Starting pandas

BIOF 440 Week 2

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pandas

`pandas` is the Python Data Analysis package.

It allows for data ingestion, transformation and cleaning, and creates objects that can then be passed on to analytic packages like `statsmodels` and `scikit-learn` for modeling and packages like `matplotlib`, `seaborn`, and `plotly` for visualization.

`pandas` is built on top of `numpy`, so many numpy functions are commonly used in manipulating `pandas` objects.

> `pandas` is a pretty extensive package, and we'll only be able to cover some of its features. For more details, there is free online documentation at pandas.pydata.org. You can also look at the book "Python for Data Analysis (2nd edition)" by Wes McKinney, the original developer of the pandas package, for more details.

Starting pandas

As with any Python module, you have to "activate" `pandas` by using `import`. The "standard" alias for `pandas` is `pd`. We will also import `numpy`, since `pandas` uses some `numpy` functions in the workflow.

```
import numpy as np
import pandas as pd
```

Data import and export

Most data sets you will work with are set up in tables, so are rectangular in shape. Think Excel spreadsheets.

In `pandas` the structure that will hold this kind of data is a `DataFrame`.

We can read external data into a `DataFrame` using one of many `read_*` functions.

We can also write from a `DataFrame` to a variety of formats using `to_*` functions.

Format type	Description	reader	writer
text	CSV	read_csv	to_csv
	Excel	read_excel	to_excel
text	JSON	read_json	to_json
binary	Feather	read_feather	to_feather
binary	SAS	read_sas	
SQL	SQL	read_sql	to_sql

Data import and export

We'll start by reading in the `mtcars` dataset stored as a CSV file

```
pd.read_csv('data/mtcars.csv')
```

```
                make   mpg  cyl   disp   hp  ...   qsec  vs  am  gear  carb
0          Mazda RX4  21.0    6  160.0  110  ...  16.46   0   1     4     4
1      Mazda RX4 Wag  21.0    6  160.0  110  ...  17.02   0   1     4     4
2         Datsun 710  22.8    4  108.0   93  ...  18.61   1   1     4     1
3     Hornet 4 Drive  21.4    6  258.0  110  ...  19.44   1   0     3     1
4  Hornet Sportabout  18.7    8  360.0  175  ...  17.02   0   0     3     2
5            Valiant  18.1    6  225.0  105  ...  20.22   1   0     3     1
6         Duster 360  14.3    8  360.0  245  ...  15.84   0   0     3     4
7          Merc 240D  24.4    4  146.7   62  ...  20.00   1   0     4     2

[8 rows x 12 columns]
```

This just prints out the data, but then it's lost. To use this data, we have to give it a name, so it's stored in Python's memory

```
mtcars = pd.read_csv('data/mtcars.csv')
```

Exploring a data set

We would like to get some idea about this data set. There are a bunch of functions linked to the `DataFrame` object that help us in this. First we will use `head` to see the first 8 rows of this data set

```
mtcars.head(8)
```

```
                make   mpg  cyl   disp   hp  ...   qsec  vs  am  gear  carb
0          Mazda RX4  21.0    6  160.0  110  ...  16.46   0   1     4     4
1      Mazda RX4 Wag  21.0    6  160.0  110  ...  17.02   0   1     4     4
2         Datsun 710  22.8    4  108.0   93  ...  18.61   1   1     4     1
3     Hornet 4 Drive  21.4    6  258.0  110  ...  19.44   1   0     3     1
4  Hornet Sportabout  18.7    8  360.0  175  ...  17.02   0   0     3     2
5            Valiant  18.1    6  225.0  105  ...  20.22   1   0     3     1
6         Duster 360  14.3    8  360.0  245  ...  15.84   0   0     3     4
7          Merc 240D  24.4    4  146.7   62  ...  20.00   1   0     4     2

[8 rows x 12 columns]
```

This is our first look into this data. We notice a few things. Each column has a name, and each row has an *index*, starting at 0.

