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)

> **Warning:** Indexing on an integer-based Index with floats has been clarified in 0.18.0, for a summary of the changes, see here.

See the MultiIndex / Advanced Indexing for `MultiIndex` and more advanced indexing documentation.

See the cookbook for some advanced strategies

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
  - A `callable` function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

    New in version 0.18.1.

  See more at Selection by Label
- `.iloc` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing. (this conforms with python/numpy *slice* semantics). Allowed inputs are:
  - An integer e.g. `5`
  - A list or array of integers `[4, 3, 0]`
  - A slice object with ints `1:7`
  - A boolean array
  - A `callable` function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing (one of the above)

    New in version 0.18.1.

  See more at Selection by Position

  See more at Advanced Indexing and Advanced Hierarchical.
- `.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. See more at Selection By Callable.

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but applies to `.iloc` as well). Any of the axes accessors may be the null slice `:`. Axes left out of the specification are assumed to be `:`. (e.g. `p.loc['a']` is equiv to `p.loc['a', :, :]`)

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Object Type	Indexers
Series	`s.loc[indexer]`
DataFrame	`df.loc[row_indexer,column_indexer]`

Object Type	Indexers
Panel	p.loc[item_indexer,major_indexer,minor_indexer]

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 corresponding to the itemname

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [1]: dates = pd.date_range('1/1/2000', periods=8)

In [2]: df = pd.DataFrame(np.random.randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])

In [3]: df
Out[3]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [4]: panel = pd.Panel({'one' : df, 'two' : df - df.mean()})

In [5]: panel
Out[5]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 8 (major_axis) x 4 (minor_axis)
Items axis: one to two
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-08 00:00:00
Minor_axis axis: A to D
```

Note: None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using `[]`:

```
In [6]: s = df['A']

In [7]: s[dates[5]]
Out[7]: -0.67368970808837059

In [8]: panel['two']
Out[8]:
                   A         B         C         D
```

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```
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.

Warning: pandas aligns all AXES when setting `Series` and `DataFrame` from `.loc`, and `.iloc`.

This will **not** modify `df` because the column alignment is before value assignment.

```
In [12]: df[['A', 'B']]
Out[12]: 
                   A         B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647

In [13]: df.loc[:,['B', 'A']] = df[['A', 'B']]
```

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```
In [14]: df[['A', 'B']]
Out[14]: 
                   A         B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647
```

The correct way is to use raw values

```
In [15]: df.loc[:,['B', 'A']] = df[['A', 'B']].values

In [16]: df[['A', 'B']]
Out[16]: 
                   A         B
2000-01-01  0.469112 -0.282863
2000-01-02  1.212112 -0.173215
2000-01-03 -0.861849 -2.104569
2000-01-04  0.721555 -0.706771
2000-01-05 -0.424972  0.567020
2000-01-06 -0.673690  0.113648
2000-01-07  0.404705  0.577046
2000-01-08 -0.370647 -1.157892
```

Attribute Access

You may access an index on a `Series`, column on a `DataFrame`, and an item on a `Panel` directly as an attribute:

```
In [17]: sa = pd.Series([1,2,3],index=list('abc'))

In [18]: dfa = df.copy()
```

```
In [19]: sa.b
Out[19]: 2

In [20]: dfa.A
Out[20]: 
2000-01-01    0.469112
2000-01-02    1.212112
2000-01-03   -0.861849
2000-01-04    0.721555
2000-01-05   -0.424972
2000-01-06   -0.673690
2000-01-07    0.404705
2000-01-08   -0.370647
Freq: D, Name: A, dtype: float64

In [21]: panel.one
Out[21]: 
```

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```
                   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 [22]: sa.a = 5

In [23]: sa
Out[23]:
a    5
b    2
c    3
dtype: int64

In [24]: dfa.A = list(range(len(dfa.index)))  # ok if A already exists

In [25]: dfa
Out[25]:
            A         B         C         D
2000-01-01  0 -0.282863 -1.509059 -1.135632
2000-01-02  1 -0.173215  0.119209 -1.044236
2000-01-03  2 -2.104569 -0.494929  1.071804
2000-01-04  3 -0.706771 -1.039575  0.271860
2000-01-05  4  0.567020  0.276232 -1.087401
2000-01-06  5  0.113648 -1.478427  0.524988
2000-01-07  6  0.577046 -1.715002 -1.039268
2000-01-08  7 -1.157892 -1.344312  0.844885

In [26]: dfa['A'] = list(range(len(dfa.index)))  # use this form to create a new column

In [27]: dfa
Out[27]:
            A         B         C         D
2000-01-01  0 -0.282863 -1.509059 -1.135632
2000-01-02  1 -0.173215  0.119209 -1.044236
2000-01-03  2 -2.104569 -0.494929  1.071804
2000-01-04  3 -0.706771 -1.039575  0.271860
2000-01-05  4  0.567020  0.276232 -1.087401
2000-01-06  5  0.113648 -1.478427  0.524988
2000-01-07  6  0.577046 -1.715002 -1.039268
2000-01-08  7 -1.157892 -1.344312  0.844885
```

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.

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- 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 [28]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})

In [29]: x.iloc[1] = dict(x=9, y=99)

In [30]: x
Out[30]:
   x   y
0  1   3
1  9  99
2  3   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 [31]: s[:5]
Out[31]:
2000-01-01    0.469112
2000-01-02    1.212112
2000-01-03   -0.861849
2000-01-04    0.721555
2000-01-05   -0.424972
Freq: D, Name: A, dtype: float64

In [32]: s[::2]
Out[32]:
2000-01-01    0.469112
2000-01-03   -0.861849
2000-01-05   -0.424972
2000-01-07    0.404705
Freq: 2D, Name: A, dtype: float64

In [33]: s[::-1]
Out[33]:
2000-01-08   -0.370647
2000-01-07    0.404705
2000-01-06   -0.673690
```

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```
2000-01-05   -0.424972
2000-01-04    0.721555
2000-01-03   -0.861849
2000-01-02    1.212112
2000-01-01    0.469112
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [34]: s2 = s.copy()

In [35]: s2[:5] = 0

In [36]: s2
Out[36]: 
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06   -0.673690
2000-01-07    0.404705
2000-01-08   -0.370647
Freq: D, Name: A, dtype: float64
```

With DataFrame, slicing inside of `[]` **slices the rows**. This is provided largely as a convenience since it is such a common operation.

```
In [37]: df[:3]
Out[37]: 
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804

In [38]: df[::-1]
Out[38]: 
                   A         B         C         D
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
```

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

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Warning:

`.loc` is strict when you present slicers that are not compatible (or convertible) with the index type. For example using integers in a `DatetimeIndex`. These will raise a `TypeError`.

