Merge, join, and concatenate

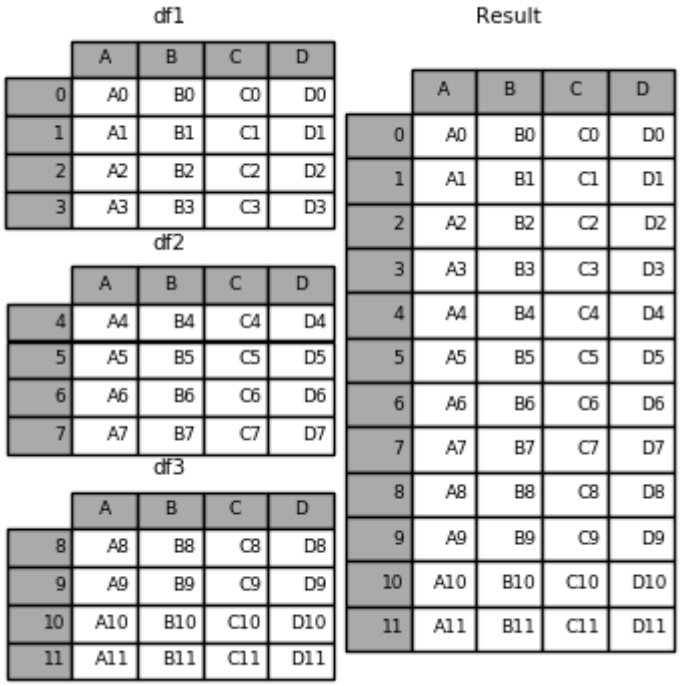
pandas provides various facilities for easily combining together Series or DataFrame with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

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)
```



	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

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

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

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

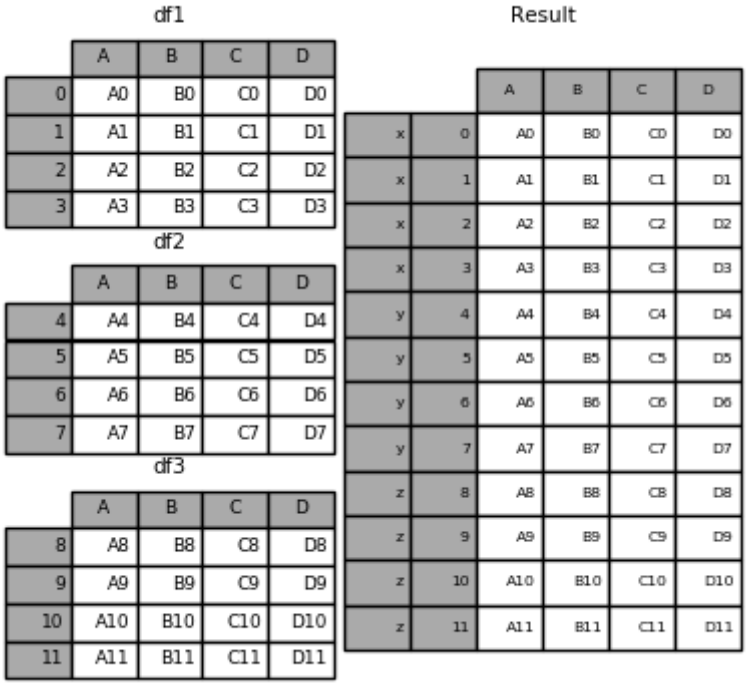
Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

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

- `objs` : a sequence or mapping of Series or DataFrame 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.
- `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'])
```



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 two 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'`.

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

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

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

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

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

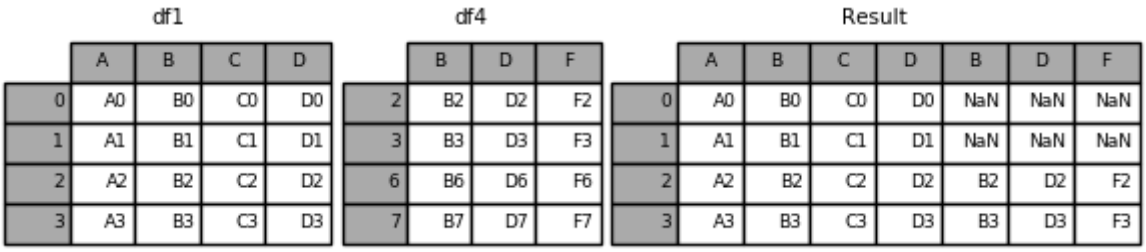
	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

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

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

Similarly, we could index before the concatenation:

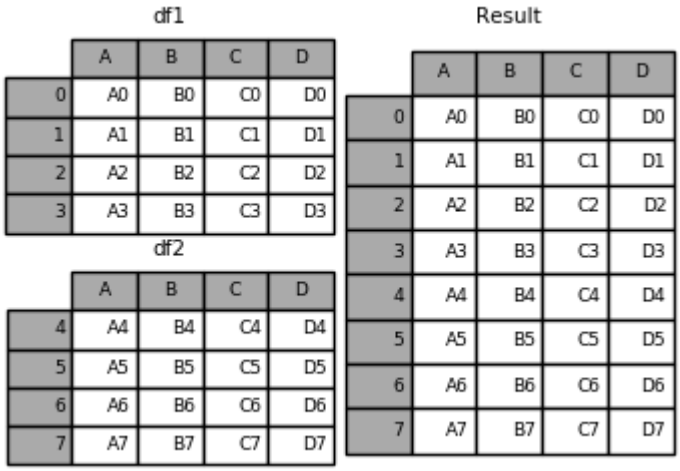
```
In [12]: pd.concat([df1, df4.reindex(df1.index)], axis=1)
Out[12]:
    A   B   C   D    B    D    F
0  A0  B0  C0  D0  NaN  NaN  NaN
1  A1  B1  C1  D1  NaN  NaN  NaN
2  A2  B2  C2  D2   B2   D2   F2
3  A3  B3  C3  D3   B3   D3   F3
```