> If you're interested in the last N rows, there is a corresponding `tail` function

Exploring a data set

Let's look at the data types of each of the columns

```
mtcars.dtypes
```

```
make     object
mpg     float64
cyl       int64
disp    float64
hp        int64
drat    float64
wt      float64
qsec    float64
vs        int64
am        int64
gear      int64
carb      int64
dtype: object
```

This tells us that some of the variables, like `mpg` and `disp`, are floating point (decimal) numbers,

several are integers,

and `make` is an "object".

The `dtypes` function borrows from `numpy`, where there isn't really a type for character or categorical variables. So most often, when you see "object" in the output of `dtypes`, you think it's a character or categorical variable.

Exploring a data set

We can also look at the data structure in a bit more detail.

```
mtcars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   make    32 non-null     object 
 1   mpg     32 non-null     float64
 2   cyl     32 non-null     int64  
 3   disp    32 non-null     float64
 4   hp      32 non-null     int64  
 5   drat    32 non-null     float64
 6   wt      32 non-null     float64
 7   qsec    32 non-null     float64
 8   vs      32 non-null     int64  
 9   am      32 non-null     int64  
 10  gear    32 non-null     int64  
 11  carb    32 non-null     int64  
dtypes: float64(5), int64(6), object(1)
memory usage: 3.1+ KB
```

This tells us that this is indeed a `DataFrame`, wth 12 columns, each with 32 valid observations. We also get the approximate size of this object in memory.

You can also quickly find the number of rows and columns of a data set by using `shape`, which is borrowed from numpy.

```
mtcars.shape
```

```
(32, 12)
```

Exploring a data set

More generally, we can get a summary of each variable using the `describe` function

```
mtcars.describe()
```

```
              mpg        cyl         disp  ...         am       gear     carb
count   32.000000  32.000000   32.000000  ...  32.000000  32.000000  32.0000
mean    20.090625   6.187500  230.721875  ...   0.406250   3.687500   2.8125
std      6.026948   1.785922  123.938694  ...   0.498991   0.737804   1.6152
min     10.400000   4.000000   71.100000  ...   0.000000   3.000000   1.0000
25%     15.425000   4.000000  120.825000  ...   0.000000   3.000000   2.0000
50%     19.200000   6.000000  196.300000  ...   0.000000   4.000000   2.0000
75%     22.800000   8.000000  326.000000  ...   1.000000   4.000000   4.0000
max     33.900000   8.000000  472.000000  ...   1.000000   5.000000   8.0000

[8 rows x 11 columns]
```

This provides a summary of the numeric variables

Exploring a data set

```
mtcars.describe(include = ['O'])
```

```
                     make
count                  32
unique                 32
top     Hornet Sportabout
freq                    1
```

You get a slightly different output when you just include "object" or non-numeric variables

Data structures and types

pandas.Series

pandas has two main data types: `Series` and `DataFrame`. These are analogous to vectors and matrices, in that a `Series` is 1-dimensional while a `DataFrame` is 2-dimensional.

The `Series` object holds data from a single input variable, and is required, much like numpy arrays, to be homogeneous in type. You can create `Series` objects from lists or numpy arrays quite easily

```
s = pd.Series([1,3,5,np.nan, 9, 13])
s
```

```
0     1.0
1     3.0
2     5.0
3     NaN
4     9.0
5    13.0
dtype: float64
```

`np.nan` is the representation of missing data used in the PyData ecosystem

```
s2 = pd.Series(np.arange(1,10))
s2
```

```
0    1
1    2
2    3
3    4
4    5
5    6
6    7
7    8
8    9
dtype: int64
```

pandas.Series

You can access elements of a `Series` much like a `dict`

```
s2[4]
```

```
5
```

There is no requirement that the index of a `Series` has to be numeric. It can be any kind of scalar object

```
s3 = pd.Series(np.random.normal(0,1, (5,)), index = ['a','b','c','d','e'])
```

```
s3
```

```
a    0.734971
b    0.123558
c    0.712505
d   -0.249043
e   -1.615459
dtype: float64
```

```
s3['d']
```

```
-0.24904270743734003
```

pandas.Series

```
s3['a':'d']
```

```
a    0.734971
b    0.123558
c    0.712505
d   -0.249043
dtype: float64
```

Well, slicing worked, but it gave us something different than expected. It gave us both the start and end of the slice, which is unlike what we've encountered so far!!

