

Merge, join, and concatenate

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

Concatenating objects

The `concat()` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say “if any” because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```
In [1]: df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
...:                       'B': ['B0', 'B1', 'B2', 'B3'],
...:                       'C': ['C0', 'C1', 'C2', 'C3'],
...:                       'D': ['D0', 'D1', 'D2', 'D3']},
...:                       index=[0, 1, 2, 3])

In [2]: df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
...:                       'B': ['B4', 'B5', 'B6', 'B7'],
...:                       'C': ['C4', 'C5', 'C6', 'C7'],
...:                       'D': ['D4', 'D5', 'D6', 'D7']},
...:                       index=[4, 5, 6, 7])

In [3]: df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
...:                       'B': ['B8', 'B9', 'B10', 'B11'],
...:                       'C': ['C8', 'C9', 'C10', 'C11'],
...:                       'D': ['D8', 'D9', 'D10', 'D11']},
...:                       index=[8, 9, 10, 11])

In [4]: frames = [df1, df2, df3]

In [5]: result = pd.concat(frames)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3
df2					4	A4	B4	C4	D4
	A	B	C	D	5	A5	B5	C5	D5
4	A4	B4	C4	D4	6	A6	B6	C6	D6
5	A5	B5	C5	D5	7	A7	B7	C7	D7
6	A6	B6	C6	D6	8	A8	B8	C8	D8
7	A7	B7	C7	D7	9	A9	B9	C9	D9
df3					10	A10	B10	C10	D10
	A	B	C	D	11	A11	B11	C11	D11
8	A8	B8	C8	D8					
9	A9	B9	C9	D9					
10	A10	B10	C10	D10					
11	A11	B11	C11	D11					

Like its sibling function on `ndarrays`, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

```
pd.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
          keys=None, levels=None, names=None, verify_integrity=False,
          copy=True)
```

- `objs` : a sequence or mapping of Series, DataFrame, or Panel objects. If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a `ValueError` will be raised.
- `axis` : {0, 1, ...}, default 0. The axis to concatenate along.
- `join` : {'inner', 'outer'}, default 'outer'. How to handle indexes on other axis(es). Outer for union and inner for intersection.
- `ignore_index` : boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.
- `join_axes` : list of Index objects. Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic.
- `keys` : sequence, default None. Construct hierarchical index using the passed keys as the outermost level. If multiple levels passed, should contain tuples.
- `levels` : list of sequences, default None. Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.
- `names` : list, default None. Names for the levels in the resulting hierarchical index.
- `verify_integrity` : boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.
- `copy` : boolean, default True. If False, do not copy data unnecessarily.

Without a little bit of context many of these arguments don't make much sense. Let's revisit the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```
In [6]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

df1					Result					
	A	B	C	D			A	B	C	D
0	A0	B0	C0	D0	x	0	A0	B0	C0	D0
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2					y	4	A4	B4	C4	D4
	A	B	C	D	y	5	A5	B5	C5	D5
4	A4	B4	C4	D4	y	6	A6	B6	C6	D6
5	A5	B5	C5	D5	y	7	A7	B7	C7	D7
6	A6	B6	C6	D6	z	8	A8	B8	C8	D8
7	A7	B7	C7	D7	z	9	A9	B9	C9	D9
df3					z	10	A10	B10	C10	D10
	A	B	C	D	z	11	A11	B11	C11	D11
8	A8	B8	C8	D8						
9	A9	B9	C9	D9						
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

As you can see (if you've read the rest of the documentation), the resulting object's index has a [hierarchical index](#). This means that we can now select out each chunk by key:

```
In [7]: result.loc['y']
```

```
Out[7]:
```

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

It's not a stretch to see how this can be very useful. More detail on this functionality below.

Note: It is worth noting that `concat()` (and therefore `append()`) makes a full copy of the data, and that constantly reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```

Set logic on the other axes

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following three ways:

- Take the union of them all, `join='outer'`. This is the default option as it results in zero information loss.
- Take the intersection, `join='inner'`.
- Use a specific index, as passed to the `join_axes` argument.

Here is an example of each of these methods. First, the default `join='outer'` behavior:

```
In [8]: df4 = pd.DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
...:                      'D': ['D2', 'D3', 'D6', 'D7'],
...:                      'F': ['F2', 'F3', 'F6', 'F7']},
...:                      index=[2, 3, 6, 7])

In [9]: result = pd.concat([df1, df4], axis=1, sort=False)
```

df1					df4				Result							

Warning:

Changed in version 0.23.0.

The default behavior with `join='outer'` is to sort the other axis (columns in this case). In a future version of pandas, the default will be to not sort. We specified `sort=False` to opt in to the new behavior now.

Here is the same thing with `join='inner'`:

```
In [10]: result = pd.concat([df1, df4], axis=1, join='inner')
```

df1					df4				Result							
	A	B	C	D		B	D	F		A	B	C	D	B	D	F
0	A0	B0	C0	D0	2	B2	D2	F2	2	A2	B2	C2	D2	B2	D2	F2
1	A1	B1	C1	D1	3	B3	D3	F3	3	A3	B3	C3	D3	B3	D3	F3
2	A2	B2	C2	D2												
3	A3	B3	C3	D3	6	B6	D6	F6								
					7	B7	D7	F7								

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:

```
In [11]: result = pd.concat([df1, df4], axis=1, join_axes=[df1.index])
```

df1					df4				Result							
	A	B	C	D		B	D	F		A	B	C	D	B	D	F
0	A0	B0	C0	D0	2	B2	D2	F2	0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	3	B3	D3	F3	1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	6	B6	D6	F6	2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	7	B7	D7	F7	3	A3	B3	C3	D3	B3	D3	F3

Concatenating using `append`

A useful shortcut to `concat()` are the `append()` instance methods on `Series` and `DataFrame`. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

```
In [12]: result = df1.append(df2)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3
df2					4	A4	B4	C4	D4
	A	B	C	D	4	A4	B4	C4	D4
4	A4	B4	C4	D4	5	A5	B5	C5	D5
5	A5	B5	C5	D5	6	A6	B6	C6	D6
6	A6	B6	C6	D6	7	A7	B7	C7	D7
7	A7	B7	C7	D7					

In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

```
In [13]: result = df1.append(df4, sort=False)
```

df1					Result					
	A	B	C	D		A	B	C	D	F
0	A0	B0	C0	D0	0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	3	A3	B3	C3	D3	NaN
df4					2	NaN	B2	NaN	D2	F2
	B	D	F		3	NaN	B3	NaN	D3	F3
2	B2	D2	F2		6	NaN	B6	NaN	D6	F6
3	B3	D3	F3		7	NaN	B7	NaN	D7	F7
6	B6	D6	F6							
7	B7	D7	F7							

`append` may take multiple objects to concatenate:

```
In [14]: result = df1.append([df2, df3])
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3
df2					4	A4	B4	C4	D4
	A	B	C	D	5	A5	B5	C5	D5
4	A4	B4	C4	D4	6	A6	B6	C6	D6
5	A5	B5	C5	D5	7	A7	B7	C7	D7
6	A6	B6	C6	D6	8	A8	B8	C8	D8
7	A7	B7	C7	D7	9	A9	B9	C9	D9
df3					10	A10	B10	C10	D10
	A	B	C	D	11	A11	B11	C11	D11
8	A8	B8	C8	D8					
9	A9	B9	C9	D9					
10	A10	B10	C10	D10					
11	A11	B11	C11	D11					

Note: Unlike the `append()` method, which appends to the original list and returns `None`, `append()` here **does not** modify `df1` and returns its copy with `df2` appended.

Ignoring indexes on the concatenation axis

For `DataFrame` objects which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the `ignore_index` argument:

```
In [15]: result = pd.concat([df1, df4], ignore_index=True, sort=False)
```

df1					Result					
	A	B	C	D		A	B	C	D	F
0	A0	B0	C0	D0	0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	3	A3	B3	C3	D3	NaN
df4					4	NaN	B2	NaN	D2	F2
	B	D	F		5	NaN	B3	NaN	D3	F3
2	B2	D2	F2	6	NaN	B6	NaN	D6	F6	
3	B3	D3	F3	7	NaN	B7	NaN	D7	F7	
6	B6	D6	F6							
7	B7	D7	F7							

This is also a valid argument to `DataFrame.append()`:

```
In [16]: result = df1.append(df4, ignore_index=True, sort=False)
```

df1					Result					
	A	B	C	D		A	B	C	D	F
0	A0	B0	C0	D0	0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	3	A3	B3	C3	D3	NaN
df4					4	NaN	B2	NaN	D2	F2
	B	D	F		5	NaN	B3	NaN	D3	F3
2	B2	D2	F2	6	NaN	B6	NaN	D6	F6	
3	B3	D3	F3	7	NaN	B7	NaN	D7	F7	
6	B6	D6	F6							
7	B7	D7	F7							

Concatenating with mixed ndims

You can concatenate a mix of `Series` and `DataFrame` objects. The `Series` will be transformed to `DataFrame` with the column name as the name of the `Series`.

```
In [17]: s1 = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')
```

```
In [18]: result = pd.concat([df1, s1], axis=1)
```

df1					s1		Result					
	A	B	C	D		X		A	B	C	D	X
0	A0	B0	C0	D0	0	X0	0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	1	X1	1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	2	X2	2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	3	X3	3	A3	B3	C3	D3	X3

Note: Since we're concatenating a `Series` to a `DataFrame`, we could have achieved the same result with `DataFrame.assign()`. To concatenate an arbitrary number of pandas objects (`DataFrame` or `Series`), use `concat`.

If unnamed `Series` are passed they will be numbered consecutively.

```
In [19]: s2 = pd.Series(['_0', '_1', '_2', '_3'])
In [20]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

df1					s2		Result							
	A	B	C	D				A	B	C	D	0	1	2
0	A0	B0	C0	D0	0	_0	0	A0	B0	C0	D0	_0	_0	_0
1	A1	B1	C1	D1	1	_1	1	A1	B1	C1	D1	_1	_1	_1
2	A2	B2	C2	D2	2	_2	2	A2	B2	C2	D2	_2	_2	_2
3	A3	B3	C3	D3	3	_3	3	A3	B3	C3	D3	_3	_3	_3

Passing `ignore_index=True` will drop all name references.

```
In [21]: result = pd.concat([df1, s1], axis=1, ignore_index=True)
```

df1					s1		Result					
	A	B	C	D		X		0	1	2	3	4
0	A0	B0	C0	D0	0	X0	0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	1	X1	1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	2	X2	2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	3	X3	3	A3	B3	C3	D3	X3

More concatenating with group keys

A fairly common use of the `keys` argument is to override the column names when creating a new `DataFrame` based on existing `Series`. Notice how the default behaviour consists on letting the resulting `DataFrame` inherit the parent `Series`' name, when these existed.

```
In [22]: s3 = pd.Series([0, 1, 2, 3], name='foo')
```



```
In [23]: s4 = pd.Series([0, 1, 2, 3])

In [24]: s5 = pd.Series([0, 1, 4, 5])

In [25]: pd.concat([s3, s4, s5], axis=1)
Out[25]:
   foo  0  1
0    0  0  0
1    1  1  1
2    2  2  4
3    3  3  5
```

Through the `keys` argument we can override the existing column names.

```
In [26]: pd.concat([s3, s4, s5], axis=1, keys=['red', 'blue', 'yellow'])
Out[26]:
   red  blue  yellow
0    0    0      0
1    1    1      1
2    2    2      4
3    3    3      5
```

Let's consider a variation of the very first example presented:

```
In [27]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

df1					Result					
	A	B	C	D			A	B	C	D
0	A0	B0	C0	D0	x	0	A0	B0	C0	D0
1	A1	B1	C1	D1		1	A1	B1	C1	D1
2	A2	B2	C2	D2		2	A2	B2	C2	D2
3	A3	B3	C3	D3		3	A3	B3	C3	D3
df2					y	4	A4	B4	C4	D4
4	A4	B4	C4	D4		5	A5	B5	C5	D5
5	A5	B5	C5	D5		6	A6	B6	C6	D6
6	A6	B6	C6	D6		7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	A8	B8	C8	D8
df3						9	A9	B9	C9	D9
8	A8	B8	C8	D8		10	A10	B10	C10	D10
9	A9	B9	C9	D9		11	A11	B11	C11	D11
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```
In [28]: pieces = {'x': df1, 'y': df2, 'z': df3}

In [29]: result = pd.concat(pieces)
```

df1					Result					
	A	B	C	D			A	B	C	D
0	A0	B0	C0	D0	x	0	A0	B0	C0	D0
1	A1	B1	C1	D1		1	A1	B1	C1	D1
2	A2	B2	C2	D2		2	A2	B2	C2	D2
3	A3	B3	C3	D3		3	A3	B3	C3	D3
df2					y	4	A4	B4	C4	D4
4	A4	B4	C4	D4		5	A5	B5	C5	D5
5	A5	B5	C5	D5		6	A6	B6	C6	D6
6	A6	B6	C6	D6		7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	A8	B8	C8	D8
df3						9	A9	B9	C9	D9
	A	B	C	D		10	A10	B10	C10	D10
8	A8	B8	C8	D8 <th>11</th> <td>A11</td> <td>B11</td> <td>C11</td> <td>D11</td>		11	A11	B11	C11	D11
9	A9	B9	C9	D9						
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

