Lecture 10

Data Aggregations on Multi-Indices ¶

We've previously seen that Pandas has built-in data aggregation methods, such as `mean()` , `sum()` , and `max()` . For hierarchically indexed data, these can be passed a `level` parameter that controls which subset of the data the aggregate is computed on.

For example, let's return to our health data:

In [58]:

```
health_data
```

Out[58]:

	subject	Bob		Guido		Sue	
	type	HR	Temp	HR	Temp	HR	Temp
year	visit						
2013	**1**	43.0	36.7	54.0	37.3	27.0	37.0
	2	26.0	37.6	46.0	35.0	22.0	36.7
2014	**1**	27.0	37.9	24.0	38.1	52.0	38.3
	2	42.0	35.5	43.0	35.9	45.0	37.9

Perhaps we'd like to average-out the measurements in the two visits each year. We can do this by naming the index level we'd like to explore, in this case the year:

In [59]:

```
data_mean = health_data.mean(level='year')
data_mean
```

Out[59]:

subject	Bob		Guido		Sue	
type	HR	Temp	HR	Temp	HR	Temp
year						
2013	34.5	37.15	50.0	36.15	24.5	36.85
2014	34.5	36.70	33.5	37.00	48.5	38.10

By further making use of the `axis` keyword, we can take the mean among levels on the columns as well:

In [61]:

```
data_mean.mean(axis=1, level='type')
```

Out[61]:

type	HR	Temp
year		
2013	36.333333	36.716667
2014	38.833333	37.266667

In [62]:

```
# without levet it makes no sence
data_mean.mean(axis=1)
```

Out[62]:

```
year
2013    36.525
2014    38.050
dtype: float64
```

Thus in two lines, we've been able to find the average heart rate and temperature measured among all subjects in all visits each year.

Combining Datasets: Concat and Append

Some of the most interesting studies of data come from combining different data sources. These operations can involve anything from very straightforward concatenation of two different datasets, to more complicated database-style joins and merges that correctly handle any overlaps between the datasets. `Series` and `DataFrame` s are built with this type of operation in mind, and Pandas includes functions and methods that make this sort of data wrangling fast and straightforward.

Here we'll take a look at simple concatenation of `Series` and `DataFrame` s with the `pd.concat` function; later we'll dive into more sophisticated in-memory merges and joins implemented in Pandas.

For convenience, we'll define this function which creates a `DataFrame` of a particular form that will be useful below:

In [68]:

```python
def make_df(cols, ind):
    """Quickly make a DataFrame"""
    data = {c: [str(c) + str(i) for i in ind]
            for c in cols}
    return pd.DataFrame(data, ind)

# example DataFrame
make_df('ABC', range(3))
```

Out[68]:

	A	B	C
0	A0	B0	C0
1	A1	B1	C1
2	A2	B2	C2

In addition, we'll create a quick class that allows us to display multiple `DataFrame` s side by side. The code makes use of the special `_repr_html_` method, which IPython uses to implement its rich object display:

In [69]:

```python
eval("2 + 3 * len('hello')")
```

Out[69]:

17

In [168]:

```python
class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier, monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a, eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

The use of this will become clearer as we continue our discussion in the following section.

Recall: Concatenation of NumPy Arrays

Concatenation of `Series` and `DataFrame` objects is very similar to concatenation of Numpy arrays, which can be done via the `np.concatenate` function:

In [71]:

```
x = [1, 2, 3]
y = [4, 5, 6]
z = [7, 8, 9]
np.concatenate([x, y, z])
```

Out[71]:

```
array([1, 2, 3, 4, 5, 6, 7, 8, 9])
```

The first argument is a list or tuple of arrays to concatenate. Additionally, it takes an `axis` keyword that allows you to specify the axis along which the result will be concatenated:

In [72]:

```
x = [[1, 2],
     [3, 4]]
np.concatenate([x, x], axis=1)
```

Out[72]:

```
array([[1, 2, 1, 2],
       [3, 4, 3, 4]])
```

Simple Concatenation with `pd.concat`

Pandas has a function, `pd.concat()`, which has a similar syntax to `np.concatenate` but contains a number of options that we'll discuss momentarily:

```
# Signature in Pandas v0.18
pd.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
          keys=None, levels=None, names=None, verify_integrity=False,
          copy=True)
```

`pd.concat()` can be used for a simple concatenation of `Series` or `DataFrame` objects, just as `np.concatenate()` can be used for simple concatenations of arrays:

In [75]:

```
ser1 = pd.Series(['A', 'B', 'C'], index=[1, 2, 3])
ser2 = pd.Series(['D', 'E', 'F'], index=[4, 5, 6])
pd.concat([ser1, ser2])
```

Out[75]:

```
1    A
2    B
3    C
4    D
5    E
6    F
dtype: object
```

It also works to concatenate higher-dimensional objects, such as `DataFrame` s:

In [169]:

```
df1 = make_df('AB', [1, 2])
df2 = make_df('AB', [3, 4])
display('df1', 'df2', 'pd.concat([df1, df2])')
```

Out[169]:

df1

	A	B
1	A1	B1
2	A2	B2

df2

	A	B
3	A3	B3
4	A4	B4

pd.concat([df1, df2])

	A	B
1	A1	B1
2	A2	B2
3	A3	B3
4	A4	B4

By default, the concatenation takes place row-wise within the `DataFrame` (i.e., `axis=0`). Like `np.concatenate` , `pd.concat` allows specification of an axis along which concatenation will take place. Consider the following example:

In [95]:

```
df3 = make_df('AB', [0, 1])
df4 = make_df('CD', [0, 1])
display('df3', 'df4', "pd.concat([df3, df4], axis='columns')")
```

Out[95]:

df3

	A	B
0	A0	B0
1	A1	B1

df4

	C	D
0	C0	D0
1	C1	D1

pd.concat([df3, df4], axis='columns')

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1

We could have equivalently specified `axis=1` ; here we've used the more intuitive `axis='columns` .

Duplicate indices

One important difference between `np.concatenate` and `pd.concat` is that Pandas concatenation *preserves indices*, even if the result will have duplicate indices! Consider this simple example:

In [96]:

```
x = make_df('AB', [0, 1])
y = make_df('AB', [2, 3])
y.index = x.index  # make duplicate indices!
display('x', 'y', 'pd.concat([x, y])')
```

Out[96]:

x

	A	B
0	A0	B0
1	A1	B1

y

	A	B
0	A2	B2
1	A3	B3

pd.concat([x, y])

	A	B
0	A0	B0
1	A1	B1
0	A2	B2
1	A3	B3

Notice the repeated indices in the result. While this is valid within `DataFrame` s, the outcome is often undesirable. `pd.concat()` gives us a few ways to handle it.

Catching the repeats as an error

If you'd like to simply verify that the indices in the result of `pd.concat()` do not overlap, you can specify the `verify_integrity` flag. With this set to True, the concatenation will raise an exception if there are duplicate indices. Here is an example, where for clarity we'll catch and print the error message:

In [97]:

```
try:
    pd.concat([x, y], verify_integrity=True)
except ValueError as e:
    print("ValueError:", e)
```

```
ValueError: Indexes have overlapping values: Int64Index([0, 1], dtype='int
64')
```

Ignoring the index

Sometimes the index itself does not matter, and you would prefer it to simply be ignored. This option can be specified using the `ignore_index` flag. With this set to true, the concatenation will create a new integer index for the resulting `Series` :

In [98]:

```
display('x', 'y', 'pd.concat([x, y], ignore_index=True)')
```

Out[98]:

x

	A	B
0	A0	B0
1	A1	B1

y

	A	B
0	A2	B2
1	A3	B3

pd.concat([x, y], ignore_index=True)

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

Adding MultiIndex keys

Another option is to use the `keys` option to specify a label for the data sources; the result will be a hierarchically indexed series containing the data:

In [99]:

```
display('x', 'y', "pd.concat([x, y], keys=['x', 'y'])")
```

Out[99]:

x

	A	B
0	A0	B0
1	A1	B1

y

	A	B
0	A2	B2
1	A3	B3

pd.concat([x, y], keys=['x', 'y'])

		A	B
x	**0**	A0	B0
	1	A1	B1
y	**0**	A2	B2
	1	A3	B3

The result is a multiply indexed `DataFrame`

Concatenation with joins

In the simple examples we just looked at, we were mainly concatenating `DataFrame` s with shared column names. In practice, data from different sources might have different sets of column names, and `pd.concat` offers several options in this case. Consider the concatenation of the following two `DataFrame` s, which have some (but not all!) columns in common:

In [100]:

```
df5 = make_df('ABC', [1, 2])
df6 = make_df('BCD', [3, 4])
display('df5', 'df6', 'pd.concat([df5, df6])')
```

Out[100]:

df5

	A	B	C
1	A1	B1	C1
2	A2	B2	C2

df6

	B	C	D
3	B3	C3	D3
4	B4	C4	D4

pd.concat([df5, df6])

	A	B	C	D
1	A1	B1	C1	NaN
2	A2	B2	C2	NaN
3	NaN	B3	C3	D3
4	NaN	B4	C4	D4

By default, the entries for which no data is available are filled with NA values. To change this, we can specify one of several options for the `join` parameters of the concatenate function. By default, the join is a union of the input columns (`join='outer'`), but we can change this to an intersection of the columns using `join='inner'` :

In [101]:

```
display('df5', 'df6',
        "pd.concat([df5, df6], join='inner')")
```

Out[101]:

df5

	A	B	C
1	A1	B1	C1
2	A2	B2	C2

df6

	B	C	D
3	B3	C3	D3
4	B4	C4	D4

pd.concat([df5, df6], join='inner')

	B	C
1	B1	C1
2	B2	C2
3	B3	C3
4	B4	C4

The `append()` method

Because direct array concatenation is so common, `Series` and `DataFrame` objects have an `append` method that can accomplish the same thing in fewer keystrokes. For example, rather than calling `pd.concat([df1, df2])` , you can simply call `df1.append(df2)` :

In [103]:

```
display('df1', 'df2', 'df1.append(df2)')
```

Out[103]:

df1

	A	B
1	A1	B1
2	A2	B2

df2

	A	B
3	A3	B3
4	A4	B4

df1.append(df2)

	A	B
1	A1	B1
2	A2	B2
3	A3	B3
4	A4	B4

Keep in mind that unlike the `append()` and `extend()` methods of Python lists, the `append()` method in Pandas does not modify the original object–instead it creates a new object with the combined data. It also is not a very efficient method, because it involves creation of a new index *and* data buffer. Thus, if you plan to do multiple `append` operations, it is generally better to build a list of `DataFrame` s and pass them all at once to the `concat()` function.

In the next section, we'll look at another more powerful approach to combining data from multiple sources, the database-style merges/joins implemented in `pd.merge` .

Combining Datasets: Merge and Join

One essential feature offered by Pandas is its high-performance, in-memory join and merge operations. If you have ever worked with databases, you should be familiar with this type of data interaction. The main interface for this is the `pd.merge` function, and we'll see few examples of how this can work in practice.

For convenience, we will start by redefining the `display()` functionality from the previous section:

Relational Algebra

The behavior implemented in `pd.merge()` is a subset of what is known as *relational algebra*, which is a formal set of rules for manipulating relational data, and forms the conceptual foundation of operations available in most databases. The strength of the relational algebra approach is that it proposes several primitive operations, which become the building blocks of more complicated operations on any dataset. With this lexicon of fundamental operations implemented efficiently in a database or other program, a wide range of fairly complicated composite operations can be performed.

Pandas implements several of these fundamental building-blocks in the `pd.merge()` function and the related `join()` method of `Series` and `Dataframe` s. As we will see, these let you efficiently link data from different sources.

Categories of Joins

The `pd.merge()` function implements a number of types of joins: the *one-to-one*, *many-to-one*, and *many-to-many* joins. All three types of joins are accessed via an identical call to the `pd.merge()` interface; the type of join performed depends on the form of the input data. Here we will show simple examples of the three types of merges, and discuss detailed options further below.

One-to-one joins

Perhaps the simplest type of merge expresion is the one-to-one join, which is in many ways very similar to the column-wise concatenation. As a concrete example, consider the following two `DataFrames` which contain information on several employees in a company:

In [104]:

```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering', 'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})
display('df1', 'df2')
```

Out[104]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df2

	employee	hire_date
0	Lisa	2004
1	Bob	2008
2	Jake	2012
3	Sue	2014

To combine this information into a single `DataFrame`, we can use the `pd.merge()` function:

In [105]:

```
df3 = pd.merge(df1, df2)
df3
```

Out[105]:

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

The `pd.merge()` function recognizes that each `DataFrame` has an "employee" column, and automatically joins using this column as a key. The result of the merge is a new `DataFrame` that combines the information from the two inputs. Notice that the order of entries in each column is not necessarily maintained: in this case, the order of the "employee" column differs between `df1` and `df2`, and the `pd.merge()` function correctly accounts for this. Additionally, keep in mind that the merge in general discards the index, except in the special case of merges by index (see the `left_index` and `right_index` keywords).

Many-to-one joins

Many-to-one joins are joins in which one of the two key columns contains duplicate entries. For the many-to-one case, the resulting `DataFrame` will preserve those duplicate entries as appropriate. Consider the following example of a many-to-one join:

In [108]:

```
df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                    'supervisor': ['Carly', 'Guido', 'Steve']})
display('df3', 'df4', 'pd.merge(df3, df4)')
```

Out[108]:

df3

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

df4

	group	supervisor
0	Accounting	Carly
1	Engineering	Guido
2	HR	Steve

pd.merge(df3, df4)

	employee	group	hire_date	supervisor
0	Bob	Accounting	2008	Carly
1	Jake	Engineering	2012	Guido
2	Lisa	Engineering	2004	Guido
3	Sue	HR	2014	Steve

The resulting `DataFrame` has an aditional column with the "supervisor" information, where the information is repeated in one or more locations as required by the inputs.

Many-to-many joins

Many-to-many joins are a bit confusing conceptually, but are nevertheless well defined. If the key column in both the left and right array contains duplicates, then the result is a many-to-many merge. This will be perhaps most clear with a concrete example. Consider the following, where we have a `DataFrame` showing one or more skills associated with a particular group. By performing a many-to-many join, we can recover the skills associated with any individual person:

In [110]:

```
df5 = pd.DataFrame({'group': ['Accounting', 'Accounting',
                              'Engineering', 'Engineering', 'HR', 'HR'],
                    'skills': ['math', 'spreadsheets', 'coding', 'linux',
                               'spreadsheets', 'organization']})
display('df1', 'df5', "pd.merge(df1, df5)")
```

Out[110]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df5

	group	skills
0	Accounting	math
1	Accounting	spreadsheets
2	Engineering	coding
3	Engineering	linux
4	HR	spreadsheets
5	HR	organization

pd.merge(df1, df5)

	employee	group	skills
0	Bob	Accounting	math
1	Bob	Accounting	spreadsheets
2	Jake	Engineering	coding
3	Jake	Engineering	linux
4	Lisa	Engineering	coding
5	Lisa	Engineering	linux
6	Sue	HR	spreadsheets
7	Sue	HR	organization

These three types of joins can be used with other Pandas tools to implement a wide array of functionality. But in practice, datasets are rarely as clean as the one we're working with here. In the following section we'll consider some of the options provided by `pd.merge()` that enable you to tune how the join operations work.

Specification of the Merge Key

We've already seen the default behavior of `pd.merge()` : it looks for one or more matching column names between the two inputs, and uses this as the key. However, often the column names will not match so nicely, and `pd.merge()` provides a variety of options for handling this.

The `on` keyword

Most simply, you can explicitly specify the name of the key column using the `on` keyword, which takes a column name or a list of column names:

In [111]:

```
display('df1', 'df2', "pd.merge(df1, df2, on='employee')")
```

Out[111]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df2

	employee	hire_date
0	Lisa	2004
1	Bob	2008
2	Jake	2012
3	Sue	2014

pd.merge(df1, df2, on='employee')

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

This option works only if both the left and right `DataFrame` s have the specified column name.

The `left_on` and `right_on` keywords

At times you may wish to merge two datasets with different column names; for example, we may have a dataset in which the employee name is labeled as "name" rather than "employee". In this case, we can use the `left_on` and `right_on` keywords to specify the two column names:

In [114]:

```
df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'salary': [70000, 80000, 120000, 90000]})
display('df1', 'df3', 'pd.merge(df1, df3, left_on="employee", right_on="name")')
```

Out[114]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df3

	name	salary
0	Bob	70000
1	Jake	80000
2	Lisa	120000
3	Sue	90000

pd.merge(df1, df3, left_on="employee", right_on="name")

	employee	group	name	salary
0	Bob	Accounting	Bob	70000
1	Jake	Engineering	Jake	80000
2	Lisa	Engineering	Lisa	120000
3	Sue	HR	Sue	90000

The result has a redundant column that we can drop if desired–for example, by using the `drop()` method of `DataFrame` s:

In [115]:

```
pd.merge(df1, df3, left_on="employee", right_on="name").drop('name', axis=1)
```

Out[115]:

	employee	group	salary
0	Bob	Accounting	70000
1	Jake	Engineering	80000
2	Lisa	Engineering	120000
3	Sue	HR	90000

The `left_index` and `right_index` keywords

Sometimes, rather than merging on a column, you would instead like to merge on an index. For example, your data might look like this:

In [116]:

```
df1a = df1.set_index('employee')
df2a = df2.set_index('employee')
display('df1a', 'df2a')
```

Out[116]:

df1a

employee	group
Bob	Accounting
Jake	Engineering
Lisa	Engineering
Sue	HR

df2a

employee	hire_date
Lisa	2004
Bob	2008
Jake	2012
Sue	2014

You can use the index as the key for merging by specifying the `left_index` and/or `right_index` flags in `pd.merge()` :

In [119]:

```
display('df1a', 'df2a',
        "pd.merge(df1a, df2a, left_index=True, right_index=True)")
```

Out[119]:

df1a

employee	group
Bob	Accounting
Jake	Engineering
Lisa	Engineering
Sue	HR

df2a

employee	hire_date
Lisa	2004
Bob	2008
Jake	2012
Sue	2014

pd.merge(df1a, df2a, left_index=True, right_index=True)

employee	group	hire_date
Bob	Accounting	2008
Jake	Engineering	2012
Lisa	Engineering	2004
Sue	HR	2014

For convenience, `DataFrame` s implement the `join()` method, which performs a merge that defaults to joining on indices:

In [120]:

```
display('df1a', 'df2a', 'df1a.join(df2a)')
```

Out[120]:

df1a

	group
employee	
Bob	Accounting
Jake	Engineering
Lisa	Engineering
Sue	HR

df2a

	hire_date
employee	
Lisa	2004
Bob	2008
Jake	2012
Sue	2014

df1a.join(df2a)

	group	hire_date
employee		
Bob	Accounting	2008
Jake	Engineering	2012
Lisa	Engineering	2004
Sue	HR	2014

If you'd like to mix indices and columns, you can combine `left_index` with `right_on` or `left_on` with `right_index` to get the desired behavior:

In [121]:

```
display('df1a', 'df3', "pd.merge(df1a, df3, left_index=True, right_on='name')")
```

Out[121]:

df1a

	group
employee	
Bob	Accounting
Jake	Engineering
Lisa	Engineering
Sue	HR

df3

	name	salary
0	Bob	70000
1	Jake	80000
2	Lisa	120000
3	Sue	90000

pd.merge(df1a, df3, left_index=True, right_on='name')

	group	name	salary
0	Accounting	Bob	70000
1	Engineering	Jake	80000
2	Engineering	Lisa	120000
3	HR	Sue	90000

All of these options also work with multiple indices and/or multiple columns; the interface for this behavior is very intuitive. For more information on this, see the ["Merge, Join, and Concatenate" section (http://pandas.pydata.org/pandas-docs/stable/merging.html)](http://pandas.pydata.org/pandas-docs/stable/merging.html) of the Pandas documentation.

Specifying Set Arithmetic for Joins

In all the preceding examples we have glossed over one important consideration in performing a join: the type of set arithmetic used in the join. This comes up when a value appears in one key column but not the other. Consider this example:

In [122]:

```
df6 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                    'food': ['fish', 'beans', 'bread']},
                   columns=['name', 'food'])
df7 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                    'drink': ['wine', 'beer']},
                   columns=['name', 'drink'])
display('df6', 'df7', 'pd.merge(df6, df7)')
```

Out[122]:

df6

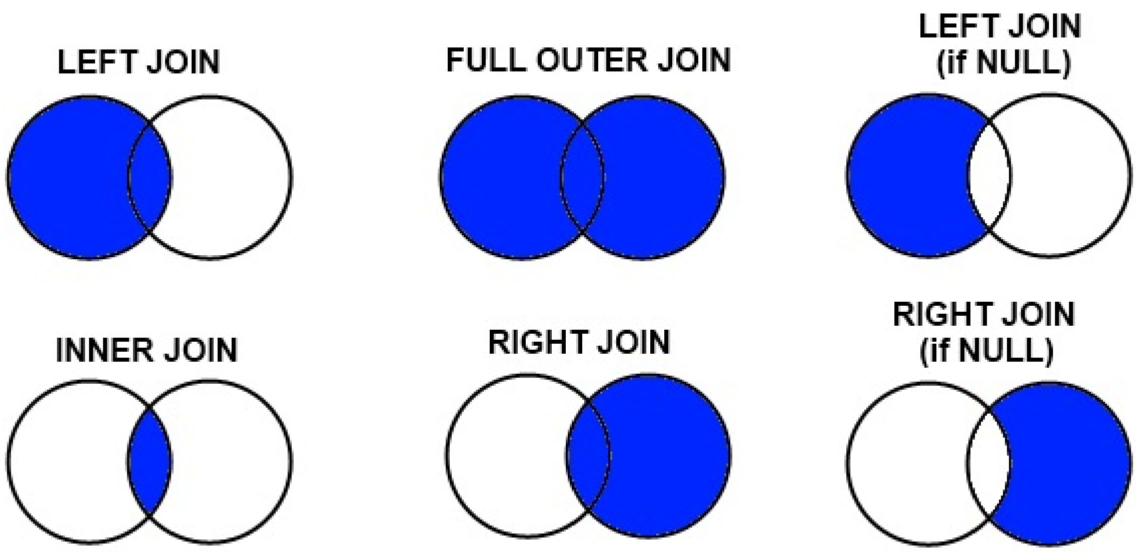
	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread

df7

	name	drink
0	Mary	wine
1	Joseph	beer

pd.merge(df6, df7)

	name	food	drink
0	Mary	bread	wine



Here we have merged two datasets that have only a single "name" entry in common: Mary. By default, the result contains the *intersection* of the two sets of inputs; this is what is known as an *inner join*. We can specify this explicitly using the `how` keyword, which defaults to `"inner"` :

In [123]:

```
pd.merge(df6, df7, how='inner')
```

Out[123]:

	name	food	drink
0	Mary	bread	wine

Other options for the `how` keyword are `'outer'`, `'left'`, and `'right'`. An *outer join* returns a join over the union of the input columns, and fills in all missing values with NAs:

In [124]:

```
display('df6', 'df7', "pd.merge(df6, df7, how='outer')")
```

Out[124]:

df6

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread

df7

	name	drink
0	Mary	wine
1	Joseph	beer

pd.merge(df6, df7, how='outer')

	name	food	drink
0	Peter	fish	NaN
1	Paul	beans	NaN
2	Mary	bread	wine
3	Joseph	NaN	beer

The *left join* and *right join* return joins over the left entries and right entries, respectively. For example:

In [125]:

```
display('df6', 'df7', "pd.merge(df6, df7, how='left')")
```

Out[125]:

df6

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread

df7

	name	drink
0	Mary	wine
1	Joseph	beer

pd.merge(df6, df7, how='left')

	name	food	drink
0	Peter	fish	NaN
1	Paul	beans	NaN
2	Mary	bread	wine

The output rows now correspond to the entries in the left input. Using `how='right'` works in a similar manner.

All of these options can be applied straightforwardly to any of the preceding join types.

In [126]:

```
display('df6', 'df7', "pd.merge(df6, df7, how='right')")
```

Out[126]:

df6

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread

df7

	name	drink
0	Mary	wine
1	Joseph	beer

pd.merge(df6, df7, how='right')

	name	food	drink
0	Mary	bread	wine
1	Joseph	NaN	beer

Overlapping Column Names: The `suffixes` Keyword

Finally, you may end up in a case where your two input `DataFrame` s have conflicting column names. Consider this example:

In [127]:

```
df8 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'rank': [1, 2, 3, 4]})
df9 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'rank': [3, 1, 4, 2]})
display('df8', 'df9', 'pd.merge(df8, df9, on="name")')
```

Out[127]:

df8

	name	rank
0	Bob	1
1	Jake	2
2	Lisa	3
3	Sue	4

df9

	name	rank
0	Bob	3
1	Jake	1
2	Lisa	4
3	Sue	2

pd.merge(df8, df9, on="name")

	name	rank_x	rank_y
0	Bob	1	3
1	Jake	2	1
2	Lisa	3	4
3	Sue	4	2

Because the output would have two conflicting column names, the merge function automatically appends a suffix `_x` or `_y` to make the output columns unique. If these defaults are inappropriate, it is possible to specify a custom suffix using the `suffixes` keyword:

In [128]:

```
display('df8', 'df9', 'pd.merge(df8, df9, on="name", suffixes=["_L", "_R"])')
```

Out[128]:

df8

	name	rank
0	Bob	1
1	Jake	2
2	Lisa	3
3	Sue	4

df9

	name	rank
0	Bob	3
1	Jake	1
2	Lisa	4
3	Sue	2

pd.merge(df8, df9, on="name", suffixes=["_L", "_R"])

	name	rank_L	rank_R
0	Bob	1	3
1	Jake	2	1
2	Lisa	3	4
3	Sue	4	2

These suffixes work in any of the possible join patterns, and work also if there are multiple overlapping columns.

Also see the [Pandas "Merge, Join and Concatenate" documentation (http://pandas.pydata.org/pandas-docs/stable/merging.html)](http://pandas.pydata.org/pandas-docs/stable/merging.html) for further discussion of these topics.

Example: US States Data

Merge and join operations come up most often when combining data from different sources. Here we will consider an example of some data about US states and their populations.

In [ ]:

```
# Following are shell commands to download the data
# !curl -O https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-populat
ion.csv
# !curl -O https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-areas.c
sv
# !curl -O https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-abbrev
s.csv
```

Let's take a look at the three datasets, using the Pandas `read_csv()` function:

In [129]:

```
pop = pd.read_csv('D:\Света\Фреймворки пайтон\Лекции\lect_10\state-population.csv')
areas = pd.read_csv('D:\Света\Фреймворки пайтон\Лекции\lect_10\state-areas.csv')
abbrevs = pd.read_csv('D:\Света\Фреймворки пайтон\Лекции\lect_10\state-abbrevs.csv')

display('pop.head()', 'areas.head()', 'abbrevs.head()')
```

Out[129]:

pop.head()

	state/region	ages	year	population
0	AL	under18	2012	1117489.0
1	AL	total	2012	4817528.0
2	AL	under18	2010	1130966.0
3	AL	total	2010	4785570.0
4	AL	under18	2011	1125763.0

areas.head()

	state	area (sq. mi)
0	Alabama	52423
1	Alaska	656425
2	Arizona	114006
3	Arkansas	53182
4	California	163707

abbrevs.head()

	state	abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA

Given this information, say we want to compute a relatively straightforward result: rank US states and territories by their 2010 population density. We clearly have the data here to find this result, but we'll have to combine the datasets to find the result.

We'll start with a many-to-one merge that will give us the full state name within the population `DataFrame` . We want to merge based on the `state/region` column of `pop` , and the `abbreviation` column of `abbrevs` . We'll use `how='outer'` to make sure no data is thrown away due to mismatched labels.

In [132]:

```
merged = pd.merge(pop, abbrevs, how='outer',
                  left_on='state/region', right_on='abbreviation')
merged.head()
```

Out[132]:

	state/region	ages	year	population	state	abbreviation
0	AL	under18	2012	1117489.0	Alabama	AL
1	AL	total	2012	4817528.0	Alabama	AL
2	AL	under18	2010	1130966.0	Alabama	AL
3	AL	total	2010	4785570.0	Alabama	AL
4	AL	under18	2011	1125763.0	Alabama	AL

In [134]:

```
merged = merged.drop('abbreviation',1) # drop duplicate info, 1 is an axis
merged.head()
```

Out[134]:

	state/region	ages	year	population	state
0	AL	under18	2012	1117489.0	Alabama
1	AL	total	2012	4817528.0	Alabama
2	AL	under18	2010	1130966.0	Alabama
3	AL	total	2010	4785570.0	Alabama
4	AL	under18	2011	1125763.0	Alabama

Let's double-check whether there were any mismatches here, which we can do by looking for rows with nulls:

In [136]:

```
merged.isna().any()
```

Out[136]:

```
state/region    False
ages            False
year            False
population       True
state            True
dtype: bool
```

Some of the `population` info is null; let's figure out which these are!

In [137]:

```
merged[merged['population'].isna()].head()
```

Out[137]:

	state/region	ages	year	population	state
2448	PR	under18	1990	NaN	NaN
2449	PR	total	1990	NaN	NaN
2450	PR	total	1991	NaN	NaN
2451	PR	under18	1991	NaN	NaN
2452	PR	total	1993	NaN	NaN

It appears that all the null population values are from Puerto Rico prior to the year 2000; this is likely due to this data not being available from the original source.

More importantly, we see also that some of the new `state` entries are also null, which means that there was no corresponding entry in the `abbrevs` key! Let's figure out which regions lack this match:

In [138]:

```
merged.loc[merged['state'].isnull(), 'state/region'].unique()
```

Out[138]:

```
array(['PR', 'USA'], dtype=object)
```

We can quickly infer the issue: our population data includes entries for Puerto Rico (PR) and the United States as a whole (USA), while these entries do not appear in the state abbreviation key. We can fix these quickly by filling in appropriate entries:

In [139]:

```
merged.loc[merged['state/region'] == 'PR', 'state'] = 'Puerto Rico'
merged.loc[merged['state/region'] == 'USA', 'state'] = 'United States'
merged.isnull().any()
```

Out[139]:

```
state/region    False
ages            False
year            False
population       True
state           False
dtype: bool
```

No more nulls in the `state` column: we're all set!

Now we can merge the result with the area data using a similar procedure. Examining our results, we will want to join on the `state` column in both:

In [156]:

```
final = pd.merge(merged, areas, on='state', how='left')
final.head()
```

Out[156]:

	state/region	ages	year	population	state	area (sq. mi)
0	AL	under18	2012	1117489.0	Alabama	52423.0
1	AL	total	2012	4817528.0	Alabama	52423.0
2	AL	under18	2010	1130966.0	Alabama	52423.0
3	AL	total	2010	4785570.0	Alabama	52423.0
4	AL	under18	2011	1125763.0	Alabama	52423.0

Again, let's check for nulls to see if there were any mismatches:

In [157]:

```
final.isnull().any()
```

Out[157]:

```
state/region     False
ages             False
year             False
population        True
state            False
area (sq. mi)     True
dtype: bool
```

There are nulls in the `area` column; we can take a look to see which regions were ignored here:

In [158]:

```
final['state'][final['area (sq. mi)'].isnull()].unique()
```

Out[158]:

```
array(['United States'], dtype=object)
```

We see that our `areas` `DataFrame` does not contain the area of the United States as a whole. We could insert the appropriate value (using the sum of all state areas, for instance), but in this case we'll just drop the null values because the population density of the entire United States is not relevant to our current discussion:

In [159]:

```
final.dropna(inplace=True)
final.head()
```

Out[159]:

	state/region	ages	year	population	state	area (sq. mi)
0	AL	under18	2012	1117489.0	Alabama	52423.0
1	AL	total	2012	4817528.0	Alabama	52423.0
2	AL	under18	2010	1130966.0	Alabama	52423.0
3	AL	total	2010	4785570.0	Alabama	52423.0
4	AL	under18	2011	1125763.0	Alabama	52423.0

Now we have all the data we need. To answer the question of interest, let's first select the portion of the data corresponding with the year 2000, and the total population. We'll use the `query()` function to do this quickly:

In [160]:

```
data2010 = final.query("year == 2010 & ages == 'total'")
data2010.head()
```

Out[160]:

	state/region	ages	year	population	state	area (sq. mi)
3	AL	total	2010	4785570.0	Alabama	52423.0
91	AK	total	2010	713868.0	Alaska	656425.0
101	AZ	total	2010	6408790.0	Arizona	114006.0
189	AR	total	2010	2922280.0	Arkansas	53182.0
197	CA	total	2010	37333601.0	California	163707.0

Now let's compute the population density and display it in order. We'll start by re-indexing our data on the state, and then compute the result:

In [162]:

```
data2010.set_index('state', inplace=True)
data2010.head()
```

Out[162]:

	state/region	ages	year	population	area (sq. mi)
state					
Alabama	AL	total	2010	4785570.0	52423.0
Alaska	AK	total	2010	713868.0	656425.0
Arizona	AZ	total	2010	6408790.0	114006.0
Arkansas	AR	total	2010	2922280.0	53182.0
California	CA	total	2010	37333601.0	163707.0

In [163]:

```
density = data2010['population'] / data2010['area (sq. mi)']
```

In [164]:

```
density.sort_values(ascending=False, inplace=True)
density.head()
```

Out[164]:

```
state
District of Columbia    8898.897059
Puerto Rico             1058.665149
New Jersey              1009.253268
Rhode Island             681.339159
Connecticut              645.600649
dtype: float64
```

The result is a ranking of US states plus Washington, DC, and Puerto Rico in order of their 2010 population density, in residents per square mile. We can see that by far the densest region in this dataset is Washington, DC (i.e., the District of Columbia); among states, the densest is New Jersey.

We can also check the end of the list:

In [165]:

```
density.tail()
```

Out[165]:

```
state
South Dakota    10.583512
North Dakota     9.537565
Montana          6.736171
Wyoming          5.768079
Alaska           1.087509
dtype: float64
```

We see that the least dense state, by far, is Alaska, averaging slightly over one resident per square mile.

This type of messy data merging is a common task when trying to answer questions using real-world data sources. I hope that this example has given you an idea of the ways you can combine tools we've covered in order to gain insight from your data!

In [ ]:

```

```