It turns out that in pandas, slicing by index actually does this. It is a discrepancy from numpy and Python in general that we have to be careful about.

You can extract the actual values into a numpy array

```
s3.to_numpy()
```

```
array([ 0.73497103,  0.12355762,  0.71250472, -0.24904271, -1.61545899])
```

In fact, you'll see that much of pandas' structures are build on top of numpy arrays. This is a good thing, since you can take advantage of the powerful numpy functions that are built for fast, efficient scientific computing.

pandas.Series

Making the point about slicing again,

```
s3.to_numpy()[0:3]
```

```
array([0.73497103, 0.12355762, 0.71250472])
```

This is different from index-based slicing done earlier.

pandas.DataFrame

The `DataFrame` object holds a rectangular data set.

Each column of a `DataFrame` is a `Series` object.

This means that each column of a `DataFrame` must be comprised of data of the same type, but different columns can hold data of different types. This structure is extremely useful in practical data science.

The invention of this structure was, in my opinion, transformative in making Python an effective data science tool.

Creating a DataFrame

The `DataFrame` can be created by importing data, as we saw in the previous section. It can also be created by a few methods within Python.

First, it can be created from a 2-dimensional `numpy` array.

```
rng = np.random.RandomState(25)
d1 = pd.DataFrame(rng.normal(0,1, (4,5)))
d1
```

```
          0         1         2         3         4
0  0.228273  1.026890 -0.839585 -0.591182 -0.956888
1 -0.222326 -0.619915  1.837905 -2.053231  0.868583
2 -0.920734 -0.232312  2.152957 -1.334661  0.076380
3 -1.246089  1.202272 -1.049942  1.056610 -0.419678
```

You will notice that it creates default column names, that are merely the column number, starting from 0. We can also create the column names and row index (similar to the `Series` index we saw earlier) directly during creation.

Creating a DataFrame

```
d2 = pd.DataFrame(rng.normal(0,1, (4, 5)),
                  columns = ['A','B','C','D','E'],
                  index = ['a','b','c','d'])
d2
```

```
          A         B         C         D         E
a  2.294842 -2.594487  2.822756  0.680889 -1.577693
b -1.976254  0.533340 -0.290870 -0.513520  1.982626
c  0.226001 -1.839905  1.607671  0.388292  0.399732
d  0.405477  0.217002 -0.633439  0.246622 -1.939546
```

We could also create a `DataFrame` from a list of lists, as long as things line up, just as we showed for `numpy` arrays. However, to me, other ways, including the `dict` method we'll see next, is more expressive.

Creating a DataFrame

We can change the column names (which can be extracted and replaced with the `columns` attribute) and the index values (using the `index` attribute).

```
d2.columns
```

```
Index(['A', 'B', 'C', 'D', 'E'], dtype='object
```

We can change the column names, if we like.

```
d2.columns = pd.Index(['V'+str(i) for i in rang
d2
```

```
          V1        V2        V3        V4
a  2.294842 -2.594487  2.822756  0.680889 -1.5
b -1.976254  0.533340 -0.290870 -0.513520  1.9
c  0.226001 -1.839905  1.607671  0.388292  0.3
d  0.405477  0.217002 -0.633439  0.246622 -1.9
```

```
d2.index = ['o1','o2','o3','o4']
d2
```

```
          V1        V2        V3        V4
o1  2.294842 -2.594487  2.822756  0.680889 -1.5
o2 -1.976254  0.533340 -0.290870 -0.513520  1.9
o3  0.226001 -1.839905  1.607671  0.388292  0.3
o4  0.405477  0.217002 -0.633439  0.246622 -1.9
```

Creating a DataFrame

You can also extract data from a homogeneous `DataFrame` to a `numpy` array

```
d1.to_numpy()
```

```
array([[ 0.22827309,  1.0268903 , -0.83958485, -0.59118152, -0.9568883 ],
       [-0.22232569, -0.61991511,  1.83790458, -2.05323076,  0.86858305],
       [-0.92073444, -0.23231186,  2.1529569 , -1.33466147,  0.07637965],
       [-1.24608928,  1.20227231, -1.04994158,  1.05661011, -0.41967767]])
```

> It turns out that you can use `to_numpy` for a non-homogeneous `DataFrame` as well. `numpy` just makes it homogeneous by assigning each column the data type `object`. This also limits what you can do in `numpy` with the array and may require changing data types using the `astype` function.