```
In [30]: result = pd.concat(pieces, keys=['z', 'y'])
```

df1					Result					
	A	B	C	D			A	B	C	D
0	A0	B0	C0	D0	z	8	A8	B8	C8	D8
1	A1	B1	C1	D1		9	A9	B9	C9	D9
2	A2	B2	C2	D2		10	A10	B10	C10	D10
3	A3	B3	C3	D3		11	A11	B11	C11	D11
df2					y	4	A4	B4	C4	D4
	A	B	C	D		5	A5	B5	C5	D5
4	A4	B4	C4	D4		6	A6	B6	C6	D6
5	A5	B5	C5	D5		7	A7	B7	C7	D7
6	A6	B6	C6	D6						
7	A7	B7	C7	D7						
df3					y	4	A4	B4	C4	D4
	A	B	C	D		5	A5	B5	C5	D5
8	A8	B8	C8	D8 <th>6</th> <td>A6</td> <td>B6</td> <td>C6</td> <td>D6</td>		6	A6	B6	C6	D6
9	A9	B9	C9	D9 <th>7</th> <td>A7</td> <td>B7</td> <td>C7</td> <td>D7</td>		7	A7	B7	C7	D7
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame `pieces`:

```
In [31]: result.index.levels
Out[31]: FrozenList([['z', 'y'], [4, 5, 6, 7, 8, 9, 10, 11]])
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [32]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
.....:                      levels=[['z', 'y', 'x', 'w']],
.....:                      names=['group_key'])
.....:
```

df1					Result					
	A	B	C	D			A	B	C	D
0	A0	B0	C0	D0	x	0	A0	B0	C0	D0
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2					y	4	A4	B4	C4	D4
	A	B	C	D	y	5	A5	B5	C5	D5
4	A4	B4	C4	D4	y	6	A6	B6	C6	D6
5	A5	B5	C5	D5	y	7	A7	B7	C7	D7
6	A6	B6	C6	D6	z	8	A8	B8	C8	D8
7	A7	B7	C7	D7	z	9	A9	B9	C9	D9
df3					z	10	A10	B10	C10	D10
	A	B	C	D	z	11	A11	B11	C11	D11
8	A8	B8	C8	D8						
9	A9	B9	C9	D9						
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

```
In [33]: result.index.levels
Out[33]: FrozenList([['z', 'y', 'x', 'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

This is fairly esoteric, but it is actually necessary for implementing things like `GroupBy` where the order of a categorical variable is meaningful.

Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a `DataFrame` by passing a `Series` or `dict` to `append`, which returns a new `DataFrame` as above.

```
In [34]: s2 = pd.Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])
In [35]: result = df1.append(s2, ignore_index=True)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3
s2					4	X0	X1	X2	X3
	A			X0					
	B			X1					
	C			X2					
	D			X3					

You should use `ignore_index` with this method to instruct `DataFrame` to discard its index. If you wish to preserve the index, you should construct an appropriately-indexed `DataFrame` and append or concatenate those objects.

You can also pass a list of dicts or Series:

```
In [36]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4},
.....:           {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
.....:

In [37]: result = df1.append(dicts, ignore_index=True, sort=False)
```

df1					Result						
	A	B	C	D		A	B	C	D	X	Y
0	A0	B0	C0	D0	0	A0	B0	C0	D0	NaN	NaN
1	A1	B1	C1	D1	1	A1	B1	C1	D1	NaN	NaN
2	A2	B2	C2	D2	2	A2	B2	C2	D2	NaN	NaN
3	A3	B3	C3	D3	3	A3	B3	C3	D3	NaN	NaN
dicts					4	1	2	3	NaN	4.0	NaN
	A	B	C	X	5	5	6	7	NaN	NaN	8.0
0	1	2	3	4.0	NaN						
1	5	6	7	NaN	8.0						

Database-style DataFrame or named Series joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and the internal layout of the data in `DataFrame`.

See the [cookbook](#) for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a [comparison with SQL](#).

pandas provides a single function, `merge()`, as the entry point for all standard database join operations between `DataFrame` or named `Series` objects:

```
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
         left_index=False, right_index=False, sort=True,
         suffixes=('_x', '_y'), copy=True, indicator=False,
         validate=None)
```

- `left`: A `DataFrame` or named `Series` object.
- `right`: Another `DataFrame` or named `Series` object.
- `on`: Column or index level names to join on. Must be found in both the left and right `DataFrame` and/or `Series` objects. If not passed and `left_index` and `right_index` are `False`, the intersection of the columns in the `DataFrames` and/or `Series` will be inferred to be the join keys.
- `left_on`: Columns or index levels from the left `DataFrame` or `Series` to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the `DataFrame` or `Series`.
- `right_on`: Columns or index levels from the right `DataFrame` or `Series` to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the `DataFrame` or `Series`.
- `left_index`: If `True`, use the index (row labels) from the left `DataFrame` or `Series` as its join key(s). In the case of a `DataFrame` or `Series` with a `MultiIndex` (hierarchical), the number of levels must match the number of join keys from the right `DataFrame` or `Series`.
- `right_index`: Same usage as `left_index` for the right `DataFrame` or `Series`
- `how`: One of 'left', 'right', 'outer', 'inner'. Defaults to `inner`. See below for more detailed description of each method.
- `sort`: Sort the result `DataFrame` by the join keys in lexicographical order. Defaults to `True`, setting to `False` will improve performance substantially in many cases.
- `suffixes`: A tuple of string suffixes to apply to overlapping columns. Defaults to `('_x', '_y')`.
- `copy`: Always copy data (default `True`) from the passed `DataFrame` or named `Series` objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.
- `indicator`: Add a column to the output `DataFrame` called `_merge` with information on the source of each row. `_merge` is Categorical-type and takes on a value of `left_only` for observations whose merge key only appears in 'left' `DataFrame` or `Series`, `right_only` for observations whose merge key only appears in 'right' `DataFrame` or `Series`, and `both` if the observation's merge key is found in both.
- `validate`: string, default `None`. If specified, checks if merge is of specified type.

- “one_to_one” or “1:1”: checks if merge keys are unique in both left and right datasets.
- “one_to_many” or “1:m”: checks if merge keys are unique in left dataset.
- “many_to_one” or “m:1”: checks if merge keys are unique in right dataset.
- “many_to_many” or “m:m”: allowed, but does not result in checks.

New in version 0.21.0.

Note: Support for specifying index levels as the `on`, `left_on`, and `right_on` parameters was added in version 0.23.0. Support for merging named `Series` objects was added in version 0.24.0.

The return type will be the same as `left`. If `left` is a `DataFrame` or named `Series` and `right` is a subclass of `DataFrame`, the return type will still be `DataFrame`.

`merge` is a function in the pandas namespace, and it is also available as a `DataFrame` instance method `merge()`, with the calling `DataFrame` being implicitly considered the left object in the join.

The related `join()` method, uses `merge` internally for the index-on-index (by default) and column(s)-on-index join. If you are joining on index only, you may wish to use `DataFrame.join` to save yourself some typing.

Brief primer on merge methods (relational algebra)

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (`DataFrame` objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two `DataFrame` objects on their indexes (which must contain unique values).
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a different `DataFrame`.
- **many-to-many** joins: joining columns on columns.

Note: When joining columns on columns (potentially a many-to-many join), any indexes on the passed `DataFrame` objects **will be discarded**.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```
In [38]: left = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
.....:                       'A': ['A0', 'A1', 'A2', 'A3'],
.....:                       'B': ['B0', 'B1', 'B2', 'B3']})

In [39]: right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
.....:                        'C': ['C0', 'C1', 'C2', 'C3'],
.....:                        'D': ['D0', 'D1', 'D2', 'D3']})

In [40]: result = pd.merge(left, right, on='key')
```