```
In [39]: dfl = pd.DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=pd.date_range(

In [40]: dfl
Out[40]:
                   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 the
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [41]: dfl.loc['20130102':'20130104']
Out[41]:
                   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
- A `callable`, see Selection By Callable

```
In [42]: s1 = pd.Series(np.random.randn(6),index=list('abcdef'))

In [43]: s1
Out[43]:
a    1.431256
b    1.340309
c   -1.170299
```

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```
d   -0.226169
e    0.410835
f    0.813850
dtype: float64

In [44]: s1.loc['c':]
Out[44]:
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64

In [45]: s1.loc['b']
Out[45]: 1.3403088497993827
```

Note that setting works as well:

```
In [46]: s1.loc['c':] = 0

In [47]: s1
Out[47]:
a    1.431256
b    1.340309
c    0.000000
d    0.000000
e    0.000000
f    0.000000
dtype: float64
```

With a DataFrame

```
In [48]: df1 = pd.DataFrame(np.random.randn(6,4),
   ....:                    index=list('abcdef'),
   ....:                    columns=list('ABCD'))
   ....:

In [49]: df1
Out[49]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
c  1.024180  0.569605  0.875906 -2.211372
d  0.974466 -2.006747 -0.410001 -0.078638
e  0.545952 -1.219217 -1.226825  0.769804
f -1.281247 -0.727707 -0.121306 -0.097883

In [50]: df1.loc[['a', 'b', 'd'], :]
Out[50]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
d  0.974466 -2.006747 -0.410001 -0.078638
```

Accessing via label slices

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```
In [51]: df1.loc['d':, 'A':'C']
Out[51]:
          A         B         C
d  0.974466 -2.006747 -0.410001
e  0.545952 -1.219217 -1.226825
f -1.281247 -0.727707 -0.121306
```

For getting a cross section using a label (equiv to `df.xs('a')`)

```
In [52]: df1.loc['a']
Out[52]:
A    0.132003
B   -0.827317
C   -0.076467
D   -1.187678
Name: a, dtype: float64
```

For getting values with a boolean array

```
In [53]: df1.loc['a'] > 0
Out[53]:
A     True
B    False
C    False
D    False
Name: a, dtype: bool

In [54]: df1.loc[:, df1.loc['a'] > 0]
Out[54]:
          A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247
```

For getting a value explicitly (equiv to deprecated `df.get_value('a','A')`)

```
# this is also equivalent to ``df1.at['a','A']``
In [55]: df1.loc['a', 'A']
Out[55]: 0.13200317033032932
```

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

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Pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely python and numpy slicing. These are `0-based` indexing. When slicing, the start bounds is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a **valid** label will raise an `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. `5`
- A list or array of integers `[4, 3, 0]`
- A slice object with ints `1:7`
- A boolean array
- A `callable`, see Selection By Callable

```
In [56]: s1 = pd.Series(np.random.randn(5), index=list(range(0,10,2)))

In [57]: s1
Out[57]:
0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64

In [58]: s1.iloc[:3]
Out[58]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64

In [59]: s1.iloc[3]
Out[59]: -1.1103361028911669
```

Note that setting works as well:

```
In [60]: s1.iloc[:3] = 0

In [61]: s1
Out[61]:
0    0.000000
2    0.000000
4    0.000000
6   -1.110336
8   -0.619976
dtype: float64
```

With a DataFrame

```
In [62]: df1 = pd.DataFrame(np.random.randn(6,4),
   ....:                    index=list(range(0,12,2)),
   ....:                    columns=list(range(0,8,2)))
   ....:

In [63]: df1
Out[63]:
          0         2         4         6
0   0.149748 -0.732339  0.687738  0.176444
2   0.403310 -0.154951  0.301624 -2.179861
```

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```
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 [64]: df1.iloc[:3]
Out[64]:
          0         2         4         6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [65]: df1.iloc[1:5, 2:4]
Out[65]:
          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 [66]: df1.iloc[[1, 3, 5], [1, 3]]
Out[66]:
           2         6
2  -0.154951 -2.179861
6  -0.345352  0.690579
10 -1.236269 -0.487602
```

```
In [67]: df1.iloc[1:3, :]
Out[67]:
          0         2         4         6
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
```

```
In [68]: df1.iloc[:, 1:3]
Out[68]:
           2         4
0  -0.732339  0.687738
2  -0.154951  0.301624
4  -0.954208  1.462696
6  -0.345352  1.314232
8   2.396780  0.014871
10 -1.236269  0.896171
```

```
# this is also equivalent to ``df1.iat[1,1]``
In [69]: df1.iloc[1, 1]
Out[69]: -0.15495077442490321
```

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For getting a cross section using an integer position (equiv to `df.xs(1)`)

```
In [70]: df1.iloc[1]
Out[70]: 
0    0.403310
2   -0.154951
4    0.301624
6   -2.179861
Name: 2, dtype: float64
```

Out of range slice indexes are handled gracefully just as in Python/Numpy.

```
# these are allowed in python/numpy.
# Only works in Pandas starting from v0.14.0.
In [71]: x = list('abcdef')

In [72]: x
Out[72]: ['a', 'b', 'c', 'd', 'e', 'f']

In [73]: x[4:10]
Out[73]: ['e', 'f']

In [74]: x[8:10]
Out[74]: []

In [75]: s = pd.Series(x)

In [76]: s
Out[76]: 
0    a
1    b
2    c
3    d
4    e
5    f
dtype: object

In [77]: s.iloc[4:10]
Out[77]: 
4    e
5    f
dtype: object

In [78]: s.iloc[8:10]
Out[78]: 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 [79]: dfl = pd.DataFrame(np.random.randn(5,2), columns=list('AB'))

In [80]: dfl
Out[80]: 
          A         B
0 -0.082240 -2.182937
1  0.380396  0.084844
2  0.432390  1.519970
```

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```
3 -0.493662  0.600178
4  0.274230  0.132885

In [81]: dfl.iloc[:, 2:3]
Out[81]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [82]: dfl.iloc[:, 1:3]
Out[82]:
          B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885

In [83]: dfl.iloc[4:6]
Out[83]:
         A         B
4  0.27423  0.132885
```

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`

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

dfl.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

Selection By Callable

New in version 0.18.1.

`.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. The `callable` must be a function with one argument (the calling Series, DataFrame or Panel) and that returns valid output for indexing.

```
In [84]: df1 = pd.DataFrame(np.random.randn(6, 4),
   ....:                    index=list('abcdef'),
   ....:                    columns=list('ABCD'))
   ....:

In [85]: df1
Out[85]:
          A         B         C         D
a -0.023688  2.410179  1.450520  0.206053
b -0.251905 -2.213588  1.063327  1.266143
c  0.299368 -0.863838  0.408204 -1.048089
d -0.025747 -0.988387  0.094055  1.262731
e  1.289997  0.082423 -0.055758  0.536580
f -0.489682  0.369374 -0.034571 -2.484478

In [86]: df1.loc[lambda df: df.A > 0, :]
Out[86]:
```

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```
          A         B         C         D
c  0.299368 -0.863838  0.408204 -1.048089
e  1.289997  0.082423 -0.055758  0.536580

In [87]: df1.loc[:, lambda df: ['A', 'B']]
Out[87]:
          A         B
a -0.023688  2.410179
b -0.251905 -2.213588
c  0.299368 -0.863838
d -0.025747 -0.988387
e  1.289997  0.082423
f -0.489682  0.369374

In [88]: df1.iloc[:, lambda df: [0, 1]]
Out[88]:
          A         B
a -0.023688  2.410179
b -0.251905 -2.213588
c  0.299368 -0.863838
d -0.025747 -0.988387
e  1.289997  0.082423
f -0.489682  0.369374

In [89]: df1[lambda df: df.columns[0]]
Out[89]:
a   -0.023688
b   -0.251905
c    0.299368
d   -0.025747
e    1.289997
f   -0.489682
Name: A, dtype: float64
```

You can use callable indexing in `Series`.