Creating a DataFrame

The other easy way to create a `DataFrame` is from a `dict` object, where each component object is either a list or a numpy array, and is homogeneous in type. One exception is if a component is of size 1; then it is repeated to meet the needs of the `DataFrame`'s dimensions

```
df = pd.DataFrame({
    'A':3.,
    'B':rng.random_sample(5),
    'C': pd.Timestamp('20200512'),
    'D': np.array([6] * 5),
    'E': pd.Categorical(['yes','no','no','yes','no']),
    'F': 'NIH'})
```

```
df
```

	A	B	C	D	E	F
0	3.0	0.958092	2020-05-12	6	yes	NIH
1	3.0	0.883201	2020-05-12	6	no	NIH
2	3.0	0.295432	2020-05-12	6	no	NIH
3	3.0	0.512376	2020-05-12	6	yes	NIH
4	3.0	0.088702	2020-05-12	6	no	NIH

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A       5 non-null      float64
 1   B       5 non-null      float64
 2   C       5 non-null      datetime64[ns]
 3   D       5 non-null      int64
 4   E       5 non-null      category
 5   F       5 non-null      object
dtypes: category(1), datetime64[ns](1), float64
```

Working with a DataFrame

You can extract particular columns of a `DataFrame` by name

```
df['E']
```

```
0    yes
1     no
2     no
3    yes
4     no
Name: E, dtype: category
Categories (2, object): ['no', 'yes']
```

```
df.B
```

```
0    0.958092
1    0.883201
2    0.295432
3    0.512376
4    0.088702
Name: B, dtype: float64
```

> The `.` notation can be more convenient if we need to perform operations on a single column. If we want to extract multiple columns, this notation will not work. Also, if we want to create new columns or replace existing columns, we need to use the array notation with the column name in quotes.

Working with a DataFrame

```
df2 = pd.DataFrame(rng.randint(0,10, (5,4)),
                   index = ['a','b','c','d','e'],
                   columns = ['one','two','three','four'])
df2
```

```
   one  two  three  four
a    5    3      2     8
b    9    3      0     5
c    8    4      3     3
d    5    2      7     1
e    6    7      8     7
```

Working with a DataFrame

There are many ways to extract elements. Let's simplify things for this, and then move on to more consistent ways to extract elements of a `DataFrame`. Let's agree on two things. If we're going the direct extraction route,

1. We will extract single columns of a `DataFrame` with `[]` or `.`, i.e., `df2['one']` or `df2.one`
2. We will extract slices of rows of a `DataFrame` using location only, i.e., `df2[:3]`.

For everything else, we'll use two functions, `loc` and `iloc`.

- `loc` extracts elements like a matrix, using index and columns
- `iloc` extracts elements like a matrix, using location

Working with a DataFrame

```
df2.loc[:,'one':'three']
```

```
   one  two  three
a    5    3      2
b    9    3      0
c    8    4      3
d    5    2      7
e    6    7      8
```

```
df2.loc['a':'d',:]
```

```
   one  two  three  four
a    5    3      2     8
b    9    3      0     5
c    8    4      3     3
d    5    2      7     1
```

So `loc` works just like a matrix, but with `pandas` slicing rules (include largest index)

Working with a DataFrame

```
df2.iloc[:,1:4]
```

```
   two  three  four
a    3      2     8
b    3      0     5
c    4      3     3
d    2      7     1
e    7      8     7
```

```
df2.iloc[1:3,:]
```

```
   one  two  three  four
b    9    3      0     5
c    8    4      3     3
```

```
df2.iloc[1:3, 1:4]
```

```
   two  three  four
b    3      0     5
c    4      3     3
```

Recall that numeric slicing includes the lower index, excludes the highest index.

Working with a DataFrame

If we want to extract a single element from a dataset, there are two functions available, `iat` and `at`, with behavior corresponding to `iloc` and `loc`, respectively.