left				right				Result					
	key	A	B		key	C	D		key	A	B	C	D
0	K0	A0	B0	0	K0	C0	D0	0	K0	A0	B0	C0	D0
1	K1	A1	B1	1	K1	C1	D1	1	K1	A1	B1	C1	D1
2	K2	A2	B2	2	K2	C2	D2	2	K2	A2	B2	C2	D2
3	K3	A3	B3	3	K3	C3	D3	3	K3	A3	B3	C3	D3

Here is a more complicated example with multiple join keys. Only the keys appearing in `left` and `right` are present (the intersection), since `how='inner'` by default.

```
In [41]: left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
.....:                      'key2': ['K0', 'K1', 'K0', 'K1'],
.....:                      'A': ['A0', 'A1', 'A2', 'A3'],
.....:                      'B': ['B0', 'B1', 'B2', 'B3']})

In [42]: right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
.....:                        'key2': ['K0', 'K0', 'K0', 'K0'],
.....:                        'C': ['C0', 'C1', 'C2', 'C3'],
.....:                        'D': ['D0', 'D1', 'D2', 'D3']})

In [43]: result = pd.merge(left, right, on=['key1', 'key2'])
```

left					right					Result						
	key1	key2	A	B		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C2	D2
3	K2	K1	A3	B3	3	K2	K0	C3	D3							

The `how` argument to `merge` specifies how to determine which keys are to be included in the resulting table. If a key combination **does not appear** in either the left or right tables, the values in the joined table will be `NA`. Here is a summary of the `how` options and their SQL equivalent names:

Merge method	SQL Join Name	Description
left	LEFT OUTER JOIN	Use keys from left frame only
right	RIGHT OUTER JOIN	Use keys from right frame only
outer	FULL OUTER JOIN	Use union of keys from both frames
inner	INNER JOIN	Use intersection of keys from both frames

```
In [44]: result = pd.merge(left, right, how='left', on=['key1', 'key2'])
```

left					right					Result						
	key1	key2	A	B		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C1	D1
3	K2	K1	A3	B3	3	K2	K0	C3	D3	3	K1	K0	A2	B2	C2	D2
										4	K2	K1	A3	B3	NaN	NaN

```
In [45]: result = pd.merge(left, right, how='right', on=['key1', 'key2'])
```

left					right					Result						
	key1	key2	A	B		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C2	D2
3	K2	K1	A3	B3	3	K2	K0	C3	D3	3	K2	K0	NaN	NaN	C3	D3

```
In [46]: result = pd.merge(left, right, how='outer', on=['key1', 'key2'])
```

left					right					Result							
											key1	key2	A	B	C	D	
	key1	key2	A	B		key1	key2	C	D		0	K0	K0	A0	B0	C0	D0
0	K0	K0	A0	B0	0	K0	K0	C0	D0 <th>1</th> <td>K0</td> <td>K1</td> <td>A1</td> <td>B1</td> <td>NaN</td> <td>NaN</td> <td></td>	1	K0	K1	A1	B1	NaN	NaN	
1	K0	K1	A1	B1	1	K1	K0	C1	D1 <th>2</th> <td>K1</td> <td>K0</td> <td>A2</td> <td>B2</td> <td>C1</td> <td>D1</td> <td></td>	2	K1	K0	A2	B2	C1	D1	
2	K1	K0	A2	B2	2	K1	K0	C2	D2 <th>3</th> <td>K1</td> <td>K0</td> <td>A2</td> <td>B2</td> <td>C2</td> <td>D2</td> <td></td>	3	K1	K0	A2	B2	C2	D2	
3	K2	K1	A3	B3	3	K2	K0	C3	D3 <th>4</th> <td>K2</td> <td>K1</td> <td>A3</td> <td>B3</td> <td>NaN</td> <td>NaN</td> <td></td>	4	K2	K1	A3	B3	NaN	NaN	
										5	K2	K0	NaN	NaN	C3	D3	

```
In [47]: result = pd.merge(left, right, how='inner', on=['key1', 'key2'])
```

left					right					Result						
	key1	key2	A	B		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C2	D2
3	K2	K1	A3	B3	3	K2	K0	C3	D3							

Here is another example with duplicate join keys in DataFrames:


```
In [48]: left = pd.DataFrame({'A': [1, 2], 'B': [2, 2]})
In [49]: right = pd.DataFrame({'A': [4, 5, 6], 'B': [2, 2, 2]})
In [50]: result = pd.merge(left, right, on='B', how='outer')
```

left			right			Result			
	A	B		A	B		A_x	B	A_y
0	1	2	0	4	2	0	1	2	4
1	2	2	1	5	2	1	1	2	5
			2	6	2	2	1	2	6
						3	2	2	4
						4	2	2	5
						5	2	2	6

Warning: Joining / merging on duplicate keys can cause a returned frame that is the multiplication of the row dimensions, which may result in memory overflow. It is the user's responsibility to manage duplicate values in keys before joining large DataFrames.

Checking for duplicate keys

New in version 0.21.0.