```
In [90]: df1.A.loc[lambda s: s > 0]
Out[90]:
c    0.299368
e    1.289997
Name: A, dtype: float64
```

Using these methods / indexers, you can chain data selection operations without using temporary variable.

```
In [91]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [92]: (bb.groupby(['year', 'team']).sum()
   ....:    .loc[lambda df: df.r > 100])
   ....:
Out[92]:
           stint    g    ab    r    h  X2b  X3b  hr    rbi    sb   cs   bb  \
year team
2007 CIN       6  379   745  101  203   35    2  36  125.0  10.0  1.0  105
     DET       5  301  1062  162  283   54    4  37  144.0  24.0  7.0   97
     HOU       4  311   926  109  218   47    6  14   77.0  10.0  4.0   60
     LAN      11  413  1021  153  293   61    3  36  154.0   7.0  5.0  114
     NYN      13  622  1854  240  509  101    3  61  243.0  22.0  4.0  174
     SFN       5  482  1305  198  337   67    6  40  171.0  26.0  7.0  235
     TEX       2  198   729  115  200   40    4  28  115.0  21.0  4.0   73
     TOR       4  459  1408  187  378   96    2  58  223.0   4.0  2.0  190
```

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```
                so    ibb    hbp     sh     sf   gidp
year team
2007 CIN   127.0  14.0    1.0    1.0   15.0   18.0
     DET   176.0   3.0   10.0    4.0    8.0   28.0
     HOU   212.0   3.0    9.0   16.0    6.0   17.0
     LAN   141.0   8.0    9.0    3.0    8.0   29.0
     NYN   310.0  24.0   23.0   18.0   15.0   48.0
     SFN   188.0  51.0    8.0   16.0    6.0   41.0
     TEX   140.0   4.0    5.0    2.0    8.0   16.0
     TOR   265.0  16.0   12.0    4.0   16.0   38.0
```

IX Indexer is Deprecated

Warning: Starting in 0.20.0, the `.ix` indexer is deprecated, in favor of the more strict `.iloc` and `.loc` indexers.

`.ix` offers a lot of magic on the inference of what the user wants to do. To wit, `.ix` can decide to index *positionally* OR via *labels* depending on the data type of the index. This has caused quite a bit of user confusion over the years.

The recommended methods of indexing are:

- `.loc` if you want to *label* index
- `.iloc` if you want to *positionally* index.

```
In [93]: dfd = pd.DataFrame({'A': [1, 2, 3],
   ....:                     'B': [4, 5, 6]},
   ....:                    index=list('abc'))
   ....:

In [94]: dfd
Out[94]:
   A  B
a  1  4
b  2  5
c  3  6
```

Previous Behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: dfd.ix[[0, 2], 'A']
Out[3]:
a    1
c    3
Name: A, dtype: int64
```

Using `.loc`. Here we will select the appropriate indexes from the index, then use *label* indexing.

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```
In [95]: dfd.loc[dfd.index[[0, 2]], 'A']
Out[95]:
a    1
```

```
c    3
Name: A, dtype: int64
```

This can also be expressed using `.iloc`, by explicitly getting locations on the indexers, and using *positional* indexing to select things.

```
In [96]: dfd.iloc[[0, 2], dfd.columns.get_loc('A')]
Out[96]:
a    1
c    3
Name: A, dtype: int64
```

For getting *multiple* indexers, using `.get_indexer`

```
In [97]: dfd.iloc[[0, 2], dfd.columns.get_indexer(['A', 'B'])]
Out[97]:
   A  B
a  1  4
c  3  6
```

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 [98]: s = pd.Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1 row.
In [99]: s.sample()
Out[99]:
4    4
dtype: int64

# One may specify either a number of rows:
In [100]: s.sample(n=3)
Out[100]:
0    0
4    4
1    1
dtype: int64

# Or a fraction of the rows:
In [101]: s.sample(frac=0.5)
Out[101]:
5    5
3    3
1    1
dtype: int64
```

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By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

```
In [102]: s = pd.Series([0,1,2,3,4,5])

 # Without replacement (default):
In [103]: s.sample(n=6, replace=False)
Out[103]:
0    0
1    1
5    5
3    3
2    2
4    4
dtype: int64

 # With replacement:
In [104]: s.sample(n=6, replace=True)
Out[104]:
0    0
4    4
3    3
2    2
4    4
4    4
dtype: int64
```

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a numpy array, or a Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```
In [105]: s = pd.Series([0,1,2,3,4,5])

In [106]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [107]: s.sample(n=3, weights=example_weights)
Out[107]:
5    5
4    4
3    3
dtype: int64

# Weights will be re-normalized automatically
In [108]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [109]: s.sample(n=1, weights=example_weights2)
Out[109]:
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 [110]: df2 = pd.DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})

In [111]: df2.sample(n = 3, weights = 'weight_column')
Out[111]:
   col1  weight_column
```

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```
1     8            0.4
0     9            0.5
2     7            0.1
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [112]: df3 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

In [113]: df3.sample(n=1, axis=1)
Out[113]: 
   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 [114]: df4 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

# With a given seed, the sample will always draw the same rows.
In [115]: df4.sample(n=2, random_state=2)
Out[115]: 
   col1  col2
2     3     4
1     2     3

In [116]: df4.sample(n=2, random_state=2)
Out[116]: 
   col1  col2
2     3     4
1     2     3
```

Setting With Enlargement

New in version 0.13.

The `.loc/[]` operations can perform enlargement when setting a non-existant key for that axis.

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

```
In [117]: se = pd.Series([1,2,3])

In [118]: se
Out[118]: 
0    1
1    2
2    3
dtype: int64

In [119]: se[5] = 5.

In [120]: se
Out[120]: 
```

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```
0    1.0
1    2.0
2    3.0
5    5.0
dtype: float64
```

A `DataFrame` can be enlarged on either axis via `.loc`

```
In [121]: dfi = pd.DataFrame(np.arange(6).reshape(3,2),
   .....:                 columns=['A','B'])
   .....:

In [122]: dfi
Out[122]:
   A  B
0  0  1
1  2  3
2  4  5

In [123]: dfi.loc[:,'C'] = dfi.loc[:,'A']

In [124]: dfi
Out[124]:
   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 [125]: dfi.loc[3] = 5

In [126]: dfi
Out[126]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

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`

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```
In [127]: s.iat[5]
Out[127]: 5

In [128]: df.at[dates[5], 'A']
```

```
Out[128]: -0.67368970808837069

In [129]: df.iat[3, 0]
Out[129]: 0.7215551622443669
```

You can also set using these same indexers.

```
In [130]: df.at[dates[5], 'E'] = 7

In [131]: df.iat[3, 0] = 7
```

`at` may enlarge the object in-place as above if the indexer is missing.

```
In [132]: df.at[dates[-1]+1, 0] = 7

In [133]: df
Out[133]:
                   A         B         C         D    E    0
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632  NaN  NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236  NaN  NaN
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804  NaN  NaN
2000-01-04  7.000000 -0.706771 -1.039575  0.271860  NaN  NaN
2000-01-05 -0.424972  0.567020  0.276232 -1.087401  NaN  NaN
2000-01-06 -0.673690  0.113648 -1.478427  0.524988  7.0  NaN
2000-01-07  0.404705  0.577046 -1.715002 -1.039268  NaN  NaN
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885  NaN  NaN
2000-01-09       NaN       NaN       NaN       NaN  NaN  7.0
```

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 [134]: s = pd.Series(range(-3, 4))

