalIndex.tolist

`CategoricalIndex.tolist()`
return a list of the Index values

pandas.CategoricalIndex.transpose

`CategoricalIndex.transpose()`
return the transpose, which is by definition self

pandas.CategoricalIndex.union

`CategoricalIndex.union(other)`
Form the union of two Index objects and sorts if possible

Parameters other : Index or array-like

Returns union : Index

pandas.CategoricalIndex.unique

`CategoricalIndex.unique()`
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.CategoricalIndex.value_counts

`CategoricalIndex.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters **normalize** : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.CategoricalIndex.view

`CategoricalIndex.view(cls=None)`

33.8.2 Categorical Components

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

pandas.CategoricalIndex.codes

`CategoricalIndex.codes`

pandas.CategoricalIndex.categories

`CategoricalIndex.`**`categories`**

pandas.CategoricalIndex.ordered

`CategoricalIndex.`**`ordered`**

pandas.CategoricalIndex.rename_categories

`CategoricalIndex.`**`rename_categories`**(**args*, ***kwargs*)

Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters new_categories : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns cat : Categorical with renamed categories added or None if inplace.

Raises ValueError

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

`reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.reorder_categories

`CategoricalIndex.`**`reorder_categories`**(**args*, ***kwargs*)

Reorders categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

Parameters new_categories : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns cat : Categorical with reordered categories or None if inplace.

Raises ValueError

If the new categories do not contain all old category items or any new ones

See also:

`rename_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.add_categories

`CategoricalIndex.`**`add_categories`**`(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters **new_categories** : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns **cat** : Categorical with new categories added or None if inplace.

Raises **ValueError**

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_categories

`CategoricalIndex.`**`remove_categories`**`(*args, **kwargs)`

Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters **removals** : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns **cat** : Categorical with removed categories or None if inplace.

Raises **ValueError**

If the removals are not contained in the categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_unused_categories

CategoricalIndex.**remove_unused_categories**(**args*, ***kwargs*)

Removes categories which are not used.

Parameters **inplace** : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns **cat** : Categorical with unused categories dropped or None if inplace.

See also:

rename_categories, reorder_categories, add_categories, remove_categories, set_categories

pandas.CategoricalIndex.set_categories

CategoricalIndex.**set_categories**(**args*, ***kwargs*)

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters **new_categories** : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns **cat** : Categorical with reordered categories or None if inplace.

Raises **ValueError**

If new_categories does not validate as categories

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories

pandas.CategoricalIndex.as_ordered

CategoricalIndex.**as_ordered**(**args*, ***kwargs*)

Sets the Categorical to be ordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.CategoricalIndex.as_unordered

CategoricalIndex.**as_unordered**(**args*, ***kwargs*)

Sets the Categorical to be unordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

33.9 DatetimeIndex

DatetimeIndex	Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp o

33.9.1 pandas.DatetimeIndex

class pandas.**DatetimeIndex**

Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.

Parameters **data** : array-like (1-dimensional), optional

Optional datetime-like data to construct index with

copy : bool

Make a copy of input ndarray

freq : string or pandas offset object, optional

One of pandas date offset strings or corresponding objects

start : starting value, datetime-like, optional

If data is None, start is used as the start point in generating regular timestamp data.

periods : int, optional, > 0

Number of periods to generate, if generating index. Takes precedence over end argument

end : end time, datetime-like, optional

If periods is none, generated index will extend to first conforming time on or just past end argument

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

tz : pytz.timezone or dateutil.tz.tzfile

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

name : object

Name to be stored in the index

Attributes

T	return the transpose, which is by definition self
asi8	
asobject	
base	return the base object if the memory of the underlying data is shared
data	return the data pointer of the underlying data
date	Returns numpy array of datetime.date.
day	The days of the datetime
dayofweek	The day of the week with Monday=0, Sunday=6
dayofyear	The ordinal day of the year
days_in_month	The number of days in the month
daysinmonth	The number of days in the month
dtype	
flags	
freq	get/set the frequncy of the Index
freqstr	return the frequency object as a string if its set, otherwise None
has_duplicates	
hour	The hours of the datetime
inferred_type	
is_all_dates	
is_monotonic	alias for is_monotonic_increasing (deprecated)
is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
is_monotonic_increasing	return if the index is monotonic increasing (only equal or
is_month_end	Logical indicating if last day of month (defined by frequency)
is_month_start	Logical indicating if first day of month (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
itemsize	return the size of the dtype of the item of the underlying data
microsecond	The microseconds of the datetime
millisecond	The milliseconds of the datetime

Continued on next page

Table 33.101 – continued from previous page

minute	The minutes of the datetime
month	The month as January=1, December=12
names	
nanosecond	The nanoseconds of the datetime
nbytes	return the number of bytes in the underlying data
ndim	return the number of dimensions of the underlying data, by definition 1
nlevels	
quarter	The quarter of the date
second	The seconds of the datetime
shape	return a tuple of the shape of the underlying data
size	return the number of elements in the underlying data
strides	return the strides of the underlying data
time	Returns numpy array of datetime.time.
tzinfo	Alias for tz attribute
values	return the underlying data as an ndarray
week	The week ordinal of the year
weekday	The day of the week with Monday=0, Sunday=6
weekofyear	The week ordinal of the year
year	The year of the datetime

pandas.DatetimeIndex.T

DatetimeIndex.**T**

return the transpose, which is by definition self

pandas.DatetimeIndex.asi8

DatetimeIndex.**asi8**

pandas.DatetimeIndex.asobject

DatetimeIndex.**asobject**

pandas.DatetimeIndex.base

DatetimeIndex.**base**

return the base object if the memory of the underlying data is shared

pandas.DatetimeIndex.data

DatetimeIndex.**data**

return the data pointer of the underlying data

pandas.DatetimeIndex.date

DatetimeIndex.**date**

Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.DatetimeIndex.day

`DatetimeIndex.`**`day`**
The days of the datetime

pandas.DatetimeIndex.dayofweek

`DatetimeIndex.`**`dayofweek`**
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.dayofyear

`DatetimeIndex.`**`dayofyear`**
The ordinal day of the year

pandas.DatetimeIndex.days_in_month

`DatetimeIndex.`**`days_in_month`**
The number of days in the month

New in version 0.16.0.

pandas.DatetimeIndex.daysinmonth

`DatetimeIndex.`**`daysinmonth`**
The number of days in the month

New in version 0.16.0.

pandas.DatetimeIndex.dtype

`DatetimeIndex.`**`dtype`**

pandas.DatetimeIndex.flags

`DatetimeIndex.`**`flags`**

pandas.DatetimeIndex.freq

`DatetimeIndex.`**`freq`**
get/set the frequncy of the Index

pandas.DatetimeIndex.freqstr

`DatetimeIndex.`**`freqstr`**
return the frequency object as a string if its set, otherwise None

pandas.DatetimeIndex.has_duplicates

`DatetimeIndex.has_duplicates`

pandas.DatetimeIndex.hour

`DatetimeIndex.hour`
The hours of the datetime

pandas.DatetimeIndex.inferred_type

`DatetimeIndex.inferred_type`

pandas.DatetimeIndex.is_all_dates

`DatetimeIndex.is_all_dates`

pandas.DatetimeIndex.is_monotonic

`DatetimeIndex.is_monotonic`
alias for is_monotonic_increasing (deprecated)

pandas.DatetimeIndex.is_monotonic_decreasing

`DatetimeIndex.is_monotonic_decreasing`
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.DatetimeIndex.is_monotonic_increasing

`DatetimeIndex.is_monotonic_increasing`
return if the index is monotonic increasing (only equal or increasing) values.

pandas.DatetimeIndex.is_month_end

`DatetimeIndex.is_month_end`
Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_month_start

`DatetimeIndex.is_month_start`
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_quarter_end

`DatetimeIndex.is_quarter_end`
Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_start

DatetimeIndex.**is_quarter_start**
Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_year_end

DatetimeIndex.**is_year_end**
Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.is_year_start

DatetimeIndex.**is_year_start**
Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.itemsize

DatetimeIndex.**itemsize**
return the size of the dtype of the item of the underlying data

pandas.DatetimeIndex.microsecond

DatetimeIndex.**microsecond**
The microseconds of the datetime

pandas.DatetimeIndex.millisecond

DatetimeIndex.**millisecond**
The milliseconds of the datetime

pandas.DatetimeIndex.minute

DatetimeIndex.**minute**
The minutes of the datetime

pandas.DatetimeIndex.month

DatetimeIndex.**month**
The month as January=1, December=12

pandas.DatetimeIndex.names

DatetimeIndex.**names**

pandas.DatetimeIndex.nanosecond

DatetimeIndex.**nanosecond**
The nanoseconds of the datetime

pandas.DatetimeIndex.nbytes

`DatetimeIndex.nbytes`
return the number of bytes in the underlying data

pandas.DatetimeIndex.ndim

`DatetimeIndex.ndim`
return the number of dimensions of the underlying data, by definition 1

pandas.DatetimeIndex.nlevels

`DatetimeIndex.nlevels`

pandas.DatetimeIndex.quarter

`DatetimeIndex.quarter`
The quarter of the date

pandas.DatetimeIndex.second

`DatetimeIndex.second`
The seconds of the datetime

pandas.DatetimeIndex.shape

`DatetimeIndex.shape`
return a tuple of the shape of the underlying data

pandas.DatetimeIndex.size

`DatetimeIndex.size`
return the number of elements in the underlying data

pandas.DatetimeIndex.strides

`DatetimeIndex.strides`
return the strides of the underlying data

pandas.DatetimeIndex.time

`DatetimeIndex.time`
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.tzinfo

`DatetimeIndex.tzinfo`
Alias for tz attribute

pandas.DatetimeIndex.values

DatetimeIndex.**values**
return the underlying data as an ndarray

pandas.DatetimeIndex.week

DatetimeIndex.**week**
The week ordinal of the year

pandas.DatetimeIndex.weekday

DatetimeIndex.**weekday**
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.weekofyear

DatetimeIndex.**weekofyear**
The week ordinal of the year

pandas.DatetimeIndex.year

DatetimeIndex.**year**
The year of the datetime

hasnans	
inferred_freq	
is_normalized	
is_unique	
name	
offset	
resolution	
tz	

Methods

all([other])	
any([other])	
append(other)	Append a collection of Index options together
argmax([axis])	return a ndarray of the maximum argument indexer
argmin([axis])	return a ndarray of the minimum argument indexer
argsort(*args, **kwargs)	return an ndarray indexer of the underlying data
asof(label)	For a sorted index, return the most recent label up to and including the pas
asof_locs(where, mask)	where : array of timestamps
astype(dtype)	
copy([names, name, dtype, deep])	Make a copy of this object.
delete(loc)	Make a new DatetimeIndex with passed location(s) deleted.
diff(*args, **kwargs)	
difference(other)	Compute sorted set difference of two Index objects

Continued on r

Table 33.102 – continued from previous page

drop(labels[, errors])	Make new Index with passed list of labels deleted
drop_duplicates([take_last])	Return Index with duplicate values removed
duplicated([take_last])	Return boolean np.array denoting duplicate values
equals(other)	Determines if two Index objects contain the same elements.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
format([name, formatter])	Render a string representation of the Index
get_duplicates()	
get_indexer(target[, method, limit])	Compute indexer and mask for new index given the current index.
get_indexer_for(target, **kwargs)	guaranteed return of an indexer even when non-unique
get_indexer_non_unique(target)	return an indexer suitable for taking from a non unique index
get_level_values(level)	Return vector of label values for requested level, equal to the length
get_loc(key[, method])	Get integer location for requested label
get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
get_value_maybe_box(series, key)	
get_values()	return the underlying data as an ndarray
groupby(f)	
holds_integer()	
identical(other)	Similar to equals, but check that other comparable attributes are
indexer_at_time(time[, asof])	Select values at particular time of day (e.g.
indexer_between_time(start_time, end_time[, ...])	Select values between particular times of day (e.g., 9:00-9:30AM)
insert(loc, item)	Make new Index inserting new item at location
intersection(other)	Specialized intersection for DatetimeIndex objects.
is_(other)	More flexible, faster check like `is` but that works through views
is_boolean()	
is_categorical()	
is_floating()	
is_integer()	
is_lexsorted_for_tuple(tup)	
is_mixed()	
is_numeric()	
is_object()	
is_type_compatible(typ)	
isin(values)	Compute boolean array of whether each index value is found in the
item()	return the first element of the underlying data as a python scalar
join(other[, how, level, return_indexers])	See Index.join
map(f)	
max([axis])	return the maximum value of the Index
min([axis])	return the minimum value of the Index
normalize()	Return DatetimeIndex with times to midnight.
nunique([dropna])	Return number of unique elements in the object.
order([return_indexer, ascending])	Return sorted copy of Index
putmask(mask, value)	return a new Index of the values set with the mask
ravel([order])	return an ndarray of the flattened values of the underlying data
reindex(target[, method, level, limit])	Create index with target's values (move/add/delete values as necessary)
rename(name[, inplace])	Set new names on index.
repeat(repeats[, axis])	Analogous to ndarray.repeat
searchsorted(key[, side])	
set_names(names[, level, inplace])	Set new names on index.
set_value(arr, key, value)	Fast lookup of value from 1-dimensional ndarray.
shift(n[, freq])	Specialized shift which produces a DatetimeIndex
slice_indexer([start, end, step, kind])	Return indexer for specified label slice.

Continued on r

Table 33.102 – continued from previous page

slice_locs([start, end, step, kind])	Compute slice locations for input labels.
snap([freq])	Snap time stamps to nearest occurring frequency
sort(*args, **kwargs)	
str	alias of StringMethods
summary([name])	return a summarized representation
sym_diff(other[, result_name])	Compute the sorted symmetric difference of two Index objects.
take(indices[, axis])	Analogous to ndarray.take
to_datetime([dayfirst])	
to_julian_date()	Convert DatetimeIndex to Float64Index of Julian Dates.
to_native_types([slicer])	slice and dice then format
to_period([freq])	Cast to PeriodIndex at a particular frequency
to_pydatetime()	Return DatetimeIndex as object ndarray of datetime.datetime objects
to_series([keep_tz])	Create a Series with both index and values equal to the index keys
tolist()	return a list of the underlying data
transpose()	return the transpose, which is by definition self
tz_convert(tz)	Convert tz-aware DatetimeIndex from one time zone to another (using pyt
tz_localize(*args, **kwargs)	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),
union(other)	Specialized union for DatetimeIndex objects.
union_many(others)	A bit of a hack to accelerate unioning a collection of indexes
unique()	Index.unique with handling for DatetimeIndex/PeriodIndex metadata
value_counts([normalize, sort, ascending, ...])	Returns object containing counts of unique values.
view([cls])	

pandas.DatetimeIndex.all

DatetimeIndex.**all**(*other=None*)

pandas.DatetimeIndex.any

DatetimeIndex.**any**(*other=None*)

pandas.DatetimeIndex.append

DatetimeIndex.**append**(*other*)

Append a collection of Index options together

Parameters other : Index or list/tuple of indices

Returns appended : Index

pandas.DatetimeIndex.argmax

DatetimeIndex.**argmax**(*axis=None*)

return a ndarray of the maximum argument indexer

See also:

numpy.ndarray.argmax

pandas.DatetimeIndex.argmin

DatetimeIndex.**argmin**(*axis=None*)

return a ndarray of the minimum argument indexer

See also:

numpy.ndarray.argmin

pandas.DatetimeIndex.argsort

DatetimeIndex.**argsort**(**args*, ***kwargs*)

return an ndarray indexer of the underlying data

See also:

numpy.ndarray.argsort

pandas.DatetimeIndex.asof

DatetimeIndex.**asof**(*label*)

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

get_loc asof is a thin wrapper around get_loc with method='pad'

pandas.DatetimeIndex.asof_locs

DatetimeIndex.**asof_locs**(*where*, *mask*)

where : array of timestamps mask : array of booleans where data is not NA

pandas.DatetimeIndex.astype

DatetimeIndex.**astype**(*dtype*)

pandas.DatetimeIndex.copy

DatetimeIndex.**copy**(*names=None*, *name=None*, *dtype=None*, *deep=False*)

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.DatetimeIndex.delete

`DatetimeIndex.delete(loc)`

Make a new DatetimeIndex with passed location(s) deleted.

Parameters **loc: int, slice or array of ints**

Indicate which sub-arrays to remove.

Returns **new_index** : DatetimeIndex

pandas.DatetimeIndex.diff

`DatetimeIndex.diff(*args, **kwargs)`

pandas.DatetimeIndex.difference

`DatetimeIndex.difference(other)`

Compute sorted set difference of two Index objects

Parameters **other** : Index or array-like

Returns **diff** : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.DatetimeIndex.drop

`DatetimeIndex.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters **labels** : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : Index

pandas.DatetimeIndex.drop_duplicates

`DatetimeIndex.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **deduplicated** : Index

pandas.DatetimeIndex.duplicated

`DatetimeIndex.duplicated(take_last=False)`
Return boolean np.array denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : np.array

pandas.DatetimeIndex.equals

`DatetimeIndex.equals(other)`
Determines if two Index objects contain the same elements.

pandas.DatetimeIndex.factorize

`DatetimeIndex.factorize(sort=False, na_sentinel=-1)`
Encode the object as an enumerated type or categorical variable

Parameters **sort** : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns **labels** : the indexer to the original array

uniques : the unique Index

pandas.DatetimeIndex.format

`DatetimeIndex.format(name=False, formatter=None, **kwargs)`
Render a string representation of the Index

pandas.DatetimeIndex.get_duplicates

`DatetimeIndex.get_duplicates()`

pandas.DatetimeIndex.get_indexer

`DatetimeIndex.get_indexer(target, method=None, limit=None)`
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'}

- 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

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns indexer : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.DatetimeIndex.get_indexer_for

`DatetimeIndex.`**`get_indexer_for`**(*target*, ***kwargs*)

guaranteed return of an indexer even when non-unique

pandas.DatetimeIndex.get_indexer_non_unique

`DatetimeIndex.`**`get_indexer_non_unique`**(*target*)

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.DatetimeIndex.get_level_values

`DatetimeIndex.`**`get_level_values`**(*level*)

Return vector of label values for requested level, equal to the length of the index

Parameters level : int

Returns values : ndarray

pandas.DatetimeIndex.get_loc

`DatetimeIndex.`**`get_loc`**(*key*, *method=None*)

Get integer location for requested label

Returns loc : int

pandas.DatetimeIndex.get_slice_bound

`DatetimeIndex.`**`get_slice_bound`**(*label*, *side*, *kind*)

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters **label** : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.DatetimeIndex.get_value

`DatetimeIndex.get_value(series, key)`

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.DatetimeIndex.get_value_maybe_box

`DatetimeIndex.get_value_maybe_box(series, key)`

pandas.DatetimeIndex.get_values

`DatetimeIndex.get_values()`

return the underlying data as an ndarray

pandas.DatetimeIndex.groupby

`DatetimeIndex.groupby(f)`

pandas.DatetimeIndex.holds_integer

`DatetimeIndex.holds_integer()`

pandas.DatetimeIndex.identical

`DatetimeIndex.identical(other)`

Similar to equals, but check that other comparable attributes are also equal

pandas.DatetimeIndex.indexer_at_time

`DatetimeIndex.indexer_at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : TimeSeries

pandas.DatetimeIndex.indexer_between_time

`DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of day (e.g., 9:00-9:30AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

tz : string or pytz.timezone or dateutil.tz.tzfile, default None

Returns **values_between_time** : TimeSeries

pandas.DatetimeIndex.insert

`DatetimeIndex.insert(loc, item)`

Make new Index inserting new item at location

Parameters **loc** : int

item : object

if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.

