

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 [17]: 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 [18]: s1 = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')
```

```
In [19]: 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 [20]: s2 = pd.Series(['_0', '_1', '_2', '_3'])
In [21]: 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 [22]: 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 [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'])
```

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						

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					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 [31]: 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	z	9	A9	B9	C9	D9
2	A2	B2	C2	D2	z	10	A10	B10	C10	D10
3	A3	B3	C3	D3	z	11	A11	B11	C11	D11
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						
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						

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'])
.....:
```

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
4	A4	B4	C4	D4	y	5	A5	B5	C5	D5
5	A5	B5	C5	D5	y	6	A6	B6	C6	D6
6	A6	B6	C6	D6	y	7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	A8	B8	C8	D8
df3					z	9	A9	B9	C9	D9
	A	B	C	D	z	10	A10	B10	C10	D10
8	A8	B8	C8	D8	z	11	A11	B11	C11	D11
9	A9	B9	C9	D9						
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

```
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)
```

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 [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)
```

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					5	5	6	7	NaN	NaN	8.0
0	1	2	3	4.0	NaN						
1	5	6	7	NaN	8.0						

2.4.2 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				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 [42]: left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
.....:                       'key2': ['K0', 'K1', 'K0', 'K1'],
.....:                       'A': ['A0', 'A1', 'A2', 'A3'],
.....:                       'B': ['B0', 'B1', 'B2', 'B3']})
.....:
```

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```
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					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 [45]: 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 [46]: 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 [47]: result = pd.merge(left, right, how='outer', on=['key1', 'key2'])
```

left					right					Result						

```
In [48]: 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 [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			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 [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	<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 [55]: df1 = pd.DataFrame({'coll': [0, 1], 'col_left': ['a', 'b']})
In [56]: df2 = pd.DataFrame({'coll': [1, 2, 2], 'col_right': [2, 2, 2]})
In [57]: pd.merge(df1, df2, on='coll', how='outer', indicator=True)
Out[57]:
```

	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 [58]: pd.merge(df1, df2, on='coll', how='outer', indicator='indicator_column')
Out[58]:
```

	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

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
```

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
```

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```
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 the categories' 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)
```

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 [82]: 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 [83]: 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 [84]: 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 [85]: 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 [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')
```

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 [89]: 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 [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'])
```

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 [94]: 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	C1	D1
2	A2	B2	K1	K0	K2	K2	C2	D2	3	A3	B3	K2	K1	C3	D3
3	A3	B3	K2	K1	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')
```

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 [99]: 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 [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=rightindex)
```

```
In [105]: right
```

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

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```
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'])
.....:
```

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 [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'])
```

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 [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')
```

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 [120]: 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 [121]: left = left.set_index('k')
In [122]: right = right.set_index('k')
In [123]: 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 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])
```

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

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 [129]: 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

2.4.3 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

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',
```

(continues on next page)