In [135]: s
Out[135]:
0   -3
1   -2
2   -1
3    0
4    1
5    2
6    3
dtype: int64

In [136]: s[s > 0]
Out[136]:
4    1
5    2
6    3
dtype: int64
```

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```
In [137]: s[(s < -1) | (s > 0.5)]
Out[137]:
0   -3
1   -2
4    1
5    2
6    3
dtype: int64

In [138]: s[~(s < 0)]
Out[138]:
3    0
4    1
5    2
6    3
dtype: int64
```

You may select rows from a DataFrame using a boolean vector the same length as the DataFrame's index (for example, something derived from one of the columns of the DataFrame):

```
In [139]: df[df['A'] > 0]
Out[139]:
                   A         B         C         D   E   0
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632 NaN NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236 NaN NaN
2000-01-04  7.000000 -0.706771 -1.039575  0.271860 NaN NaN
2000-01-07  0.404705  0.577046 -1.715002 -1.039268 NaN NaN
```

List comprehensions and `map` method of Series can also be used to produce more complex criteria:

```
In [140]: df2 = pd.DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
   .....:                     'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                     'c' : np.random.randn(7)})
   .....:

# only want 'two' or 'three'
In [141]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [142]: df2[criterion]
Out[142]:
       a  b         c
2    two  y  0.041290
3  three  x  0.361719
4    two  y -0.238075

# equivalent but slower
In [143]: df2[[x.startswith('t') for x in df2['a']]]
Out[143]:
       a  b         c
2    two  y  0.041290
3  three  x  0.361719
4    two  y -0.238075

# Multiple criteria
In [144]: df2[criterion & (df2['b'] == 'x')]
Out[144]:
       a  b         c
3  three  x  0.361719
```

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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 [145]: df2.loc[criterion & (df2['b'] == 'x'),'b':'c']
Out[145]:
   b         c
3  x  0.361719
```

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 [146]: s = pd.Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')

In [147]: s
Out[147]:
4    0
3    1
2    2
1    3
0    4
dtype: int64

In [148]: s.isin([2, 4, 6])
Out[148]:
4    False
3    False
2     True
1    False
0     True
dtype: bool

In [149]: s[s.isin([2, 4, 6])]
Out[149]:
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 [150]: s[s.index.isin([2, 4, 6])]
Out[150]:
4    0
2    2
dtype: int64

# compare it to the following
In [151]: s[[2, 4, 6]]
Out[151]:
2    2.0
4    0.0
```

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```
6    NaN
dtype: float64
```

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

```
In [152]: s_mi = pd.Series(np.arange(6),
   .....:                  index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']]))
   .....:

In [153]: s_mi
Out[153]:
0  a    0
   b    1
   c    2
1  a    3
   b    4
   c    5
dtype: int64

In [154]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[154]:
0  c    2
1  a    3
dtype: int64

In [155]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[155]:
0  a    0
   c    2
1  a    3
   c    5
dtype: int64
```

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 [156]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
   .....:                    'ids2': ['a', 'n', 'c', 'n']})
   .....:

In [157]: values = ['a', 'b', 1, 3]

In [158]: df.isin(values)
Out[158]:
     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.

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```
In [159]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}
```

```
In [160]: df.isin(values)
Out[160]:
     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 [161]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}

In [162]: row_mask = df.isin(values).all(1)

In [163]: df[row_mask]
Out[163]:
  ids ids2  vals
0   a    a     1
```

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 [164]: s[s > 0]
Out[164]:
3    1
2    2
1    3
0    4
dtype: int64
```

To return a Series of the same shape as the original

```
In [165]: s.where(s > 0)
Out[165]:
4    NaN
3    1.0
2    2.0
1    3.0
0    4.0
dtype: float64
```

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. Equivalent is `df.where(df < 0)`

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```
In [166]: df[df < 0]
Out[166]: 
                   A         B         C         D
2000-01-01 -2.104139 -1.309525       NaN       NaN
2000-01-02 -0.352480       NaN -1.192319       NaN
2000-01-03 -0.864883       NaN -0.227870       NaN
2000-01-04       NaN -1.222082       NaN -1.233203
2000-01-05       NaN -0.605656 -1.169184       NaN
2000-01-06       NaN -0.948458       NaN -0.684718
2000-01-07 -2.670153 -0.114722       NaN -0.048048
2000-01-08       NaN       NaN -0.048788 -0.808838
```

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [167]: df.where(df < 0, -df)
Out[167]: 
                   A         B         C         D
2000-01-01 -2.104139 -1.309525 -0.485855 -0.245166
2000-01-02 -0.352480 -0.390389 -1.192319 -1.655824
2000-01-03 -0.864883 -0.299674 -0.227870 -0.281059
2000-01-04 -0.846958 -1.222082 -0.600705 -1.233203
2000-01-05 -0.669692 -0.605656 -1.169184 -0.342416
2000-01-06 -0.868584 -0.948458 -2.297780 -0.684718
2000-01-07 -2.670153 -0.114722 -0.168904 -0.048048
2000-01-08 -0.801196 -1.392071 -0.048788 -0.808838
```

You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```
In [168]: s2 = s.copy()

In [169]: s2[s2 < 0] = 0

In [170]: s2
Out[170]: 
4    0
3    1
2    2
1    3
0    4
dtype: int64

In [171]: df2 = df.copy()

In [172]: df2[df2 < 0] = 0

In [173]: df2
Out[173]: 
                   A         B         C         D
2000-01-01  0.000000  0.000000  0.485855  0.245166
2000-01-02  0.000000  0.390389  0.000000  1.655824
2000-01-03  0.000000  0.299674  0.000000  0.281059
2000-01-04  0.846958  0.000000  0.600705  0.000000
2000-01-05  0.669692  0.000000  0.000000  0.342416
2000-01-06  0.868584  0.000000  2.297780  0.000000
2000-01-07  0.000000  0.000000  0.168904  0.000000
2000-01-08  0.801196  1.392071  0.000000  0.000000
```

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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 [174]: df_orig = df.copy()

In [175]: df_orig.where(df > 0, -df, inplace=True);

In [176]: df_orig
Out[176]:
                   A         B         C         D
2000-01-01  2.104139  1.309525  0.485855  0.245166
2000-01-02  0.352480  0.390389  1.192319  1.655824
2000-01-03  0.864883  0.299674  0.227870  0.281059
2000-01-04  0.846958  1.222082  0.600705  1.233203
2000-01-05  0.669692  0.605656  1.169184  0.342416
2000-01-06  0.868584  0.948458  2.297780  0.684718
2000-01-07  2.670153  0.114722  0.168904  0.048048
2000-01-08  0.801196  1.392071  0.048788  0.808838
```

Note: The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

```
In [177]: df.where(df < 0, -df) == np.where(df < 0, df, -df)
Out[177]:
               A     B     C     D
2000-01-01  True  True  True  True
2000-01-02  True  True  True  True
2000-01-03  True  True  True  True
2000-01-04  True  True  True  True
2000-01-05  True  True  True  True
2000-01-06  True  True  True  True
2000-01-07  True  True  True  True
2000-01-08  True  True  True  True
```

alignment

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.loc` (but on the contents rather than the axis labels)

```
In [178]: df2 = df.copy()

In [179]: df2[ df2[1:4] > 0 ] = 3

In [180]: df2
Out[180]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525  0.485855  0.245166
2000-01-02 -0.352480  3.000000 -1.192319  3.000000
2000-01-03 -0.864883  3.000000 -0.227870  3.000000
2000-01-04  3.000000 -1.222082  3.000000 -1.233203
2000-01-05  0.669692 -0.605656 -1.169184  0.342416
2000-01-06  0.868584 -0.948458  2.297780 -0.684718
```

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```
2000-01-07 -2.670153 -0.114722  0.168904 -0.048048
2000-01-08  0.801196  1.392071 -0.048788 -0.808838
```

New in version 0.13.