```
df2.iat[2,3]
```

```
3
```

```
df2.at['b','three']
```

```
0
```

Working with a DataFrame

We can also use tests to extract data from a `DataFrame`. For example, we can extract only rows where column labeled `one` is greater than 3.

```
df2[df2.one > 3]
```

```
   one  two  three  four
a    5    3      2     8
b    9    3      0     5
c    8    4      3     3
d    5    2      7     1
e    6    7      8     7
```

We can also do composite tests. Here we ask for rows where `one` is greater than 3 and `three` is less than 9

```
df2[(df2.one > 3) & (df2.three < 9)]
```

```
   one  two  three  four
a    5    3      2     8
b    9    3      0     5
c    8    4      3     3
d    5    2      7     1
e    6    7      8     7
```

Working with a DataFrame

query

`DataFrame`'s have a `query` method allowing selection using a Python expression

```
n = 10
df = pd.DataFrame(np.random.rand(n, 3), columns = list('abc'))
df
```

```
          a         b         c
0  0.002048  0.616018  0.018633
1  0.123496  0.581216  0.348200
2  0.741596  0.749493  0.394329
3  0.734978  0.526084  0.303296
4  0.624240  0.068623  0.692832
5  0.144814  0.498171  0.761625
6  0.224956  0.338892  0.613188
7  0.254847  0.214019  0.461525
8  0.489898  0.042269  0.124523
9  0.165313  0.884789  0.862262
```

Working with a DataFrame

query

```
df[(df.a < df.b) & (df.b < df.c)]
```

```
          a         b         c
5  0.144814  0.498171  0.761625
6  0.224956  0.338892  0.613188
```

We can equivalently write this query as

```
df.query('(a < b) & (b < c)')
```

```
          a         b         c
5  0.144814  0.498171  0.761625
6  0.224956  0.338892  0.613188
```

Working with a DataFrame

Replacing values in a DataFrame

We can replace values within a DataFrame either by position or using a query.

```
df2
```

```
   one  two  three  four
a    5    3      2     8
b    9    3      0     5
c    8    4      3     3
d    5    2      7     1
e    6    7      8     7
```

```
df2['one'] = [2,5,2,5,2]
df2
```

```
   one  two  three  four
a    2    3      2     8
b    5    3      0     5
c    2    4      3     3
d    5    2      7     1
e    2    7      8     7
```

Working with a DataFrame

Let's now replace values using `replace` which is more flexible.

```
df2.replace(0, -9) # replace 0 with -9
```

```
   one  two  three  four
a    2    3      2     8
b    5    3     -9     5
c    2    4      3     3
d    5    2      7     1
e    2    7      8     7
```

```
df2.replace({'one': {5: 500}, 'three': {0: -9, 8: 800}})
# different replacements in different columns
```

```
   one  two  three  four
a    2    3      2     8
b  500    3     -9     5
c    2    4      3     3
d  500    2      7     1
e    2    7    800     7
```

See more examples in the documentation

Categorical data

`pandas` provides a `Categorical` function and a `category` object type to Python. This type is analogous to the `factor` data type in R. It is meant to address categorical or discrete variables, where we need to use them in analyses. Categorical variables typically take on a small number of unique values, like gender, blood type, country of origin, race, etc.

You can create categorical `Series` in a couple of ways:

```
s = pd.Series(['a','b','c'], dtype='category')
```

```
df = pd.DataFrame({
    'A':3.,
    'B':rng.random_sample(5),
    'C': pd.Timestamp('20200512'),
    'D': np.array([6] * 5),
    'E': pd.Categorical(['yes','no','no','yes','no']),
    'F': 'NIH'})

df['F'].astype('category')
```

```
0    NIH
1    NIH
2    NIH
3    NIH
4    NIH
```

Categorical data

You can also create `DataFrame`'s where each column is categorical

```
df = pd.DataFrame({'A': list('abcd'), 'B': list('bdca')})
df_cat = df.astype('category')
df_cat.dtypes
```

```
A    category
B    category
dtype: object
```

Categorical data

You can explore categorical data in a variety of ways