Returns **new_index** : Index

pandas.DatetimeIndex.intersection

`DatetimeIndex.intersection(other)`

Specialized intersection for DatetimeIndex objects. May be much faster than Index.intersection

Parameters **other** : DatetimeIndex or array-like

Returns **y** : Index or DatetimeIndex

pandas.DatetimeIndex.is

`DatetimeIndex.is_(other)`

More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters **other** : object

other object to compare against.

Returns **True if both have same underlying data, False otherwise** : bool

pandas.DatetimeIndex.is_boolean

`DatetimeIndex.is_boolean()`

pandas.DatetimeIndex.is_categorical

`DatetimeIndex.is_categorical()`

pandas.DatetimeIndex.is_floating

`DatetimeIndex.is_floating()`

pandas.DatetimeIndex.is_integer

`DatetimeIndex.is_integer()`

pandas.DatetimeIndex.is_lexsorted_for_tuple

`DatetimeIndex.is_lexsorted_for_tuple(tup)`

pandas.DatetimeIndex.is_mixed

`DatetimeIndex.is_mixed()`

pandas.DatetimeIndex.is_numeric

`DatetimeIndex.is_numeric()`

pandas.DatetimeIndex.is_object

`DatetimeIndex.is_object()`

pandas.DatetimeIndex.is_type_compatible

`DatetimeIndex.is_type_compatible(typ)`

pandas.DatetimeIndex.isin

`DatetimeIndex.isin(values)`

Compute boolean array of whether each index value is found in the passed set of values

Parameters values : set or sequence of values

Returns is_contained : ndarray (boolean dtype)

pandas.DatetimeIndex.item

`DatetimeIndex.item()`

return the first element of the underlying data as a python scalar

pandas.DatetimeIndex.join

`DatetimeIndex.join(other, how='left', level=None, return_indexers=False)`

See Index.join

pandas.DatetimeIndex.map

`DatetimeIndex.map(f)`

pandas.DatetimeIndex.max

`DatetimeIndex.max(axis=None)`
return the maximum value of the Index

See also:

`numpy.ndarray.max`

pandas.DatetimeIndex.min

`DatetimeIndex.min(axis=None)`
return the minimum value of the Index

See also:

`numpy.ndarray.min`

pandas.DatetimeIndex.normalize

`DatetimeIndex.normalize()`
Return DatetimeIndex with times to midnight. Length is unaltered

Returns normalized : DatetimeIndex

pandas.DatetimeIndex.nunique

`DatetimeIndex.nunique(dropna=True)`
Return number of unique elements in the object.

Excludes NA values by default.

Parameters dropna : boolean, default True

Don't include NaN in the count.

Returns nunique : int

pandas.DatetimeIndex.order

`DatetimeIndex.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.DatetimeIndex.putmask

`DatetimeIndex.putmask(mask, value)`
return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.DatetimeIndex.ravel

`DatetimeIndex.`**`ravel`**(*order='C'*)

return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.DatetimeIndex.reindex

`DatetimeIndex.`**`reindex`**(*target*, *method=None*, *level=None*, *limit=None*)

Create index with target's values (move/add/delete values as necessary)

Parameters **target** : an iterable

Returns **new_index** : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.DatetimeIndex.rename

`DatetimeIndex.`**`rename`**(*name*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters **name** : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.DatetimeIndex.repeat

`DatetimeIndex.`**`repeat`**(*repeats*, *axis=None*)

Analogous to ndarray.repeat

pandas.DatetimeIndex.searchsorted

`DatetimeIndex.`**`searchsorted`**(*key*, *side='left'*)

pandas.DatetimeIndex.set_names

`DatetimeIndex.`**`set_names`**(*names*, *level=None*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters **names** : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                  (2, u'one'), (2, u'two')],
                                 names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

pandas.DatetimeIndex.set_value

`DatetimeIndex.set_value(arr, key, value)`
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.DatetimeIndex.shift

`DatetimeIndex.shift(n, freq=None)`
Specialized shift which produces a DatetimeIndex

Parameters **n** : int

Periods to shift by

freq : DateOffset or timedelta-like, optional

Returns **shifted** : DatetimeIndex

pandas.DatetimeIndex.slice_indexer

`DatetimeIndex.slice_indexer(start=None, end=None, step=None, kind=None)`
Return indexer for specified label slice. Index.slice_indexer, customized to handle time slicing.

In addition to functionality provided by Index.slice_indexer, does the following:

- if both *start* and *end* are instances of *datetime.time*, it invokes *indexer_between_time*
- if *start* and *end* are both either string or None perform value-based selection in non-monotonic cases.

pandas.DatetimeIndex.slice_locs

`DatetimeIndex.slice_locs(start=None, end=None, step=None, kind=None)`
Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

pandas.DatetimeIndex.snap

`DatetimeIndex.snap(freq='S')`
Snap time stamps to nearest occurring frequency

pandas.DatetimeIndex.sort

`DatetimeIndex.sort(*args, **kwargs)`

pandas.DatetimeIndex.summary

`DatetimeIndex.summary(name=None)`
return a summarized representation

pandas.DatetimeIndex.sym_diff

`DatetimeIndex.sym_diff(other, result_name=None)`
Compute the sorted symmetric difference of two Index objects.

Parameters **other** : Index or array-like

result_name : str

Returns **sym_diff** : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing `NaN` values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.DatetimeIndex.take

`DatetimeIndex.`**`take`**(*indices*, *axis=0*)
Analogous to ndarray.take

pandas.DatetimeIndex.to_datetime

`DatetimeIndex.`**`to_datetime`**(*dayfirst=False*)

pandas.DatetimeIndex.to_julian_date

`DatetimeIndex.`**`to_julian_date`**()
Convert DatetimeIndex to Float64Index of Julian Dates. 0 Julian date is noon January 1, 4713 BC. http://en.wikipedia.org/wiki/Julian_day

pandas.DatetimeIndex.to_native_types

`DatetimeIndex.`**`to_native_types`**(*slicer=None*, ***kwargs*)
slice and dice then format

pandas.DatetimeIndex.to_period

`DatetimeIndex.`**`to_period`**(*freq=None*)
Cast to PeriodIndex at a particular frequency

pandas.DatetimeIndex.to_pydatetime

`DatetimeIndex.`**`to_pydatetime`**()
Return DatetimeIndex as object ndarray of datetime.datetime objects

Returns **datetimes** : ndarray

pandas.DatetimeIndex.to_series

`DatetimeIndex.`**`to_series`**(*keep_tz=False*)
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Parameters **keep_tz** : optional, defaults False.

return the data keeping the timezone.

If keep_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype. Otherwise the Series will have an object dtype; the tz will be preserved.

If keep_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Returns Series

pandas.DatetimeIndex.tolist

`DatetimeIndex.tolist()`

return a list of the underlying data

pandas.DatetimeIndex.transpose

`DatetimeIndex.transpose()`

return the transpose, which is by definition self

pandas.DatetimeIndex.tz_convert

`DatetimeIndex.tz_convert(tz)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns **normalized** : DatetimeIndex

Raises **TypeError**

If DatetimeIndex is tz-naive.

pandas.DatetimeIndex.tz_localize

`DatetimeIndex.tz_localize(*args, **kwargs)`

Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order

- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError

If the DatetimeIndex is tz-aware and tz is not None.

pandas.DatetimeIndex.union

`DatetimeIndex.`**`union`**(*other*)

Specialized union for DatetimeIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

Parameters other : DatetimeIndex or array-like

Returns y : Index or DatetimeIndex

pandas.DatetimeIndex.union_many

`DatetimeIndex.`**`union_many`**(*others*)

A bit of a hack to accelerate unioning a collection of indexes

pandas.DatetimeIndex.unique

`DatetimeIndex.`**`unique`**()

Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result : DatetimeIndex or PeriodIndex

pandas.DatetimeIndex.value_counts

`DatetimeIndex.`**`value_counts`**(*normalize=False, sort=True, ascending=False, bins=None, dropna=True*)

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns counts : Series

pandas.DatetimeIndex.view

`DatetimeIndex.view(cls=None)`

33.9.2 Time/Date Components

DatetimeIndex.year	The year of the datetime
DatetimeIndex.month	The month as January=1, December=12
DatetimeIndex.day	The days of the datetime
DatetimeIndex.hour	The hours of the datetime
DatetimeIndex.minute	The minutes of the datetime
DatetimeIndex.second	The seconds of the datetime
DatetimeIndex.microsecond	The microseconds of the datetime
DatetimeIndex.nanosecond	The nanoseconds of the datetime
DatetimeIndex.date	Returns numpy array of datetime.date.
DatetimeIndex.time	Returns numpy array of datetime.time.
DatetimeIndex.dayofyear	The ordinal day of the year
DatetimeIndex.weekofyear	The week ordinal of the year
DatetimeIndex.week	The week ordinal of the year
DatetimeIndex.dayofweek	The day of the week with Monday=0, Sunday=6
DatetimeIndex.weekday	The day of the week with Monday=0, Sunday=6
DatetimeIndex.quarter	The quarter of the date
DatetimeIndex.tz	
DatetimeIndex.freq	get/set the frequncy of the Index
DatetimeIndex.freqstr	return the frequency object as a string if its set, otherwise None
DatetimeIndex.is_month_start	Logical indicating if first day of month (defined by frequency)
DatetimeIndex.is_month_end	Logical indicating if last day of month (defined by frequency)
DatetimeIndex.is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
DatetimeIndex.is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
DatetimeIndex.is_year_start	Logical indicating if first day of year (defined by frequency)
DatetimeIndex.is_year_end	Logical indicating if last day of year (defined by frequency)
DatetimeIndex.inferred_freq	

pandas.DatetimeIndex.year

`DatetimeIndex.year`

The year of the datetime

pandas.DatetimeIndex.month

`DatetimeIndex.`**`month`**
The month as January=1, December=12

pandas.DatetimeIndex.day

`DatetimeIndex.`**`day`**
The days of the datetime

pandas.DatetimeIndex.hour

`DatetimeIndex.`**`hour`**
The hours of the datetime

pandas.DatetimeIndex.minute

`DatetimeIndex.`**`minute`**
The minutes of the datetime

pandas.DatetimeIndex.second

`DatetimeIndex.`**`second`**
The seconds of the datetime

pandas.DatetimeIndex.microsecond

`DatetimeIndex.`**`microsecond`**
The microseconds of the datetime

pandas.DatetimeIndex.nanosecond

`DatetimeIndex.`**`nanosecond`**
The nanoseconds of the datetime

pandas.DatetimeIndex.date

`DatetimeIndex.`**`date`**
Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.DatetimeIndex.time

`DatetimeIndex.`**`time`**
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.dayofyear

`DatetimeIndex.`**`dayofyear`**
The ordinal day of the year

pandas.DatetimeIndex.weekofyear

`DatetimeIndex.`**`weekofyear`**
The week ordinal of the year

pandas.DatetimeIndex.week

`DatetimeIndex.`**`week`**
The week ordinal of the year

pandas.DatetimeIndex.dayofweek

`DatetimeIndex.`**`dayofweek`**
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.weekday

`DatetimeIndex.`**`weekday`**
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.quarter

`DatetimeIndex.`**`quarter`**
The quarter of the date

pandas.DatetimeIndex.tz

`DatetimeIndex.`**`tz`** **= None**

pandas.DatetimeIndex.freq

`DatetimeIndex.`**`freq`**
get/set the frequncy of the Index

pandas.DatetimeIndex.freqstr

`DatetimeIndex.`**`freqstr`**
return the frequency object as a string if its set, otherwise None

pandas.DatetimeIndex.is_month_start

`DatetimeIndex.`**`is_month_start`**
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_month_end

DatetimeIndex.**is_month_end**
Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_quarter_start

DatetimeIndex.**is_quarter_start**
Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_end

DatetimeIndex.**is_quarter_end**
Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_year_start

DatetimeIndex.**is_year_start**
Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.is_year_end

DatetimeIndex.**is_year_end**
Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.inferred_freq

DatetimeIndex.**inferred_freq** = **None**

33.9.3 Selecting

DatetimeIndex.indexer_at_time(time[, asof])	Select values at particular time of day (e.g.
DatetimeIndex.indexer_between_time(...[, ...])	Select values between particular times of day (e.g., 9:00-9:30AM)

pandas.DatetimeIndex.indexer_at_time

DatetimeIndex.**indexer_at_time**(*time*, *asof=False*)
Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : TimeSeries

pandas.DatetimeIndex.indexer_between_time

DatetimeIndex.**indexer_between_time**(*start_time*, *end_time*, *include_start=True*, *include_end=True*)
Select values between particular times of day (e.g., 9:00-9:30AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

tz : string or pytz.timezone or dateutil.tz.tzfile, default None

Returns **values_between_time** : TimeSeries

33.9.4 Time-specific operations

`DatetimeIndex.normalize()`	Return DatetimeIndex with times to midnight.
`DatetimeIndex.snap([freq])`	Snap time stamps to nearest occurring frequency
`DatetimeIndex.tz_convert(tz)`	Convert tz-aware DatetimeIndex from one time zone to another (using pytz/
`DatetimeIndex.tz_localize(*args, **kwargs)`	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),

pandas.DatetimeIndex.normalize

`DatetimeIndex.normalize()`

Return DatetimeIndex with times to midnight. Length is unaltered

Returns **normalized** : DatetimeIndex

pandas.DatetimeIndex.snap

`DatetimeIndex.snap(freq='S')`

Snap time stamps to nearest occurring frequency

pandas.DatetimeIndex.tz_convert

`DatetimeIndex.tz_convert(tz)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns **normalized** : DatetimeIndex

Raises **TypeError**

If DatetimeIndex is tz-naive.

pandas.DatetimeIndex.tz_localize

`DatetimeIndex.tz_localize(*args, **kwargs)`

Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters **tz** : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError

If the DatetimeIndex is tz-aware and tz is not None.

33.9.5 Conversion

`DatetimeIndex.to_datetime`([dayfirst])	
`DatetimeIndex.to_period`([freq])	Cast to PeriodIndex at a particular frequency
`DatetimeIndex.to_pydatetime`()	Return DatetimeIndex as object ndarray of datetime.datetime objects
`DatetimeIndex.to_series`([keep_tz])	Create a Series with both index and values equal to the index keys

pandas.DatetimeIndex.to_datetime

`DatetimeIndex.`**`to_datetime`**(*dayfirst=False*)

pandas.DatetimeIndex.to_period

`DatetimeIndex.`**`to_period`**(*freq=None*)

Cast to PeriodIndex at a particular frequency

pandas.DatetimeIndex.to_pydatetime

`DatetimeIndex.`**`to_pydatetime`**()

Return DatetimeIndex as object ndarray of datetime.datetime objects

Returns datetimes : ndarray

pandas.DatetimeIndex.to_series

`DatetimeIndex.`**`to_series`**(*keep_tz=False*)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Parameters keep_tz : optional, defaults False.

return the data keeping the timezone.

If keep_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype. Otherwise the Series will have an object dtype; the tz will be preserved.

If keep_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Returns Series

33.10 TimedeltaIndex

`TimedeltaIndex`	Immutable ndarray of timedelta64 data, represented internally as int64, and

33.10.1 pandas.TimedeltaIndex

class `pandas.`**`TimedeltaIndex`**

Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects

Parameters **data** : array-like (1-dimensional), optional

Optional timedelta-like data to construct index with

unit: unit of the arg (D,h,m,s,ms,us,ns) denote the unit, optional

which is an integer/float number

freq: a frequency for the index, optional

copy : bool

Make a copy of input ndarray

start : starting value, timedelta-like, optional

If data is None, start is used as the start point in generating regular timedelta data.

periods : int, optional, > 0

Number of periods to generate, if generating index. Takes precedence over end argument

end : end time, timedelta-like, optional

If periods is none, generated index will extend to first conforming time on or just past end argument

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

name : object

Name to be stored in the index

Attributes

T	return the transpose, which is by definition self
asi8	
asobject	
base	return the base object if the memory of the underlying data is shared
components	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds
data	return the data pointer of the underlying data
days	Number of days for each element.
dtype	
flags	
freqstr	return the frequency object as a string if its set, otherwise None
has_duplicates	
inferred_type	
is_all_dates	
is_monotonic	alias for is_monotonic_increasing (deprecated)
is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
is_monotonic_increasing	return if the index is monotonic increasing (only equal or
itemsize	return the size of the dtype of the item of the underlying data
microseconds	Number of microseconds (>= 0 and less than 1 second) for each element.
names	
nanoseconds	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
nbytes	return the number of bytes in the underlying data
ndim	return the number of dimensions of the underlying data, by definition 1
nlevels	
seconds	Number of seconds (>= 0 and less than 1 day) for each element.
shape	return a tuple of the shape of the underlying data
size	return the number of elements in the underlying data
strides	return the strides of the underlying data
values	return the underlying data as an ndarray

pandas.TimedeltaIndex.T

TimedeltaIndex.**T**
return the transpose, which is by definition self

pandas.TimedeltaIndex.asi8

TimedeltaIndex.**asi8**

pandas.TimedeltaIndex.asobject

TimedeltaIndex.**asobject**

pandas.TimedeltaIndex.base

TimedeltaIndex.**base**
return the base object if the memory of the underlying data is shared

pandas.TimedeltaIndex.components

`TimedeltaIndex.components`

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

pandas.TimedeltaIndex.data

`TimedeltaIndex.data`

return the data pointer of the underlying data

pandas.TimedeltaIndex.days

`TimedeltaIndex.days`

Number of days for each element.

pandas.TimedeltaIndex.dtype

`TimedeltaIndex.dtype`

pandas.TimedeltaIndex.flags

`TimedeltaIndex.flags`

pandas.TimedeltaIndex.freqstr

`TimedeltaIndex.freqstr`

return the frequency object as a string if its set, otherwise None

pandas.TimedeltaIndex.has_duplicates

`TimedeltaIndex.has_duplicates`

pandas.TimedeltaIndex.inferred_type

`TimedeltaIndex.inferred_type`

pandas.TimedeltaIndex.is_all_dates

`TimedeltaIndex.is_all_dates`

pandas.TimedeltaIndex.is_monotonic

`TimedeltaIndex.is_monotonic`

alias for is_monotonic_increasing (deprecated)

pandas.TimedeltaIndex.is_monotonic_decreasing

TimedeltaIndex.**is_monotonic_decreasing**
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.TimedeltaIndex.is_monotonic_increasing

TimedeltaIndex.**is_monotonic_increasing**
return if the index is monotonic increasing (only equal or increasing) values.

pandas.TimedeltaIndex.itemsize

TimedeltaIndex.**itemsize**
return the size of the dtype of the item of the underlying data

pandas.TimedeltaIndex.microseconds

TimedeltaIndex.**microseconds**
Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.names

TimedeltaIndex.**names**

pandas.TimedeltaIndex.nanoseconds

TimedeltaIndex.**nanoseconds**
Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.nbytes

TimedeltaIndex.**nbytes**
return the number of bytes in the underlying data

pandas.TimedeltaIndex.ndim

TimedeltaIndex.**ndim**
return the number of dimensions of the underlying data, by definition 1

pandas.TimedeltaIndex.nlevels

TimedeltaIndex.**nlevels**

pandas.TimedeltaIndex.seconds

TimedeltaIndex.**seconds**
Number of seconds (>= 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.shape

TimedeltaIndex.**shape**
return a tuple of the shape of the underlying data

pandas.TimedeltaIndex.size

TimedeltaIndex.**size**
return the number of elements in the underlying data

pandas.TimedeltaIndex.strides

TimedeltaIndex.**strides**
return the strides of the underlying data

pandas.TimedeltaIndex.values

TimedeltaIndex.**values**
return the underlying data as an ndarray

freq	
hasnans	
inferred_freq	
is_unique	
name	
resolution	

Methods

all([other])	
any([other])	
append(other)	Append a collection of Index options together
argmax([axis])	return a ndarray of the maximum argument indexer
argmin([axis])	return a ndarray of the minimum argument indexer
argsort(*args, **kwargs)	return an ndarray indexer of the underlying data
asof(label)	For a sorted index, return the most recent label up to and including the passed la
asof_locs(where, mask)	where : array of timestamps
astype(dtype)	
copy([names, name, dtype, deep])	Make a copy of this object.
delete(loc)	Make a new DatetimeIndex with passed location(s) deleted.
diff(*args, **kwargs)	
difference(other)	Compute sorted set difference of two Index objects
drop(labels[, errors])	Make new Index with passed list of labels deleted
drop_duplicates([take_last])	Return Index with duplicate values removed
duplicated([take_last])	Return boolean np.array denoting duplicate values
equals(other)	Determines if two Index objects contain the same elements.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable
format([name, formatter])	Render a string representation of the Index
get_duplicates()	
get_indexer(target[, method, limit])	Compute indexer and mask for new index given the current index.