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

```
In [181]: df2 = df.copy()

In [182]: df2.where(df2>0,df2['A'],axis='index')
Out[182]: 
                   A         B         C         D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

This is equivalent (but faster than) the following.

```
In [183]: df2 = df.copy()

In [184]: df.apply(lambda x, y: x.where(x>0,y), y=df['A'])
Out[184]: 
                   A         B         C         D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

New in version 0.18.1.

Where can accept a callable as condition and `other` arguments. The function must be with one argument (the calling Series or DataFrame) and that returns valid output as condition and `other` argument.

```
In [185]: df3 = pd.DataFrame({'A': [1, 2, 3],
   .....:                     'B': [4, 5, 6],
   .....:                     'C': [7, 8, 9]})
   .....: 

In [186]: df3.where(lambda x: x > 4, lambda x: x + 10)
Out[186]: 
    A   B  C
0  11  14  7
1  12   5  8
2  13   6  9
```

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mask

`mask` is the inverse boolean operation of `where`.

```
In [187]: s.mask(s >= 0)
Out[187]:
4   NaN
3   NaN
2   NaN
1   NaN
0   NaN
dtype: float64

In [188]: df.mask(df >= 0)
Out[188]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525       NaN       NaN
2000-01-02 -0.352480       NaN -1.192319       NaN
2000-01-03 -0.864883       NaN -0.227870       NaN
2000-01-04       NaN -1.222082       NaN -1.233203
2000-01-05       NaN -0.605656 -1.169184       NaN
2000-01-06       NaN -0.948458       NaN -0.684718
2000-01-07 -2.670153 -0.114722       NaN -0.048048
2000-01-08       NaN       NaN -0.048788 -0.808838
```

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 [189]: n = 10

In [190]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [191]: df
Out[191]:
          a         b         c
0  0.438921  0.118680  0.863670
1  0.138138  0.577363  0.686602
2  0.595307  0.564592  0.520630
3  0.913052  0.926075  0.616184
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
6  0.792342  0.216974  0.564056
7  0.397890  0.454131  0.915716
8  0.074315  0.437913  0.019794
9  0.559209  0.502065  0.026437

# pure python
In [192]: df[(df.a < df.b) & (df.b < df.c)]
Out[192]:
          a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
```

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```
7  0.397890  0.454131  0.915716

# query
In [193]: df.query('(a < b) & (b < c)')
Out[193]:
          a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

Do the same thing but fall back on a named index if there is no column with the name `a`.

```
In [194]: df = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))

In [195]: df.index.name = 'a'

In [196]: df
Out[196]:
   b  c
a
0  0  4
1  0  1
2  3  4
3  4  3
4  1  4
5  0  3
6  0  1
7  3  4
8  2  3
9  1  1

In [197]: df.query('a < b and b < c')
Out[197]:
   b  c
a
2  3  4
```

If instead you don’t want to or cannot name your index, you can use the name `index` in your query expression:

```
In [198]: df = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))

In [199]: df
Out[199]:
   b  c
0  3  1
1  3  0
2  5  6
3  5  2
4  7  4
5  0  1
6  2  5
7  0  1
8  6  0
9  7  9

In [200]: df.query('index < b < c')
Out[200]:
```

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```
   b  c
2  5  6
```

Note: If the name of your index overlaps with a column name, the column name is given precedence. For example,

```
In [201]: df = pd.DataFrame({'a': np.random.randint(5, size=5)})

In [202]: df.index.name = 'a'

In [203]: df.query('a > 2') # uses the column 'a', not the index
Out[203]:
   a
a
1  3
3  3
```

You can still use the index in a query expression by using the special identifier 'index':

```
In [204]: df.query('index > 2')
Out[204]:
   a
a
3  3
4  2
```

If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

`MultiIndex` `query()` Syntax

You can also use the levels of a `DataFrame` with a **`MultiIndex`** as if they were columns in the frame:

```
In [205]: n = 10

In [206]: colors = np.random.choice(['red', 'green'], size=n)

In [207]: foods = np.random.choice(['eggs', 'ham'], size=n)

In [208]: colors
Out[208]:
array(['red', 'red', 'red', 'green', 'green', 'green', 'green', 'green',
       'green', 'green'],
      dtype='<U5')

In [209]: foods
Out[209]:
array(['ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham', 'ham', 'eggs', 'eggs',
       'eggs'],
      dtype='<U4')

In [210]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])
```

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```
In [211]: df = pd.DataFrame(np.random.randn(n, 2), index=index)

In [212]: df
Out[212]: 
                   0         1
color food                    
red   ham   0.194889 -0.381994
      ham   0.318587  2.089075
      eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
      eggs -2.029766  0.792652
      ham   0.461007 -0.542749
      ham  -0.305384 -0.479195
      eggs  0.095031 -0.270099
      eggs -0.707140 -0.773882
      eggs  0.229453  0.304418

In [213]: df.query('color == "red"')
Out[213]: 
                   0         1
color food                    
red   ham   0.194889 -0.381994
      ham   0.318587  2.089075
      eggs -0.728293 -0.090255
```

If the levels of the `MultiIndex` are unnamed, you can refer to them using special names:

```
In [214]: df.index.names = [None, None]

In [215]: df
Out[215]: 
                   0         1
red   ham   0.194889 -0.381994
      ham   0.318587  2.089075
      eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
      eggs -2.029766  0.792652
      ham   0.461007 -0.542749
      ham  -0.305384 -0.479195
      eggs  0.095031 -0.270099
      eggs -0.707140 -0.773882
      eggs  0.229453  0.304418

In [216]: df.query('ilevel_0 == "red"')
Out[216]: 
                 0         1
red ham   0.194889 -0.381994
    ham   0.318587  2.089075
    eggs -0.728293 -0.090255
```

The convention is `ilevel_0`, which means "index level 0" for the 0th level of the `index`.

`query()` Use Cases

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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 [217]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [218]: df
Out[218]: 
          a         b         c
0  0.224283  0.736107  0.139168
1  0.302827  0.657803  0.713897
2  0.611185  0.136624  0.984960
3  0.195246  0.123436  0.627712
4  0.618673  0.371660  0.047902
5  0.480088  0.062993  0.185760
6  0.568018  0.483467  0.445289
7  0.309040  0.274580  0.587101
8  0.258993  0.477769  0.370255
9  0.550459  0.840870  0.304611

In [219]: df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)

In [220]: df2
Out[220]: 
           a         b         c
0   0.357579  0.229800  0.596001
1   0.309059  0.957923  0.965663
2   0.123102  0.336914  0.318616
3   0.526506  0.323321  0.860813
4   0.518736  0.486514  0.384724
5   0.190804  0.505723  0.614533
6   0.891939  0.623977  0.676639
7   0.480559  0.378528  0.460858
8   0.420223  0.136404  0.141295
9   0.732206  0.419540  0.604675
10  0.604466  0.848974  0.896165
11  0.589168  0.920046  0.732716

In [221]: expr = '0.0 <= a <= c <= 0.5'

In [222]: map(lambda frame: frame.query(expr), [df, df2])
Out[222]: <map at 0x1383aa6a0>
```

