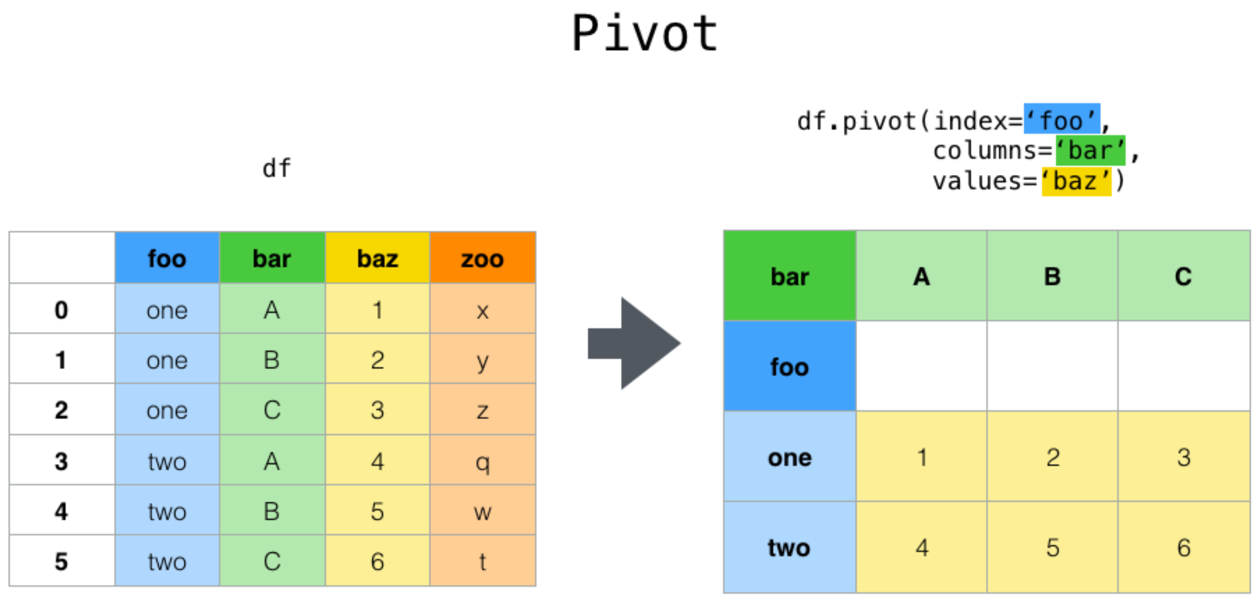
Reshaping and pivot tables

pandas.pydata.org/pandas-docs/stable/user_guide/reshaping.html

Reshaping by pivoting DataFrame objects



Data is often stored in so-called “stacked” or “record” format:

```
In [1]: df
Out[1]:
        date variable     value
0  2000-01-03        A  0.469112
1  2000-01-04        A -0.282863
2  2000-01-05        A -1.509059
3  2000-01-03        B -1.135632
4  2000-01-04        B  1.212112
5  2000-01-05        B -0.173215
6  2000-01-03        C  0.119209
7  2000-01-04        C -1.044236
8  2000-01-05        C -0.861849
9  2000-01-03        D -2.104569
10 2000-01-04        D -0.494929
11 2000-01-05        D  1.071804
```

For the curious here is how the above `DataFrame` was created:

```
import pandas.util.testing as tm

tm.N = 3


def unpivot(frame):
    N, K = frame.shape
    data = {'value': frame.to_numpy().ravel('F'),
            'variable': np.asarray(frame.columns).repeat(N),
            'date': np.tile(np.asarray(frame.index), K)}
    return pd.DataFrame(data, columns=['date', 'variable', 'value'])


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, we use the DataFrame.pivot() method (also implemented as a top level function pivot()):

```
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
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(index='date', columns='variable')

In [6]: pivoted
Out[6]:
              value                                 value2
variable          A         B         C         D        A         B         C         D
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569  0.938225 -2.271265  0.238417 -4.209138
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224 -2.088472 -0.989859
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429 -1.723698  2.143608
```

You 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
```

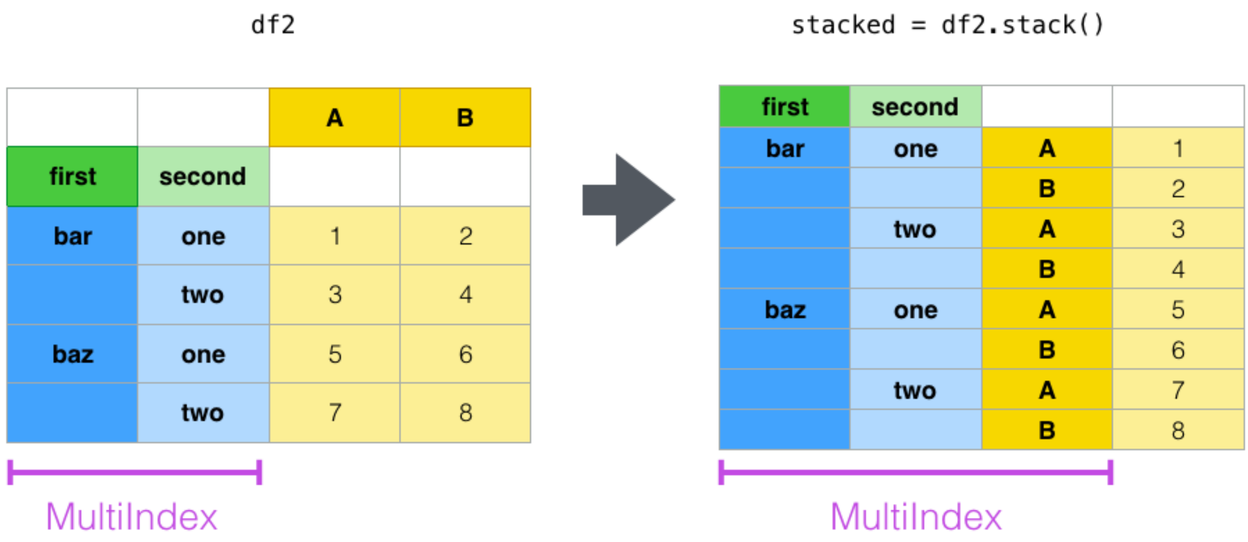
Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