Continued on next pa

Table 33.109 – continued from previous page

get_indexer_for(target, **kwargs)	guaranteed return of an indexer even when non-unique
get_indexer_non_unique(target)	return an indexer suitable for taking from a non unique index
get_level_values(level)	Return vector of label values for requested level, equal to the length
get_loc(key[, method])	Get integer location for requested label
get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
get_value_maybe_box(series, key)	
get_values()	return the underlying data as an ndarray
groupby(f)	
holds_integer()	
identical(other)	Similar to equals, but check that other comparable attributes are
insert(loc, item)	Make new Index inserting new item at location
intersection(other)	Specialized intersection for TimedeltaIndex objects.
is_(other)	More flexible, faster check like is but that works through views
is_boolean()	
is_categorical()	
is_floating()	
is_integer()	
is_lexsorted_for_tuple(tup)	
is_mixed()	
is_numeric()	
is_object()	
is_type_compatible(typ)	
isin(values)	Compute boolean array of whether each index value is found in the
item()	return the first element of the underlying data as a python scalar
join(other[, how, level, return_indexers])	See Index.join
map(f)	
max([axis])	return the maximum value of the Index
min([axis])	return the minimum value of the Index
nunique([dropna])	Return number of unique elements in the object.
order([return_indexer, ascending])	Return sorted copy of Index
putmask(mask, value)	return a new Index of the values set with the mask
ravel([order])	return an ndarray of the flattened values of the underlying data
reindex(target[, method, level, limit])	Create index with target's values (move/add/delete values as necessary)
rename(name[, inplace])	Set new names on index.
repeat(repeats[, axis])	Analogous to ndarray.repeat
searchsorted(key[, side])	
set_names(names[, level, inplace])	Set new names on index.
set_value(arr, key, value)	Fast lookup of value from 1-dimensional ndarray.
shift(n[, freq])	Specialized shift which produces a DatetimeIndex
slice_indexer([start, end, step, kind])	For an ordered Index, compute the slice indexer for input labels and
slice_locs([start, end, step, kind])	Compute slice locations for input labels.
sort(*args, **kwargs)	
str	alias of StringMethods
summary([name])	return a summarized representation
sym_diff(other[, result_name])	Compute the sorted symmetric difference of two Index objects.
take(indices[, axis])	Analogous to ndarray.take
to_datetime([dayfirst])	For an Index containing strings or datetime.datetime objects, attempt
to_native_types([slicer])	slice and dice then format
to_pytimedelta()	Return TimedeltaIndex as object ndarray of datetime.timedelta objects
to_series(**kwargs)	Create a Series with both index and values equal to the index keys
tolist()	return a list of the underlying data

Continued on next page

Table 33.109 – continued from previous page

transpose()	return the transpose, which is by definition self
union(other)	Specialized union for TimedeltaIndex objects.
unique()	Index.unique with handling for DatetimeIndex/PeriodIndex metadata
value_counts([normalize, sort, ascending, ...])	Returns object containing counts of unique values.
view([cls])	

pandas.TimedeltaIndex.all

TimedeltaIndex.**all**(*other=None*)

pandas.TimedeltaIndex.any

TimedeltaIndex.**any**(*other=None*)

pandas.TimedeltaIndex.append

TimedeltaIndex.**append**(*other*)

Append a collection of Index options together

Parameters other : Index or list/tuple of indices

Returns appended : Index

pandas.TimedeltaIndex.argmax

TimedeltaIndex.**argmax**(*axis=None*)

return a ndarray of the maximum argument indexer

See also:

numpy.ndarray.argmax

pandas.TimedeltaIndex.argmin

TimedeltaIndex.**argmin**(*axis=None*)

return a ndarray of the minimum argument indexer

See also:

numpy.ndarray.argmin

pandas.TimedeltaIndex.argsort

TimedeltaIndex.**argsort**(**args*, ***kwargs*)

return an ndarray indexer of the underlying data

See also:

numpy.ndarray.argsort

pandas.TimedeltaIndex.asof

`TimedeltaIndex.asof(label)`

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` asof is a thin wrapper around get_loc with method='pad'

pandas.TimedeltaIndex.asof_locs

`TimedeltaIndex.asof_locs(where, mask)`

where : array of timestamps mask : array of booleans where data is not NA

pandas.TimedeltaIndex.astype

`TimedeltaIndex.astype(dtype)`

pandas.TimedeltaIndex.copy

`TimedeltaIndex.copy(names=None, name=None, dtype=None, deep=False)`

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.TimedeltaIndex.delete

`TimedeltaIndex.delete(loc)`

Make a new DatetimeIndex with passed location(s) deleted.

Parameters **loc: int, slice or array of ints**

Indicate which sub-arrays to remove.

Returns **new_index** : TimedeltaIndex

pandas.TimedeltaIndex.diff

`TimedeltaIndex.diff(*args, **kwargs)`

pandas.TimedeltaIndex.difference

`TimedeltaIndex.`**`difference`**(*other*)

Compute sorted set difference of two Index objects

Parameters **other** : Index or array-like

Returns **diff** : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.TimedeltaIndex.drop

`TimedeltaIndex.`**`drop`**(*labels*, *errors='raise'*)

Make new Index with passed list of labels deleted

Parameters **labels** : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : Index

pandas.TimedeltaIndex.drop_duplicates

`TimedeltaIndex.`**`drop_duplicates`**(*take_last=False*)

Return Index with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **deduplicated** : Index

pandas.TimedeltaIndex.duplicated

`TimedeltaIndex.`**`duplicated`**(*take_last=False*)

Return boolean np.array denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : np.array

pandas.TimedeltaIndex.equals

`TimedeltaIndex.`**`equals`**(*other*)

Determines if two Index objects contain the same elements.

pandas.TimedeltaIndex.factorize

TimedeltaIndex.**factorize**(*sort=False*, *na_sentinel=-1*)
Encode the object as an enumerated type or categorical variable

Parameters sort : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns labels : the indexer to the original array

uniques : the unique Index

pandas.TimedeltaIndex.format

TimedeltaIndex.**format**(*name=False*, *formatter=None*, ***kwargs*)
Render a string representation of the Index

pandas.TimedeltaIndex.get_duplicates

TimedeltaIndex.**get_duplicates**()

pandas.TimedeltaIndex.get_indexer

TimedeltaIndex.**get_indexer**(*target*, *method=None*, *limit=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'}

- 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

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns indexer : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.TimedeltaIndex.get_indexer_for

TimedeltaIndex.**get_indexer_for**(*target*, ***kwargs*)
guaranteed return of an indexer even when non-unique

pandas.TimedeltaIndex.get_indexer_non_unique

TimedeltaIndex.**get_indexer_non_unique**(*target*)
return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.TimedeltaIndex.get_level_values

TimedeltaIndex.**get_level_values**(*level*)
Return vector of label values for requested level, equal to the length of the index

Parameters **level** : int

Returns **values** : ndarray

pandas.TimedeltaIndex.get_loc

TimedeltaIndex.**get_loc**(*key*, *method=None*)
Get integer location for requested label

Returns **loc** : int

pandas.TimedeltaIndex.get_slice_bound

TimedeltaIndex.**get_slice_bound**(*label*, *side*, *kind*)
Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters **label** : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.TimedeltaIndex.get_value

TimedeltaIndex.**get_value**(*series*, *key*)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.TimedeltaIndex.get_value_maybe_box

TimedeltaIndex.**get_value_maybe_box**(*series*, *key*)

pandas.TimedeltaIndex.get_values

`TimedeltaIndex.get_values()`
return the underlying data as an ndarray

pandas.TimedeltaIndex.groupby

`TimedeltaIndex.groupby(f)`

pandas.TimedeltaIndex.holds_integer

`TimedeltaIndex.holds_integer()`

pandas.TimedeltaIndex.identical

`TimedeltaIndex.identical(other)`
Similar to equals, but check that other comparable attributes are also equal

pandas.TimedeltaIndex.insert

`TimedeltaIndex.insert(loc, item)`
Make new Index inserting new item at location

Parameters **loc** : int

item : object

if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.

Returns **new_index** : Index

pandas.TimedeltaIndex.intersection

`TimedeltaIndex.intersection(other)`
Specialized intersection for TimedeltaIndex objects. May be much faster than Index.intersection

Parameters **other** : TimedeltaIndex or array-like

Returns **y** : Index or TimedeltaIndex

pandas.TimedeltaIndex.is

`TimedeltaIndex.is_(other)`
More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters **other** : object

other object to compare against.

Returns **True if both have same underlying data, False otherwise** : bool

pandas.TimedeltaIndex.is_boolean

TimedeltaIndex.**is_boolean**()

pandas.TimedeltaIndex.is_categorical

TimedeltaIndex.**is_categorical**()

pandas.TimedeltaIndex.is_floating

TimedeltaIndex.**is_floating**()

pandas.TimedeltaIndex.is_integer

TimedeltaIndex.**is_integer**()

pandas.TimedeltaIndex.is_lexsorted_for_tuple

TimedeltaIndex.**is_lexsorted_for_tuple**(*tup*)

pandas.TimedeltaIndex.is_mixed

TimedeltaIndex.**is_mixed**()

pandas.TimedeltaIndex.is_numeric

TimedeltaIndex.**is_numeric**()

pandas.TimedeltaIndex.is_object

TimedeltaIndex.**is_object**()

pandas.TimedeltaIndex.is_type_compatible

TimedeltaIndex.**is_type_compatible**(*typ*)

pandas.TimedeltaIndex.isin

TimedeltaIndex.**isin**(*values*)

Compute boolean array of whether each index value is found in the passed set of values

Parameters values : set or sequence of values

Returns is_contained : ndarray (boolean dtype)

pandas.TimedeltaIndex.item

`TimedeltaIndex.item()`
return the first element of the underlying data as a python scalar

pandas.TimedeltaIndex.join

`TimedeltaIndex.join`(*other*, *how='left'*, *level=None*, *return_indexers=False*)
See Index.join

pandas.TimedeltaIndex.map

`TimedeltaIndex.map`(*f*)

pandas.TimedeltaIndex.max

`TimedeltaIndex.max`(*axis=None*)
return the maximum value of the Index

See also:

`numpy.ndarray.max`

pandas.TimedeltaIndex.min

`TimedeltaIndex.min`(*axis=None*)
return the minimum value of the Index

See also:

`numpy.ndarray.min`

pandas.TimedeltaIndex.nunique

`TimedeltaIndex.nunique`(*dropna=True*)
Return number of unique elements in the object.

Excludes NA values by default.

Parameters **dropna** : boolean, default True

Don't include NaN in the count.

Returns **nunique** : int

pandas.TimedeltaIndex.order

`TimedeltaIndex.order`(*return_indexer=False*, *ascending=True*)
Return sorted copy of Index

pandas.TimedeltaIndex.putmask

`TimedeltaIndex.putmask(mask, value)`

return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.TimedeltaIndex.ravel

`TimedeltaIndex.ravel(order='C')`

return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.TimedeltaIndex.reindex

`TimedeltaIndex.reindex(target, method=None, level=None, limit=None)`

Create index with target's values (move/add/delete values as necessary)

Parameters **target** : an iterable

Returns **new_index** : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.TimedeltaIndex.rename

`TimedeltaIndex.rename(name, inplace=False)`

Set new names on index. Defaults to returning new index.

Parameters **name** : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.TimedeltaIndex.repeat

`TimedeltaIndex.repeat(repeats, axis=None)`

Analogous to ndarray.repeat

pandas.TimedeltaIndex.searchsorted

`TimedeltaIndex.searchsorted(key, side='left')`

pandas.TimedeltaIndex.set_names

TimedeltaIndex.**set_names**(*names*, *level=None*, *inplace=False*)
Set new names on index. Defaults to returning new index.

Parameters **names** : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                   (2, u'one'), (2, u'two')],
                                  names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

pandas.TimedeltaIndex.set_value

TimedeltaIndex.**set_value**(*arr*, *key*, *value*)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

pandas.TimedeltaIndex.shift

TimedeltaIndex.**shift**(*n*, *freq=None*)
Specialized shift which produces a DatetimeIndex

Parameters **n** : int

Periods to shift by

freq : DateOffset or timedelta-like, optional

Returns **shifted** : DatetimeIndex

pandas.TimedeltaIndex.slice_indexer

`TimedeltaIndex.slice_indexer(start=None, end=None, step=None, kind=None)`
For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.TimedeltaIndex.slice_locs

`TimedeltaIndex.slice_locs(start=None, end=None, step=None, kind=None)`
Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

pandas.TimedeltaIndex.sort

`TimedeltaIndex.sort(*args, **kwargs)`

pandas.TimedeltaIndex.summary

`TimedeltaIndex.summary(name=None)`
return a summarized representation

pandas.TimedeltaIndex.sym_diff

TimedeltaIndex.**sym_diff**(*other*, *result_name=None*)

Compute the sorted symmetric difference of two Index objects.

Parameters other : Index or array-like

result_name : str

Returns sym_diff : Index

Notes

sym_diff contains elements that appear in either idx1 or idx2 but not both. Equivalent to the Index created by (idx1 - idx2) + (idx2 - idx1) with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.TimedeltaIndex.take

TimedeltaIndex.**take**(*indices*, *axis=0*)

Analogous to ndarray.take

pandas.TimedeltaIndex.to_datetime

TimedeltaIndex.**to_datetime**(*dayfirst=False*)

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.TimedeltaIndex.to_native_types

TimedeltaIndex.**to_native_types**(*slicer=None*, ***kwargs*)

slice and dice then format

pandas.TimedeltaIndex.to_pytimedelta

TimedeltaIndex.**to_pytimedelta**()

Return TimedeltaIndex as object ndarray of datetime.timedelta objects

Returns datetimes : ndarray

pandas.TimedeltaIndex.to_series

`TimedeltaIndex.to_series(**kwargs)`

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.TimedeltaIndex.tolist

`TimedeltaIndex.tolist()`

return a list of the underlying data

pandas.TimedeltaIndex.transpose

`TimedeltaIndex.transpose()`

return the transpose, which is by definition self

pandas.TimedeltaIndex.union

`TimedeltaIndex.union(other)`

Specialized union for TimedeltaIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

Parameters other : TimedeltaIndex or array-like

Returns y : Index or TimedeltaIndex

pandas.TimedeltaIndex.unique

`TimedeltaIndex.unique()`

Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result : DatetimeIndex or PeriodIndex

pandas.TimedeltaIndex.value_counts

`TimedeltaIndex.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns counts : Series

pandas.TimedeltaIndex.view

`TimedeltaIndex.view(cls=None)`

33.10.2 Components

TimedeltaIndex.days	Number of days for each element.
TimedeltaIndex.seconds	Number of seconds (>= 0 and less than 1 day) for each element.
TimedeltaIndex.microseconds	Number of microseconds (>= 0 and less than 1 second) for each element.
TimedeltaIndex.nanoseconds	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
TimedeltaIndex.components	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, micr
TimedeltaIndex.inferred_freq	

pandas.TimedeltaIndex.days

`TimedeltaIndex.days`

Number of days for each element.

pandas.TimedeltaIndex.seconds

`TimedeltaIndex.seconds`

Number of seconds (>= 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.microseconds

`TimedeltaIndex.microseconds`

Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.nanoseconds

`TimedeltaIndex.nanoseconds`

Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.components

`TimedeltaIndex.components`

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

pandas.TimedeltaIndex.inferred_freq

`TimedeltaIndex.`**`inferred_freq`** = **None**

33.10.3 Conversion

TimedeltaIndex.to_pytimedelta()	Return TimedeltaIndex as object ndarray of datetime.timedelta objects
TimedeltaIndex.to_series(**kwargs)	Create a Series with both index and values equal to the index keys

pandas.TimedeltaIndex.to_pytimedelta

`TimedeltaIndex.`**`to_pytimedelta`**`()`

Return TimedeltaIndex as object ndarray of datetime.timedelta objects

Returns datetimes : ndarray

pandas.TimedeltaIndex.to_series

`TimedeltaIndex.`**`to_series`**`(`*`**kwargs`*`)`

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

33.11 GroupBy

GroupBy objects are returned by groupby calls: `pandas.DataFrame.groupby()`, `pandas.Series.groupby()`, etc.

33.11.1 Indexing, iteration

GroupBy.__iter__()	Groupby iterator
GroupBy.groups	dict {group name -> group labels}
GroupBy.indices	dict {group name -> group indices}
GroupBy.get_group(name[, obj])	Constructs NDFrame from group with provided name

pandas.core.groupby.GroupBy.__iter__

`GroupBy.`**`__iter__`**`()`

Groupby iterator

Returns Generator yielding sequence of (name, subsetted object)

for each group

pandas.core.groupby.GroupBy.groups

GroupBy.**groups**
dict {group name -> group labels}

pandas.core.groupby.GroupBy.indices

GroupBy.**indices**
dict {group name -> group indices}

pandas.core.groupby.GroupBy.get_group

GroupBy.**get_group**(*name*, *obj=None*)
Constructs NDFrame from group with provided name

Parameters **name** : object

the name of the group to get as a DataFrame

obj : NDFrame, default None

the NDFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used

Returns **group** : type of obj

Grouper([key, level, freq, axis, sort])	A Grouper allows the user to specify a groupby instruction for a target object

pandas.Grouper

class pandas.**Grouper**(*key=None*, *level=None*, *freq=None*, *axis=0*, *sort=False*)
A Grouper allows the user to specify a groupby instruction for a target object

This specification will select a column via the key parameter, or if the level and/or axis parameters are given, a level of the index of the target object.

These are local specifications and will override 'global' settings, that is the parameters axis and level which are passed to the groupby itself.