`query()` Python versus pandas Syntax Comparison

Full numpy-like syntax

```
In [223]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=list('abc'))

In [224]: df
Out[224]: 
   a  b  c
0  7  8  9
1  1  0  7
2  2  7  2
3  6  2  2
4  2  6  3
5  3  8  2
6  1  7  2
7  5  1  5
8  9  8  0
```

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```
9  1  5  0

In [225]: df.query('(a < b) & (b < c)')
Out[225]:
   a  b  c
0  7  8  9

In [226]: df[(df.a < df.b) & (df.b < df.c)]
Out[226]:
   a  b  c
0  7  8  9
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&`/`|`)

```
In [227]: df.query('a < b & b < c')
Out[227]:
   a  b  c
0  7  8  9
```

Use English instead of symbols

```
In [228]: df.query('a < b and b < c')
Out[228]:
   a  b  c
0  7  8  9
```

Pretty close to how you might write it on paper

```
In [229]: df.query('a < b < c')
Out[229]:
   a  b  c
0  7  8  9
```

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 [230]: df = pd.DataFrame({'a': list('aabbccddeeff'), 'b': list('aaaabbbbcccc'),
   .....:                    'c': np.random.randint(5, size=12),
   .....:                    'd': np.random.randint(9, size=12)})
   .....:

In [231]: df
Out[231]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
```

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```
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

In [232]: df.query('a in b')
Out[232]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2

# How you'd do it in pure Python
In [233]: df[df.a.isin(df.b)]
Out[233]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2

In [234]: df.query('a not in b')
Out[234]:
    a  b  c  d
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

# pure Python
In [235]: df[~df.a.isin(df.b)]
Out[235]:
    a  b  c  d
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2
```

You can combine this with other expressions for very succinct queries:

```
# rows where cols a and b have overlapping values and col c's values are less than col d's
In [236]: df.query('a in b and c < d')
Out[236]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
4  c  b  3  6
5  c  b  0  2

# pure Python
```

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```
In [237]: df[df.b.isin(df.a) & (df.c < df.d)]
Out[237]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
4   c  b  3  6
5   c  b  0  2
10  f  c  0  6
11  f  c  1  2
```

Note: Note that `in` and `not in` are evaluated in Python, since `numexpr` has no equivalent of this operation. However, **only the** `in`/`not in` **expression itself** is evaluated in vanilla Python. For example, in the expression

```
df.query('a in b + c + d')
```

`(b + c + d)` is evaluated by `numexpr` and *then* the `in` operation is evaluated in plain Python. In general, any operations that can be evaluated using `numexpr` will be.

Special use of the `==` operator with `list` objects

Comparing a `list` of values to a column using `==`/`!=` works similarly to `in`/`not in`

```
In [238]: df.query('b == ["a", "b", "c"]')
Out[238]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

# pure Python
In [239]: df[df.b.isin(["a", "b", "c"])]
Out[239]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
```

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```
10   f  c  0  6
11   f  c  1  2

In [240]: df.query('c == [1, 2]')
Out[240]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2

In [241]: df.query('c != [1, 2]')
Out[241]:
    a  b  c  d
1   a  a  4  7
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
8   e  c  4  3
10  f  c  0  6

# using in/not in
In [242]: df.query('[1, 2] in c')
Out[242]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2

In [243]: df.query('[1, 2] not in c')
Out[243]:
    a  b  c  d
1   a  a  4  7
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
8   e  c  4  3
10  f  c  0  6

# pure Python
In [244]: df[df.c.isin([1, 2])]
Out[244]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2
```

Boolean Operators

You can negate boolean expressions with the word `not` or the `~` operator.

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```
In [245]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [246]: df['bools'] = np.random.rand(len(df)) > 0.5

In [247]: df.query('~bools')
Out[247]:
          a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [248]: df.query('not bools')
Out[248]:
          a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [249]: df.query('not bools') == df[~df.bools]
Out[249]:
      a     b     c  bools
2  True  True  True   True
7  True  True  True   True
8  True  True  True   True
```

Of course, expressions can be arbitrarily complex too

```
# short query syntax
In [250]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [251]: longer = df[(df.a < df.b) & (df.b < df.c) & (~df.bools) | (df.bools > 2)]

In [252]: shorter
Out[252]:
          a         b         c  bools
7  0.275396  0.691034  0.826619  False

In [253]: longer
Out[253]:
          a         b         c  bools
7  0.275396  0.691034  0.826619  False

In [254]: shorter == longer
Out[254]:
      a     b     c  bools
7  True  True  True   True
```

Performance of `query()`

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames

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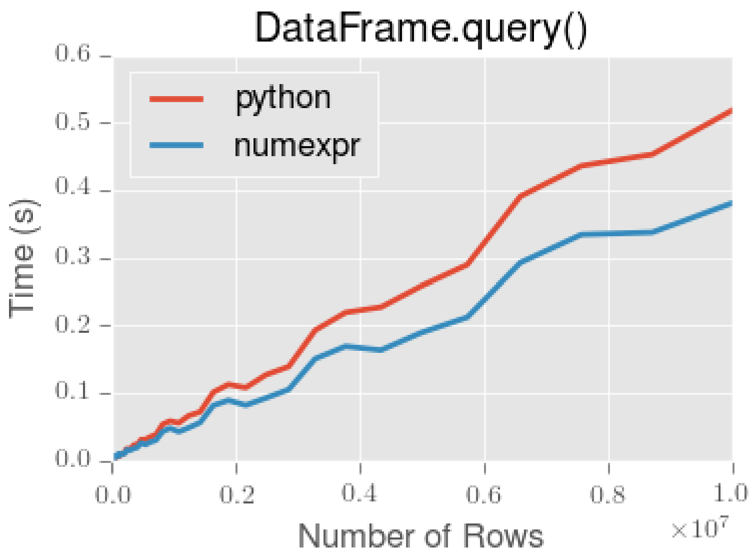
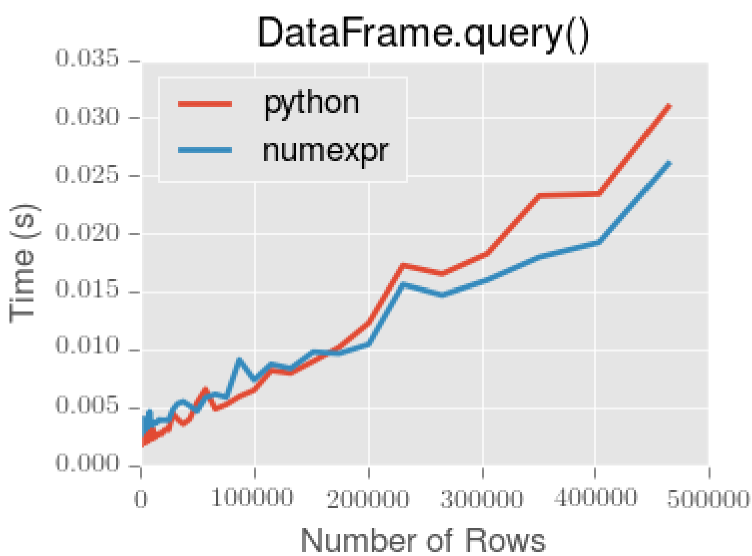


Note: You will only see the performance benefits of using the `numexpr` engine with `DataFrame.query()` if your frame has more than approximately 200,000 rows



This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

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.

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By default, the first observed row of a duplicate set is considered unique, but each method has a `keep` parameter to specify targets to be kept.

- `keep='first'` (default): mark / drop duplicates except for the first occurrence.
- `keep='last'`: mark / drop duplicates except for the last occurrence.
- `keep=False`: mark / drop all duplicates.