Note

pivot() will error with a `ValueError: Index contains duplicate entries, cannot reshape` if the index/column pair is not unique. In this case, consider using pivot_table() which is a generalization of pivot that can handle duplicate values for one index/column pair.

Reshaping by stacking and unstacking

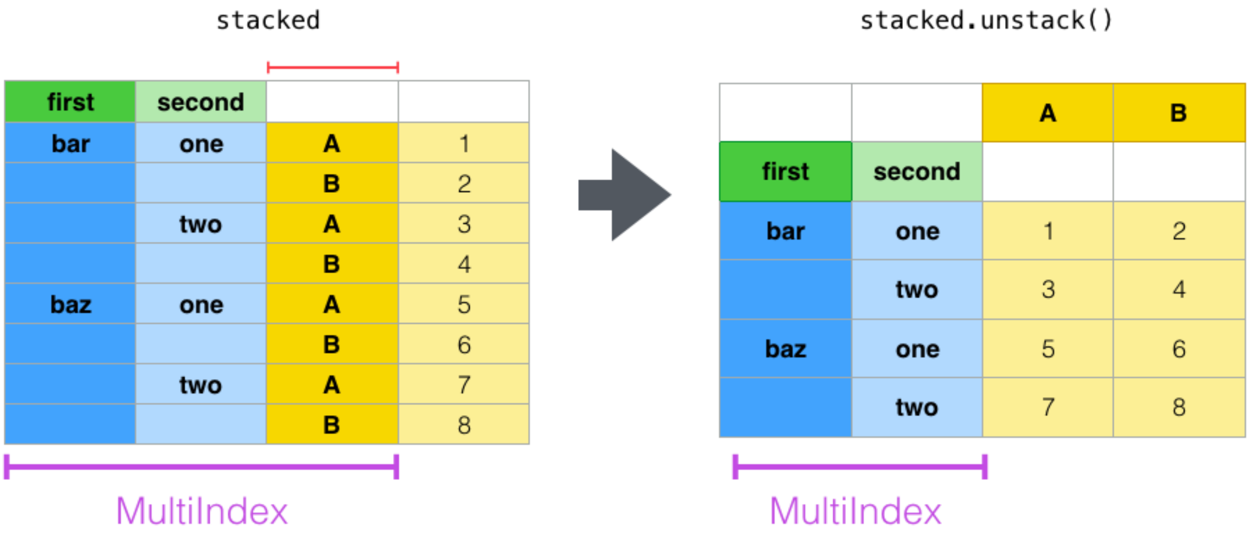
Stack



Closely related to the pivot() method are the related stack() and unstack() methods available on `Series` and `DataFrame`. These methods are designed to work together with `MultiIndex` objects (see the section on hierarchical indexing). Here are essentially what these methods do:

- `stack`: "pivot" a level of the (possibly hierarchical) column labels, returning a `DataFrame` with an index with a new inner-most level of row labels.
- `unstack`: (inverse operation of `stack`) "pivot" a level of the (possibly hierarchical) row index to the column axis, producing a reshaped `DataFrame` with a new inner-most level of column labels.

Unstack



The clearest way to explain is by example. Let's take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
   ...:                     'foo', 'foo', 'qux', 'qux'],
   ...:                    ['one', 'two', 'one', 'two',
   ...:                     'one', 'two', 'one', 'two']]))
   ...:

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [11]: df2 = df[:4]

In [12]: df2
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:

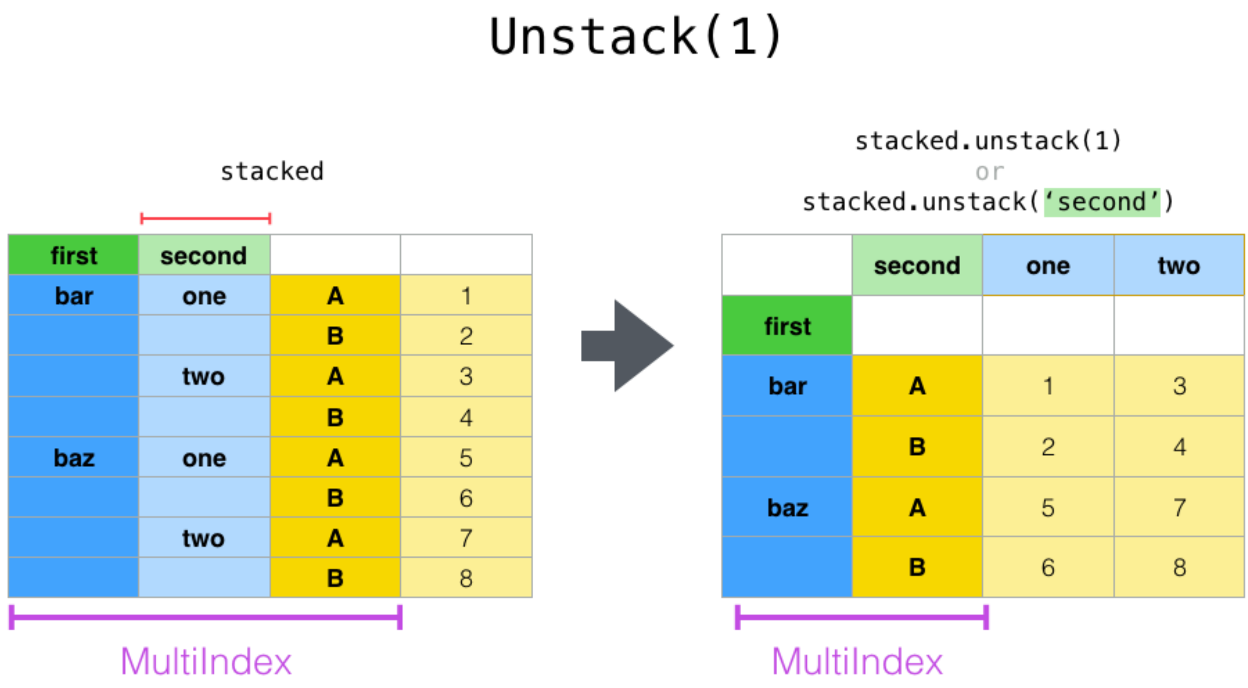
- A `Series`, in the case of a simple column Index.
- A `DataFrame`, in the case of a `MultiIndex` in the columns.

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
```

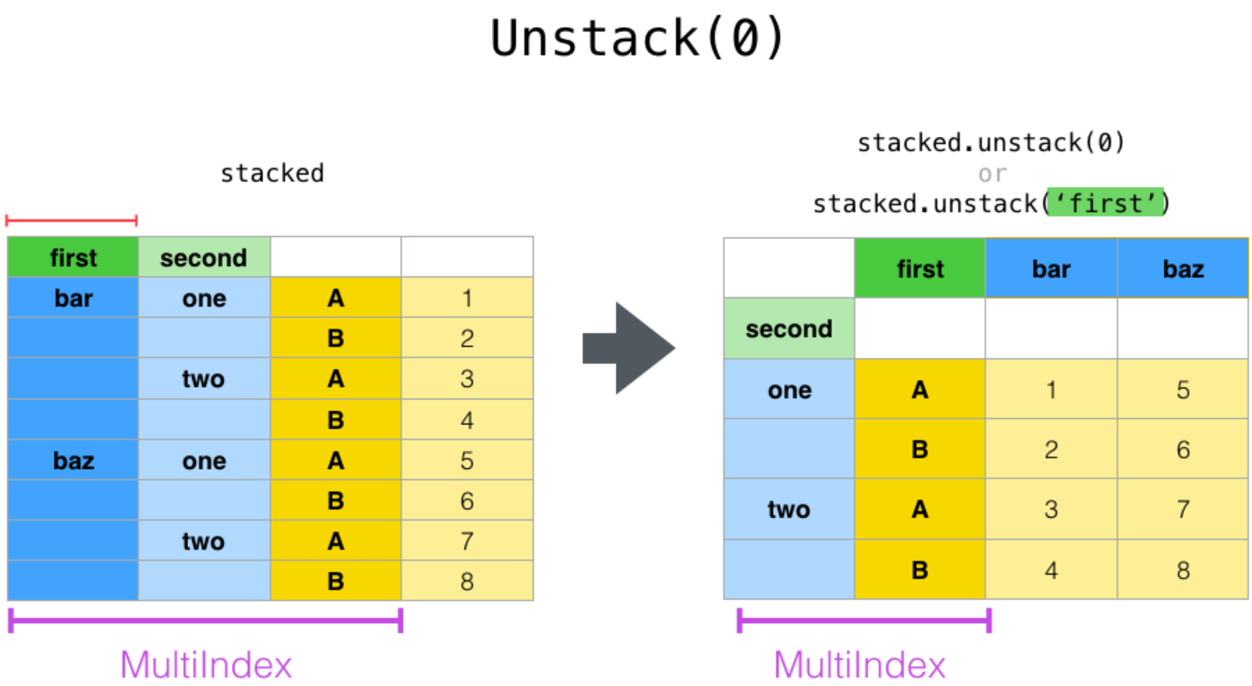
With a “stacked” `DataFrame` or `Series` (having a `MultiIndex` as the `index`), the inverse operation of `stack` is `unstack`, which by default unstacks the **last level**:

```
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 vice versa, will result in a **sorted** copy of the original `DataFrame` or `Series`:

```
In [19]: index = pd.MultiIndex.from_product([[2, 1], ['a', 'b']])

In [20]: df = pd.DataFrame(np.random.randn(4), index=index, columns=['A'])

In [21]: df
Out[21]:
            A
2 a -0.370647
  b -1.157892
1 a -1.344312
  b  0.844885

In [22]: all(df.unstack().stack() == df.sort_index())
Out[22]: True
```

The above code will raise a `TypeError` if the call to `sort_index` is removed.