Parameters **key** : string, defaults to None

groupby key, which selects the grouping column of the target

level : name/number, defaults to None

the level for the target index

freq : string / freqency object, defaults to None

This will groupby the specified frequency if the target selection (via key or level) is a datetime-like object

axis : number/name of the axis, defaults to 0

sort : boolean, default to False

whether to sort the resulting labels

additional kwargs to control time-like groupers (when freq is passed)

closed : closed end of interval; left or right

label : interval boundary to use for labeling; left or right

convention : {'start', 'end', 'e', 's'}

If grouper is PeriodIndex

Returns A specification for a groupby instruction

Examples

```
>>> df.groupby(Grouper(key='A')) : syntactic sugar for df.groupby('A')
>>> df.groupby(Grouper(key='date',freq='60s')) : specify a resample on the column 'date'
>>> df.groupby(Grouper(level='date',freq='60s',axis=1)) :
    specify a resample on the level 'date' on the columns axis with a frequency of 60s
```

Attributes

`ax`	
`groups`	

pandas.Grouper.ax

Grouper.**ax**

pandas.Grouper.groups

Grouper.**groups**

33.11.2 Function application

`GroupBy.apply`(func, *args, **kwargs)	Apply function and combine results together in an intelligent way.
`GroupBy.aggregate`(func, *args, **kwargs)	
`GroupBy.transform`(func, *args, **kwargs)	

pandas.core.groupby.GroupBy.apply

GroupBy.**apply**(*func*, **args*, ***kwargs*)

Apply function and combine results together in an intelligent way. The split-apply-combine combination rules attempt to be as common sense based as possible. For example:

case 1: group DataFrame apply aggregation function (f(chunk) -> Series) yield DataFrame, with group axis having group labels

case 2: group DataFrame apply transform function ((f(chunk) -> DataFrame with same indexes) yield DataFrame with resulting chunks glued together

case 3: group Series apply function with f(chunk) -> DataFrame yield DataFrame with result of chunks glued together

Parameters **func** : function

Returns **applied** : type depending on grouped object and function

See also:

aggregate, transform

Notes

See online documentation for full exposition on how to use apply.

In the current implementation apply calls func twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first group.

pandas.core.groupby.GroupBy.aggregate

GroupBy.**aggregate**(*func*, **args*, ***kwargs*)

pandas.core.groupby.GroupBy.transform

GroupBy.**transform**(*func*, **args*, ***kwargs*)

33.11.3 Computations / Descriptive Stats

GroupBy.count([axis])	
GroupBy.cumcount([ascending])	Number each item in each group from 0 to the length of that group - 1.
GroupBy.first()	Compute first of group values
GroupBy.head([n])	Returns first n rows of each group.
GroupBy.last()	Compute last of group values
GroupBy.max()	Compute max of group values
GroupBy.mean()	Compute mean of groups, excluding missing values
GroupBy.median()	Compute median of groups, excluding missing values
GroupBy.min()	Compute min of group values
GroupBy.nth(n[, dropna])	Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.
GroupBy.ohlc()	Compute sum of values, excluding missing values
GroupBy.prod()	Compute prod of group values
GroupBy.size()	Compute group sizes
GroupBy.sem([ddof])	Compute standard error of the mean of groups, excluding missing values
GroupBy.std([ddof])	Compute standard deviation of groups, excluding missing values
GroupBy.sum()	Compute sum of group values
GroupBy.var([ddof])	Compute variance of groups, excluding missing values
GroupBy.tail([n])	Returns last n rows of each group

pandas.core.groupby.GroupBy.count

GroupBy.**count**(*axis=0*)

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

```
>>> self.apply(lambda x: Series(np.arange(len(x)), x.index))
```

Parameters ascending : bool, default True

If False, number in reverse, from length of group - 1 to 0.

Examples

```
>>> df = pd.DataFrame([['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
...                   columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
0    3
1    2
2    1
3    1
4    0
5    0
dtype: int64
```

pandas.core.groupby.GroupBy.first

GroupBy.**first**()

Compute first of group values

pandas.core.groupby.GroupBy.head

GroupBy.**head**(*n=5*)

Returns first n rows of each group.

Essentially equivalent to `.apply(lambda x: x.head(n))`, except ignores as_index flag.

Examples

```
>>> 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
>>> df.groupby('A').head(1)
   A  B
0  1  2
2  5  6
```

pandas.core.groupby.GroupBy.last

GroupBy.**last**()

Compute last of group values

pandas.core.groupby.GroupBy.max

GroupBy.**max**()

Compute max of group values

pandas.core.groupby.GroupBy.mean

GroupBy.**mean**()

Compute mean of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.median

GroupBy.**median**()

Compute median of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.min

GroupBy.**min**()

Compute min of group values

pandas.core.groupby.GroupBy.nth

GroupBy.**nth**(*n*, *dropna=None*)

Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.

If dropna, will take the nth non-null row, dropna is either Truthy (if a Series) or 'all', 'any' (if a DataFrame); this is equivalent to calling dropna(how=dropna) before the groupby.

Parameters n : int or list of ints

a single nth value for the row or a list of nth values

dropna : None or str, optional

apply the specified dropna operation before counting which row is the nth row. Needs to be None, 'any' or 'all'

Examples

```
>>> df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g.nth(0)
   A   B
0  1 NaN
2  5   6
>>> g.nth(1)
   A  B
1  1  4
>>> g.nth(-1)
   A  B
1  1  4
2  5  6
>>> g.nth(0, dropna='any')
   B
A
1  4
5  6
>>> g.nth(1, dropna='any')  # NaNs denote group exhausted when using dropna
    B
A
1 NaN
5 NaN
```

pandas.core.groupby.GroupBy.ohlc

GroupBy.**ohlc**()

Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.prod

GroupBy.**prod**()

Compute prod of group values

pandas.core.groupby.GroupBy.size

GroupBy.**size**()

Compute group sizes

pandas.core.groupby.GroupBy.sem

GroupBy.**sem**(*ddof=1*)

Compute standard error of the mean of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.std

`GroupBy.std(ddof=1)`

Compute standard deviation of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.sum

`GroupBy.sum()`

Compute sum of group values

pandas.core.groupby.GroupBy.var

`GroupBy.var(ddof=1)`

Compute variance of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.tail

`GroupBy.tail(n=5)`

Returns last n rows of each group

Essentially equivalent to `.apply(lambda x:  x.tail(n))`, except ignores as_index flag.

Examples

```
>>> 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
>>> 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.

`DataFrameGroupBy.bfill`([axis, inplace, ...])	Synonym for NDFrame.fillna(method='bfill')
`DataFrameGroupBy.cummax`([axis, dtype, out, ...])	Return cumulative max over requested axis.
`DataFrameGroupBy.cummin`([axis, dtype, out, ...])	Return cumulative min over requested axis.
`DataFrameGroupBy.cumprod`([axis, dtype, out, ...])	Return cumulative prod over requested axis.
`DataFrameGroupBy.cumsum`([axis, dtype, out, ...])	Return cumulative sum over requested axis.
`DataFrameGroupBy.describe`([...])	Generate various summary statistics, excluding NaN values.
`DataFrameGroupBy.all`([axis, bool_only, ...])	Return whether all elements are True over requested axis
`DataFrameGroupBy.any`([axis, bool_only, ...])	Return whether any element is True over requested axis
`DataFrameGroupBy.corr`([method, min_periods])	Compute pairwise correlation of columns, excluding NA/null values

Continue

Table 33.117 – continued from previous page

DataFrameGroupBy.cov([min_periods])	Compute pairwise covariance of columns, excluding NA/null values
DataFrameGroupBy.diff([periods, axis])	1st discrete difference of object
DataFrameGroupBy.ffill([axis, inplace, ...])	Synonym for NDFrame.fillna(method='ffill')
DataFrameGroupBy.fillna([value, method, ...])	Fill NA/NaN values using the specified method
DataFrameGroupBy.hist(data[, column, by, ...])	Draw histogram of the DataFrame's series using matplotlib / pylab.
DataFrameGroupBy.idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
DataFrameGroupBy.idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
DataFrameGroupBy.irow(i[, copy])	
DataFrameGroupBy.mad([axis, skipna, level])	Return the mean absolute deviation of the values for the requested axis
DataFrameGroupBy.pct_change([periods, ...])	Percent change over given number of periods.
DataFrameGroupBy.plot(data[, x, y, kind, ...])	Make plots of DataFrame using matplotlib / pylab.
DataFrameGroupBy.quantile([q, axis, ...])	Return values at the given quantile over requested axis, a la numpy.perce
DataFrameGroupBy.rank([axis, numeric_only, ...])	Compute numerical data ranks (1 through n) along axis.
DataFrameGroupBy.resample(rule[, how, axis, ...])	Convenience method for frequency conversion and resampling of regular
DataFrameGroupBy.shift([periods, freq, axis])	Shift index by desired number of periods with an optional time freq
DataFrameGroupBy.skew([axis, skipna, level, ...])	Return unbiased skew over requested axis
DataFrameGroupBy.take(indices[, axis, ...])	Analogous to ndarray.take
DataFrameGroupBy.tshift([periods, freq, axis])	Shift the time index, using the index's frequency if available

pandas.core.groupby.DataFrameGroupBy.bfill

DataFrameGroupBy.**bfill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for NDFrame.fillna(method='bfill')

pandas.core.groupby.DataFrameGroupBy.cummax

DataFrameGroupBy.**cummax**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative max over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : Series

pandas.core.groupby.DataFrameGroupBy.cummin

DataFrameGroupBy.**cummin**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative min over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : Series

pandas.core.groupby.DataFrameGroupBy.cumprod

`DataFrameGroupBy.`**`cumprod`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative prod over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : Series

pandas.core.groupby.DataFrameGroupBy.cumsum

`DataFrameGroupBy.`**`cumsum`**(*axis=None*, *dtype=None*, *out=None*, *skipna=True*, ***kwargs*)

Return cumulative sum over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Series

pandas.core.groupby.DataFrameGroupBy.describe

`DataFrameGroupBy.`**`describe`**(*percentile_width=None*, *percentiles=None*, *include=None*, *exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.core.groupby.DataFrameGroupBy.all

`DataFrameGroupBy.`**`all`**(*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether all elements are True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.any

`DataFrameGroupBy.`**`any`**(*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether any element is True over requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.corr

`DataFrameGroupBy.corr`(*method='pearson'*, *min_periods=1*)

Compute pairwise correlation of columns, excluding NA/null values

Parameters **method** : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result. Currently only available for pearson and spearman correlation

Returns **y** : DataFrame

pandas.core.groupby.DataFrameGroupBy.cov

`DataFrameGroupBy.cov`(*min_periods=None*)

Compute pairwise covariance of columns, excluding NA/null values

Parameters **min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns **y** : DataFrame

Notes

y contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.core.groupby.DataFrameGroupBy.diff

`DataFrameGroupBy.diff`(*periods=1*, *axis=0*)

1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

axis : {0 or 'index', 1 or 'columns'}, default 0

Take difference over rows (0) or columns (1).

Returns **diffed** : DataFrame

pandas.core.groupby.DataFrameGroupBy.ffill

`DataFrameGroupBy.ffill`(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for NDFrame.fillna(method='ffill')

pandas.core.groupby.DataFrameGroupBy.fillna

`DataFrameGroupBy.fillna`(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*, ***kwargs*)

Fill NA/NaN values using the specified method

Parameters **value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

axis : {0, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : DataFrame

See also:

`reindex`, `asfreq`

pandas.core.groupby.DataFrameGroupBy.hist

`DataFrameGroupBy.hist`(*data*, *column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, *figsize=None*, *layout=None*, *bins=10*, ***kwds*)

Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters **data** : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.core.groupby.DataFrameGroupBy.idxmax

`DataFrameGroupBy.`**`idxmax`**(*axis=0*, *skipna=True*)

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns **idxmax** : Series

See also:

`Series.idxmax`

Notes

This method is the DataFrame version of `ndarray.argmax`.

pandas.core.groupby.DataFrameGroupBy.idxmin

`DataFrameGroupBy.`**`idxmin`**(*axis=0*, *skipna=True*)

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' for row-wise, 1 or 'columns' for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **idxmin** : Series

See also:

`Series.idxmin`

Notes

This method is the DataFrame version of `ndarray.argmin`.

pandas.core.groupby.DataFrameGroupBy.irow

`DataFrameGroupBy.`**`irow`**(*i*, *copy=False*)

pandas.core.groupby.DataFrameGroupBy.mad

`DataFrameGroupBy.`**`mad`**(*axis=None*, *skipna=None*, *level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.pct_change

`DataFrameGroupBy.`**`pct_change`**(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, ***kwargs*)

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.core.groupby.DataFrameGroupBy.plot

`DataFrameGroupBy.`**`plot`**(*data*, *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.

Parameters data : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)
- If *kind* = 'scatter' and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = 'hexbin', you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each *(x, y)* point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each *(x, y)* point and

reduce_C_function is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.**quantile**(*q=0.5*, *axis=0*, *numeric_only=True*)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

axis : {0, 1, 'index', 'columns'} (default 0)

0 or 'index' for row-wise, 1 or 'columns' for column-wise

Returns **quantiles** : Series or DataFrame

If q is an array, a DataFrame will be returned where the index is q, the columns are the columns of self, and the values are the quantiles. If q is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                   columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
       a     b
0.1  1.3   3.7
0.5  2.5  55.0
```

pandas.core.groupby.DataFrameGroupBy.rank

DataFrameGroupBy.**rank**(*axis=0*, *numeric_only=None*, *method='average'*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters **axis** : {0 or 'index', 1 or 'columns'}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array

- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep', 'top', 'bottom'}

- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns ranks : DataFrame

pandas.core.groupby.DataFrameGroupBy.resample

DataFrameGroupBy.**resample**(*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.core.groupby.DataFrameGroupBy.shift

`DataFrameGroupBy.shift(periods=1, freq=None, axis=0, **kwargs)`

Shift index by desired number of periods with an optional time freq

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns **shifted** : DataFrame

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.core.groupby.DataFrameGroupBy.skew

`DataFrameGroupBy.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.take

`DataFrameGroupBy.take(indices, axis=0, convert=True, is_copy=True)`

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.core.groupby.DataFrameGroupBy.tshift

`DataFrameGroupBy.tshift(periods=1, freq=None, axis=0, **kwargs)`

Shift the time index, using the index's frequency if available

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, default None

Increment to use from datetools module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns **shifted** : NDFrame

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

The following methods are available only for `SeriesGroupBy` objects.

`SeriesGroupBy.nlargest`([n, take_last])	Return the largest *n* elements.
`SeriesGroupBy.nsmallest`([n, take_last])	Return the smallest *n* elements.
`SeriesGroupBy.nunique`([dropna])	Return number of unique elements in the object.
`SeriesGroupBy.unique`()	Return array of unique values in the object.
`SeriesGroupBy.value_counts`([normalize, ...])	Returns object containing counts of unique values.

pandas.core.groupby.SeriesGroupBy.nlargest

`SeriesGroupBy.nlargest(n=5, take_last=False)`

Return the largest *n* elements.

Parameters **n** : int

Return this many descending sorted values

take_last [bool] Where there are duplicate values, take the last duplicate

Returns **top_n** : Series

The n largest values in the Series, in sorted order

Notes

Faster than `.order(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
```

```
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

pandas.core.groupby.SeriesGroupBy.nsmallest

SeriesGroupBy.**nsmallest**(*n=5*, *take_last=False*)

Return the smallest *n* elements.

Parameters n : int

Return this many ascending sorted values

take_last [bool] Where there are duplicate values, take the last duplicate

Returns bottom_n : Series

The n smallest values in the Series, in sorted order

Notes

Faster than `.order().head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

pandas.core.groupby.SeriesGroupBy.nunique

SeriesGroupBy.**nunique**(*dropna=True*)

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.core.groupby.SeriesGroupBy.unique

SeriesGroupBy.**unique**()

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.core.groupby.SeriesGroupBy.value_counts

`SeriesGroupBy.value_counts`(*normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*)

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

The following methods are available only for `DataFrameGroupBy` objects.

`DataFrameGroupBy.corrwith`(other[, axis, drop])	Compute pairwise correlation between rows or columns of two DataFrame
`DataFrameGroupBy.boxplot`(grouped[, ...])	Make box plots from DataFrameGroupBy data.

pandas.core.groupby.DataFrameGroupBy.corrwith

`DataFrameGroupBy.corrwith`(*other*, *axis=0*, *drop=False*)

Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters **other** : DataFrame

axis : {0 or 'index', 1 or 'columns'}, default 0

0 or 'index' to compute column-wise, 1 or 'columns' for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns **correls** : Series

pandas.core.groupby.DataFrameGroupBy.boxplot

`DataFrameGroupBy.boxplot`(*grouped*, *subplots=True*, *column=None*, *fontsize=None*, *rot=0*, *grid=True*, *ax=None*, *figsize=None*, *layout=None*, ***kwds*)

Make box plots from DataFrameGroupBy data.

Parameters **grouped** : Grouped DataFrame

subplots :

- `False` - no subplots will be used
- `True` - create a subplot for each group

column : column name or list of names, or vector

Can be any valid input to groupby

fontsize : int or string

rot : label rotation angle

grid : Setting this to True will show the grid

ax : Matplotlib axis object, default None

figsize : A tuple (width, height) in inches

layout : tuple (optional)

(rows, columns) for the layout of the plot

kwds : other plotting keyword arguments to be passed to matplotlib boxplot

function

Returns dict of key/value = group key/DataFrame.boxplot return value

or DataFrame.boxplot return value in case subplots=figures=False

Examples

```
>>> 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)
```

33.12 General utility functions

33.12.1 Working with options

`describe_option`(pat[, _print_desc])	Prints the description for one or more registered options.
`reset_option`(pat)	Reset one or more options to their default value.
`get_option`(pat)	Retrieves the value of the specified option.
`set_option`(pat, value)	Sets the value of the specified option.
`option_context`(*args)	Context manager to temporarily set options in the *with* statement context.

pandas.describe_option

`pandas.describe_option(pat, _print_desc=False)` = **<pandas.core.config.CallableDynamicDoc object at 0xb56d488c>**

Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters **pat** : str

Regexp pattern. All matching keys will have their description displayed.

_print_desc : bool, default True

If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

Returns None by default, the description(s) as a unicode string if _print_desc

is False

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]

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.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]

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: True] [currently: True]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.reset_option

`pandas.reset_option(pat)` = **<pandas.core.config.CallableDynamicDoc object at 0xb56d486c>**

Reset one or more options to their default value.

Pass "all" as argument to reset all options.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters **pat** : str/regex

If specified only options matching *prefix** will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns None

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]

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.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]

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: True] [currently: True]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.get_option

`pandas.get_option(pat)` = **<pandas.core.config.CallableDynamicDoc object at 0xb56c4e8c>**

Retrieves the value of the specified option.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters **pat** : str

Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns **result** : the value of the option

Raises **OptionError** : if no such option exists

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

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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: 7] [currently: 7]

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.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]

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]

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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]

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mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.set_option

`pandas.set_option`(*pat*, *value*) **= <pandas.core.config.CallableDynamicDoc object at 0xb56d484c>**

Sets the value of the specified option.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters **pat** : str

Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

value :

new value of option.

Returns None

Raises OptionError if no such option exists

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

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display.column_space No description available. [default: 12] [currently: 12]

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io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: True] [currently: True]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.option_context

class `pandas.option_context(*args)`

Context manager to temporarily set options in the *with* statement context.

You need to invoke as `option_context(pat, val, [(pat, val), ...])`.

Examples

```
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
        ...
```

CHAPTER

THIRTYFOUR

INTERNALS

This section will provide a look into some of pandas internals.