Users can use the `validate` argument to automatically check whether there are unexpected duplicates in their merge keys. Key uniqueness is checked before merge operations and so should protect against memory overflows. Checking key uniqueness is also a good way to ensure user data structures are as expected.

In the following example, there are duplicate values of `B` in the `right` `DataFrame`. As this is not a one-to-one merge – as specified in the `validate` argument – an exception will be raised.

```
In [51]: left = pd.DataFrame({'A' : [1,2], 'B' : [1, 2]})
In [52]: right = pd.DataFrame({'A' : [4,5,6], 'B': [2, 2, 2]})

In [53]: result = pd.merge(left, right, on='B', how='outer', validate="one_to_one")
...
MergeError: Merge keys are not unique in right dataset; not a one-to-one merge
```

If the user is aware of the duplicates in the `right` `DataFrame` but wants to ensure there are no duplicates in the `left` `DataFrame`, one can use the `validate='one_to_many'` argument instead, which will not raise an exception.

```
In [53]: pd.merge(left, right, on='B', how='outer', validate="one_to_many")
Out[53]:
   A_x  B  A_y
0    1  1  NaN
```

```
1    2    2    4.0
2    2    2    5.0
3    2    2    6.0
```

The merge indicator

`merge()` accepts the argument `indicator`. If `True`, a Categorical-type column called `_merge` will be added to the output object that takes on values:

Observation Origin	<code>_merge</code> value
Merge key only in 'left' frame	<code>left_only</code>
Merge key only in 'right' frame	<code>right_only</code>
Merge key in both frames	<code>both</code>

```
In [54]: df1 = pd.DataFrame({'coll': [0, 1], 'col_left': ['a', 'b']})
In [55]: df2 = pd.DataFrame({'coll': [1, 2, 2], 'col_right': [2, 2, 2]})
In [56]: pd.merge(df1, df2, on='coll', how='outer', indicator=True)
Out[56]:
   coll col_left col_right  _merge
0     0         a        NaN  left_only
1     1         b         2.0    both
2     2        NaN         2.0  right_only
3     2        NaN         2.0  right_only
```

The `indicator` argument will also accept string arguments, in which case the indicator function will use the value of the passed string as the name for the indicator column.

```
In [57]: pd.merge(df1, df2, on='coll', how='outer', indicator='indicator_column')
Out[57]:
   coll col_left col_right indicator_column
0     0         a        NaN      left_only
1     1         b         2.0         both
2     2        NaN         2.0      right_only
3     2        NaN         2.0      right_only
```

Merge Dtypes

New in version 0.19.0.

Merging will preserve the dtype of the join keys.

```
In [58]: left = pd.DataFrame({'key': [1], 'v1': [10]})
In [59]: left
Out[59]:
   key  v1
0    1  10
In [60]: right = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})
In [61]: right
Out[61]:
   key  v1
```

```
0    1    20
1    2    30
```

We are able to preserve the join keys:

```
In [62]: pd.merge(left, right, how='outer')
Out[62]:
   key  v1
0    1  10
1    1  20
2    2  30

In [63]: pd.merge(left, right, how='outer').dtypes
Out[63]:
key      int64
v1      int64
dtype: object
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast.

```
In [64]: pd.merge(left, right, how='outer', on='key')
Out[64]:
   key  v1_x  v1_y
0    1  10.0   20
1    2   NaN   30

In [65]: pd.merge(left, right, how='outer', on='key').dtypes
Out[65]:
key      int64
v1_x    float64
v1_y     int64
dtype: object
```

New in version 0.20.0.

Merging will preserve `category` dtypes of the mergands. See also the section on [categoricals](#).

The left frame.

```
In [66]: from pandas.api.types import CategoricalDtype

In [67]: X = pd.Series(np.random.choice(['foo', 'bar'], size=(10,)))

In [68]: X = X.astype(CategoricalDtype(categories=['foo', 'bar']))

In [69]: left = pd.DataFrame({'X': X,
.....:                       'Y': np.random.choice(['one', 'two', 'three'],
.....:                                                size=(10,))})
.....:

In [70]: left
Out[70]:
   X      Y
0  bar  one
1  foo  one
2  foo three
3  bar three
4  foo  one
5  bar  one
6  bar three
7  bar three
```

```

8 bar three
9 foo three

In [71]: left.dtypes
Out[71]:
X    category
Y      object
dtype: object

```

The right frame.

```

In [72]: right = pd.DataFrame({'X': pd.Series(['foo', 'bar'],
.....:                                     dtype=CategoricalDtype(['foo', 'bar']))
.....:                        'Z': [1, 2]})
.....:

In [73]: right
Out[73]:
   X  Z
0  foo  1
1  bar  2

In [74]: right.dtypes
Out[74]:
X    category
Z      int64
dtype: object

```

The merged result:

```

In [75]: result = pd.merge(left, right, how='outer')

In [76]: result
Out[76]:
   X      Y  Z
0  bar  one  2
1  bar  three  2
2  bar  one  2
3  bar  three  2
4  bar  three  2
5  bar  three  2
6  foo  one  1
7  foo  three  1
8  foo  one  1
9  foo  three  1

In [77]: result.dtypes
Out[77]:
X    category
Y      object
Z      int64
dtype: object

```

Note: The category dtypes must be *exactly* the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to `object` dtype.

Note: Merging on `category` dtypes that are the same can be quite performant compared to `object` dtype merging.

Joining on index

`DataFrame.join()` is a convenient method for combining the columns of two potentially differently-indexed `DataFrames` into a single result `DataFrame`. Here is a very basic example:

```
In [78]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                       'B': ['B0', 'B1', 'B2']},
.....:                       index=['K0', 'K1', 'K2'])

In [79]: right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
.....:                         'D': ['D0', 'D2', 'D3']},
.....:                         index=['K0', 'K2', 'K3'])

In [80]: result = left.join(right)
```

left			right			Result				
	A	B		C	D		A	B	C	D
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K1	A1	B1	NaN	NaN
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2

```
In [81]: result = left.join(right, how='outer')
```

left			right			Result				
	A	B		C	D		A	B	C	D
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K1	A1	B1	NaN	NaN
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2
						K3	NaN	NaN	C3	D3

The same as above, but with `how='inner'`.