Multiple levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.

```
In [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
```

Missing data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sort_index`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
   ....:                                      ('B', 'cat'), ('A', 'dog')],
   ....:                                     names=['exp', 'animal'])
   ....:

In [29]: index = pd.MultiIndex.from_product([('bar', 'baz', 'foo', 'qux'),
   ....:                                     ('one', 'two')],
   ....:                                    names=['first', 'second'])
   ....:

In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.iloc[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
exp                  A         B                   A
animal             cat       dog       cat       dog
first second
bar   one     0.895717  0.805244 -1.206412  2.565646
      two     1.431256  1.340309 -1.170299 -0.226169
baz   one     0.410835  0.813850  0.132003 -0.827317
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
```

Unstacking can result in missing values if subgroups do not have the same set of labels. By default, missing values will be replaced with the default fill value for that data type, `NaN` for float, `NaT` for datetimelike, etc. For integer types, by default data will converted to float and missing values will be set to `NaN`.

```
In [35]: df3 = df.iloc[[0, 1, 4, 7], [1, 2]]

In [36]: df3
Out[36]:
exp                  B
animal             dog       cat
first second
bar   one     0.805244 -1.206412
      two     1.340309 -1.170299
foo   one     1.607920  1.024180
qux   two     0.769804 -1.281247

In [37]: df3.unstack()
Out[37]:
exp           B
animal      dog                 cat
second       one       two       one       two
first
bar     0.805244  1.340309 -1.206412 -1.170299
foo     1.607920       NaN  1.024180       NaN
qux          NaN  0.769804       NaN -1.281247
```

New in version 0.18.0.

Alternatively, unstack takes an optional `fill_value` argument, for specifying the value of missing data.

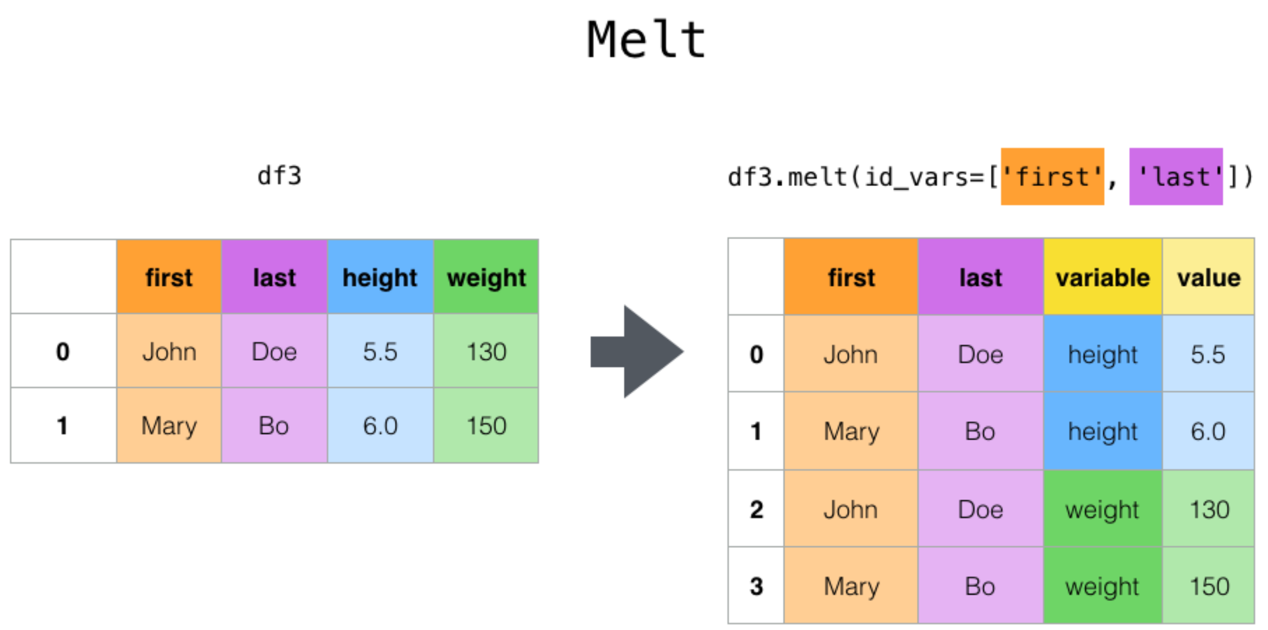
```
In [38]: df3.unstack(fill_value=-1e9)
Out[38]:
exp               B
animal          dog                         cat
second           one           two           one           two
first
bar     8.052440e-01  1.340309e+00 -1.206412e+00 -1.170299e+00
foo     1.607920e+00 -1.000000e+09  1.024180e+00 -1.000000e+09
qux    -1.000000e+09  7.698036e-01 -1.000000e+09 -1.281247e+00
```

With a MultiIndex

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```
In [39]: df[:3].unstack(0)
Out[39]:
exp         A                 B                        A
animal      cat               dog            cat            dog
first       bar       baz     bar      baz   bar      baz   bar      baz
second
one      0.895717  0.410835  0.805244  0.81385 -1.206412  0.132003  2.565646 -0.827317
two      1.431256       NaN  1.340309      NaN -1.170299       NaN -0.226169       NaN

In [40]: df2.unstack(1)
Out[40]:
exp         A                 B                        A
animal      cat               dog            cat            dog
second      one      two      one      two      one      two      one      two
first
bar      0.895717  1.431256  0.805244  1.340309 -1.206412 -1.170299  2.565646 -0.226169
baz      0.410835       NaN  0.813850       NaN  0.132003       NaN -0.827317       NaN
foo     -1.413681  0.875906  1.607920 -2.211372  1.024180  0.974466  0.569605 -2.006747
qux           NaN -1.226825       NaN  0.769804       NaN -1.281247       NaN -0.727707
```