Concatenating using `append`

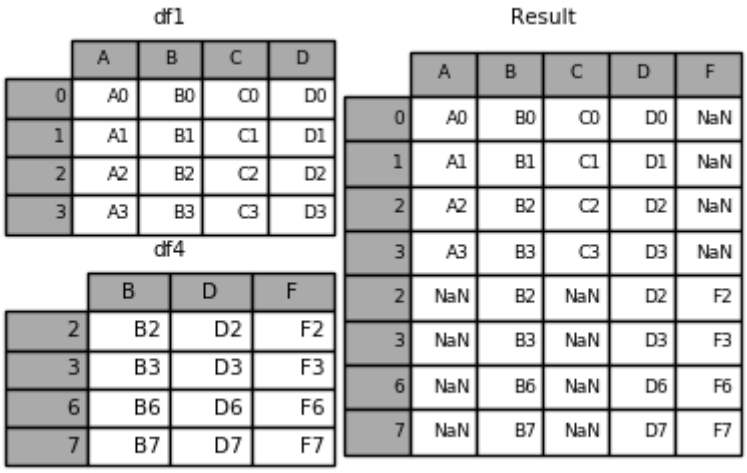
A useful shortcut to **`concat()`** are the **`append()`** instance methods on `Series` and `DataFrame`. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

```
In [13]: result = df1.append(df2)
```



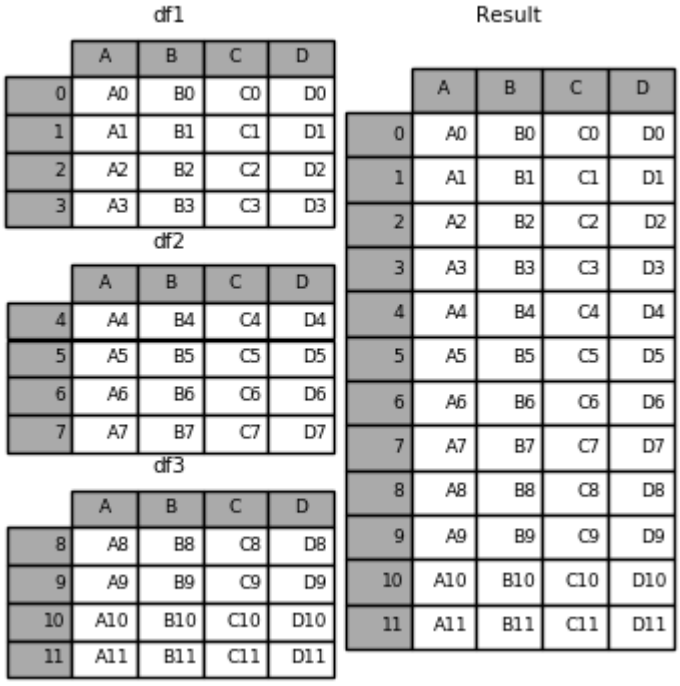
In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

```
In [14]: result = df1.append(df4, sort=False)
```



`append` may take multiple objects to concatenate:

```
In [15]: result = df1.append([df2, df3])
```

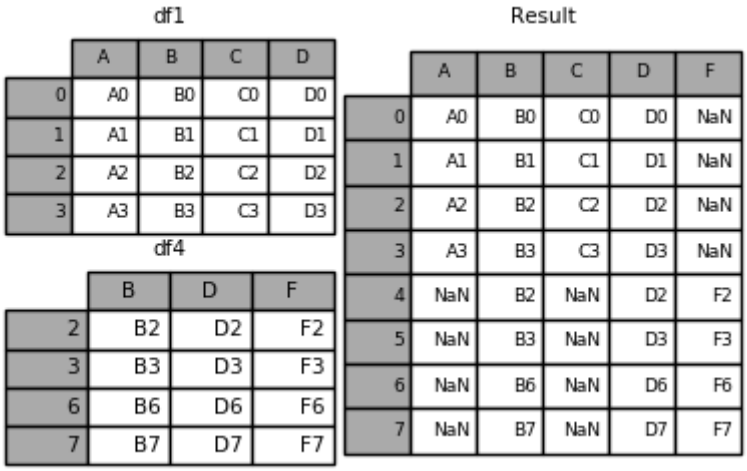


Note: Unlike the **`append()`** method, which appends to the original list and returns `None`, **`append()`** here **does not** modify `df1` and returns its copy with `df2` appended.

Ignoring indexes on the concatenation axis

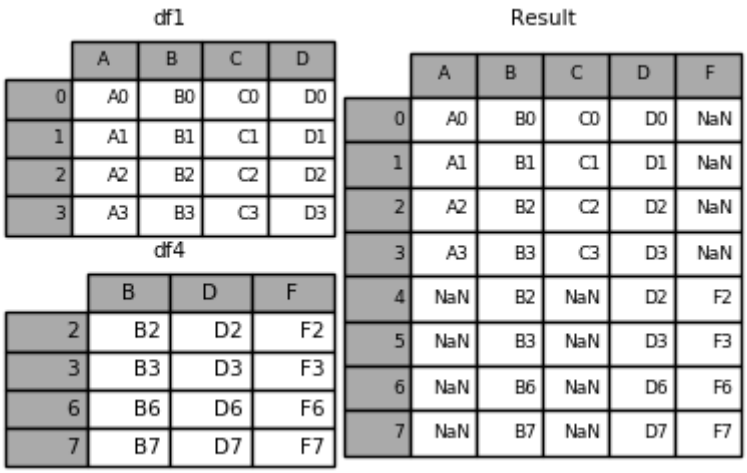
For `DataFrame` objects which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the `ignore_index` argument:

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



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

```
In [17]: result = df1.append(df4, ignore_index=True, sort=False)
```



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

In [19]: result = pd.concat([df1, s1], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

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

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 [20]: s2 = pd.Series(['_0', '_1', '_2', '_3'])

In [21]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s2

0	_0
1	_1
2	_2
3	_3

Result

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

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

```
In [22]: result = pd.concat([df1, s1], axis=1, ignore_index=True)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

	0	1	2	3	4
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

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

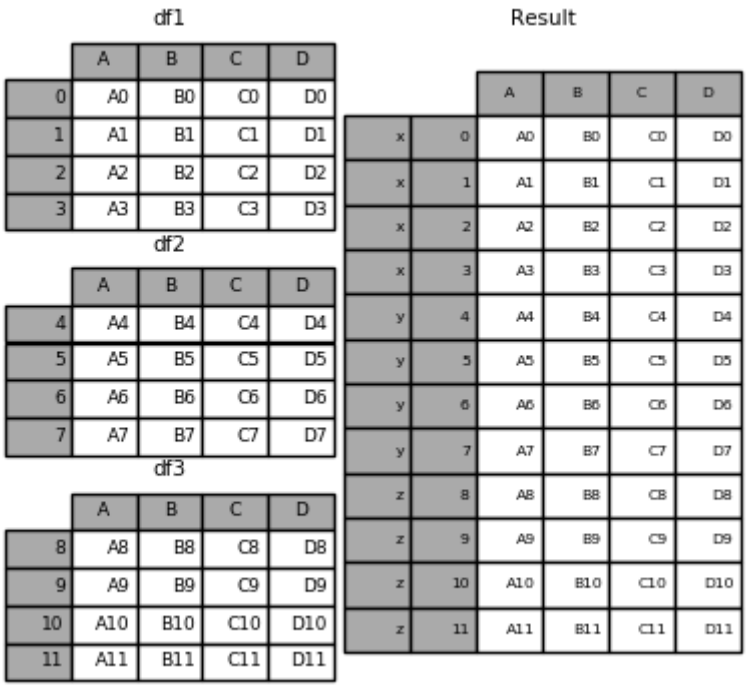
```
In [24]: s4 = pd.Series([0, 1, 2, 3])

In [25]: s5 = pd.Series([0, 1, 4, 5])

In [26]: pd.concat([s3, s4, s5], axis=1)
Out[26]:
   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 [27]: pd.concat([s3, s4, s5], axis=1, keys=['red', 'blue', 'yellow'])
Out[27]:
   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 [28]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```



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

```
In [29]: pieces = {'x': df1, 'y': df2, 'z': df3}

In [30]: result = pd.concat(pieces)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

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

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

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

```
In [31]: result = pd.concat(pieces, keys=['z', 'y'])
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

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

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

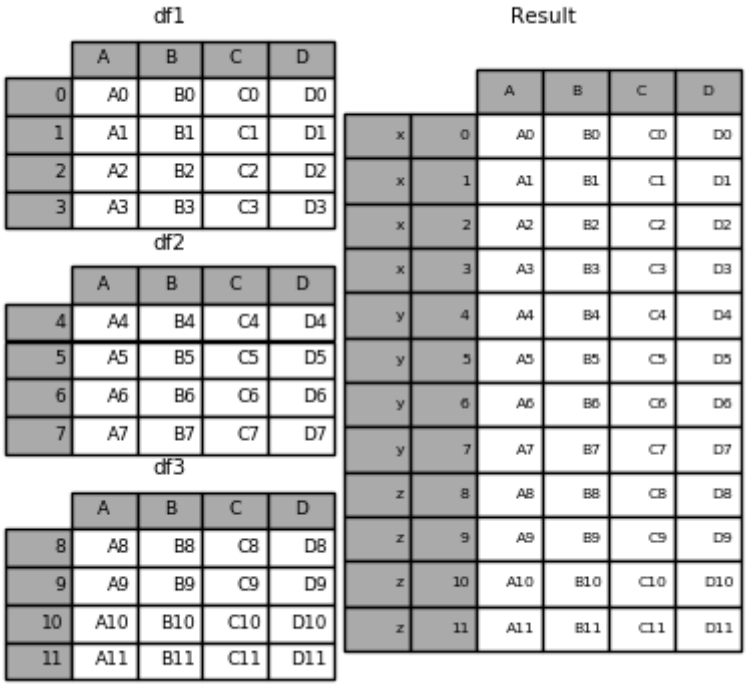
		A	B	C	D
z	8	A8	B8	C8	D8
z	9	A9	B9	C9	D9
z	10	A10	B10	C10	D10
z	11	A11	B11	C11	D11
y	4	A4	B4	C4	D4
y	5	A5	B5	C5	D5
y	6	A6	B6	C6	D6
y	7	A7	B7	C7	D7

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

```
In [32]: result.index.levels
Out[32]: 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 [33]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
   ....:                    levels=[['z', 'y', 'x', 'w']],
   ....:                    names=['group_key'])
   ....:
```