```
df_cat['A'].describe()
```

```
count     4
unique    4
top       a
freq      1
Name: A, dtype: object
```

```
df['A'].value_counts()
```

```
d    1
a    1
c    1
b    1
Name: A, dtype: int64
```

Categorical data

One issue with categories is that, if a particular level of a category is not seen before, it can create an error. So you can pre-specify the categories you expect

```
df_cat['B'] = pd.Categorical(list('aabb'), categories = ['a','b','c','d'])
df_cat['B'].value_counts()
```

```
a    2
b    2
c    0
d    0
Name: B, dtype: int64
```

Categorical data

Re-organizing categories

In categorical data, there is often the concept of a "first" or "reference" category, and an ordering of categories. This tends to be important in visualization. Both aspects of a category can be addressed using the `reorder_categories` function.

In our earlier example, we can see that the `A` variable has 4 categories, with the "first" category being "a".

```
df_cat.A
```

```
0    a
1    b
2    c
3    d
Name: A, dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']
```

Categorical data

Re-organizing categories

Suppose we want to change this ordering to the reverse ordering, where "d" is the "first" category, and then it goes in reverse order.

```
df_cat['A'] = df_cat.A.cat.reorder_categories(['d','c','b','a'])
df_cat.A
```

```
0    a
1    b
2    c
3    d
Name: A, dtype: category
Categories (4, object): ['d', 'c', 'b', 'a']
```

Missing data

Both `numpy` and `pandas` allow for missing values, which are a reality in data science. The missing values are coded as `np.nan`. Let's create some data and force some missing values

```
df = pd.DataFrame(np.random.randn(5, 3), index = ['a','c','e', 'f','g'], columns = ['one','two','thr
df['four'] = 20 # add a column named "four", which will all be 20
df['five'] = df['one'] > 0
df
```

```
        one       two     three  four   five
a  0.181914 -1.451055  1.198279    20   True
c  0.495341  0.173635 -0.102456    20   True
e -0.559569  0.542329 -0.492456    20  False
f -0.084524  0.264715 -1.569520    20  False
g -0.379085  1.318055  0.584425    20  False
```

Missing data

```
df2 = df.reindex(['a','b','c','d','e','f','g'])
df2
```

```
        one       two     three  four   five
a  0.181914 -1.451055  1.198279  20.0   True
b       NaN       NaN       NaN   NaN    NaN
c  0.495341  0.173635 -0.102456  20.0   True
d       NaN       NaN       NaN   NaN    NaN
e -0.559569  0.542329 -0.492456  20.0  False
f -0.084524  0.264715 -1.569520  20.0  False
g -0.379085  1.318055  0.584425  20.0  False
```

The code above is creating new blank rows based on the new index values, some of which are present in the existing data and some of which are missing.

Missing data

We can create *masks* of the data indicating where missing values reside in a data set.

```
df2.isna()
```

```
     one    two  three   four   five
a  False  False  False  False  False
b   True   True   True   True   True
c  False  False  False  False  False
d   True   True   True   True   True
e  False  False  False  False  False
f  False  False  False  False  False
g  False  False  False  False  False
```

```
df2['one'].notna()
```

```
a     True
b    False
c     True
d    False
e     True
f     True
g     True
Name: one, dtype: bool
```

Missing data

We can obtain complete data by dropping any row that has any missing value. This is called *complete case analysis*, and you should be very careful using it. It is *only* valid if we belive that the missingness is missing at random, and not related to some characteristic of the data or the data gathering process.

```
df2.dropna(how='any')
```

```
        one       two     three  four   five
a  0.181914 -1.451055  1.198279  20.0   True
c  0.495341  0.173635 -0.102456  20.0   True
e -0.559569  0.542329 -0.492456  20.0  False
f -0.084524  0.264715 -1.569520  20.0  False
g -0.379085  1.318055  0.584425  20.0  False
```

Missing data

You can also fill in, or *impute*, missing values. This can be done using a single value..