```
In [82]: result = left.join(right, how='inner')
```

left			right			Result				
	A	B		C	D		A	B	C	D
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2					
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2

The data alignment here is on the indexes (row labels). This same behavior can be achieved using `merge` plus additional arguments instructing it to use the indexes:

```
In [83]: result = pd.merge(left, right, left_index=True, right_index=True, how='outer')
```

left			right			Result				
	A	B		C	D		A	B	C	D
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K1	A1	B1	NaN	NaN
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2
						K3	NaN	NaN	C3	D3

```
In [84]: result = pd.merge(left, right, left_index=True, right_index=True, how='inner')
```

left			right			Result				
	A	B		C	D		A	B	C	D
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K2	A2	B2	C2	D2
K2	A2	B2	K3	C3	D3					

Joining key columns on an index

`join()` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed `DataFrame` is to be aligned on that column in the `DataFrame`. These two function calls are completely equivalent:

```
left.join(right, on=key_or_keys)
pd.merge(left, right, left_on=key_or_keys, right_index=True,
         how='left', sort=False)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the `DataFrame`'s is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```
In [85]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                      'B': ['B0', 'B1', 'B2', 'B3'],
.....:                      'key': ['K0', 'K1', 'K0', 'K1']})

In [86]: right = pd.DataFrame({'C': ['C0', 'C1'],
.....:                       'D': ['D0', 'D1']},
.....:                       index=['K0', 'K1'])

In [87]: result = left.join(right, on='key')
```

left				right			Result					
	A	B	key		C	D		A	B	key	C	D
0	A0	B0	K0				0	A0	B0	K0	C0	D0
1	A1	B1	K1	K0	C0	D0	1	A1	B1	K1	C1	D1
2	A2	B2	K0	K1	C1	D1	2	A2	B2	K0	C0	D0
3	A3	B3	K1				3	A3	B3	K1	C1	D1

```
In [88]: result = pd.merge(left, right, left_on='key', right_index=True,
.....:                    how='left', sort=False);
.....:
```

left				right			Result					
	A	B	key		C	D		A	B	key	C	D
0	A0	B0	K0				0	A0	B0	K0	C0	D0
1	A1	B1	K1	K0	C0	D0	1	A1	B1	K1	C1	D1
2	A2	B2	K0	K1	C1	D1	2	A2	B2	K0	C0	D0
3	A3	B3	K1				3	A3	B3	K1	C1	D1

To join on multiple keys, the passed DataFrame must have a `MultiIndex`:

```
In [89]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                      'B': ['B0', 'B1', 'B2', 'B3'],
.....:                      'key1': ['K0', 'K0', 'K1', 'K2'],
.....:                      'key2': ['K0', 'K1', 'K0', 'K1']})

In [90]: index = pd.MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'),
.....:                                     ('K2', 'K0'), ('K2', 'K1')])

In [91]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                       'D': ['D0', 'D1', 'D2', 'D3']},
.....:                       index=index)
```

Now this can be joined by passing the two key column names:

```
In [92]: result = left.join(right, on=['key1', 'key2'])
```

left					right				Result						
	A	B	key1	key2			C	D		A	B	key1	key2	C	D
0	A0	B0	K0	K0	K0	K0	C0	D0	0	A0	B0	K0	K0	C0	D0
1	A1	B1	K0	K1	K1	K0	C1	D1	1	A1	B1	K0	K1	NaN	NaN
2	A2	B2	K1	K0	K2	K0	C2	D2	2	A2	B2	K1	K0	C1	D1
3	A3	B3	K2	K1	K2	K1	C3	D3	3	A3	B3	K2	K1	C3	D3

The default for `DataFrame.join` is to perform a left join (essentially a “VLOOKUP” operation, for Excel users), which uses only the keys found in the calling `DataFrame`. Other join types, for example inner join, can be just as easily performed:

```
In [93]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

left					right				Result						
	A	B	key1	key2			C	D		A	B	key1	key2	C	D
0	A0	B0	K0	K0	K0	K0	C0	D0	0	A0	B0	K0	K0	C0	D0
1	A1	B1	K0	K1	K1	K0	C1	D1							
2	A2	B2	K1	K0	K2	K0	C2	D2	2	A2	B2	K1	K0	C1	D1
3	A3	B3	K2	K1	K2	K1	C3	D3	3	A3	B3	K2	K1	C3	D3

As you can see, this drops any rows where there was no match.

Joining a single Index to a MultiIndex

You can join a singly-indexed `DataFrame` with a level of a MultiIndexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the MultiIndexed frame.

```
In [94]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                       'B': ['B0', 'B1', 'B2']},
.....:                       index=pd.Index(['K0', 'K1', 'K2'], name='key'))
.....:

In [95]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....:                                     ('K2', 'Y2'), ('K2', 'Y3')],
.....:                                     names=['key', 'Y'])
.....:

In [96]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                         'D': ['D0', 'D1', 'D2', 'D3']},
.....:                         index=index)
.....:

In [97]: result = left.join(right, how='inner')
```


left			right				Result					
	A	B			C	D			A	B	C	D
K0	A0	B0	K0	Y0	C0	D0	K0	Y0	A0	B0	C0	D0
K1	A1	B1	K1	Y1	C1	D1	K1	Y1	A1	B1	C1	D1
K2	A2	B2	K2	Y2	C2	D2	K2	Y2	A2	B2	C2	D2
			K2	Y3	C3	D3	K2	Y3	A2	B2	C3	D3

This is equivalent but less verbose and more memory efficient / faster than this.

```
In [98]: result = pd.merge(left.reset_index(), right.reset_index(),
.....:                     on=['key'], how='inner').set_index(['key', 'Y'])
.....:
```

left			right				Result							
		A	B			C	D				A	B	C	D
K0		A0	B0	K0	Y0	C0	D0	K0	Y0	A0	B0	C0	D0	
K1		A1	B1	K1	Y1	C1	D1	K1	Y1	A1	B1	C1	D1	
K2		A2	B2	K2	Y2	C2	D2	K2	Y2	A2	B2	C2	D2	
				K2	Y3	C3	D3	K2	Y3	A2	B2	C3	D3	

Joining with two MultiIndexes

This is supported in a limited way, provided that the index for the right argument is completely used in the join, and is a subset of the indices in the left argument, as in this example:

```
In [99]: leftindex = pd.MultiIndex.from_product([list('abc'), list('xy'), [1, 2]],
.....:                                         names=['abc', 'xy', 'num'])
.....:

In [100]: left = pd.DataFrame({'v1': range(12)}, index=leftindex)

In [101]: left
Out[101]:
      v1
abc xy num
a  x   1    0
   2    1
   y   1    2
   2    3
b  x   1    4
   2    5
   y   1    6
   2    7
c  x   1    8
   2    9
   y   1   10
   2   11

In [102]: rightindex = pd.MultiIndex.from_product([list('abc'), list('xy')],
.....:                                             names=['abc', 'xy'])
.....:

In [103]: right = pd.DataFrame({'v2': [100 * i for i in range(1, 7)]}, index=rightindex)

In [104]: right
```

```

Out[104]:
      v2
abc xy
a  x   100
   y   200
b  x   300
   y   400
c  x   500
   y   600

In [105]: left.join(right, on=['abc', 'xy'], how='inner')
Out[105]:
      v1  v2
abc xy num
a  x   1    0  100
   2    1  100
   y   1    2  200
   2    3  200
b  x   1    4  300
   2    5  300
   y   1    6  400
   2    7  400
c  x   1    8  500
   2    9  500
   y   1   10  600
   2   11  600