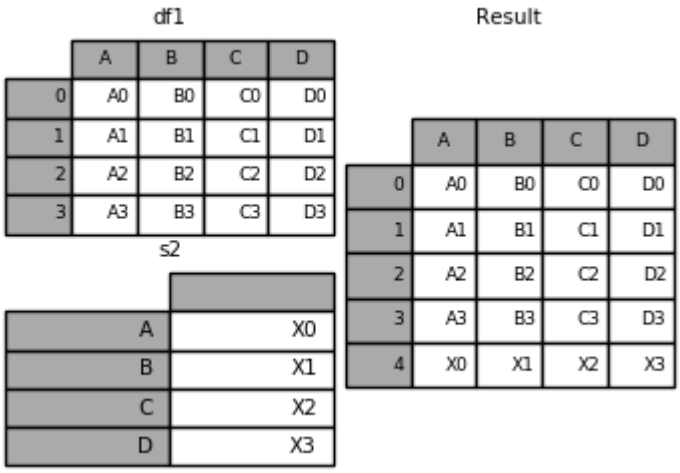

```
In [34]: result.index.levels
Out[34]: FrozenList([['z', 'y', 'x', 'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

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.

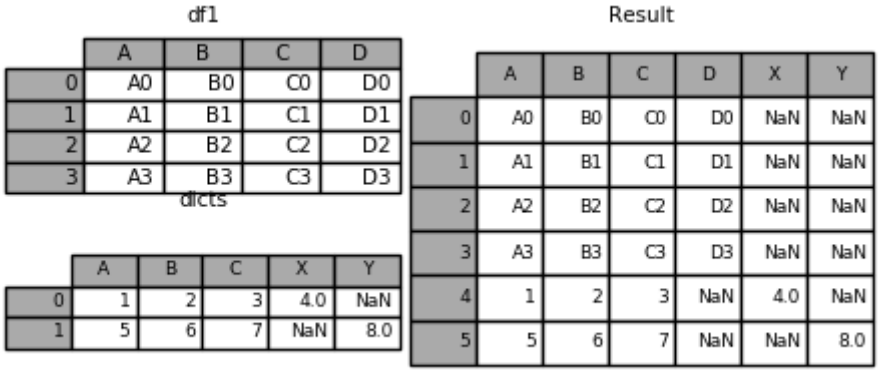
```
In [35]: s2 = pd.Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])

In [36]: result = df1.append(s2, ignore_index=True)
```



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

You can also pass a list of dicts or Series:

```
In [37]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4},
   ....:          {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
   ....:

In [38]: result = df1.append(dicts, ignore_index=True, sort=False)
```



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

In [40]: right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
   ....:                       'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D1', 'D2', 'D3']})
   ....:

In [41]: result = pd.merge(left, right, on='key')
```

left

	key	A	B
0	K0	A0	B0
1	K1	A1	B1
2	K2	A2	B2
3	K3	A3	B3

right

	key	C	D
0	K0	C0	D0
1	K1	C1	D1
2	K2	C2	D2
3	K3	C3	D3

Result

	key	A	B	C	D
0	K0	A0	B0	C0	D0
1	K1	A1	B1	C1	D1
2	K2	A2	B2	C2	D2
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 [42]: left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
   ....:                      'key2': ['K0', 'K1', 'K0', 'K1'],
   ....:                      'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                      'B': ['B0', 'B1', 'B2', 'B3']})
   ....:

In [43]: right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
   ....:                       'key2': ['K0', 'K0', 'K0', 'K0'],
   ....:                       'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D1', 'D2', 'D3']})
   ....:

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

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

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

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

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

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

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

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

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2
3	K2	K0	NaN	NaN	C3	D3

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

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

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

```
In [48]: result = pd.merge(left, right, how='inner', on=['key1', 'key2'])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

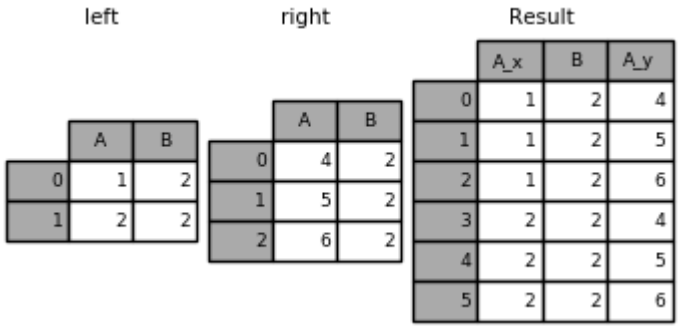
	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

Here is another example with duplicate join keys in DataFrames:

```
In [49]: left = pd.DataFrame({'A': [1, 2], 'B': [2, 2]})

In [50]: right = pd.DataFrame({'A': [4, 5, 6], 'B': [2, 2, 2]})

In [51]: result = pd.merge(left, right, on='B', how='outer')
```



left

	A	B
0	1	2
1	2	2

right

	A	B
0	4	2
1	5	2
2	6	2

Result

	A_x	B	A_y
0	1	2	4
1	1	2	5
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 [52]: left = pd.DataFrame({'A' : [1,2], 'B' : [1, 2]})

In [53]: 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 [54]: pd.merge(left, right, on='B', how='outer', validate="one_to_many")
Out[54]:
   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	`_merge` value
Merge key only in `'left'` frame	`left_only`
Merge key only in `'right'` frame	`right_only`
Merge key in both frames	`both`

```
In [55]: df1 = pd.DataFrame({'col1': [0, 1], 'col_left': ['a', 'b']})

In [56]: df2 = pd.DataFrame({'col1': [1, 2, 2], 'col_right': [2, 2, 2]})

In [57]: pd.merge(df1, df2, on='col1', how='outer', indicator=True)
Out[57]:
   col1 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 [58]: pd.merge(df1, df2, on='col1', how='outer', indicator='indicator_column')
Out[58]:
   col1 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 [59]: left = pd.DataFrame({'key': [1], 'v1': [10]})

In [60]: left
Out[60]:
   key  v1
0    1  10

In [61]: right = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})

In [62]: right
Out[62]:
   key  v1
```

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

We are able to preserve the join keys:

```
In [63]: pd.merge(left, right, how='outer')
Out[63]:
   key  v1
0    1  10
1    1  20
2    2  30

In [64]: pd.merge(left, right, how='outer').dtypes
Out[64]:
key    int64
v1     int64
dtype: object
```

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

```
In [65]: pd.merge(left, right, how='outer', on='key')
Out[65]:
   key  v1_x  v1_y
0    1  10.0    20
1    2   NaN    30

In [66]: pd.merge(left, right, how='outer', on='key').dtypes
Out[66]:
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 [67]: from pandas.api.types import CategoricalDtype

In [68]: X = pd.Series(np.random.choice(['foo', 'bar'], size=(10,)))

In [69]: X = X.astype(CategoricalDtype(categories=['foo', 'bar']))

In [70]: left = pd.DataFrame({'X': X,
   ....:                      'Y': np.random.choice(['one', 'two', 'three'],
   ....:                                            size=(10,))})
   ....:

In [71]: left
Out[71]:
     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 [72]: left.dtypes
Out[72]:
X    category
Y      object
dtype: object
```

The right frame.