34.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- `Index`: the generic "ordered set" object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do `O(1)` lookups.
- `Int64Index`: a version of `Index` highly optimized for 64-bit integer data, such as time stamps
- `Float64Index`: a version of `Index` highly optimized for 64-bit float data
- `MultiIndex`: the standard hierarchical index object
- `DatetimeIndex`: An Index object with `Timestamp` boxed elements (impl are the int64 values)
- `TimedeltaIndex`: An Index object with `Timedelta` boxed elements (impl are the in64 values)
- `PeriodIndex`: An Index object with Period elements

These are range generates to 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

34.1.1 MultiIndex

Internally, the `MultiIndex` consists of a few things: the **levels**, the integer **labels**, and the level **names**:

```
In [1]: index = MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])

In [2]: index
Out[2]:
MultiIndex(levels=[[0, 1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=[u'first', u'second'])

In [3]: index.levels
Out[3]: FrozenList([[0, 1, 2], [u'one', u'two']])

In [4]: index.labels
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])

In [5]: index.names
Out[5]: FrozenList([u'first', u'second'])
```

You can probably guess that the labels determine which unique element is identified with that location at each layer of the index. It's important to note that sortedness is determined **solely** from the integer labels and does not check (or care) whether the levels themselves are sorted. Fortunately, the constructors `from_tuples` and `from_arrays` ensure that this is true, but if you compute the levels and labels yourself, please be careful.

34.2 Subclassing pandas Data Structures

Warning: There are some easier alternatives before considering subclassing `pandas` data structures.

1. Extensible method chains with *pipe*
2. Use *composition*. See here.

This section describes how to subclass `pandas` data structures to meet more specific needs. There are 2 points which need attention:

1. Override constructor properties.
2. Define original properties

Note: You can find a nice example in geopandas project.

34.2.1 Override Constructor Properties

Each data structure has constructor properties to specifying data constructors. By overriding these properties, you can retain defined-classes through `pandas` data manipulations.

There are 3 constructors to be defined:

- `_constructor`: Used when a manipulation result has the same dimesions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as `DataFrame` single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as `Series.to_frame()` and `DataFrame.to_panel()`.

Following table shows how `pandas` data structures define constructor properties by default.

Property Attributes	Series	DataFrame	Panel
`_constructor`	`Series`	`DataFrame`	`Panel`
`_constructor_sliced`	`NotImplementedError`	`Series`	`DataFrame`
`_constructor_expanddim`	`DataFrame`	`Panel`	`NotImplementedError`

Below example shows how to define `SubclassedSeries` and `SubclassedDataFrame` overriding constructor properties.

```
class SubclassedSeries(Series):

    @property
    def _constructor(self):
        return SubclassedSeries

    @property
    def _constructor_expanddim(self):
        return SubclassedDataFrame

class SubclassedDataFrame(DataFrame):

    @property
    def _constructor(self):
        return SubclassedDataFrame

    @property
    def _constructor_sliced(self):
        return SubclassedSeries
```

```
>>> s = SubclassedSeries([1, 2, 3])
>>> type(s)
<class '__main__.SubclassedSeries'>

>>> to_framed = s.to_frame()
>>> type(to_framed)
<class '__main__.SubclassedDataFrame'>

>>> df = SubclassedDataFrame({'A', [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```

```
>>> 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'>
```

34.2.2 Define Original Properties

To let original data structures have additional properties, you should let `pandas` knows 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 2 original properties, "internal_cache" as a temporary property and "added_property" as a normal property

```
class SubclassedDataFrame2(DataFrame):

    # temporary properties
    _internal_names = 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
```

CHAPTER

THIRTYFIVE

RELEASE NOTES

This is the list of changes to pandas between each release. For full details, see the commit logs at http://github.com/pydata/pandas

What is it

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

Where to get it

- Source code: http://github.com/pydata/pandas
- Binary installers on PyPI: http://pypi.python.org/pypi/pandas
- Documentation: http://pandas.pydata.org

35.1 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.

35.1.1 Thanks

- Andrew Rosenfeld
- Artemy Kolchinsky
- Bernard Willers
- Christer van der Meeren
- Christian Hudon
- Constantine Glen Evans

- Daniel Julius Lasiman
- Evan Wright
- Francesco Brundu
- Gaëtan de Menten
- Jake VanderPlas
- James Hiebert
- Jeff Reback
- Joris Van den Bossche
- Justin Lecher
- Ka Wo Chen
- Kevin Sheppard
- Mortada Mehyar
- Morton Fox
- Robin Wilson
- Thomas Grainger
- Tom Ajamian
- Tom Augspurger
- Yoshiki Vázquez Baeza
- Younggun Kim
- austinc
- behzad nouri
- jreback
- lexual
- rekcahpassyla
- scls19fr
- sinhrks

35.2 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.

35.2.1 Thanks

- Alfonso MHC
- Andy Hayden
- Artemy Kolchinsky
- Chris Gilmer
- Chris Grinolds
- Dan Birken
- David BROCHART
- David Hirschfeld
- David Stephens
- Dr. Leo
- Evan Wright
- Frans van Dunné
- Hatem Nassrat
- Henning Sperr
- Hugo Herter
- Jan Schulz
- Jeff Blackburne
- Jeff Reback
- Jim Crist
- Jonas Abernot
- Joris Van den Bossche
- Kerby Shedden
- Leo Razoumov
- Manuel Riel
- Mortada Mehyar
- Nick Burns
- Nick Eubank
- Olivier Grisel
- Phillip Cloud
- Pietro Battiston
- Roy Hyunjin Han
- Sam Zhang
- Scott Sanderson
- Stephan Hoyer
- Tiago Antao

- Tom Ajamian
- Tom Augspurger
- Tomaz Berisa
- Vikram Shirgur
- Vladimir Filimonov
- William Hogman
- Yasin A
- Younggun Kim
- behzad nouri
- dsm054
- floydsoft
- flying-sheep
- gfr
- jnmclarty
- jreback
- ksanghai
- lucas
- mschmohl
- ptype
- rockg
- scls19fr
- sinhrks

35.3 pandas 0.16.0

Release date: (March 22, 2015)

This is a major release from 0.15.2 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- `DataFrame.assign` method, see *here*
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see *here*
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see *here*
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see *here*
- Changes to the default for ordering in the `Categorical` constructor, see *here*
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like seaborn, pandas-qt and rpy2 for similar or equivalent functionality, see *here*

See the *v0.16.0 Whatsnew* overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.16.0.

35.3.1 Thanks

- Aaron Toth
- Alan Du
- Alessandro Amici
- Artemy Kolchinsky
- Ashwini Chaudhary
- Ben Schiller
- Bill Letson
- Brandon Bradley
- Chau Hoang
- Chris Reynolds
- Chris Whelan
- Christer van der Meeren
- David Cottrell
- David Stephens
- Ehsan Azarnasab
- Garrett-R
- Guillaume Gay
- Jake Torcasso
- Jason Sexauer
- Jeff Reback
- John McNamara
- Joris Van den Bossche
- Joschka zur Jacobsmühlen
- Juarez Bochi
- Junya Hayashi
- K.-Michael Aye
- Kerby Shedden
- Kevin Sheppard
- Kieran O'Mahony
- Kodi Arfer
- Matti Airas
- Min RK

- Mortada Mehyar
- Robert
- Scott E Lasley
- Scott Lasley
- Sergio Pascual
- Skipper Seabold
- Stephan Hoyer
- Thomas Grainger
- Tom Augspurger
- TomAugspurger
- Vladimir Filimonov
- Vyomkesh Tripathi
- Will Holmgren
- Yulong Yang
- behzad nouri
- bertrandhaut
- bjonen
- cel4
- clham
- hsperr
- ischwabacher
- jnmclarty
- josham
- jreback
- omtinez
- roch
- sinhrks
- unutbu

35.4 pandas 0.15.2

Release date: (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs.

See the *v0.15.2 Whatsnew* overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.2.

35.4.1 Thanks

- Aaron Staple
- Angelos Evripiotis
- Artemy Kolchinsky
- Benoit Pointet
- Brian Jacobowski
- Charalampos Papaloizou
- Chris Warth
- David Stephens
- Fabio Zanini
- Francesc Via
- Henry Kleynhans
- Jake VanderPlas
- Jan Schulz
- Jeff Reback
- Jeff Tratner
- Joris Van den Bossche
- Kevin Sheppard
- Matt Suggit
- Matthew Brett
- Phillip Cloud
- Rupert Thompson
- Scott E Lasley
- Stephan Hoyer
- Stephen Simmons
- Sylvain Corlay
- Thomas Grainger
- Tiago Antao
- Trent Hauck
- Victor Chaves
- Victor Salgado
- Vikram Bhandoh
- WANG Aiyong
- Will Holmgren
- behzad nouri
- broessli

- charalampos papaloizou
- immerrr
- jnmclarty
- jreback
- mgilbert
- onesandzeroes
- peadarcoyle
- rockg
- seth-p
- sinhrks
- unutbu
- wavedatalab
- Åsmund Hjulstad

35.5 pandas 0.15.1

Release date: (November 9, 2014)

This is a minor release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

See the *v0.15.1 Whatsnew* overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.1.

35.5.1 Thanks

- Aaron Staple
- Andrew Rosenfeld
- Anton I. Sipos
- Artemy Kolchinsky
- Bill Letson
- Dave Hughes
- David Stephens
- Guillaume Horel
- Jeff Reback
- Joris Van den Bossche
- Kevin Sheppard
- Nick Stahl
- Sanghee Kim
- Stephan Hoyer

- TomAugspurger
- WANG Aiyong
- behzad nouri
- immerrr
- jnmclarty
- jreback
- pallav-fdsi
- unutbu

35.6 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.

35.6.1 Thanks

- Aaron Schumacher
- Adam Greenhall
- Andy Hayden
- Anthony O'Brien
- Artemy Kolchinsky
- behzad nouri
- Benedikt Sauer

- benjamin
- Benjamin Thyreau
- Ben Schiller
- bjonen
- BorisVerk
- Chris Reynolds
- Chris Stoafer
- Dav Clark
- dlovell
- DSM
- dsm054
- FragLegs
- German Gomez-Herrero
- Hsiaoming Yang
- Huan Li
- hunterowens
- Hyungtae Kim
- immerrr
- Isaac Slavitt
- ischwabacher
- Jacob Schaer
- Jacob Wasserman
- Jan Schulz
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- jmorris0x0
- jnmclarty
- Joe Bradish
- Joerg Rittinger
- John W. O'Brien
- Joris Van den Bossche
- jreback
- Kevin Sheppard
- klonuo
- Kyle Meyer
- lexual

- Max Chang
- mcjcode
- Michael Mueller
- Michael W Schatzow
- Mike Kelly
- Mortada Mehyar
- mtrbean
- Nathan Sanders
- Nathan Typanski
- onesandzeroes
- Paul Masurel
- Phillip Cloud
- Pietro Battiston
- RenzoBertocchi
- rockg
- Ross Petchler
- seth-p
- Shahul Hameed
- Shashank Agarwal
- sinhrks
- someben
- stahlous
- stas-sl
- Stephan Hoyer
- thatneat
- tom-alcorn
- TomAugspurger
- Tom Augspurger
- Tony Lorenzo
- unknown
- unutbu
- Wes Turner
- Wilfred Hughes
- Yevgeniy Grechka
- Yoshiki VÃ¡zquez Baeza
- zachcp

35.7 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.

35.7.1 Thanks

- Andrew Rosenfeld
- Andy Hayden
- Benjamin Adams
- Benjamin M. Gross
- Brian Quistorff
- Brian Wignall
- bwignall
- clham
- Daniel Waeber
- David Bew
- David Stephens
- DSM
- dsm054
- helger
- immerrr
- Jacob Schaer
- jaimefrio
- Jan Schulz
- John David Reaver
- John W. O'Brien
- Joris Van den Bossche

- jreback
- Julien Danjou
- Kevin Sheppard
- K.-Michael Aye
- Kyle Meyer
- lexual
- Matthew Brett
- Matt Wittmann
- Michael Mueller
- Mortada Mehyar
- onesandzeroes
- Phillip Cloud
- Rob Levy
- rockg
- sanguineturtle
- Schaer, Jacob C
- seth-p
- sinhrks
- Stephan Hoyer
- Thomas Kluyver
- Todd Jennings
- TomAugspurger
- unknown
- yelite

35.8 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.

35.8.1 Thanks

- Acanthostega
- Adam Marcus
- agijsberts
- akittredge
- Alex Gaudio
- Alex Rothberg
- AllenDowney
- Andrew Rosenfeld
- Andy Hayden
- ankostis
- anomrake
- Antoine Mazières
- anton-d
- bashtage
- Benedikt Sauer
- benjamin
- Brad Buran
- bwignall
- cgohlke
- chebee7i
- Christopher Whelan
- Clark Fitzgerald
- clham
- Dale Jung
- Dan Allan
- Dan Birken
- danielballan
- Daniel Waeber
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- David Stephens
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- Guillaume Poulin
- hshimizu77
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- immerrr
- ischwabacher
- Jacob Howard
- Jacob Schaer
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- Jeff Reback
- Jeffrey Starr
- Jeff Tratner
- John David Reaver
- John McNamara
- John W. O'Brien
- Jonathan Chambers
- Joris Van den Bossche
- jreback
- jsexauer
- Julia Evans
- Júlio
- Katie Atkinson
- kdiether
- Kelsey Jordahl
- Kevin Sheppard
- K.-Michael Aye
- Matthias Kuhn
- Matt Wittmann
- Max Grender-Jones
- Michael E. Gruen
- michaelws

- mikebailey
- Mike Kelly
- Nipun Batra
- Noah Spies
- ojdo
- onesandzeroes
- Patrick O'Keeffe
- phaebz
- Phillip Cloud
- Pietro Battiston
- PKEuS
- Randy Carnevale
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- Robert Gibboni
- rockg
- sinhrks
- Skipper Seabold
- SplashDance
- Stephan Hoyer
- Tim Cera
- Tobias Brandt
- Todd Jennings
- TomAugspurger
- Tom Augspurger
- unutbu
- westurner
- Yaroslav Halchenko
- y-p
- zach powers

35.9 pandas 0.13.1

Release date: (February 3, 2014)

35.9.1 New Features

- Added `date_format` and `datetime_format` attribute to `ExcelWriter`. (GH4133)

35.9.2 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).

35.9.3 Experimental Features

35.9.4 Improvements to existing features

- perf improvements in Series datetime/timedelta binary operations (GH5801)
- *option_context* context manager now available as top-level API (GH5752)
- df.info() view now display dtype info per column (GH5682)
- df.info() now honors option max_info_rows, disable null counts for large frames (GH5974)
- perf improvements in DataFrame `count/dropna` for `axis=1`
- Series.str.contains now has a *regex=False* keyword which can be faster for plain (non-regex) string patterns. (GH5879)
- support `dtypes` property on `Series/Panel/Panel4D`
- extend `Panel.apply` to allow arbitrary functions (rather than only ufuncs) (GH1148) allow multiple axes to be used to operate on slabs of a `Panel`
- The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array (GH3401)
- `pd.show_versions()` is now available for convenience when reporting issues.
- perf improvements to Series.str.extract (GH5944)
- perf improvements in `dtypes/ftypes` methods (GH5968)
- perf improvements in indexing with object dtypes (GH5968)
- improved dtype inference for `timedelta` like passed to constructors (GH5458, GH5689)
- escape special characters when writing to latex (:issue: *5374*)
- perf improvements in `DataFrame.apply` (GH6013)
- `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexual for suggesting and @danbirken for rapidly implementing. (GH5490,:issue:*6021*)

- add ability to recognize '%p' format code (am/pm) to date parsers when the specific format is supplied (GH5361)
- Fix performance regression in JSON IO (GH5765)
- performance regression in Index construction from Series (GH6150)

35.9.5 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 propogating _ref_locs during construction of a DataFrame with dups index/columns (GH6121)
- Bug in `DataFrame.apply` when using mixed datelike reductions (GH6125)
- Bug in `DataFrame.append` when appending a row with different columns (GH6129)
- Bug in DataFrame construction with recarray and non-ns datetime dtype (GH6140)
- Bug in `.loc` setitem indexing with a 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)

35.10 pandas 0.13.0

Release date: January 3, 2014

35.10.1 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 indicies 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)

35.10.2 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)

35.10.3 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 PeriodIndex and added test to vbench (GH4705 and GH4722)
- Add `axis` and `level` keywords to `where`, so that the `other` argument can now be an alignable pandas object.
- `to_datetime` with a format of '%Y%m%d' now parses much faster
- It's now easier to hook new Excel writers into pandas (just subclass `ExcelWriter` and register your engine). You can specify an `engine` in `to_excel` or in `ExcelWriter`. You can also specify which writers you want to use by default with config options `io.excel.xlsx.writer` and `io.excel.xls.writer`. (GH4745, GH4750)
- `Panel.to_excel()` now accepts keyword arguments that will be passed to its `DataFrame`'s `to_excel()` methods. (GH4750)
- Added XlsxWriter as an optional `ExcelWriter` engine. This is about 5x faster than the default openpyxl xlsx writer and is equivalent in speed to the xlwt xls writer module. (GH4542)

- allow DataFrame constructor to accept more list-like objects, e.g. list of `collections.Sequence` and `array.Array` objects (GH3783, GH4297, GH4851), thanks @lgautier
- DataFrame constructor now accepts a numpy masked record array (GH3478), thanks @jnothman
- `__getitem__` with `tuple` key (e.g., `[:, 2]`) on `Series` without `MultiIndex` raises `ValueError` (GH4759, GH4837)
- `read_json` now raises a (more informative) `ValueError` when the dict contains a bad key and `orient='split'` (GH4730, GH4838)
- `read_stata` now accepts Stata 13 format (GH4291)
- `ExcelWriter` and `ExcelFile` can be used as contextmanagers. (GH3441, GH4933)
- `pandas` is now tested with two different versions of `statsmodels` (0.4.3 and 0.5.0) (GH4981).
- Better string representations of `MultiIndex` (including ability to roundtrip via `repr`). (GH3347, GH4935)
- Both ExcelFile and read_excel to accept an xlrd.Book for the io (formerly path_or_buf) argument; this requires engine to be set. (GH4961).
- `concat` now gives a more informative error message when passed objects that cannot be concatenated (GH4608).
- Add `halflife` option to exponentially weighted moving functions (PR GH4998)
- `to_dict` now takes `records` as a possible outtype. Returns an array of column-keyed dictionaries. (GH4936)
- `tz_localize` can infer a fall daylight savings transition based on the structure of unlocalized data (GH4230)
- DatetimeIndex is now in the API documentation
- Improve support for converting R datasets to pandas objects (more informative index for timeseries and numeric, support for factors, dist, and high-dimensional arrays).
- `read_html()` now supports the `parse_dates`, `tupleize_cols` and `thousands` parameters (GH4770).
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. *See the docs* (GH1067)
- `DataFrame.from_records()` will now accept generators (GH4910)
- `DataFrame.interpolate()` and `Series.interpolate()` have been expanded to include interpolation methods from scipy. (GH4434, GH1892)
- `Series` now supports a `to_frame` method to convert it to a single-column DataFrame (GH5164)
- DatetimeIndex (and date_range) can now be constructed in a left- or right-open fashion using the `closed` parameter (GH4579)
- Python csv parser now supports usecols (GH4335)
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. (GH5271)
- `NDFrame.drop()` now accepts names as well as integers for the axis argument. (GH5354)
- Added short docstrings to a few methods that were missing them + fixed the docstrings for Panel flex methods. (GH5336)
- `NDFrame.drop()`, `NDFrame.dropna()`, and `.drop_duplicates()` all accept `inplace` as a keyword argument; however, this only means that the wrapper is updated inplace, a copy is still made internally. (GH1960, GH5247, GH5628, and related GH2325 [still not closed])
- Fixed bug in *tools.plotting.andrews_curvres* 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` in `to_excel()` to merge cells in MultiIndex and Hierarchical Rows. Note: using this option it is no longer possible to round trip Excel files with merged MultiIndex and Hierarchical Rows. Set the `merge_cells` to `False` to restore the previous behaviour. (GH5254)
- The FRED DataReader now accepts multiple series (:issue'3413')
- StataWriter adjusts variable names to Stata's limitations (GH5709)

35.10.4 API Changes

- `DataFrame.reindex()` and forward/backward filling now raises ValueError if either index is not monotonic (GH4483, GH4484).
- `pandas` now is Python 2/3 compatible without the need for 2to3 thanks to @jtratner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson's `six` library into compat. (GH4384, GH4375, GH4372)
- `pandas.util.compat` and `pandas.util.py3compat` have been merged into `pandas.compat`. `pandas.compat` now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of range, filter, map and zip, plus other necessary elements for Python 3 compatibility. `lmap`, `lzip`, `lrange` and `lfilter` all produce lists instead of iterators, for compatibility with `numpy`, subscripting and `pandas` constructors.(GH4384, GH4375, GH4372)
- deprecated `iterkv`, which will be removed in a future release (was just an alias of iteritems used to get around `2to3`'s changes). (GH4384, GH4375, GH4372)
- `Series.get` with negative indexers now returns the same as `[]` (GH4390)
- allow `ix/loc` for Series/DataFrame/Panel to set on any axis even when the single-key is not currently contained in the index for that axis (GH2578, GH5226, GH5632, GH5720, GH5744, GH5756)
- Default export for `to_clipboard` is now csv with a sep of *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 unserialiable 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 to `fillna/ffill/bfill` (GH4604)
- `__nonzero__` for all NDFrame objects, will now raise a `ValueError`, this reverts back to (GH1073, GH4633) behavior. Add `.bool()` method to `NDFrame` objects to facilitate evaluating of single-element boolean Series

- DataFrame.update() no longer raises a DataConflictError, it now will raise a ValueError instead (if necessary) (GH4732)
- Series.isin() and DataFrame.isin() now raise a TypeError when passed a string (GH4763). Pass a list of one element (containing the string) instead.
- Remove undocumented/unused kind keyword argument from read_excel, and ExcelFile. (GH4713, GH4712)
- The method argument of NDFrame.replace() is valid again, so that a a list can be passed to to_replace (GH4743).
- provide automatic dtype conversions on _reduce operations (GH3371)
- exclude non-numerics if mixed types with datelike in _reduce operations (GH3371)
- default for tupleize_cols is now False for both to_csv and read_csv. Fair warning in 0.12 (GH3604)
- moved timedeltas support to pandas.tseries.timedeltas.py; add timedeltas string parsing, add top-level to_timedelta function
- NDFrame now is compatible with Python's toplevel abs() function (GH4821).
- raise a TypeError on invalid comparison ops on Series/DataFrame (e.g. integer/datetime) (GH4968)
- Added a new index type, Float64Index. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes [],ix,loc for scalar indexing and slicing work exactly the same. Indexing on other index types are preserved (and positional fallback for [],ix), with the exception, that floating point slicing on indexes on non Float64Index will raise a TypeError, e.g. Series(range(5))[3.5:4.5] (GH263,:issue:*5375*)
- Make Categorical repr nicer (GH4368)
- Remove deprecated Factor (GH3650)
- Remove deprecated set_printoptions/reset_printoptions (:issue:3046)
- Remove deprecated _verbose_info (GH3215)
- Begin removing methods that don't make sense on GroupBy objects (GH4887).
- Remove deprecated read_clipboard/to_clipboard/ExcelFile/ExcelWriter from pandas.io.parsers (GH3717)
- All non-Index NDFrames (Series, DataFrame, Panel, Panel4D, SparsePanel, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). SparsePanel does not support pow or mod with non-scalars. (GH3765)
- Arithmetic func factories are now passed real names (suitable for using with super) (GH5240)
- Provide numpy compatibility with 1.7 for a calling convention like np.prod(pandas_object) as numpy call with additional keyword args (GH4435)
- Provide __dir__ method (and local context) for tab completion / remove ipython completers code (GH4501)
- Support non-unique axes in a Panel via indexing operations (GH4960)
- .truncate will raise a ValueError if invalid before and afters dates are given (GH5242)
- Timestamp now supports now/today/utcnow class methods (GH5339)
- default for *display.max_seq_len* is now 100 rather then *None*. This activates truncated display ("...") of long sequences in various places. (GH3391)

- **All** division with `NDFrame` - likes is now truedivision, regardless of the future import. You can use `//` and `floordiv` to do integer division.