```
out1 = df2.fillna(value = 5)
out1
```

	one	two	three	four	five
a	0.181914	-1.451055	1.198279	20.0	True
b	5.000000	5.000000	5.000000	5.0	5
c	0.495341	0.173635	-0.102456	20.0	True
d	5.000000	5.000000	5.000000	5.0	5
e	-0.559569	0.542329	-0.492456	20.0	False
f	-0.084524	0.264715	-1.569520	20.0	False
g	-0.379085	1.318055	0.584425	20.0	False

or a computed value like a column mean

```
df3 = df2.copy()
df3 = df3.select_dtypes(exclude=[object])   # 
out2 = df3.fillna(df3.mean())  # df3.mean() co
out2
```

	one	two	three	four
a	0.181914	-1.451055	1.198279	20.0
b	-0.069185	0.169536	-0.076346	20.0
c	0.495341	0.173635	-0.102456	20.0
d	-0.069185	0.169536	-0.076346	20.0
e	-0.559569	0.542329	-0.492456	20.0
f	-0.084524	0.264715	-1.569520	20.0
g	-0.379085	1.318055	0.584425	20.0

Missing data

You can also impute based on the principle of *last value carried forward* which is common in time series. This means that the missing value is imputed with the previous recorded value.

```
out3 = df2.fillna(method = 'ffill') # Fill for
out3
```

	one	two	three	four	five
a	0.181914	-1.451055	1.198279	20.0	True
b	0.181914	-1.451055	1.198279	20.0	True
c	0.495341	0.173635	-0.102456	20.0	True
d	0.495341	0.173635	-0.102456	20.0	True
e	-0.559569	0.542329	-0.492456	20.0	False
f	-0.084524	0.264715	-1.569520	20.0	False
g	-0.379085	1.318055	0.584425	20.0	False

```
out4 = df2.fillna(method = 'bfill') # Fill bac
out4
```

	one	two	three	four	five
a	0.181914	-1.451055	1.198279	20.0	True
b	0.495341	0.173635	-0.102456	20.0	True
c	0.495341	0.173635	-0.102456	20.0	True
d	-0.559569	0.542329	-0.492456	20.0	False
e	-0.559569	0.542329	-0.492456	20.0	False
f	-0.084524	0.264715	-1.569520	20.0	False
g	-0.379085	1.318055	0.584425	20.0	False

Data transformation

Arithmetic operations

If you have a `Series` or `DataFrame` that is all numeric, you can add or multiply single numbers to all the elements together.

```
A = pd.DataFrame(np.random.randn(3,3))
print(A)
```

```
          0         1         2
0 -0.750816 -0.451248  0.606251
1  0.522714 -0.450816  1.075945
2 -0.558849  0.243841 -0.170975
```

```
print(A + 6)
```

```
          0         1         2
0  5.249184  5.548752  6.606251
1  6.522714  5.549184  7.075945
2  5.441151  6.243841  5.829025
```

```
print(A * -10)
```

```
          0         1          2
0  7.508161  4.512485  -6.062512
1 -5.227138  4.508165 -10.759446
2  5.588490 -2.438415   1.709746
```

Data transformation

Arithmetic operations

If you have two compatible (same dimension) numeric `DataFrame`s, you can add, subtract, multiply and divide elementwise

```
B = pd.DataFrame(np.random.randn(3,3) + 4)
print(A + B)
```

```
          0         1         2
0  2.595383  3.556978  2.976657
1  4.858211  3.544277  4.393956
2  2.901065  5.001003  4.965892
```

```
print(A * B)
```

```
           0         1         2
0 -2.512380 -1.808706  1.437061
1  2.266224 -1.801054  3.569996
2 -1.933570  1.159993 -0.878274
```

Data transformation

Arithmetic operations

If you have a `Series` with the same number of elements as the number of columns of a `DataFrame`, you can do arithmetic operations, with each element of the `Series` acting upon each column of the `DataFrame`

```
c = pd.Series([1,2,3,4,5])
print(A + c)
```

```
          0         1         2   3   4
0  0.249184  1.548752  3.606251 NaN NaN
1  1.522714  1.549184  4.075945 NaN NaN
2  0.441151  2.243841  2.829025 NaN NaN
```

```
print(A * c)
```

```
          0         1         2   3   4
0 -0.750816 -0.902497  1.818754 NaN NaN
1  0.522714 -0.901633  3.227834 NaN NaN
2 -0.558849  0.487683 -0.512924 NaN NaN
```

Data transformation

Arithmetic operations

This idea can be used to standardize a dataset, i.e. make each column have mean 0 and standard deviation 1.