```
In [73]: right = pd.DataFrame({'X': pd.Series(['foo', 'bar'],
   ....:                                       dtype=CategoricalDtype(['foo', 'bar']
   ....:                       'Z': [1, 2]})
   ....:

In [74]: right
Out[74]:
     X  Z
0  foo  1
1  bar  2

In [75]: right.dtypes
Out[75]:
X    category
Z       int64
dtype: object
```

The merged result:

```
In [76]: result = pd.merge(left, right, how='outer')

In [77]: result
Out[77]:
     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 [78]: result.dtypes
Out[78]:
X    category
Y      object
Z       int64
dtype: object
```

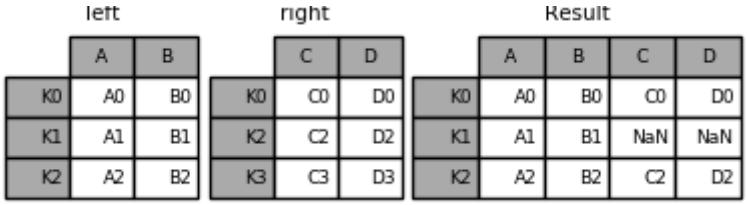
Note: The category dtypes must be *exactly* the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to `object` dtype.

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

In [80]: right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D2', 'D3']},
   ....:                      index=['K0', 'K2', 'K3'])
   ....:

In [81]: result = left.join(right)
```

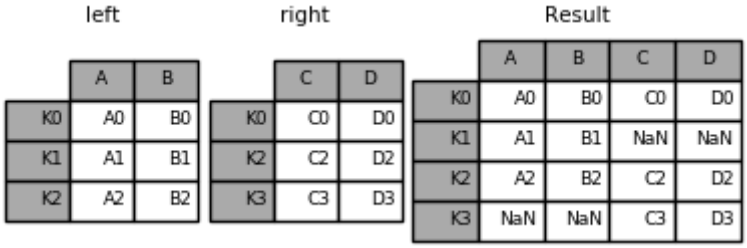


	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2

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



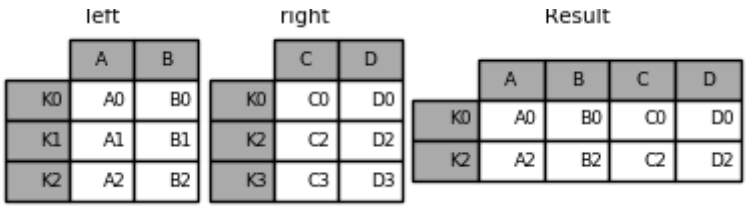
	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

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

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

```
In [83]: result = left.join(right, how='inner')
```



	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

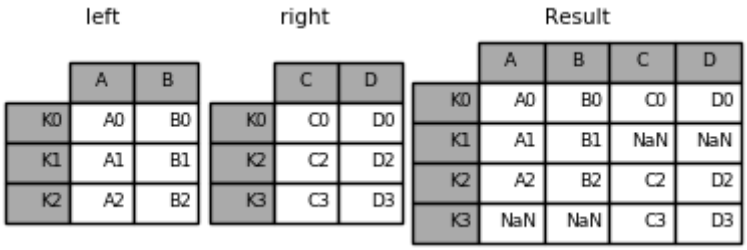
	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

	A	B	C	D
K0	A0	B0	C0	D0
K2	A2	B2	C2	D2

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

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

```
```



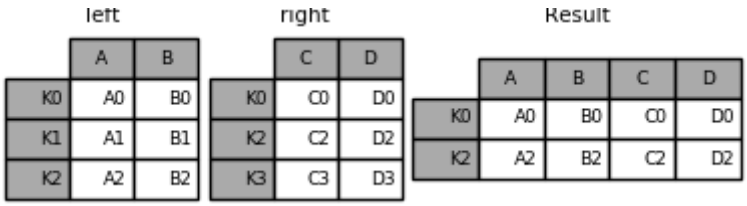
	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

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

```
In [85]: result = pd.merge(left, right, left_index=True, right_index=True, how='inne
```

```
```



	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

	A	B	C	D
K0	A0	B0	C0	D0
K2	A2	B2	C2	D2

Joining key columns on an index

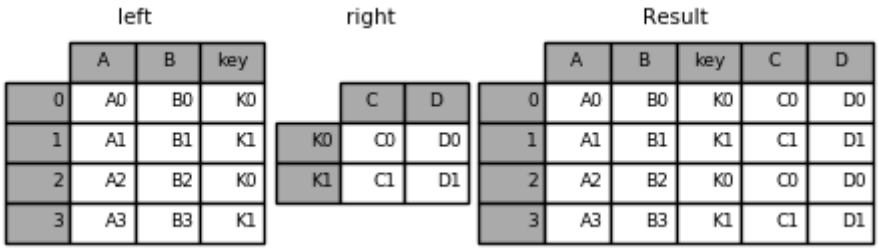
`join()` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed `DataFrame` is to be aligned on that column in the `DataFrame`. These two function calls are completely equivalent:

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

In [87]: right = pd.DataFrame({'C': ['C0', 'C1'],
   ....:                       'D': ['D0', 'D1']},
   ....:                      index=['K0', 'K1'])
   ....:
```