```
In [3]: arr = np.array([1, 2, 3, 4])

In [4]: arr2 = np.array([5, 3, 2, 1])

In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])

In [6]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[6]:
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)

35.10.5 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/DataFame, 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)

35.10.6 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 cparser 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 lazay 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 indicies (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 MultIndex (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 bug with reading compressed files in as `bytes` rather than `str` in Python 3. Simplifies bytes-producing file-handling in Python 3 (GH3963, GH4785).
- 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 where `DatetimeIndex` joins with `PeriodIndex` caused a stack overflow (GH3899).
- Fixed a bug where `groupby` objects didn't allow plots (GH5102).
- Fixed a bug where `groupby` objects weren't tab-completing column names (GH5102).
- Fixed a bug where `groupby.plot()` and friends were duplicating figures multiple times (GH5102).
- Provide automatic conversion of `object` dtypes on fillna, related (GH5103)
- Fixed a bug where default options were being overwritten in the option parser cleaning (GH5121).
- Treat a list/ndarray identically for `iloc` indexing with list-like (GH5006)
- Fix `MultiIndex.get_level_values()` with missing values (GH5074)
- Fix bound checking for Timestamp() with datetime64 input (GH4065)
- Fix a bug where `TestReadHtml` wasn't calling the correct `read_html()` function (GH5150).
- Fix a bug with `NDFrame.replace()` which made replacement appear as though it was (incorrectly) using regular expressions (GH5143).
- Fix better error message for to_datetime (GH4928)
- Made sure different locales are tested on travis-ci (GH4918). Also adds a couple of utilities for getting locales and setting locales with a context manager.
- Fixed segfault on `isnull(MultiIndex)` (now raises an error instead) (GH5123, GH5125)
- Allow duplicate indices when performing operations that align (GH5185, GH5639)
- Compound dtypes in a constructor raise `NotImplementedError` (GH5191)
- Bug in comparing duplicate frames (GH4421) related
- Bug in describe on duplicate frames
- Bug in `to_datetime` with a format and `coerce=True` not raising (GH5195)
- Bug in `loc` setting with multiple indexers and a rhs of a Series that needs broadcasting (GH5206)
- Fixed bug where inplace setting of levels or labels on `MultiIndex` would not clear cached `values` property and therefore return wrong `values`. (GH5215)
- Fixed bug where filtering a grouped DataFrame or Series did not maintain the original ordering (GH4621).
- Fixed `Period` with a business date freq to always roll-forward if on a non-business date. (GH5203)
- Fixed bug in Excel writers where frames with duplicate column names weren't written correctly. (GH5235)
- Fixed issue with `drop` and a non-unique index on Series (GH5248)
- Fixed seg fault in C parser caused by passing more names than columns in the file. (GH5156)
- Fix `Series.isin` with date/time-like dtypes (GH5021)

- C and Python Parser can now handle the more common multi-index column format which doesn't have a row for index names (GH4702)
- Bug when trying to use an out-of-bounds date as an object dtype (GH5312)
- Bug when trying to display an embedded PandasObject (GH5324)
- Allows operating of Timestamps to return a datetime if the result is out-of-bounds related (GH5312)
- Fix return value/type signature of `initObjToJSON()` to be compatible with numpy's `import_array()` (GH5334, GH5326)
- Bug when renaming then set_index on a DataFrame (GH5344)
- Test suite no longer leaves around temporary files when testing graphics. (GH5347) (thanks for catching this @yarikoptic!)
- Fixed html tests on win32. (GH4580)
- Make sure that `head/tail` are `iloc` based, (GH5370)
- Fixed bug for `PeriodIndex` string representation if there are 1 or 2 elements. (GH5372)
- The GroupBy methods `transform` and `filter` can be used on Series and DataFrames that have repeated (non-unique) indices. (GH4620)
- Fix empty series not printing name in repr (GH4651)
- Make tests create temp files in temp directory by default. (GH5419)
- `pd.to_timedelta` of a scalar returns a scalar (GH5410)
- `pd.to_timedelta` accepts `NaN` and `NaT`, returning `NaT` instead of raising (GH5437)
- performance improvements in `isnull` on larger size pandas objects
- Fixed various setitem with 1d ndarray that does not have a matching length to the indexer (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)

35.11 pandas 0.12.0

Release date: 2013-07-24

35.11.1 New Features

- `pd.read_html()` can now parse HTML strings, files or urls and returns a list of `DataFrame` s courtesy of @cpcloud. (GH3477, GH3605, GH3606)
- Support for reading Amazon S3 files. (GH3504)
- Added module for reading and writing JSON strings/files: pandas.io.json includes `to_json` DataFrame/Series method, and a `read_json` top-level reader various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
- Added module for reading and writing Stata files: pandas.io.stata (GH1512) includes `to_stata` DataFrame method, and a `read_stata` top-level reader
- Added support for writing in `to_csv` and reading in `read_csv`, multi-index columns. The `header` option in `read_csv` now accepts a list of the rows from which to read the index. Added the option, `tupleize_cols` to provide compatibility for the pre 0.12 behavior of writing and reading multi-index columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a multi-index column. Note: The default value will change in 0.12 to make the default *to* write and read multi-index columns in the new format. (GH3571, GH1651, GH3141)
- Add iterator to `Series.str` (GH3638)
- `pd.set_option()` now allows N option, value pairs (GH3667).
- Added keyword parameters for different types of scatter_matrix subplots
- A `filter` method on grouped Series or DataFrames returns a subset of the original (GH3680, GH919)
- Access to historical Google Finance data in pandas.io.data (GH3814)
- DataFrame plotting methods can sample column colors from a Matplotlib colormap via the `colormap` keyword. (GH3860)

35.11.2 Improvements to existing features

- Fixed various issues with internal pprinting code, the repr() for various objects including TimeStamp and Index now produces valid python code strings and can be used to recreate the object, (GH3038, GH3379, GH3251, GH3460)
- `convert_objects` now accepts a `copy` parameter (defaults to `True`)
- `HDFStore`
  - will retain index attributes (freq,tz,name) on recreation (GH3499,:issue:*4098*)
  - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as data_columns (GH2852)
  - table writing performance improvements.
  - support python3 (via `PyTables 3.0.0`) (GH3750)
- Add modulo operator to Series, DataFrame
- Add `date` method to DatetimeIndex
- Add `dropna` argument to pivot_table (:issue: *3820*)
- Simplified the API and added a describe method to Categorical

- `melt` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame (GH3649), thanks @hoechenberger. If `var_name` is not specified and `dataframe.columns.name` is not None, then this will be used as the `var_name` (GH4144). Also support for MultiIndex columns.
- clipboard functions use pyperclip (no dependencies on Windows, alternative dependencies offered for Linux) (GH3837).
- Plotting functions now raise a `TypeError` before trying to plot anything if the associated objects have have a dtype of `object` (GH1818, GH3572, GH3911, GH3912), but they will try to convert object arrays to numeric arrays if possible so that you can still plot, for example, an object array with floats. This happens before any drawing takes place which eliminates any spurious plots from showing up.
- Added Faq section on repr display options, to help users customize their setup.
- `where` operations that result in block splitting are much faster (GH3733)
- Series and DataFrame hist methods now take a `figsize` argument (GH3834)
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations (GH3877)
- Add `unit` keyword to `Timestamp` and `to_datetime` to enable passing of integers or floats that are in an epoch unit of `D, s, ms, us, ns`, thanks @mtkini (GH3969) (e.g. unix timestamps or epoch `s`, with fractional seconds allowed) (GH3540)
- DataFrame corr method (spearman) is now cythonized.
- Improved `network` test decorator to catch `IOError` (and therefore `URLError` as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. (GH3910, GH3914)
- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters
- Added `layout` keyword to DataFrame.hist() for more customizable layout (GH4050)
- Timestamp.min and Timestamp.max now represent valid Timestamp instances instead of the default datetime.min and datetime.max (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and BeautifulSoup==4.2.0 is detected (GH4214)

35.11.3 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)

35.11.4 Experimental Features

- Added experimental CustomBusinessDay class to support DateOffsets with custom holiday calendars and custom weekmasks. (GH2301)

35.11.5 Bug Fixes

- Fixed an esoteric excel reading bug, xlrd>= 0.9.0 now required for excel support. Should provide python3 support (for reading) which has been lacking. (GH3164)
- Disallow Series constructor called with MultiIndex which caused segfault (GH4187)
- Allow unioning of date ranges sharing a timezone (GH3491)
- Fix to_csv issue when having a large number of rows and NaT in some columns (GH3437)
- .loc was not raising when passed an integer list (GH3449)
- Unordered time series selection was misbehaving when using label slicing (GH3448)
- Fix sorting in a frame with a list of columns which contains datetime64[ns] dtypes (GH3461)
- DataFrames fetched via FRED now handle '.' as a NaN. (GH3469)
- Fix regression in a DataFrame apply with axis=1, objects were not being converted back to base dtypes correctly (GH3480)
- Fix issue when storing uint dtypes in an HDFStore. (GH3493)
- Non-unique index support clarified (GH3468)
  - Addressed handling of dupe columns in df.to_csv new and old (GH3454, GH3457)
  - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
  - Fix construction of a DataFrame with a duplicate index
  - ref_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) (GH2194)
  - applymap on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
  - Fix to_csv to handle non-unique columns (GH3495)
  - Duplicate indexes with getitem will return items in the correct order (GH3455, GH3457) and handle missing elements like unique indices (GH3561)
  - Duplicate indexes with and empty DataFrame.from_records will return a correct frame (GH3562)
  - Concat to produce a non-unique columns when duplicates are across dtypes is fixed (GH3602)
  - Non-unique indexing with a slice via loc and friends fixed (GH3659)

  - Allow insert/delete to non-unique columns (GH3679)
  - Extend `reindex` to correctly deal with non-unique indices (GH3679)
  - `DataFrame.itertuples()` now works with frames with duplicate column names (GH3873)
  - Bug in non-unique indexing via `iloc` (GH4017); added `takeable` argument to `reindex` for location-based taking
  - Allow non-unique indexing in series via `.ix/.loc` and `__getitem__` (GH4246)
  - Fixed non-unique indexing memory allocation issue with `.ix/.loc` (GH4280)
- Fixed bug in groupby with empty series referencing a variable before assignment. (GH3510)
- Allow index name to be used in groupby for non MultiIndex (GH4014)
- Fixed bug in mixed-frame assignment with aligned series (GH3492)
- Fixed bug in selecting month/quarter/year from a series would not select the time element on the last day (GH3546)
- Fixed a couple of MultiIndex rendering bugs in df.to_html() (GH3547, GH3553)
- Properly convert np.datetime64 objects in a Series (GH3416)
- Raise a `TypeError` on invalid datetime/timedelta operations e.g. add datetimes, multiple timedelta x datetime
- Fix `.diff` on datelike and timedelta operations (GH3100)
- `combine_first` not returning the same dtype in cases where it can (GH3552)
- Fixed bug with `Panel.transpose` argument aliases (GH3556)
- Fixed platform bug in `PeriodIndex.take` (GH3579)
- Fixed bud 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 similary to `float` dtypes to return `np.nan` or `np.inf` as appropriate (GH3590)
- Fix incorrect dtype on groupby with `as_index=False` (GH3610)
- Fix `read_csv/read_excel` to correctly encode identical na_values, e.g. `na_values=[-999.0,-999]` was failing (GH3611)
- Disable HTML output in qtconsole again. (GH3657)
- Reworked the new repr display logic, which users found confusing. (GH3663)
- Fix indexing issue in ndim >= 3 with `iloc` (GH3617)
- Correctly parse date columns with embedded (nan/NaT) into datetime64[ns] dtype in `read_csv` when `parse_dates` is specified (GH3062)
- Fix not consolidating before to_csv (GH3624)
- Fix alignment issue when setitem in a DataFrame with a piece of a DataFrame (GH3626) or a mixed DataFrame and a Series (GH3668)
- Fix plotting of unordered DatetimeIndex (GH3601)

- `sql.write_frame` failing when writing a single column to sqlite (GH3628), thanks to @stonebig
- Fix pivoting with `nan` in the index (GH3558)
- Fix running of bs4 tests when it is not installed (GH3605)
- Fix parsing of html table (GH3606)
- `read_html()` now only allows a single backend: `html5lib` (GH3616)
- `convert_objects` with `convert_dates='coerce'` was parsing some single-letter strings into today's date
- `DataFrame.from_records` did not accept empty recarrays (GH3682)
- `DataFrame.to_csv` will succeed with the deprecated option `nanRep`, @tdsmith
- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument (GH3702)
- Fix file tokenization error with r delimiter and quoted fields (GH3453)
- Groupby transform with item-by-item not upcasting correctly (GH3740)
- Incorrectly read a HDFStore multi-index Frame with a column specification (GH3748)
- `read_html` now correctly skips tests (GH3741)
- PandasObjects raise TypeError when trying to hash (GH3882)
- Fix incorrect arguments passed to concat that are not list-like (e.g. concat(df1,df2)) (GH3481)
- Correctly parse when passed the `dtype=str` (or other variable-len string dtypes) in `read_csv` (GH3795)
- Fix index name not propagating when using `loc/ix` (GH3880)
- Fix groupby when applying a custom function resulting in a returned DataFrame was not converting dtypes (GH3911)
- Fixed a bug where `DataFrame.replace` with a compiled regular expression in the `to_replace` argument wasn't working (GH3907)
- Fixed `__truediv__` in Python 2.7 with `numexpr` installed to actually do true division when dividing two integer arrays with at least 10000 cells total (GH3764)
- Indexing with a string with seconds resolution not selecting from a time index (GH3925)
- csv parsers would loop infinitely if `iterator=True` but no `chunksize` was specified (GH3967), python parser failing with `chunksize=1`
- Fix index name not propagating when using `shift`
- Fixed dropna=False being ignored with multi-index stack (GH3997)
- Fixed flattening of columns when renaming MultiIndex columns DataFrame (GH4004)
- Fix `Series.clip` for datetime series. NA/NaN threshold values will now throw ValueError (GH3996)
- Fixed insertion issue into DataFrame, after rename (GH4032)
- Fixed testing issue where too many sockets where open thus leading to a connection reset issue (GH3982, GH3985, GH4028, GH4054)
- Fixed failing tests in test_yahoo, test_google where symbols were not retrieved but were being accessed (GH3982, GH3985, GH4028, GH4054)
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a 1xN DataFrame would barf on a 1xN mask (GH4071)

- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way (GH4062, GH4063)
- Fixed bug where sharex and sharey were not being passed to grouped_hist (GH4089)
- Fix bug where `HDFStore` will fail to append because of a different block ordering on-disk (GH4096)
- Better error messages on inserting incompatible columns to a frame (GH4107)
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when regex=False (GH4115)
- Fixed bug in `convert_objects(convert_numeric=True)` where a mixed numeric and object Series/Frame was not converting properly (GH4119)
- Fixed bugs in multi-index selection with column multi-index and duplicates (GH4145, GH4146)
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` (GH4152)
- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
- Fixed bug in `Series.where` where broadcasting a single element input vector to the length of the series resulted in multiplying the value inside the input (GH4192)
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 (GH4215)
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
- Fixed bug where Index slices weren't carrying the name attribute (GH4226)
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
- Fixed bug where html5lib wasn't being properly skipped (GH4265)
- Fixed bug where get_data_famafrench wasn't using the correct file edges (GH4281)

35.12 pandas 0.11.0

Release date: 2013-04-22

35.12.1 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)

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

In [2]: p
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D

In [3]: p.reindex(items=['ItemA']).squeeze()
Out[3]:
```

```
                   A         B         C         D
2001-01-02  0.469112 -0.282863 -1.509059 -1.135632
2001-01-03  1.212112 -0.173215  0.119209 -1.044236
2001-01-04 -0.861849 -2.104569 -0.494929  1.071804
2001-01-05  0.721555 -0.706771 -1.039575  0.271860

In [4]: p.reindex(items=['ItemA'],minor=['B']).squeeze()
Out[4]:
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 = date_range("2001-10-1", periods=5, freq='M')

In [6]: ts = 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 = DataFrame(dict(A = ts))