Reshaping by Melt



The top-level melt() function and the corresponding DataFrame.melt() are useful to massage a `DataFrame` into a format where one or more columns are *identifier variables*, while all other columns, considered *measured variables*, are "unpivoted" to the row axis, leaving just two non-identifier columns, "variable" and "value". The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```
In [41]: cheese = pd.DataFrame({'first': ['John', 'Mary'],
   ....:                        'last': ['Doe', 'Bo'],
   ....:                        'height': [5.5, 6.0],
   ....:                        'weight': [130, 150]})
   ....:

In [42]: cheese
Out[42]:
  first last  height  weight
0  John  Doe     5.5     130
1  Mary   Bo     6.0     150

In [43]: cheese.melt(id_vars=['first', 'last'])
Out[43]:
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [44]: cheese.melt(id_vars=['first', 'last'], var_name='quantity')
Out[44]:
  first last quantity  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0
```

Another way to transform is to use the wide_to_long() panel data convenience function. It is less flexible than melt(), but more user-friendly.

```
In [45]: dft = pd.DataFrame({"A1970": {0: "a", 1: "b", 2: "c"},
   ....:                     "A1980": {0: "d", 1: "e", 2: "f"},
   ....:                     "B1970": {0: 2.5, 1: 1.2, 2: .7},
   ....:                     "B1980": {0: 3.2, 1: 1.3, 2: .1},
   ....:                     "X": dict(zip(range(3), np.random.randn(3)))
   ....:                    })
   ....:

In [46]: dft["id"] = dft.index

In [47]: dft
Out[47]:
  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 [48]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
Out[48]:
                X  A    B
id year
0  1970 -0.121306  a  2.5
1  1970 -0.097883  b  1.2
2  1970  0.695775  c  0.7
0  1980 -0.121306  d  3.2
1  1980 -0.097883  e  1.3
2  1980  0.695775  f  0.1
```

Combining with stats and GroupBy

It should be no shock that combining `pivot` / `stack` / `unstack` with GroupBy and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

```
In [49]: df
Out[49]:
exp                 A          B                    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 [50]: df.stack().mean(1).unstack()
Out[50]:
animal            cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

# same result, another way
In [51]: df.groupby(level=1, axis=1).mean()
Out[51]:
animal            cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

In [52]: df.stack().groupby(level=1).mean()
Out[52]:
exp           A         B
second
one     0.071448  0.455513
two    -0.424186 -0.204486

In [53]: df.mean().unstack(0)
Out[53]:
exp           A         B
animal
cat     0.060843  0.018596
dog    -0.413580  0.232430
```

Pivot tables

While pivot() provides general purpose pivoting with various data types (strings, numerics, etc.), pandas also provides pivot_table() for pivoting with aggregation of numeric data.

The function pivot_table() can be used to create spreadsheet-style pivot tables. See the cookbook for some advanced strategies.

It takes a number of arguments:

- `data` : a DataFrame object.
- `values` : a column or a list of columns to aggregate.
- `index` : a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns` : a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc` : function to use for aggregation, defaulting to `numpy.mean` .

Consider a data set like this:

```
In [54]: import datetime

In [55]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 6,
   ....:                    'B': ['A', 'B', 'C'] * 8,
   ....:                    'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 4,
   ....:                    'D': np.random.randn(24),
   ....:                    'E': np.random.randn(24),
   ....:                    'F': [datetime.datetime(2013, i, 1) for i in range(1, 13)]
   ....:                    + [datetime.datetime(2013, i, 15) for i in range(1, 13)]})
   ....:

In [56]: df
Out[56]:
        A  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
..    ... ..  ...       ...       ...        ...
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 [57]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[57]:
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 [58]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[58]:
A       one             three               two
C       bar       foo       bar       foo       bar       foo
B
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360

In [59]: pd.pivot_table(df, values=['D', 'E'], index=['B'], columns=['A', 'C'],
   ....:                aggfunc=np.sum)
   ....:
Out[59]:
          D                                                      E
A       one             three               two                one             three               two
C       bar       foo       bar       foo       bar       foo       bar       foo       bar       foo       bar       foo
B
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971  2.786113 -0.043211  1.922577
NaN       NaN  0.128491
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN  1.368280 -1.103384       NaN -
2.128743 -0.194294       NaN
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360 -1.976883  1.495717 -0.263660
NaN       NaN  0.872482
```

The result object is a `DataFrame` having potentially hierarchical indexes on the rows and columns. If the `values` column name is not given, the pivot table will include all of the data that can be aggregated in an additional level of hierarchy in the columns:

```
In [60]: pd.pivot_table(df, index=['A', 'B'], columns=['C'])
Out[60]:
                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 [61]: pd.pivot_table(df, values='D', index=pd.Grouper(freq='M', key='F'),
   ....:                columns='C')
   ....:
Out[61]:
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 [62]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])

In [63]: 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, i.e. DataFrame.pivot_table().