```
In [88]: result = left.join(right, on='key')
```

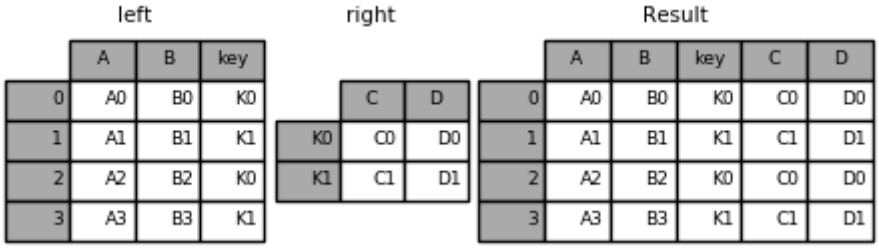


	A	B	key
0	A0	B0	K0
1	A1	B1	K1
2	A2	B2	K0
3	A3	B3	K1

	C	D
K0	C0	D0
K1	C1	D1

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

```
In [89]: result = pd.merge(left, right, left_on='key', right_index=True,
   ....:                   how='left', sort=False);
   ....:
```



	A	B	key
0	A0	B0	K0
1	A1	B1	K1
2	A2	B2	K0
3	A3	B3	K1

	C	D
K0	C0	D0
K1	C1	D1

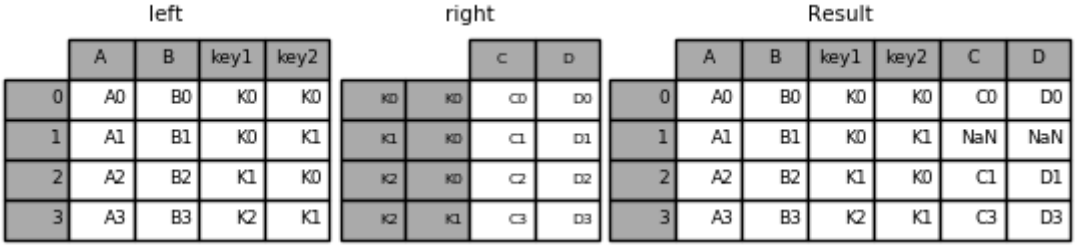
	A	B	key	C	D
0	A0	B0	K0	C0	D0
1	A1	B1	K1	C1	D1
2	A2	B2	K0	C0	D0
3	A3	B3	K1	C1	D1

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

```
In [90]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                      'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                      'key1': ['K0', 'K0', 'K1', 'K2'],
   ....:                      'key2': ['K0', 'K1', 'K0', 'K1']})
   ....:

In [91]: index = pd.MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'),
   ....:                                    ('K2', 'K0'), ('K2', 'K1')])
   ....:

In [92]: 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 [93]: result = left.join(right, on=['key1', 'key2'])
```



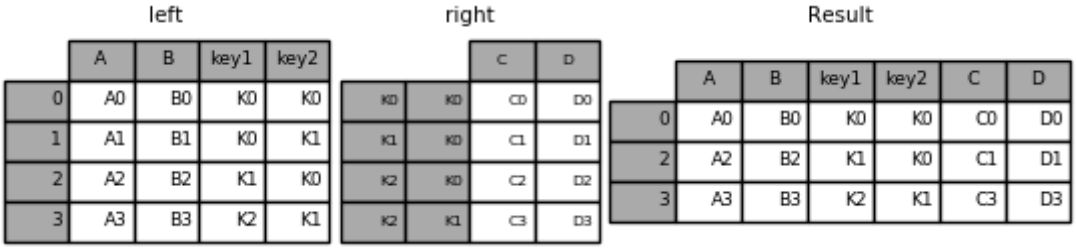
	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

		C	D
K0	K0	C0	D0
K1	K0	C1	D1
K2	K0	C2	D2
K2	K1	C3	D3

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

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

```
In [94]: result = left.join(right, on=['key1', 'key2'], how='inner')
```



	A	B	key1	key2
0	A0	B0	K0	K0
1	A1	B1	K0	K1
2	A2	B2	K1	K0
3	A3	B3	K2	K1

		C	D
K0	K0	C0	D0
K1	K0	C1	D1
K2	K0	C2	D2
K2	K1	C3	D3

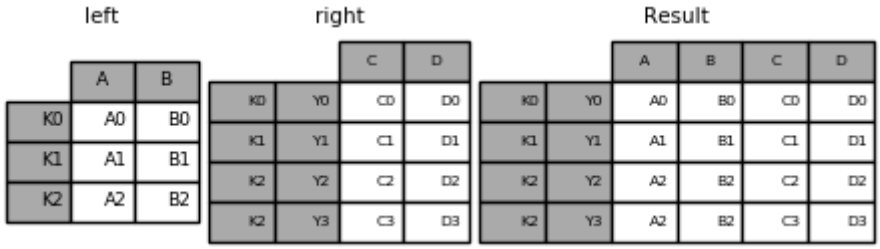
	A	B	key1	key2	C	D
0	A0	B0	K0	K0	C0	D0
2	A2	B2	K1	K0	C1	D1
3	A3	B3	K2	K1	C3	D3

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

Joining a single Index to a MultiIndex

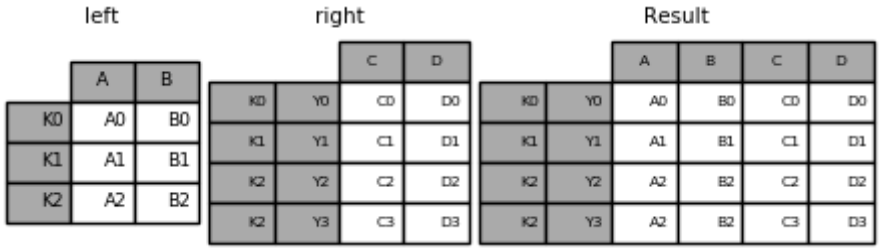
You can join a singly-indexed `DataFrame` with a level of a MultiIndexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the MultiIndexed frame.