In [9]: df['2001']
Out[9]:
                   A
2001-10-31  0.838796
2001-11-30  0.897333
2001-12-31  0.732592
```

- added option *display.mpl_style* providing a sleeker visual style for plots. Based on https://gist.github.com/huyng/816622 (GH3075).
- Improved performance across several core functions by taking memory ordering of arrays into account. Courtesy of @stephenwlin (GH3130)
- Improved performance of groupby transform method (GH2121)
- Handle "ragged" CSV files missing trailing delimiters in rows with missing fields when also providing explicit list of column names (so the parser knows how many columns to expect in the result) (GH2981)
- On a mixed DataFrame, allow setting with indexers with ndarray/DataFrame on rhs (GH3216)

- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- Add `time` method to DatetimeIndex (GH3180)
- Return NA when using Series.str[...] for values that are not long enough (GH3223)
- Display cursor coordinate information in time-series plots (GH1670)
- to_html() now accepts an optional "escape" argument to control reserved HTML character escaping (enabled by default) and escapes `&`, in addition to < and >. (GH2919)

35.12.3 API Changes

- Do not automatically upcast numeric specified dtypes to `int64` or `float64` (GH622 and GH797)
- DataFrame construction of lists and scalars, with no dtype present, will result in casting to `int64` or `float64`, regardless of platform. This is not an apparent change in the API, but noting it.
- Guarantee that `convert_objects()` for Series/DataFrame always returns a copy
- groupby operations will respect dtypes for numeric float operations (float32/float64); other types will be operated on, and will try to cast back to the input dtype (e.g. if an int is passed, as long as the output doesn't have nans, then an int will be returned)
- backfill/pad/take/diff/ohlc will now support `float32/int16/int8` operations
- Block types will upcast as needed in where/masking operations (GH2793)
- Series now automatically will try to set the correct dtype based on passed datetimelike objects (datetime/Timestamp)
  - timedelta64 are returned in appropriate cases (e.g. Series - Series, when both are datetime64)
  - mixed datetimes and objects (GH2751) in a constructor will be cast correctly
  - astype on datetimes to object are now handled (as well as NaT conversions to np.nan)
  - all timedelta like objects will be correctly assigned to `timedelta64` with mixed `NaN` and/or `NaT` allowed
- arguments to DataFrame.clip were inconsistent to numpy and Series clipping (GH2747)
- util.testing.assert_frame_equal now checks the column and index names (GH2964)
- Constructors will now return a more informative ValueError on failures when invalid shapes are passed
- Don't suppress TypeError in GroupBy.agg (GH3238)
- Methods return None when inplace=True (GH1893)
- `HDFStore`
  - added the method `select_column` to select a single column from a table as a Series.
  - deprecated the `unique` method, can be replicated by `select_column(key,column).unique()`
  - `min_itemsize` parameter will now automatically create data_columns for passed keys
- Downcast on pivot if possible (GH3283), adds argument `downcast` to `fillna`
- Introduced options *display.height/width* for explicitly specifying terminal height/width in characters. Deprecated display.line_width, now replaced by display.width. These defaults are in effect for scripts as well, so unless disabled, previously very wide output will now be output as "expand_repr" style wrapped output.
- Various defaults for options (including display.max_rows) have been revised, after a brief survey concluded they were wrong for everyone. Now at w=80,h=60.

- HTML repr output in IPython qtconsole is once again controlled by the option *display.notebook_repr_html*, and on by default.

35.12.4 Bug Fixes

- Fix seg fault on empty data frame when fillna with `pad` or `backfill` (GH2778)
- Single element ndarrays of datetimelike objects are handled (e.g. np.array(datetime(2001,1,1,0,0))), w/o dtype being passed
- 0-dim ndarrays with a passed dtype are handled correctly (e.g. np.array(0.,dtype='float32'))
- Fix some boolean indexing inconsistencies in Series.__getitem__/__setitem__ (GH2776)
- Fix issues with DataFrame and Series constructor with integers that overflow `int64` and some mixed typed type lists (GH2845)
- `HDFStore`
  - Fix weird PyTables error when using too many selectors in a where also correctly filter on any number of values in a Term expression (so not using numexpr filtering, but isin filtering)
  - Internally, change all variables to be private-like (now have leading underscore)
  - Fixes for query parsing to correctly interpret boolean and != (GH2849, GH2973)
  - Fixes for pathological case on SparseSeries with 0-len array and compression (GH2931)
  - Fixes bug with writing rows if part of a block was all-nan (GH3012)
  - Exceptions are now ValueError or TypeError as needed
  - A table will now raise if min_itemsize contains fields which are not queryables
- Bug showing up in applymap where some object type columns are converted (GH2909) had an incorrect default in convert_objects
- TimeDeltas
  - Series ops with a Timestamp on the rhs was throwing an exception (GH2898) added tests for Series ops with datetimes,timedeltas,Timestamps, and datelike Series on both lhs and rhs
  - Fixed subtle timedelta64 inference issue on py3 & numpy 1.7.0 (GH3094)
  - Fixed some formatting issues on timedelta when negative
  - Support null checking on timedelta64, representing (and formatting) with NaT
  - Support setitem with np.nan value, converts to NaT
  - Support min/max ops in a Dataframe (abs not working, nor do we error on non-supported ops)
  - Support idxmin/idxmax/abs/max/min in a Series (GH2989, GH2982)
- Bug on in-place putmasking on an `integer` series that needs to be converted to `float` (GH2746)
- Bug in argsort of `datetime64[ns]` Series with `NaT` (GH2967)
- Bug in value_counts of `datetime64[ns]` Series (GH3002)
- Fixed printing of `NaT` in an index
- Bug in idxmin/idxmax of `datetime64[ns]` Series with `NaT` (GH2982)
- Bug in `icol, take` with negative indicies was producing incorrect return values (see GH2922, GH2892), also check for out-of-bounds indices (GH3029)

- Bug in DataFrame column insertion when the column creation fails, existing frame is left in an irrecoverable state (GH3010)
- Bug in DataFrame update, combine_first where non-specified values could cause dtype changes (GH3016, GH3041)
- Bug in groupby with first/last where dtypes could change (GH3041, GH2763)
- Formatting of an index that has `nan` was inconsistent or wrong (would fill from other values), (GH2850)
- Unstack of a frame with no nans would always cause dtype upcasting (GH2929)
- Fix scalar datetime.datetime parsing bug in read_csv (GH3071)
- Fixed slow printing of large Dataframes, due to inefficient dtype reporting (GH2807)
- Fixed a segfault when using a function as grouper in groupby (GH3035)
- Fix pretty-printing of infinite data structures (closes GH2978)
- Fixed exception when plotting timeseries bearing a timezone (closes GH2877)
- str.contains ignored na argument (GH2806)
- Substitute warning for segfault when grouping with categorical grouper of mismatched length (GH3011)
- Fix exception in SparseSeries.density (GH2083)
- Fix upsampling bug with closed='left' and daily to daily data (GH3020)
- Fixed missing tick bars on scatter_matrix plot (GH3063)
- Fixed bug in Timestamp(d,tz=foo) when d is date() rather then datetime() (GH2993)
- series.plot(kind='bar') now respects pylab color schem (GH3115)
- Fixed bug in reshape if not passed correct input, now raises TypeError (GH2719)
- Fixed a bug where Series ctor did not respect ordering if OrderedDict passed in (GH3282)
- Fix NameError issue on RESO_US (GH2787)
- Allow selection in an *unordered* timeseries to work similary to an *ordered* timeseries (GH2437).
- Fix implemented `.xs` when called with `axes=1` and a level parameter (GH2903)
- Timestamp now supports the class method fromordinal similar to datetimes (GH3042)
- Fix issue with indexing a series with a boolean key and specifiying 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 priniting of sets (GH3294)
- Panel() and Panel.from_dict() now respects ordering when give OrderedDict (GH3303)
- DataFrame where with a datetimelike incorrectly selecting (GH3311)
- Ensure index casts work even in Int64Index
- Fix set_index segfault when passing MultiIndex (GH3308)
- Ensure pickles created in py2 can be read in py3
- Insert ellipsis in MultiIndex summary repr (GH3348)
- Groupby will handle mutation among an input groups columns (and fallback to non-fast apply) (GH3380)
- Eliminated unicode errors on FreeBSD when using MPL GTK backend (GH3360)
- Period.strftime should return unicode strings always (GH3363)
- Respect passed read_* chunksize in get_chunk function (GH3406)

35.13 pandas 0.10.1

Release date: 2013-01-22

35.13.1 New Features

- Add data interface to World Bank WDI pandas.io.wb (GH2592)

35.13.2 API Changes

- Restored inplace=True behavior returning self (same object) with deprecation warning until 0.11 (GH1893)
- `HDFStore`
  - refactored HFDStore 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

35.13.3 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 automagic 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)

35.13.4 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 occuring 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)

35.14 pandas 0.10.0

Release date: 2012-12-17

35.14.1 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)

35.14.2 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

35.14.3 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

35.14.4 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)

35.14.5 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)

35.15 pandas 0.9.1

Release date: 2012-11-14

35.15.1 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)

35.15.2 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)

35.15.3 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)

35.15.4 Bug Fixes

- Fix some duplicate-column DataFrame constructor issues (GH2079)
- Fix bar plot color cycle issues (GH2082)
- Fix off-center grid for stacked bar plots (GH2157)
- Fix plotting bug if inferred frequency is offset with N > 1 (GH2126)
- Implement comparisons on date offsets with fixed delta (GH2078)
- Handle inf/-inf correctly in read_* parser functions (GH2041)
- Fix matplotlib unicode interaction bug
- Make WLS r-squared match statsmodels 0.5.0 fixed value
- Fix zero-trimming DataFrame formatting bug
- Correctly compute/box datetime64 min/max values from Series.min/max (GH2083)
- Fix unstacking edge case with unrepresented groups (GH2100)
- Fix Series.str failures when using pipe pattern '|' (GH2119)
- Fix pretty-printing of dict entries in Series, DataFrame (GH2144)
- Cast other datetime64 values to nanoseconds in DataFrame ctor (GH2095)
- Alias Timestamp.astimezone to tz_convert, so will yield Timestamp (GH2060)
- Fix timedelta64 formatting from Series (GH2165, GH2146)

- Handle None values gracefully in dict passed to Panel constructor (GH2075)
- Box datetime64 values as Timestamp objects in Series/DataFrame.iget (GH2148)
- Fix Timestamp indexing bug in DatetimeIndex.insert (GH2155)
- Use index name(s) (if any) in DataFrame.to_records (GH2161)
- Don't lose index names in Panel.to_frame/DataFrame.to_panel (GH2163)
- Work around length-0 boolean indexing NumPy bug (GH2096)
- Fix partial integer indexing bug in DataFrame.xs (GH2107)
- Fix variety of cut/qcut string-bin formatting bugs (GH1978, GH1979)
- Raise Exception when xs view not possible of MultiIndex'd DataFrame (GH2117)
- Fix groupby(...).first() issue with datetime64 (GH2133)
- Better floating point error robustness in some rolling_* functions (GH2114, GH2527)
- Fix ewma NA handling in the middle of Series (GH2128)
- Fix numerical precision issues in diff with integer data (GH2087)
- Fix bug in MultiIndex.__getitem__ with NA values (GH2008)
- Fix DataFrame.from_records dict-arg bug when passing columns (GH2179)
- Fix Series and DataFrame.diff for integer dtypes (GH2087, GH2174)
- Fix bug when taking intersection of DatetimeIndex with empty index (GH2129)
- Pass through timezone information when calling DataFrame.align (GH2127)
- Properly sort when joining on datetime64 values (GH2196)
- Fix indexing bug in which False/True were being coerced to 0/1 (GH2199)
- Many unicode formatting fixes (GH2201)
- Fix improper MultiIndex conversion issue when assigning e.g. DataFrame.index (GH2200)
- Fix conversion of mixed-type DataFrame to ndarray with dup columns (GH2236)
- Fix duplicate columns issue (GH2218, GH2219)
- Fix SparseSeries.__pow__ issue with NA input (GH2220)
- Fix icol with integer sequence failure (GH2228)
- Fixed resampling tz-aware time series issue (GH2245)
- SparseDataFrame.icol was not returning SparseSeries (GH2227, GH2229)
- Enable ExcelWriter to handle PeriodIndex (GH2240)
- Fix issue constructing DataFrame from empty Series with name (GH2234)
- Use console-width detection in interactive sessions only (GH1610)
- Fix parallel_coordinates legend bug with mpl 1.2.0 (GH2237)
- Make tz_localize work in corner case of empty Series (GH2248)

35.16 pandas 0.9.0

Release date: 10/7/2012

35.16.1 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)

35.16.2 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)

35.16.3 API Changes

- Change default header names in read_* functions to more Pythonic X0, X1, etc. instead of X.1, X.2. (GH2000)
- Deprecated `day_of_year` API removed from PeriodIndex, use `dayofyear` (GH1723)
- Don't modify NumPy suppress printoption at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by HDFStore (GH1834, GH1824)
- Legacy cruft removed: pandas.stats.misc.quantileTS
- Use ISO8601 format for Period repr: monthly, daily, and on down (GH1776)
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) (GH1783)
- Setting parts of DataFrame/Panel using ix now aligns input Series/DataFrame (GH1630)
- *first* and *last* methods in *GroupBy* no longer drop non-numeric columns (GH1809)
- Resolved inconsistencies in specifying custom NA values in text parser. *na_values* of type dict no longer 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*

35.16.4 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 ancxhored date ranges (GH1778)
- Fix issue calling sort on result of Series.unique (GH1807)
- Fix numerical issue leading to square root of negative number in rolling_std (GH1840)
- Let Series.str.split accept no arguments (like str.split) (GH1859)
- Allow user to have dateutil 2.1 installed on a Python 2 system (GH1851)
- Catch ImportError less aggressively in pandas/__init__.py (GH1845)
- Fix pip source installation bug when installing from GitHub (GH1805)
- Fix error when window size > array size in rolling_apply (GH1850)

- Fix pip source installation issues via SSH from GitHub
- Fix OLS.summary when column is a tuple (GH1837)
- Fix bug in __doc__ patching when -OO passed to interpreter (GH1792 GH1741 GH1774)
- Fix unicode console encoding issue in IPython notebook (GH1782, GH1768)
- Fix unicode formatting issue with Series.name (GH1782)
- Fix bug in DataFrame.duplicated with datetime64 columns (GH1833)
- Fix bug in Panel internals resulting in error when doing fillna after truncate not changing size of panel (GH1823)
- Prevent segfault due to MultiIndex not being supported in HDFStore table format (GH1848)
- Fix UnboundLocalError in Panel.__setitem__ and add better error (GH1826)
- Fix to_csv issues with list of string entries. Isnull works on list of strings now too (GH1791)
- Fix Timestamp comparisons with datetime values outside the nanosecond range (1677-2262)
- Revert to prior behavior of normalize_date with datetime.date objects (return datetime)
- Fix broken interaction between np.nansum and Series.any/all
- Fix bug with multiple column date parsers (GH1866)
- DatetimeIndex.union(Int64Index) was broken
- Make plot x vs y interface consistent with integer indexing (GH1842)
- set_index inplace modified data even if unique check fails (GH1831)
- Only use Q-OCT/NOV/DEC in quarterly frequency inference (GH1789)
- Upcast to dtype=object when unstacking boolean DataFrame (GH1820)
- Fix float64/float32 merging bug (GH1849)
- Fixes to Period.start_time for non-daily frequencies (GH1857)
- Fix failure when converter used on index_col in read_csv (GH1835)
- Implement PeriodIndex.append so that pandas.concat works correctly (GH1815)
- Avoid Cython out-of-bounds access causing segfault sometimes in pad_2d, backfill_2d
- Fix resampling error with intraday times and anchored target time (like AS-DEC) (GH1772)
- Fix .ix indexing bugs with mixed-integer indexes (GH1799)
- Respect passed color keyword argument in Series.plot (GH1890)
- Fix rolling_min/max when the window is larger than the size of the input array. Check other malformed inputs (GH1899, GH1897)
- Rolling variance / standard deviation with only a single observation in window (GH1884)
- Fix unicode sheet name failure in to_excel (GH1828)
- Override DatetimeIndex.min/max to return Timestamp objects (GH1895)
- Fix column name formatting issue in length-truncated column (GH1906)
- Fix broken handling of copying Index metadata to new instances created by view(...) calls inside the NumPy infrastructure
- Support datetime.date again in DateOffset.rollback/rollforward
- Raise Exception if set passed to Series constructor (GH1913)

- Add TypeError when appending HDFStore table w/ wrong index type (GH1881)
- Don't raise exception on empty inputs in EW functions (e.g. ewma) (GH1900)
- Make asof work correctly with PeriodIndex (GH1883)
- Fix extlinks in doc build
- Fill boolean DataFrame with NaN when calling shift (GH1814)
- Fix setuptools bug causing pip not to Cythonize .pyx files sometimes
- Fix negative integer indexing regression in .ix from 0.7.x (GH1888)
- Fix error while retrieving timezone and utc offset from subclasses of datetime.tzinfo without .zone and ._utcoffset attributes (GH1922)
- Fix DataFrame formatting of small, non-zero FP numbers (GH1911)
- Various fixes by upcasting of date -> datetime (GH1395)
- Raise better exception when passing multiple functions with the same name, such as lambdas, to GroupBy.aggregate
- Fix DataFrame.apply with axis=1 on a non-unique index (GH1878)
- Proper handling of Index subclasses in pandas.unique (GH1759)
- Set index names in DataFrame.from_records (GH1744)
- Fix time series indexing error with duplicates, under and over hash table size cutoff (GH1821)
- Handle list keys in addition to tuples in DataFrame.xs when partial-indexing a hierarchically-indexed DataFrame (GH1796)
- Support multiple column selection in DataFrame.__getitem__ with duplicate columns (GH1943)
- Fix time zone localization bug causing improper fields (e.g. hours) in time zones that have not had a UTC transition in a long time (GH1946)
- Fix errors when parsing and working with 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)

35.17 pandas 0.8.1

Release date: July 22, 2012

35.17.1 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)

35.17.2 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)

35.17.3 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)

35.18 pandas 0.8.0

Release date: 6/29/2012

35.18.1 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

35.18.2 Improvements to existing features

- Switch to klib/khash-based hash tables in Index classes for better performance in many cases and lower memory footprint
- Shipping some functions from scipy.stats to reduce dependency, e.g. Series.describe and DataFrame.describe (GH1092)
- Can create MultiIndex by passing list of lists or list of arrays to Series, DataFrame constructor, etc. (GH831)
- Can pass arrays in addition to column names to DataFrame.set_index (GH402)
- Improve the speed of "square" reindexing of homogeneous DataFrame objects by significant margin (GH836)
- Handle more dtypes when passed MaskedArrays in DataFrame constructor (GH406)
- Improved performance of join operations on integer keys (GH682)

- Can pass multiple columns to GroupBy object, e.g. grouped[[col1, col2]] to only aggregate a subset of the value columns (GH383)
- Add histogram / kde plot options for scatter_matrix diagonals (GH1237)
- Add inplace option to Series/DataFrame.rename and sort_index, DataFrame.drop_duplicates (GH805, GH207)
- More helpful error message when nothing passed to Series.reindex (GH1267)
- Can mix array and scalars as dict-value inputs to DataFrame ctor (GH1329)
- Use DataFrame columns' name for legend title in plots
- Preserve frequency in DatetimeIndex when possible in boolean indexing operations
- Promote datetime.date values in data alignment operations (GH867)
- Add `order` method to Index classes (GH1028)
- Avoid hash table creation in large monotonic hash table indexes (GH1160)
- Store time zones in HDFStore (GH1232)
- Enable storage of sparse data structures in HDFStore (GH85)
- Enable Series.asof to work with arrays of timestamp inputs
- Cython implementation of DataFrame.corr speeds up by > 100x (GH1349, GH1354)
- Exclude "nuisance" columns automatically in GroupBy.transform (GH1364)
- Support functions-as-strings in GroupBy.transform (GH1362)
- Use index name as xlabel/ylabel in plots (GH1415)
- Add `convert_dtype` option to Series.apply to be able to leave data as dtype=object (GH1414)
- Can specify all index level names in concat (GH1419)
- Add `dialect` keyword to parsers for quoting conventions (GH1363)
- Enable DataFrame[bool_DataFrame] += value (GH1366)
- Add `retries` argument to `get_data_yahoo` to try to prevent Yahoo! API 404s (GH826)
- Improve performance of reshaping by using O(N) categorical sorting
- Series names will be used for index of DataFrame if no index passed (GH1494)
- Header argument in DataFrame.to_csv can accept a list of column names to use instead of the object's columns (GH921)
- Add `raise_conflict` argument to DataFrame.update (GH1526)
- Support file-like objects in ExcelFile (GH1529)

35.18.3 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)

35.18.4 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 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)

35.19 pandas 0.7.3

Release date: April 12, 2012

35.19.1 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)

35.19.2 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)

35.19.3 Bug Fixes

- Fix logic error when selecting part of a row in a DataFrame with a MultiIndex index (GH1013)
- Series comparison with Series of differing length causes crash (GH1016).
- Fix bug in indexing when selecting section of hierarchically-indexed row (GH1013)
- DataFrame.plot(logy=True) has no effect (GH1011).
- Broken arithmetic operations between SparsePanel-Panel (GH1015)
- Unicode repr issues in MultiIndex with non-ASCII characters (GH1010)
- DataFrame.lookup() returns inconsistent results if exact match not present (GH1001)
- DataFrame arithmetic operations not treating None as NA (GH992)
- DataFrameGroupBy.apply returns incorrect result (GH991)
- Series.reshape returns incorrect result for multiple dimensions (GH989)
- Series.std and Series.var ignores ddof parameter (GH934)
- DataFrame.append loses index names (GH980)
- DataFrame.plot(kind='bar') ignores color argument (GH958)
- Inconsistent Index comparison results (GH948)
- Improper int dtype DataFrame construction from data with NaN (GH846)
- Removes default 'result' name in groupby results (GH995)

- DataFrame.from_records no longer mutate input columns (GH975)
- Use Index name when grouping by it (GH1313)

35.20 pandas 0.7.2

Release date: March 16, 2012

35.20.1 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

35.20.2 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)

35.20.3 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)

35.20.4 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 inconsistant 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)

35.21 pandas 0.7.1

Release date: February 29, 2012

35.21.1 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

35.21.2 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)

35.21.3 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 redudant groupby computation (GH775)
- Catch possible NA assignment to int/bool series with exception (GH839)

35.22 pandas 0.7.0

Release date: 2/9/2012

35.22.1 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

35.22.2 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)

35.22.3 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)

35.22.4 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)

35.22.5 Thanks

- Craig Austin
- Chris Billington
- Marius Cobzarenco
- Mario Gamboa-Cavazos
- Hans-Martin Gaudecker
- Arthur Gerigk
- Yaroslav Halchenko
- Jeff Hammerbacher
- Matt Harrison
- Andreas Hilboll
- Luc Kesters
- Adam Klein
- Gregg Lind
- Solomon Negusse
- Wouter Overmeire
- Christian Prinoth
- Jeff Reback
- Sam Reckoner
- Craig Reeson
- Jan Schulz
- Skipper Seabold
- Ted Square
- Graham Taylor
- Aman Thakral
- Chris Uga
- Dieter Vandenbussche
- Texas P.
- Pinxing Ye
- ... and everyone I forgot

35.23 pandas 0.6.1

Release date: 12/13/2011

35.23.1 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)

35.23.2 New Features

- Can pass Series to DataFrame.append with ignore_index=True for appending a single row (GH430)
- Add Spearman and Kendall correlation options to Series.corr and DataFrame.corr (GH428)
- Add new *get_value* and *set_value* methods to Series, DataFrame, and Panel to very low-overhead access to scalar elements. df.get_value(row, column) is about 3x faster than df[column][row] by handling fewer cases (GH437, GH438). Add similar methods to sparse data structures for compatibility
- Add Qt table widget to sandbox (GH435)
- DataFrame.align can accept Series arguments, add axis keyword (GH461)
- Implement new SparseList and SparseArray data structures. SparseSeries now derives from SparseArray (GH463)
- max_columns / max_rows options in set_printoptions (GH453)
- Implement Series.rank and DataFrame.rank, fast versions of scipy.stats.rankdata (GH428)
- Implement DataFrame.from_items alternate constructor (GH444)
- DataFrame.convert_objects method for inferring better dtypes for object columns (GH302)
- Add rolling_corr_pairwise function for computing Panel of correlation matrices (GH189)
- Add *margins* option to *pivot_table* for computing subgroup aggregates (GH GH114)
- Add *Series.from_csv* function (GH482)

35.23.3 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

35.23.4 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)

35.23.5 Thanks

- Ralph Bean
- Luca Beltrame
- Marius Cobzarenco
- Andreas Hilboll
- Jev Kuznetsov
- Adam Lichtenstein
- Wouter Overmeire
- Fernando Perez
- Nathan Pinger
- Christian Prinoth
- Alex Reyfman
- Joon Ro
- Chang She
- Ted Square
- Chris Uga
- Dieter Vandenbussche

35.24 pandas 0.6.0

Release date: 11/25/2011

35.24.1 API Changes

- Arithmetic methods like *sum* will attempt to sum dtype=object values by default instead of excluding them (GH382)

35.24.2 New Features

- Add *melt* function to *pandas.core.reshape*
- Add *level* parameter to group by level in Series and DataFrame descriptive statistics (GH313)
- Add *head* and *tail* methods to Series, analogous to to DataFrame (PR GH296)
- Add *Series.isin* function which checks if each value is contained in a passed sequence (GH289)
- Add *float_format* option to *Series.to_string*
- Add *skip_footer* (GH291) and *converters* (GH343) options to *read_csv* and *read_table*
- Add proper, tested weighted least squares to standard and panel OLS (GH GH303)
- Add *drop_duplicates* and *duplicated* functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively (GH319)

- Implement logical (boolean) operators `&`, `|`, `^` on DataFrame (GH347)
- Add *Series.mad*, mean absolute deviation, matching DataFrame
- Add *QuarterEnd* DateOffset (GH321)
- Add matrix multiplication function *dot* to DataFrame (GH65)
- Add *orient* option to *Panel.from_dict* to ease creation of mixed-type Panels (GH359, GH301)
- Add *DataFrame.from_dict* with similar *orient* option
- Can now pass list of tuples or list of lists to *DataFrame.from_records* for fast conversion to DataFrame (GH357)
- Can pass multiple levels to groupby, e.g. *df.groupby(level=[0, 1])* (GH GH103)
- Can sort by multiple columns in *DataFrame.sort_index* (GH92, GH362)
- Add fast *get_value* and *put_value* methods to DataFrame and micro-performance tweaks (GH360)
- Add *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)

35.24.3 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

35.24.4 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 *swaplavel* (GH379)
- Don't lose index names in *MultiIndex.droplevel* (GH394)
- Infer more proper return type in *DataFrame.apply* when no columns or rows depending on whether the passed function is a reduction (GH389)
- Always return NA/NaN from Series.min/max and DataFrame.min/max when all of a row/column/values are NA (GH384)
- Enable partial setting with .ix / advanced indexing (GH397)
- Handle mixed-type DataFrames correctly in unstack, do not lose type information (GH403)
- Fix integer name formatting bug in Index.format and in Series.__repr__
- Handle label types other than string passed to groupby (GH405)
- Fix bug in .ix-based indexing with partial retrieval when a label is not contained in a level
- Index name was not being pickled (GH408)
- Level name should be passed to result index in GroupBy.apply (GH416)

35.24.5 Thanks

- Craig Austin
- Marius Cobzarenco
- Joel Cross
- Jeff Hammerbacher
- Adam Klein
- Thomas Kluyver
- Jev Kuznetsov
- Kieran O'Mahony
- Wouter Overmeire
- Nathan Pinger
- Christian Prinoth
- Skipper Seabold
- Chang She

- Ted Square
- Aman Thakral
- Chris Uga
- Dieter Vandenbussche
- carljv
- rsamson

35.25 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.

35.25.1 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*
  - *_firstTimeWithValue* use *first_valid_index*

   - *_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*

35.25.2 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

35.25.3 New Features

- Added *DataFrame.align* method with standard join options
- Added *parse_dates* option to *read_csv* and *read_table* methods to optionally try to parse dates in the index columns

- Add *nrows*, *chunksize*, and *iterator* arguments to *read_csv* and *read_table*. The last two return a new *TextParser* class capable of lazily iterating through chunks of a flat file (GH242)
- Added ability to join on multiple columns in *DataFrame.join* (GH214)
- Added private *_get_duplicates* function to *Index* for identifying duplicate values more easily
- Added column attribute access to DataFrame, e.g. df.A equivalent to df['A'] if 'A' is a column in the DataFrame (GH213)
- Added IPython tab completion hook for DataFrame columns. (GH233, GH230)
- Implement *Series.describe* for Series containing objects (GH241)
- Add inner join option to *DataFrame.join* when joining on key(s) (GH248)
- Can select set of DataFrame columns by passing a list to *__getitem__* (GH GH253)
- Can use & and | to intersection / union Index objects, respectively (GH GH261)
- Added *pivot_table* convenience function to pandas namespace (GH234)
- Implemented *Panel.rename_axis* function (GH243)
- DataFrame will show index level names in console output
- Implemented *Panel.take*
- Add *set_eng_float_format* function for setting alternate DataFrame floating point string formatting
- Add convenience *set_index* function for creating a DataFrame index from its existing columns

35.25.4 Improvements to existing features

- Major performance improvements in file parsing functions *read_csv* and *read_table*
- Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations
- File parsing functions like *read_csv* and *read_table* will explicitly check if a parsed index has duplicates and raise a more helpful exception rather than deferring the check until later
- Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)
- Improved speed of *DataFrame.xs* on mixed-type DataFrame objects by about 5x, regression from 0.3.0 (GH215)
- With new *DataFrame.align* method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.
- Significantly sped up conversion of nested dict into DataFrame (GH212)
- Can pass hierarchical index level name to *groupby* instead of the level number if desired (GH223)
- Add support for different delimiters in *DataFrame.to_csv* (GH244)
- Add more helpful error message when importing pandas post-installation from the source directory (GH250)
- Significantly speed up DataFrame *__repr__* and *count* on large mixed-type DataFrame objects
- Better handling of pyx file dependencies in Cython module build (GH271)

35.25.5 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

35.25.6 Thanks

- Thomas Kluyver
- Daniel Fortunov
- Aman Thakral
- Luca Beltrame
- Wouter Overmeire

35.26 pandas 0.4.3

Release date: 10/9/2011

is is largely a bugfix release from 0.4.2 but also includes a handful of new d enhanced features. Also, pandas can now be installed and used on Python 3 hanks Thomas Kluyver!).

35.26.1 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)

35.26.2 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 SparseSeries objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks (GH205)
- Refactored *Series.__repr__* to be a bit more clean and consistent

35.26.3 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*

35.26.4 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

35.26.5 Thanks

- Thomas Kluyver
- rsamson

35.27 pandas 0.4.2

Release date: 10/3/2011

is is a performance optimization release with several bug fixes. The new t64Index and new merging / joining Cython code and related Python frastructure are the main new additions

35.27.1 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

35.27.2 Improvements to existing features

- Improved performance of *isnull* and *notnull*, a regression from v0.3.0 (GH187)
- Wrote templating / code generation script to auto-generate Cython code for various functions which need to be available for the 4 major data types used in pandas (float64, bool, object, int64)
- Refactored code related to *DataFrame.join* so that intermediate aligned copies of the data in each *DataFrame* argument do not need to be created. Substantial performance increases result (GH176)
- Substantially improved performance of generic *Index.intersection* and *Index.union*

- Improved performance of *DateRange.union* with overlapping ranges and non-cacheable offsets (like Minute). Implemented analogous fast *DateRange.intersection* for overlapping ranges.
- Implemented *BlockManager.take* resulting in significantly faster *take* performance on mixed-type *DataFrame* objects (GH104)
- Improved performance of *Series.sort_index*
- Significant groupby performance enhancement: removed unnecessary integrity checks in DataFrame internals that were slowing down slicing operations to retrieve groups
- Added informative Exception when passing dict to DataFrame groupby aggregation with axis != 0

35.27.3 API Changes

35.27.4 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

35.27.5 Thanks

- Uri Laserson
- Scott Sinclair

35.28 pandas 0.4.1

Release date: 9/25/2011

is is primarily a bug fix release but includes some new features and improvements

35.28.1 New Features

- Added new *DataFrame* methods *get_dtype_counts* 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

35.28.2 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

35.28.3 API Changes

35.28.4 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

35.28.5 Thanks

- Yaroslav Halchenko
- Jeff Reback
- Skipper Seabold
- Dan Lovell
- Nick Pentreath

35.29 pandas 0.4.0

Release date: 9/12/2011

35.29.1 New Features

- *pandas.core.sparse* module: "Sparse" (mostly-NA, or some other fill value) versions of *Series*, *DataFrame*, and *Panel*. For low-density data, this will result in significant performance boosts, and smaller memory footprint. Added *to_sparse* methods to *Series*, *DataFrame*, and *Panel*. See online documentation for more on these
- Fancy indexing operator on Series / DataFrame, e.g. via .ix operator. Both getting and setting of values is supported; however, setting values will only currently work on homogeneously-typed DataFrame objects. Things like:
  - series.ix[[d1, d2, d3]]
  - frame.ix[5:10, ['C', 'B', 'A']], frame.ix[5:10, 'A':'C']
  - frame.ix[date1:date2]
- Significantly enhanced *groupby* functionality
  - Can groupby multiple keys, e.g. df.groupby(['key1', 'key2']). Iteration with multiple groupings products a flattened tuple
  - "Nuisance" columns (non-aggregatable) will automatically be excluded from DataFrame aggregation operations
  - Added automatic "dispatching to Series / DataFrame methods to more easily invoke methods on groups. e.g. s.groupby(crit).std() will work even though *std* is not implemented on the *GroupBy* class
- Hierarchical / multi-level indexing
  - New the *MultiIndex* class. Integrated *MultiIndex* into *Series* and *DataFrame* fancy indexing, slicing, __getitem__ and __setitem, reindexing, etc. Added *level* keyword argument to *groupby* to enable grouping by a level of a *MultiIndex*
- New data reshaping functions: *stack* and *unstack* on DataFrame and Series
  - Integrate with MultiIndex to enable sophisticated reshaping of data
- *Index* objects (labels for axes) are now capable of holding tuples
- *Series.describe*, *DataFrame.describe*: produces an R-like table of summary statistics about each data column
- *DataFrame.quantile*, *Series.quantile* for computing sample quantiles of data across requested axis
- Added general *DataFrame.dropna* method to replace *dropIncompleteRows* and *dropEmptyRows*, deprecated those.
- *Series* arithmetic methods with optional fill_value for missing data, e.g. a.add(b, fill_value=0). If a location is missing for both it will still be missing in the result though.
- fill_value option has been added to *DataFrame*.{add, mul, sub, div} methods similar to *Series*
- Boolean indexing with *DataFrame* objects: data[data > 0.1] = 0.1 or data[data> other] = 1.
- *pytz* / tzinfo support in *DateRange*
  - *tz_localize*, *tz_normalize*, and *tz_validate* methods added
- Added *ExcelFile* class to *pandas.io.parsers* for parsing multiple sheets out of a single Excel 2003 document

- *GroupBy* aggregations can now optionally *broadcast*, e.g. produce an object of the same size with the aggregated value propagated
- Added *select* function in all data structures: reindex axis based on arbitrary criterion (function returning boolean value), e.g. frame.select(lambda x: 'foo' in x, axis=1)
- *DataFrame.consolidate* method, API function relating to redesigned internals
- *DataFrame.insert* method for inserting column at a specified location rather than the default __setitem__ behavior (which puts it at the end)
- *HDFStore* class in *pandas.io.pytables* has been largely rewritten using patches from Jeff Reback from others. It now supports mixed-type *DataFrame* and *Series* data and can store *Panel* objects. It also has the option to query *DataFrame* and *Panel* data. Loading data from legacy *HDFStore* files is supported explicitly in the code
- Added *set_printoptions* method to modify appearance of DataFrame tabular output
- *rolling_quantile* functions; a moving version of *Series.quantile* / *DataFrame.quantile*
- Generic *rolling_apply* moving window function
- New *drop* method added to *Series*, *DataFrame*, etc. which can drop a set of labels from an axis, producing a new object
- *reindex* methods now sport a *copy* option so that data is not forced to be copied then the resulting object is indexed the same
- Added *sort_index* methods to Series and Panel. Renamed *DataFrame.sort* to *sort_index*. Leaving *DataFrame.sort* for now.
- Added `skipna` option to statistical instance methods on all the data structures
- *pandas.io.data* module providing a consistent interface for reading time series data from several different sources

35.29.2 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).

35.29.3 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

35.29.4 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

35.29.5 Thanks

- Joon Ro
- Michael Pennington
- Chris Uga
- Chris Withers
- Jeff Reback
- Ted Square
- Craig Austin
- William Ferreira
- Daniel Fortunov
- Tony Roberts
- Martin Felder
- John Marino
- Tim McNamara
- Justin Berka
- Dieter Vandenbussche
- Shane Conway
- Skipper Seabold
- Chris Jordan-Squire

35.30 pandas 0.3.0

Release date: February 20, 2011

35.30.1 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

35.30.2 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.)

35.30.3 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

35.30.4 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

PYTHON MODULE INDEX

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