Adding margins

If you pass `margins=True` to `pivot_table`, special `All` columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [64]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[64]:
                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
```

Cross tabulations

Use crosstab() to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index` : array-like, values to group by in the rows.
- `columns` : array-like, values to group by in the columns.
- `values` : array-like, optional, array of values to aggregate according to the factors.

- `aggfunc` : function, optional, If no values array is passed, computes a frequency table.
- `rownames` : sequence, default `None` , must match number of row arrays passed.
- `colnames` : sequence, default `None` , if passed, must match number of column arrays passed.
- `margins` : boolean, default `False` , Add row/column margins (subtotals)
- `normalize` : boolean, {'all', 'index', 'columns'}, or {0,1}, default `False` . Normalize by dividing all values by the sum of values.

Any `Series` passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [65]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'

In [66]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)

In [67]: b = np.array([one, one, two, one, two, one], dtype=object)

In [68]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)

In [69]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
Out[69]:
b    one        two
c   dull shiny dull shiny
a
bar    1     0    0     1
foo    2     1    1     0
```

If `crosstab` receives only two Series, it will provide a frequency table.

```
In [70]: df = pd.DataFrame({'A': [1, 2, 2, 2, 2], 'B': [3, 3, 4, 4, 4],
   ....:                    'C': [1, 1, np.nan, 1, 1]})
   ....:

In [71]: df
Out[71]:
   A  B    C
0  1  3  1.0
1  2  3  1.0
2  2  4  NaN
3  2  4  1.0
4  2  4  1.0

In [72]: pd.crosstab(df.A, df.B)
Out[72]:
B  3  4
A
1  1  0
2  1  3
```

Any input passed containing `Categorical` data will have **all** of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

```
In [73]: foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])

In [74]: bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])

In [75]: pd.crosstab(foo, bar)
Out[75]:
col_0  d  e
row_0
a      1  0
b      0  1
```

Normalization

New in version 0.18.1.

Frequency tables can also be normalized to show percentages rather than counts using the `normalize` argument:

```
In [76]: pd.crosstab(df.A, df.B, normalize=True)
Out[76]:
B    3    4
A
1  0.2  0.0
2  0.2  0.6
```

`normalize` can also normalize values within each row or within each column:

```
In [77]: pd.crosstab(df.A, df.B, normalize='columns')
Out[77]:
B    3    4
A
1  0.5  0.0
2  0.5  1.0
```

`crosstab` can also be passed a third `Series` and an aggregation function (`aggfunc`) that will be applied to the values of the third `Series` within each group defined by the first two `Series` :

```
In [78]: pd.crosstab(df.A, df.B, values=df.C, aggfunc=np.sum)
Out[78]:
B    3    4
A
1  1.0  NaN
2  1.0  2.0
```

Adding margins

Finally, one can also add margins or normalize this output.

```
In [79]: pd.crosstab(df.A, df.B, values=df.C, aggfunc=np.sum, normalize=True,
   ....:             margins=True)
   ....:
Out[79]:
B       3    4   All
A
1    0.25  0.0  0.25
2    0.25  0.5  0.75
All  0.50  0.5  1.00
```

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 [80]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [81]: pd.cut(ages, bins=3)
Out[81]:
[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (26.667, 43.333], (43.333, 60.0], (43.333, 60.0]]
Categories (3, interval[float64]): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60.0]]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [82]: c = pd.cut(ages, bins=[0, 18, 35, 70])

In [83]: c
Out[83]:
[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]]
Categories (3, interval[int64]): [(0, 18] < (18, 35] < (35, 70]]
```

New in version 0.20.0.

If the `bins` keyword is an `IntervalIndex`, then these will be used to bin the passed data.:

```
pd.cut([25, 20, 50], bins=c.categories)
```

Computing indicator / dummy variables

To convert a categorical variable into a “dummy” or “indicator” `DataFrame`, for example a column in a `DataFrame` (a `Series`) which has `k` distinct values, can derive a `DataFrame` containing `k` columns of 1s and 0s using get_dummies():

```
In [84]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})

In [85]: pd.get_dummies(df['key'])
Out[85]:
   a  b  c
0  0  1  0
1  0  1  0
2  1  0  0
3  0  0  1
4  1  0  0
5  0  1  0
```

Sometimes it's useful to prefix the column names, for example when merging the result with the original `DataFrame`:

```
In [86]: dummies = pd.get_dummies(df['key'], prefix='key')

In [87]: dummies
Out[87]:
   key_a  key_b  key_c
0      0      1      0
1      0      1      0
2      1      0      0
3      0      0      1
4      1      0      0
5      0      1      0

In [88]: df[['data1']].join(dummies)
Out[88]:
   data1  key_a  key_b  key_c
0      0      0      1      0
1      1      0      1      0
2      2      1      0      0
3      3      0      0      1
4      4      1      0      0
5      5      0      1      0
```

This function is often used along with discretization functions like `cut`:

```
In [89]: values = np.random.randn(10)

In [90]: values
Out[90]:
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29  ,
        0.0824, -0.0558,  0.5366])

In [91]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [92]: pd.get_dummies(pd.cut(values, bins))
Out[92]:
   (0.0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1.0]
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.

get_dummies() also accepts a `DataFrame`. By default all categorical variables (categorical in the statistical sense, those with *object* or *categorical* dtype) are encoded as dummy variables.

```
In [93]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
   ....:                    'C': [1, 2, 3]})
   ....:

In [94]: pd.get_dummies(df)
Out[94]:
   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 [95]: pd.get_dummies(df, columns=['A'])
Out[95]:
   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 [96]: simple = pd.get_dummies(df, prefix='new_prefix')

In [97]: simple
Out[97]:
   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 [98]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])

In [99]: from_list
Out[99]:
   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 [100]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})

In [101]: from_dict
Out[101]:
   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
```

New in version 0.18.0.