```
In [95]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
   ....:                      'B': ['B0', 'B1', 'B2']},
   ....:                     index=pd.Index(['K0', 'K1', 'K2'], name='key'))
   ....:

In [96]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
   ....:                                    ('K2', 'Y2'), ('K2', 'Y3')],
   ....:                                     names=['key', 'Y'])
   ....:

In [97]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D1', 'D2', 'D3']},
   ....:                      index=index)
   ....:

In [98]: result = left.join(right, how='inner')
```



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

```
In [99]: result = pd.merge(left.reset_index(), right.reset_index(),
   ....:                   on=['key'], how='inner').set_index(['key','Y'])
   ....:
```



Joining with two MultiIndexes

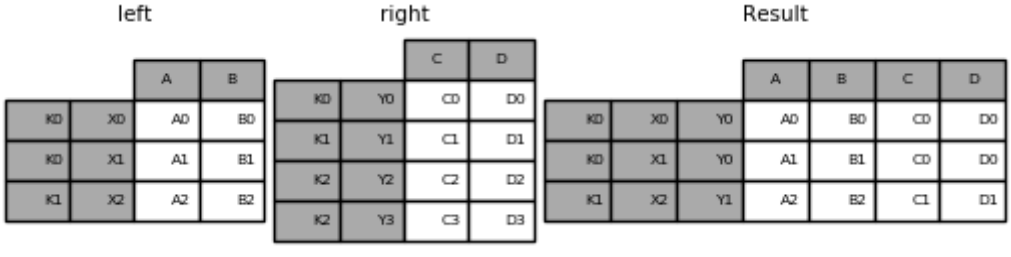
This is supported in a limited way, provided that the index for the right argument is completely used in the join, and is a subset of the indices in the left argument, as in this example:

```
In [100]: leftindex = pd.MultiIndex.from_product([list('abc'), list('xy'), [1, 2]],
   .....:                                        names=['abc', 'xy', 'num'])
   .....:

In [101]: left = pd.DataFrame({'v1': range(12)}, index=leftindex)

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

In [104]: right = pd.DataFrame({'v2': [100 * i for i in range(1, 7)]}, index=rightin

In [105]: right
```

```
Out[105]:
         v2
abc xy
a   x   100
    y   200
b   x   300
    y   400
c   x   500
    y   600

In [106]: left.join(right, on=['abc', 'xy'], how='inner')
Out[106]:
            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 [107]: leftindex = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
   .....:                                        ('K1', 'X2')],
   .....:                                       names=['key', 'X'])
   .....:

In [108]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
   .....:                      'B': ['B0', 'B1', 'B2']},
   .....:                     index=leftindex)
   .....:

In [109]: rightindex = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
   .....:                                         ('K2', 'Y2'), ('K2', 'Y3')],
   .....:                                        names=['key', 'Y'])
   .....:

In [110]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   .....:                       'D': ['D0', 'D1', 'D2', 'D3']},
   .....:                      index=rightindex)
   .....:

In [111]: result = pd.merge(left.reset_index(), right.reset_index(),
   .....:                   on=['key'], how='inner').set_index(['key', 'X', 'Y'])
   .....:
```

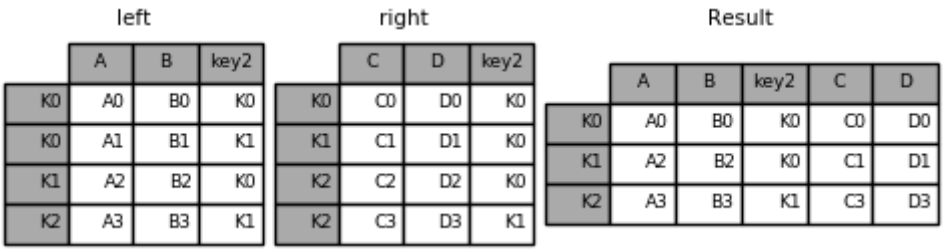


Merging on a combination of columns and index levels

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

In [113]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   .....:                      'B': ['B0', 'B1', 'B2', 'B3'],
   .....:                      'key2': ['K0', 'K1', 'K0', 'K1']},
   .....:                     index=left_index)
   .....:

In [114]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [115]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   .....:                       'D': ['D0', 'D1', 'D2', 'D3'],
   .....:                       'key2': ['K0', 'K0', 'K0', 'K1']},
   .....:                      index=right_index)
   .....:

In [116]: result = left.merge(right, on=['key1', 'key2'])
```



	A	B	key2
K0	A0	B0	K0
K0	A1	B1	K1
K1	A2	B2	K0
K2	A3	B3	K1

	C	D	key2
K0	C0	D0	K0
K1	C1	D1	K0
K2	C2	D2	K0
K2	C3	D3	K1

	A	B	key2	C	D
K0	A0	B0	K0	C0	D0
K1	A2	B2	K0	C1	D1
K2	A3	B3	K1	C3	D3

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.

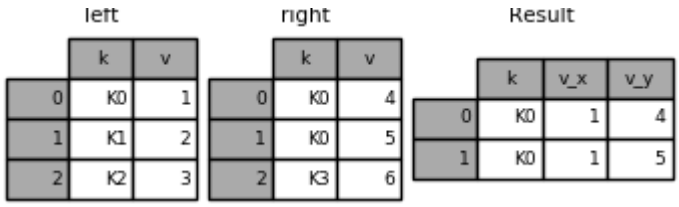
Note: When DataFrames are merged using only some of the levels of a *MultiIndex*, the extra levels will be dropped from the resulting merge. In order to preserve those levels, use `reset_index` on those level names to move those levels to columns prior to doing the merge.