```
In [255]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'two', 'two', 'three', 'four'],
   .....:                     'b': ['x', 'y', 'x', 'y', 'x', 'x', 'x'],
   .....:                     'c': np.random.randn(7)})
   .....:

In [256]: df2
Out[256]:
       a  b         c
0    one  x -1.067137
1    one  y  0.309500
2    two  x -0.211056
3    two  y -1.842023
4    two  x -0.390820
5  three  x -1.964475
6   four  x  1.298329

In [257]: df2.duplicated('a')
Out[257]:
0    False
1     True
2    False
3     True
4     True
5    False
6    False
dtype: bool

In [258]: df2.duplicated('a', keep='last')
Out[258]:
0     True
1    False
2     True
3     True
4    False
5    False
6    False
dtype: bool

In [259]: df2.duplicated('a', keep=False)
Out[259]:
0     True
1     True
2     True
3     True
4     True
5    False
6    False
dtype: bool

In [260]: df2.drop_duplicates('a')
Out[260]:
       a  b         c
0    one  x -1.067137
2    two  x -0.211056
```

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```
5  three  x -1.964475
6   four  x  1.298329

In [261]: df2.drop_duplicates('a', keep='last')
Out[261]:
       a  b         c
1    one  y  0.309500
4    two  x -0.390820
5  three  x -1.964475
6   four  x  1.298329

In [262]: df2.drop_duplicates('a', keep=False)
Out[262]:
       a  b         c
5  three  x -1.964475
6   four  x  1.298329
```

Also, you can pass a list of columns to identify duplications.

```
In [263]: df2.duplicated(['a', 'b'])
Out[263]:
0    False
1    False
2    False
3    False
4     True
5    False
6    False
dtype: bool

In [264]: df2.drop_duplicates(['a', 'b'])
Out[264]:
       a  b         c
0    one  x -1.067137
1    one  y  0.309500
2    two  x -0.211056
3    two  y -1.842023
5  three  x -1.964475
6   four  x  1.298329
```

To drop duplicates by index value, use `Index.duplicated` then perform slicing. Same options are available in `keep` parameter.

```
In [265]: df3 = pd.DataFrame({'a': np.arange(6),
   .....:                     'b': np.random.randn(6)},
   .....:                    index=['a', 'a', 'b', 'c', 'b', 'a'])
   .....:

In [266]: df3
Out[266]:
   a         b
a  0  1.440455
a  1  2.456086
b  2  1.038402
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [267]: df3.index.duplicated()
```

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```
Out[267]: array([False,  True, False, False,  True,  True], dtype=bool)

In [268]: df3[~df3.index.duplicated()]
Out[268]:
   a         b
a  0  1.440455
b  2  1.038402
c  3 -0.894409

In [269]: df3[~df3.index.duplicated(keep='last')]
Out[269]:
   a         b
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [270]: df3[~df3.index.duplicated(keep=False)]
Out[270]:
   a         b
c  3 -0.894409
```

Dictionary-like `get()` method

Each of Series, DataFrame, and Panel have a `get` method which can return a default value.

```
In [271]: s = pd.Series([1,2,3], index=['a','b','c'])

In [272]: s.get('a')               # equivalent to s['a']
Out[272]: 1

In [273]: s.get('x', default=-1)
Out[273]: -1
```

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 [274]: df.select(lambda x: x == 'A', axis=1)
Out[274]:
                   A
2000-01-01  0.355794
2000-01-02  1.635763
2000-01-03  0.854409
2000-01-04 -0.216659
2000-01-05  2.414688
2000-01-06 -1.206215
2000-01-07  0.779461
2000-01-08 -0.878999
```

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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 [275]: dflookup = pd.DataFrame(np.random.rand(20,4), columns = ['A','B','C','D'])

In [276]: dflookup.lookup(list(range(0,10,2)), ['B','C','A','B','D'])
Out[276]: array([ 0.3506,  0.4779,  0.4825,  0.9197,  0.5019])
```

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 [277]: index = pd.Index(['e', 'd', 'a', 'b'])

In [278]: index
Out[278]: Index(['e', 'd', 'a', 'b'], dtype='object')

In [279]: 'd' in index
Out[279]: True
```

You can also pass a `name` to be stored in the index:

```
In [280]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')

In [281]: index.name
Out[281]: 'something'
```

The name, if set, will be shown in the console display:

```
In [282]: index = pd.Index(list(range(5)), name='rows')

In [283]: columns = pd.Index(['A', 'B', 'C'], name='cols')

In [284]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [285]: df
Out[285]: 
cols         A         B         C
rows                              
0     1.295989  0.185778  0.436259
1     0.678101  0.311369 -0.528378
2    -0.674808 -1.103529 -0.656157
3     1.889957  2.076651 -1.102192
4    -1.211795 -0.791746  0.634724

In [286]: df['A']
```

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```
Out[286]:
rows
0    1.295989
1    0.678101
2   -0.674808
3    1.889957
4   -1.211795
Name: A, dtype: float64
```

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 [287]: ind = pd.Index([1, 2, 3])

In [288]: ind.rename("apple")
Out[288]: Int64Index([1, 2, 3], dtype='int64', name='apple')

In [289]: ind
Out[289]: Int64Index([1, 2, 3], dtype='int64')

In [290]: ind.set_names(["apple"], inplace=True)

In [291]: ind.name = "bob"

In [292]: ind
Out[292]: Int64Index([1, 2, 3], dtype='int64', name='bob')
```

New in version 0.15.0.

`set_names`, `set_levels`, and `set_labels` also take an optional *level*` argument

```
In [293]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'secon

In [294]: index
Out[294]:
MultiIndex(levels=[[0, 1, 2], ['one', 'two']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=['first', 'second'])

In [295]: index.levels[1]
Out[295]: Index(['one', 'two'], dtype='object', name='second')

In [296]: index.set_levels(["a", "b"], level=1)
Out[296]:
MultiIndex(levels=[[0, 1, 2], ['a', 'b']],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
           names=['first', 'second'])
```

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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 [297]: a = pd.Index(['c', 'b', 'a'])

In [298]: b = pd.Index(['c', 'e', 'd'])

In [299]: a | b
Out[299]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [300]: a & b
Out[300]: Index(['c'], dtype='object')

In [301]: a.difference(b)
Out[301]: Index(['a', 'b'], dtype='object')
```

Also available is the `symmetric_difference (^)` 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 [302]: idx1 = pd.Index([1, 2, 3, 4])

In [303]: idx2 = pd.Index([2, 3, 4, 5])

In [304]: idx1.symmetric_difference(idx2)
Out[304]: Int64Index([1, 5], dtype='int64')

In [305]: idx1 ^ idx2
Out[305]: Int64Index([1, 5], dtype='int64')
```

Note: The resulting index from a set operation will be sorted in ascending order.

Missing values

New in version 0.17.1.