Sometimes it will be useful to only keep k-1 levels of a categorical variable to avoid collinearity when feeding the result to statistical models. You can switch to this mode by turn on `drop_first`.

```
In [102]: s = pd.Series(list('abcaa'))

In [103]: pd.get_dummies(s)
Out[103]:
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
4  1  0  0

In [104]: pd.get_dummies(s, drop_first=True)
Out[104]:
   b  c
0  0  0
1  1  0
2  0  1
3  0  0
4  0  0
```

When a column contains only one level, it will be omitted in the result.

```
In [105]: df = pd.DataFrame({'A': list('aaaaa'), 'B': list('ababc')})

In [106]: pd.get_dummies(df)
Out[106]:
   A_a  B_a  B_b  B_c
0    1    1    0    0
1    1    0    1    0
2    1    1    0    0
3    1    0    1    0
4    1    0    0    1

In [107]: pd.get_dummies(df, drop_first=True)
Out[107]:
   B_b  B_c
0    0    0
1    1    0
2    0    0
3    1    0
4    0    1
```

By default new columns will have `np.uint8` dtype. To choose another dtype, use the `dtype` argument:

```
In [108]: df = pd.DataFrame({'A': list('abc'), 'B': [1.1, 2.2, 3.3]})

In [109]: pd.get_dummies(df, dtype=bool).dtypes
Out[109]:
B      float64
A_a       bool
A_b       bool
A_c       bool
dtype: object
```

New in version 0.23.0.

Factorizing values

To encode 1-d values as an enumerated type use factorize():

```
In [110]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])

In [111]: x
Out[111]:
0       A
1       A
2     NaN
3       B
4    3.14
5     inf
dtype: object

In [112]: labels, uniques = pd.factorize(x)

In [113]: labels
Out[113]: array([ 0,  0, -1,  1,  2,  3])

In [114]: uniques
Out[114]: Index(['A', '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 [1]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [2]: pd.factorize(x, sort=True)
Out[2]:
(array([ 2,  2, -1,  3,  0,  1]),
 Index([3.14, inf, 'A', 'B'], dtype='object'))

In [3]: np.unique(x, return_inverse=True)[::-1]
Out[3]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

Note

If you just want to handle one column as a categorical variable (like R’s factor), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on Categorical, see the Categorical introduction and the API documentation.

Examples

In this section, we will review frequently asked questions and examples. The column names and relevant column values are named to correspond with how this DataFrame will be pivoted in the answers below.

```
In [115]: np.random.seed([3, 1415])

In [116]: n = 20

In [117]: cols = np.array(['key', 'row', 'item', 'col'])

In [118]: df = cols + pd.DataFrame((np.random.randint(5, size=(n, 4))
   .....:                           // [2, 1, 2, 1]).astype(str))
   .....:

In [119]: df.columns = cols

In [120]: df = df.join(pd.DataFrame(np.random.rand(n, 2).round(2)).add_prefix('val'))

In [121]: df
Out[121]:
    key   row   item   col  val0  val1
0   key0  row3  item1  col3  0.81  0.04
1   key1  row2  item1  col2  0.44  0.07
2   key1  row0  item1  col0  0.77  0.01
3   key0  row4  item0  col2  0.15  0.59
4   key1  row0  item2  col1  0.81  0.64
..   ...   ...    ...   ...   ...   ...
15  key0  row3  item1  col1  0.31  0.23
16  key0  row0  item2  col3  0.86  0.01
17  key0  row4  item0  col3  0.64  0.21
18  key2  row2  item2  col0  0.13  0.45
19  key0  row2  item0  col4  0.37  0.70

[20 rows x 6 columns]
```

Pivoting with single aggregations

Suppose we wanted to pivot `df` such that the `col` values are columns, `row` values are the index, and the mean of `val0` are the values? In particular, the resulting DataFrame should look like:

Note

col col0 col1 col2 col3 col4 row row0 0.77 0.605 NaN 0.860 0.65 row2 0.13 NaN 0.395 0.500 0.25 row3 NaN 0.310 NaN 0.545 NaN row4 NaN 0.100 0.395 0.760 0.24

This solution uses pivot_table(). Also note that `aggfunc='mean'` is the default. It is included here to be explicit.

```
In [122]: df.pivot_table(
   .....:     values='val0', index='row', columns='col', aggfunc='mean')
   .....:
Out[122]:
col   col0   col1   col2   col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65
row2  0.13    NaN  0.395  0.500  0.25
row3   NaN  0.310    NaN  0.545   NaN
row4   NaN  0.100  0.395  0.760  0.24
```

Note that we can also replace the missing values by using the `fill_value` parameter.

```
In [123]: df.pivot_table(
   .....:     values='val0', index='row', columns='col', aggfunc='mean', fill_value=0)
   .....:
Out[123]:
col   col0   col1   col2   col3  col4
row
row0  0.77  0.605  0.000  0.860  0.65
row2  0.13  0.000  0.395  0.500  0.25
row3  0.00  0.310  0.000  0.545  0.00
row4  0.00  0.100  0.395  0.760  0.24
```

Also note that we can pass in other aggregation functions as well. For example, we can also pass in `sum`.