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 `DataFrame`s to disambiguate the result columns:

```
In [117]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [118]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

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

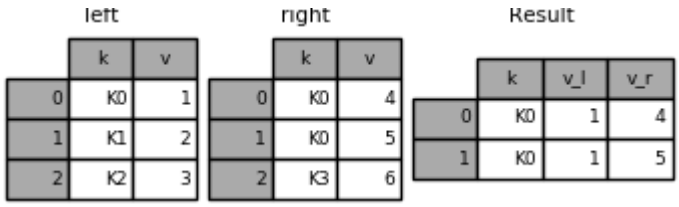


	k	v
0	K0	1
1	K1	2
2	K2	3

	k	v
0	K0	4
1	K0	5
2	K3	6

	k	v_x	v_y
0	K0	1	4
1	K0	1	5

```
In [120]: result = pd.merge(left, right, on='k', suffixes=['_l', '_r'])
```



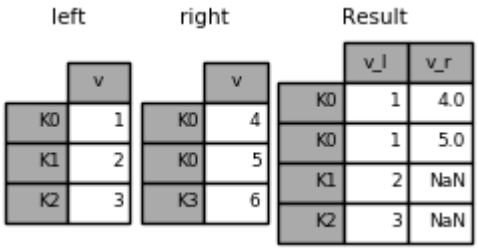
	k	v
0	K0	1
1	K1	2
2	K2	3

	k	v
0	K0	4
1	K0	5
2	K3	6

	k	v_l	v_r
0	K0	1	4
1	K0	1	5

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

```
In [121]: left = left.set_index('k')

In [122]: right = right.set_index('k')

In [123]: result = left.join(right, lsuffix='_l', rsuffix='_r')
```



	v
K0	1
K1	2
K2	3

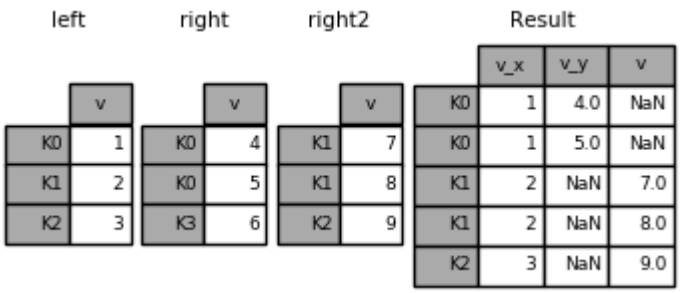
	v
K0	4
K0	5
K3	6

	v_l	v_r
K0	1	4.0
K0	1	5.0
K1	2	NaN
K2	3	NaN

Joining multiple DataFrames

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

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

In [125]: result = left.join([right, right2])
```



	v
K0	1
K1	2
K2	3

	v
K0	4
K0	5
K3	6

	v
K1	7
K1	8
K2	9

	v_x	v_y	v
K0	1	4.0	NaN
K0	1	5.0	NaN
K1	2	NaN	7.0
K1	2	NaN	8.0
K2	3	NaN	9.0

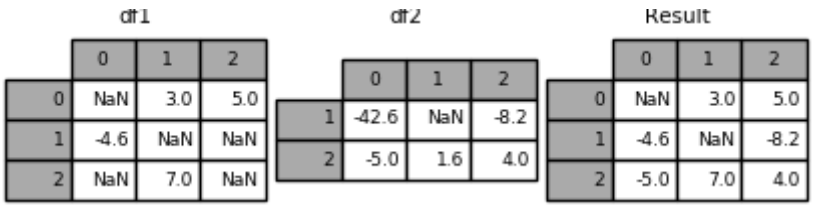
Merging together values within Series or DataFrame columns

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

In [127]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4]],
   .....:                     index=[1, 2])
   .....:
```

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

```
In [128]: result = df1.combine_first(df2)
```



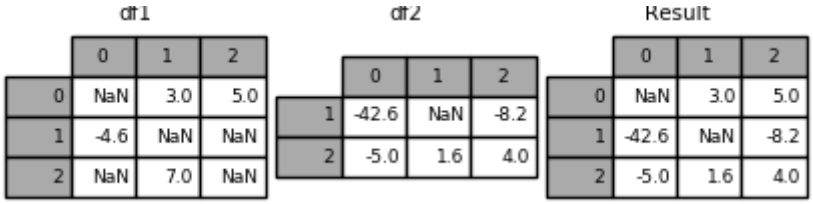
	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	NaN
2	NaN	7.0	NaN

	0	1	2
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	-8.2
2	-5.0	7.0	4.0

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

```
In [129]: df1.update(df2)
```



	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	NaN
2	NaN	7.0	NaN

	0	1	2
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

	0	1	2
0	NaN	3.0	5.0
1	-42.6	NaN	-8.2
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 [130]: left = pd.DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
   .....:                      'lv': [1, 2, 3, 4],
   .....:                      's': ['a', 'b', 'c', 'd']})
   .....:

In [131]: right = pd.DataFrame({'k': ['K1', 'K2', 'K4'],
   .....:                       'rv': [1, 2, 3]})
   .....:

In [132]: pd.merge_ordered(left, right, fill_method='ffill', left_by='s')
Out[132]:
     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 [133]: 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 [134]: 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 [135]: trades
Out[135]:
                     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 [136]: quotes
Out[136]:
                     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 [137]: pd.merge_asof(trades, quotes,
   .....:               on='time',
   .....:               by='ticker')
   .....:
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   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 [138]: pd.merge_asof(trades, quotes,
   .....:               on='time',
   .....:               by='ticker',
   .....:               tolerance=pd.Timedelta('2ms'))
   .....:
Out[138]:
                     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 [139]: pd.merge_asof(trades, quotes,
   .....:               on='time',
   .....:               by='ticker',
   .....:               tolerance=pd.Timedelta('10ms'),
   .....:               allow_exact_matches=False)
   .....:
Out[139]:
                     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
```