Important: Even though `Index` can hold missing values (`NaN`), it should be avoided if you do not want any unexpected results. For example, some operations exclude missing values implicitly. **Scroll To Top**

`Index.fillna` fills missing values with specified scalar value.

```
In [306]: idx1 = pd.Index([1, np.nan, 3, 4])

In [307]: idx1
Out[307]: Float64Index([1.0, nan, 3.0, 4.0], dtype='float64')

In [308]: idx1.fillna(2)
Out[308]: Float64Index([1.0, 2.0, 3.0, 4.0], dtype='float64')

In [309]: idx2 = pd.DatetimeIndex([pd.Timestamp('2011-01-01'), pd.NaT, pd.Timestamp('2011-01-0

In [310]: idx2
Out[310]: DatetimeIndex(['2011-01-01', 'NaT', '2011-01-03'], dtype='datetime64[ns]', freq=None

In [311]: idx2.fillna(pd.Timestamp('2011-01-02'))
Out[311]: DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], dtype='datetime64[ns]', fre
```

Set / Reset Index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you've already done so. There are a couple of different ways.

Set an index

DataFrame has a `set_index` method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`), to create a new, indexed DataFrame:

```
In [312]: data
Out[312]:
     a    b  c    d
0  bar  one  z  1.0
1  bar  two  y  2.0
2  foo  one  x  3.0
3  foo  two  w  4.0

In [313]: indexed1 = data.set_index('c')

In [314]: indexed1
Out[314]:
     a    b    d
c
z  bar  one  1.0
y  bar  two  2.0
x  foo  one  3.0
w  foo  two  4.0

In [315]: indexed2 = data.set_index(['a', 'b'])

In [316]: indexed2
Out[316]:
         c    d
a   b
bar one  z  1.0
    two  y  2.0
foo one  x  3.0
    two  w  4.0
```

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The append keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [317]: frame = data.set_index('c', drop=False)

In [318]: frame = frame.set_index(['a', 'b'], append=True)

In [319]: frame
Out[319]:
           c    d
c a   b
z bar one  z  1.0
y bar two  y  2.0
x foo one  x  3.0
w foo two  w  4.0
```

Other options in set_index allow you not drop the index columns or to add the index in-place (without creating a new object):

```
In [320]: data.set_index('c', drop=False)
Out[320]:
     a    b  c    d
c
z  bar  one  z  1.0
y  bar  two  y  2.0
x  foo  one  x  3.0
w  foo  two  w  4.0

In [321]: data.set_index(['a', 'b'], inplace=True)

In [322]: data
Out[322]:
         c    d
a   b
bar one  z  1.0
    two  y  2.0
foo one  x  3.0
    two  w  4.0
```

Reset the index

As a convenience, there is a new function on DataFrame called reset_index which transfers the index values into the DataFrame's columns and sets a simple integer index. This is the inverse operation to set_index

```
In [323]: data
Out[323]:
         c    d
a   b
bar one  z  1.0
    two  y  2.0
foo one  x  3.0
    two  w  4.0
```

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```
In [324]: data.reset_index()
Out[324]:
     a    b  c    d
0  bar  one  z  1.0
1  bar  two  y  2.0
2  foo  one  x  3.0
3  foo  two  w  4.0
```

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 [325]: frame
Out[325]:
           c    d
c a   b
z bar one  z  1.0
y bar two  y  2.0
x foo one  x  3.0
w foo two  w  4.0

In [326]: frame.reset_index(level=1)
Out[326]:
         a  c    d
c b
z one  bar  z  1.0
y two  bar  y  2.0
x one  foo  x  3.0
w two  foo  w  4.0
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

Note: The `reset_index` method used to be called `delevel` which is now deprecated.

Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

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.

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```
In [327]: dfmi = pd.DataFrame([list('abcd'),
   .....:                      list('efgh'),
   .....:                      list('ijkl'),
   .....:                      list('mnop')],
   .....:                     columns=pd.MultiIndex.from_product([['one','two'],
   .....:                                                         ['first','second']]))
   .....:

In [328]: dfmi
Out[328]:
    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 [329]: dfmi['one']['second']
Out[329]:
0    b
1    f
2    j
3    n
Name: second, dtype: object
```

```
In [330]: dfmi.loc[:,('one','second')]
Out[330]:
0    b
1    f
2    j
3    n
Name: (one, second), dtype: object
```

These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (`.loc`) is much preferred over method 1 (chained `[]`)

`dfmi['one']` selects the first level of the columns and returns a DataFrame that is singly-indexed. Then another python operation `dfmi_with_one['second']` selects the series indexed by `'second'` 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.

Why does assignment fail when using chained indexing?

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The problem in the previous section is just a performance issue. What's up with the `SettingWithCopy` warning? We don't **usually** throw warnings around when you do something that might cost a few extra milliseconds!

But it turns out that assigning to the product of chained indexing has inherently unpredictable results. To see this, think about how the Python interpreter executes this code:

```
dfmi.loc[:,('one','second')] = value
# becomes
dfmi.loc.__setitem__((slice(None), ('one', 'second')), value)
```

But this code is handled differently:

```
dfmi['one']['second'] = value
# becomes
dfmi.__getitem__('one').__setitem__('second', value)
```

See that `__getitem__` in there? Outside of simple cases, it's very hard to predict whether it will return a view or a copy (it depends on the memory layout of the array, about which *pandas* makes no guarantees), and therefore whether the `__setitem__` will modify `dfmi` or a temporary object that gets thrown out immediately afterward. **That's** what `SettingWithCopy` is warning you about!

Note: You may be wondering whether we should be concerned about the `loc` property in the first example. But `dfmi.loc` is guaranteed to be `dfmi` itself with modified indexing behavior, so `dfmi.loc.__getitem__` / `dfmi.loc.__setitem__` operate on `dfmi` directly. Of course, `dfmi.loc.__getitem__(idx)` may be a view or a copy of `dfmi`.

Sometimes a `SettingWithCopy` warning will arise at times when there's no obvious chained indexing going on. **These** are the bugs that `SettingWithCopy` is designed to catch! Pandas is probably trying to warn you that you've done this:

```
def do_something(df):
   foo = df[['bar', 'baz']]  # Is foo a view? A copy? Nobody knows!
   # ... many lines here ...
   foo['quux'] = value       # We don't know whether this will modify df or not!
   return foo
```

Yikes!

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.

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```
In [331]: dfb = pd.DataFrame({'a' : ['one', 'one', 'two',
   .....:                           'three', 'two', 'one', 'six'],
   .....:                    'c' : np.arange(7)})
   .....:

# This will show the SettingWithCopyWarning
# but the frame values will be set
In [332]: 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`

This is the correct access method

```
In [333]: dfc = pd.DataFrame({'A':['aaa','bbb','ccc'],'B':[1,2,3]})

In [334]: dfc.loc[0,'A'] = 11

In [335]: dfc
Out[335]:
     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 [336]: dfc = dfc.copy()

In [337]: dfc['A'][0] = 111

In [338]: dfc
Out[338]:
     A  B
0  111  1
1  bbb  2
2  ccc  3
```

This will **not** work at all, and so should be avoided

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```
>>> pd.set_option('mode.chained_assignment','raise')
>>> dfc.loc[0]['A'] = 1111
Traceback (most recent call last)
     ...
SettingWithCopyException:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_index,col_indexer] = value instead
```

Warning: The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertently reported.

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