```

If that condition is not satisfied, a join with two multi-indexes can be done using the following code.

```

In [106]: leftindex = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
.....:                                         ('K1', 'X2')],
.....:                                         names=['key', 'X'])
.....:

In [107]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                        'B': ['B0', 'B1', 'B2']},
.....:                        index=leftindex)
.....:

In [108]: rightindex = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....:                                           ('K2', 'Y2'), ('K2', 'Y3')],
.....:                                           names=['key', 'Y'])
.....:

In [109]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                          'D': ['D0', 'D1', 'D2', 'D3']},
.....:                          index=rightindex)
.....:

In [110]: result = pd.merge(left.reset_index(), right.reset_index(),
.....:                       on=['key'], how='inner').set_index(['key', 'X', 'Y'])
.....:

```

left				right				Result							
		A	B			C	D				A	B	C	D	
K0	X0	A0	B0	K0	Y0	C0	D0	K0	X0	Y0	A0	B0	C0	D0	
K0	X1	A1	B1	K1	Y1	C1	D1	K0	X1	Y0	A1	B1	C0	D0	
K1	X2	A2	B2	K2	Y2	C2	D2	K1	X2	Y1	A2	B2	C1	D1	
				K2	Y3	C3	D3								

Merging on a combination of columns and index levels

New in version 0.23.

Strings passed as the `on`, `left_on`, and `right_on` parameters may refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes.

```
In [111]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [112]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                        'B': ['B0', 'B1', 'B2', 'B3'],
.....:                        'key2': ['K0', 'K1', 'K0', 'K1']},
.....:                        index=left_index)

In [113]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [114]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                          'D': ['D0', 'D1', 'D2', 'D3'],
.....:                          'key2': ['K0', 'K0', 'K0', 'K1']},
.....:                          index=right_index)

In [115]: result = left.merge(right, on=['key1', 'key2'])
```

left				right				Result					
	A	B	key2		C	D	key2		A	B	key2	C	D
K0	A0	B0	K0	K0	C0	D0	K0	K0	A0	B0	K0	C0	D0
K0	A1	B1	K1	K1	C1	D1	K0	K1	A2	B2	K0	C1	D1
K1	A2	B2	K0	K2	C2	D2	K0	K2	A3	B3	K1	C3	D3
K2	A3	B3	K1	K2	C3	D3	K1						

Note: When `DataFrames` are merged on a string that matches an index level in both frames, the index level is preserved as an index level in the resulting `DataFrame`.

Note: When `DataFrames` are merged using only some of the levels of a *MultiIndex*, the extra levels will be dropped from the resulting merge. In order to preserve those levels, use `reset_index` on those level names to move those levels to columns prior to doing the merge.

Note: If a string matches both a column name and an index level name, then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

Overlapping value columns

The merge `suffixes` argument takes a tuple of list of strings to append to overlapping column names in the input `DataFrames` to disambiguate the result columns:

```
In [116]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})
In [117]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})
In [118]: result = pd.merge(left, right, on='k')
```

left			right			Result			
	k	v		k	v		k	v_x	v_y
0	K0	1	0	K0	4	0	K0	1	4
1	K1	2	1	K0	5	1	K0	1	5
2	K2	3	2	K3	6				

```
In [119]: result = pd.merge(left, right, on='k', suffixes=['_l', '_r'])
```

left			right			Result			
	k	v		k	v		k	v_l	v_r
0	K0	1	0	K0	4	0	K0	1	4
1	K1	2	1	K0	5	1	K0	1	5
2	K2	3	2	K3	6				

`DataFrame.join()` has `lsuffix` and `rsuffix` arguments which behave similarly.

```
In [120]: left = left.set_index('k')
In [121]: right = right.set_index('k')
In [122]: result = left.join(right, lsuffix='_l', rsuffix='_r')
```

left		right		Result		
	v		v		v_l	v_r
K0	1	K0	4	K0	1	4.0
K1	2	K0	5	K0	1	5.0
K2	3	K3	6	K1	2	NaN
				K2	3	NaN

Joining multiple DataFrame or Panel objects

A list or tuple of `DataFrames` can also be passed to `join()` to join them together on their indexes.

```
In [123]: right2 = pd.DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])
In [124]: result = left.join([right, right2])
```

left		right		right2		Result			
							v_x	v_y	v
	v		v		v	K0	1	4.0	NaN
K0	1	K0	4	K1	7	K0	1	5.0	NaN
K1	2	K0	5	K1	8	K1	2	NaN	7.0
K2	3	K3	6	K2	9	K1	2	NaN	8.0
						K2	3	NaN	9.0

Merging together values within Series or DataFrame columns

Another fairly common situation is to have two like-indexed (or similarly indexed) `Series` or `DataFrame` objects and wanting to “patch” values in one object from values for matching indices in the other. Here is an example:

```
In [125]: df1 = pd.DataFrame([[np.nan, 3., 5.], [-4.6, np.nan, np.nan],
.....:                        [np.nan, 7., np.nan]])
.....:

In [126]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4]],
.....:                        index=[1, 2])
.....:
```

For this, use the `combine_first()` method:

```
In [127]: result = df1.combine_first(df2)
```

df1				df2				Result			
	0	1	2		0	1	2		0	1	2
0	NaN	3.0	5.0					0	NaN	3.0	5.0
1	-4.6	NaN	NaN	1	-42.6	NaN	-8.2	1	-4.6	NaN	-8.2
2	NaN	7.0	NaN	2	-5.0	1.6	4.0	2	-5.0	7.0	4.0

Note that this method only takes values from the right `DataFrame` if they are missing in the left `DataFrame`. A related method, `update()`, alters non-NA values in place:

```
In [128]: df1.update(df2)
```

df1				df2				Result			
	0	1	2		0	1	2		0	1	2
0	NaN	3.0	5.0	1	-42.6	NaN	-8.2	0	NaN	3.0	5.0
1	-4.6	NaN	NaN	2	-5.0	1.6	4.0	1	-42.6	NaN	-8.2
2	NaN	7.0	NaN					2	-5.0	1.6	4.0