```
In [124]: df.pivot_table(
   .....:     values='val0', index='row', columns='col', aggfunc='sum', fill_value=0)
   .....:
Out[124]:
col   col0  col1  col2  col3  col4
row
row0  0.77  1.21  0.00  0.86  0.65
row2  0.13  0.00  0.79  0.50  0.50
row3  0.00  0.31  0.00  1.09  0.00
row4  0.00  0.10  0.79  1.52  0.24
```

Another aggregation we can do is calculate the frequency in which the columns and rows occur together a.k.a. “cross tabulation”. To do this, we can pass `size` to the `aggfunc` parameter.

```
In [125]: df.pivot_table(index='row', columns='col', fill_value=0, aggfunc='size')
Out[125]:
col   col0  col1  col2  col3  col4
row
row0     1     2     0     1     1
row2     1     0     2     1     2
row3     0     1     0     2     0
row4     0     1     2     2     1
```

Pivoting with multiple aggregations

We can also perform multiple aggregations. For example, to perform both a `sum` and `mean`, we can pass in a list to the `aggfunc` argument.

```
In [126]: df.pivot_table(
   .....:     values='val0', index='row', columns='col', aggfunc=['mean', 'sum'])
   .....:
Out[126]:
      mean                          sum
col   col0   col1   col2   col3  col4  col0  col1  col2  col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65  0.77  1.21   NaN  0.86  0.65
row2  0.13    NaN  0.395  0.500  0.25  0.13   NaN  0.79  0.50  0.50
row3   NaN  0.310    NaN  0.545   NaN   NaN  0.31   NaN  1.09   NaN
row4   NaN  0.100  0.395  0.760  0.24   NaN  0.10  0.79  1.52  0.24
```

Note to aggregate over multiple value columns, we can pass in a list to the `values` parameter.

```
In [127]: df.pivot_table(
   .....:     values=['val0', 'val1'], index='row', columns='col', aggfunc=['mean'])
   .....:
Out[127]:
      mean
      val0                          val1
col   col0   col1   col2   col3  col4  col0   col1  col2   col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65  0.01  0.745   NaN  0.010  0.02
row2  0.13    NaN  0.395  0.500  0.25  0.45    NaN  0.34  0.440  0.79
row3   NaN  0.310    NaN  0.545   NaN   NaN  0.230   NaN  0.075   NaN
row4   NaN  0.100  0.395  0.760  0.24   NaN  0.070  0.42  0.300  0.46
```

Note to subdivide over multiple columns we can pass in a list to the `columns` parameter.

```
In [128]: df.pivot_table(
   .....:     values=['val0'], index='row', columns=['item', 'col'], aggfunc=['mean'])
   .....:
Out[128]:
      mean
      val0
item item0             item1                         item2
col   col2  col3  col4  col0  col1  col2  col3  col4  col0   col1  col3  col4
row
row0   NaN   NaN   NaN  0.77   NaN   NaN   NaN   NaN   NaN  0.605  0.86  0.65
row2  0.35   NaN  0.37   NaN   NaN  0.44   NaN   NaN  0.13    NaN  0.50  0.13
row3   NaN   NaN   NaN   NaN  0.31   NaN  0.81   NaN   NaN    NaN  0.28   NaN
row4  0.15  0.64   NaN   NaN  0.10  0.64  0.88  0.24   NaN    NaN   NaN   NaN
```

Exploding a list-like column

New in version 0.25.0.

Sometimes the values in a column are list-like.

```
In [129]: keys = ['panda1', 'panda2', 'panda3']

In [130]: values = [['eats', 'shoots'], ['shoots', 'leaves'], ['eats', 'leaves']]

In [131]: df = pd.DataFrame({'keys': keys, 'values': values})

In [132]: df
Out[132]:
     keys            values
0  panda1    [eats, shoots]
1  panda2  [shoots, leaves]
2  panda3    [eats, leaves]
```

We can 'explode' the `values` column, transforming each list-like to a separate row, by using explode(). This will replicate the index values from the original row:

```
In [133]: df['values'].explode()
Out[133]:
0      eats
0    shoots
1    shoots
1    leaves
2      eats
2    leaves
Name: values, dtype: object
```

You can also explode the column in the `DataFrame`.

```
In [134]: df.explode('values')
Out[134]:
     keys  values
0  panda1    eats
0  panda1  shoots
1  panda2  shoots
1  panda2  leaves
2  panda3    eats
2  panda3  leaves
```

Series.explode() will replace empty lists with `np.nan` and preserve scalar entries. The dtype of the resulting `Series` is always `object`.

```
In [135]: s = pd.Series([[1, 2, 3], 'foo', [], ['a', 'b']])

In [136]: s
Out[136]:
0    [1, 2, 3]
1          foo
2           []
3       [a, b]
dtype: object

In [137]: s.explode()
Out[137]:
0      1
0      2
0      3
1    foo
2    NaN
3      a
3      b
dtype: object
```

Here is a typical usecase. You have comma separated strings in a column and want to expand this.

```
In [138]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1},
   .....:                    {'var1': 'd,e,f', 'var2': 2}])
   .....:

In [139]: df
Out[139]:
    var1  var2
0  a,b,c     1
1  d,e,f     2
```

Creating a long form DataFrame is now straightforward using explode and chained operations

```
In [140]: df.assign(var1=df.var1.str.split(',')).explode('var1')
Out[140]:
  var1  var2
0    a     1
0    b     1
0    c     1
1    d     2
1    e     2
1    f     2
```