Timeseries friendly merging

Merging Ordered Data

A `merge_ordered()` function allows combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [129]: left = pd.DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
.....:                        'lv': [1, 2, 3, 4],
.....:                        's': ['a', 'b', 'c', 'd']})
.....:

In [130]: right = pd.DataFrame({'k': ['K1', 'K2', 'K4'],
.....:                          'rv': [1, 2, 3]})
.....:

In [131]: pd.merge_ordered(left, right, fill_method='ffill', left_by='s')
Out[131]:
```

	k	lv	s	rv
0	K0	1.0	a	NaN
1	K1	1.0	a	1.0
2	K2	1.0	a	2.0
3	K4	1.0	a	3.0
4	K1	2.0	b	1.0
5	K2	2.0	b	2.0
6	K4	2.0	b	3.0
7	K1	3.0	c	1.0
8	K2	3.0	c	2.0
9	K4	3.0	c	3.0
10	K1	NaN	d	1.0
11	K2	4.0	d	2.0
12	K4	4.0	d	3.0

Merging AsOf

New in version 0.19.0.

A `merge_asof()` is similar to an ordered left-join except that we match on nearest key rather than equal keys. For each row in the `left` DataFrame, we select the last row in the `right` DataFrame whose `on` key is less than the left's key. Both DataFrames must be sorted by the key.

Optionally an asof merge can perform a group-wise merge. This matches the `by` key equally, in addition to the nearest match on the `on` key.

For example; we might have `trades` and `quotes` and we want to `asof` merge them.

```
In [132]: trades = pd.DataFrame({
.....:     'time': pd.to_datetime(['20160525 13:30:00.023',
.....:                             '20160525 13:30:00.038',
```

```

.....:                                     '20160525 13:30:00.048',
.....:                                     '20160525 13:30:00.048',
.....:                                     '20160525 13:30:00.048'])),
.....:   'ticker': ['MSFT', 'MSFT',
.....:             'GOOG', 'GOOG', 'AAPL'],
.....:   'price': [51.95, 51.95,
.....:            720.77, 720.92, 98.00],
.....:   'quantity': [75, 155,
.....:                100, 100, 100]},
.....:   columns=['time', 'ticker', 'price', 'quantity'])
.....:

In [133]: quotes = pd.DataFrame({
.....:   'time': pd.to_datetime(['20160525 13:30:00.023',
.....:                           '20160525 13:30:00.023',
.....:                           '20160525 13:30:00.030',
.....:                           '20160525 13:30:00.041',
.....:                           '20160525 13:30:00.048',
.....:                           '20160525 13:30:00.049',
.....:                           '20160525 13:30:00.072',
.....:                           '20160525 13:30:00.075'])),
.....:   'ticker': ['GOOG', 'MSFT', 'MSFT',
.....:             'MSFT', 'GOOG', 'AAPL', 'GOOG',
.....:             'MSFT'],
.....:   'bid': [720.50, 51.95, 51.97, 51.99,
.....:          720.50, 97.99, 720.50, 52.01],
.....:   'ask': [720.93, 51.96, 51.98, 52.00,
.....:          720.93, 98.01, 720.88, 52.03]},
.....:   columns=['time', 'ticker', 'bid', 'ask'])
.....:

```

In [134]: trades

Out[134]:

		time	ticker	price	quantity
0	2016-05-25	13:30:00.023	MSFT	51.95	75
1	2016-05-25	13:30:00.038	MSFT	51.95	155
2	2016-05-25	13:30:00.048	GOOG	720.77	100
3	2016-05-25	13:30:00.048	GOOG	720.92	100
4	2016-05-25	13:30:00.048	AAPL	98.00	100

In [135]: quotes

Out[135]:

		time	ticker	bid	ask
0	2016-05-25	13:30:00.023	GOOG	720.50	720.93
1	2016-05-25	13:30:00.023	MSFT	51.95	51.96
2	2016-05-25	13:30:00.030	MSFT	51.97	51.98
3	2016-05-25	13:30:00.041	MSFT	51.99	52.00
4	2016-05-25	13:30:00.048	GOOG	720.50	720.93
5	2016-05-25	13:30:00.049	AAPL	97.99	98.01
6	2016-05-25	13:30:00.072	GOOG	720.50	720.88
7	2016-05-25	13:30:00.075	MSFT	52.01	52.03

By default we are taking the asof of the quotes.

```

In [136]: pd.merge_asof(trades, quotes,
.....:                   on='time',
.....:                   by='ticker')
.....:

```

Out[136]:

		time	ticker	price	quantity	bid	ask
0	2016-05-25	13:30:00.023	MSFT	51.95	75	51.95	51.96
1	2016-05-25	13:30:00.038	MSFT	51.95	155	51.97	51.98
2	2016-05-25	13:30:00.048	GOOG	720.77	100	720.50	720.93
3	2016-05-25	13:30:00.048	GOOG	720.92	100	720.50	720.93
4	2016-05-25	13:30:00.048	AAPL	98.00	100	NaN	NaN

We only asof within 2ms between the quote time and the trade time.

```
In [137]: pd.merge_asof(trades, quotes,
.....:                  on='time',
.....:                  by='ticker',
.....:                  tolerance=pd.Timedelta('2ms'))
Out[137]:
```

		time	ticker	price	quantity	bid	ask
0	2016-05-25	13:30:00.023	MSFT	51.95	75	51.95	51.96
1	2016-05-25	13:30:00.038	MSFT	51.95	155	NaN	NaN
2	2016-05-25	13:30:00.048	GOOG	720.77	100	720.50	720.93
3	2016-05-25	13:30:00.048	GOOG	720.92	100	720.50	720.93
4	2016-05-25	13:30:00.048	AAPL	98.00	100	NaN	NaN

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. Note that though we exclude the exact matches (of the quotes), prior quotes **do** propagate to that point in time.

```
In [138]: pd.merge_asof(trades, quotes,
.....:                  on='time',
.....:                  by='ticker',
.....:                  tolerance=pd.Timedelta('10ms'),
.....:                  allow_exact_matches=False)
Out[138]:
```

		time	ticker	price	quantity	bid	ask
0	2016-05-25	13:30:00.023	MSFT	51.95	75	NaN	NaN
1	2016-05-25	13:30:00.038	MSFT	51.95	155	51.97	51.98
2	2016-05-25	13:30:00.048	GOOG	720.77	100	NaN	NaN
3	2016-05-25	13:30:00.048	GOOG	720.92	100	NaN	NaN
4	2016-05-25	13:30:00.048	AAPL	98.00	100	NaN	NaN