```
means = A.mean(axis=0)
stds = A.std(axis = 0)

(A - means)/stds
```

```
          0         1         2
0 -0.711477 -0.577889  0.162781
1  1.143362 -0.576812  0.908623
2 -0.431885  1.154700 -1.071404
```

Concatenation of data sets

Let's create some example data sets

```
df1 = pd.DataFrame({'A': ['a'+str(i) for i in range(4)],
    'B': ['b'+str(i) for i in range(4)],
    'C': ['c'+str(i) for i in range(4)],
    'D': ['d'+str(i) for i in range(4)]})

df2 =  pd.DataFrame({'A': ['a'+str(i) for i in range(4,8)],
    'B': ['b'+str(i) for i in range(4,8)],
    'C': ['c'+str(i) for i in range(4,8)],
    'D': ['d'+str(i) for i in range(4,8)]})
df3 =  pd.DataFrame({'A': ['a'+str(i) for i in range(8,12)],
    'B': ['b'+str(i) for i in range(8,12)],
    'C': ['c'+str(i) for i in range(8,12)],
    'D': ['d'+str(i) for i in range(8,12)]})
```

Concatenation of data sets

We can concatenate these `DataFrame` objects by row

```
row_concatenate = pd.concat([df1, df2, df3])
print(row_concatenate)
```

```
     A    B    C    D
0   a0   b0   c0   d0
1   a1   b1   c1   d1
2   a2   b2   c2   d2
3   a3   b3   c3   d3
0   a4   b4   c4   d4
1   a5   b5   c5   d5
2   a6   b6   c6   d6
3   a7   b7   c7   d7
0   a8   b8   c8   d8
1   a9   b9   c9   d9
2  a10  b10  c10  d10
3  a11  b11  c11  d11
```

This stacks the dataframes together. They are literally stacked, as is evidenced by the index values being repeated.

Concatenation of data sets

This same exercise can be done by the `append` function

```
df1.append(df2).append(df3)
```

```
     A    B    C    D
0   a0   b0   c0   d0
1   a1   b1   c1   d1
2   a2   b2   c2   d2
3   a3   b3   c3   d3
0   a4   b4   c4   d4
1   a5   b5   c5   d5
2   a6   b6   c6   d6
3   a7   b7   c7   d7
0   a8   b8   c8   d8
1   a9   b9   c9   d9
2  a10  b10  c10  d10
3  a11  b11  c11  d11
```

Concatenation of data sets

Suppose we want to append a new row to `df1`. Lets create a new row.

```
new_row = pd.Series(['n1','n2','n3','n4'])
pd.concat([df1, new_row])
```

```
     A    B    C    D    0
0   a0   b0   c0   d0  NaN
1   a1   b1   c1   d1  NaN
2   a2   b2   c2   d2  NaN
3   a3   b3   c3   d3  NaN
0  NaN  NaN  NaN  NaN   n1
1  NaN  NaN  NaN  NaN   n2
2  NaN  NaN  NaN  NaN   n3
3  NaN  NaN  NaN  NaN   n4
```

That's a lot of missing values. The issue is that the we don't have column names in the `new_row`, and the indices are the same, so pandas tries to append it my making a new column.

Concatenation of data sets

The solution is to make it a `DataFrame`.

```
new_row = pd.DataFrame([['n1','n2','n3','n4']], columns = ['A','B','C','D'])
print(new_row)
```

```
    A   B   C   D
0  n1  n2  n3  n4
```

```
pd.concat([df1, new_row])
```

```
    A   B   C   D
0  a0  b0  c0  d0
1  a1  b1  c1  d1
2  a2  b2  c2  d2
3  a3  b3  c3  d3
0  n1  n2  n3  n4
```

Adding columns

```
pd.concat([df1,df2,df3], axis = 1)
```

```
    A   B   C   D   A   B   C   D    A    B    C    D
0  a0  b0  c0  d0  a4  b4  c4  d4   a8   b8   c8   d8
1  a1  b1  c1  d1  a5  b5  c5  d5   a9   b9   c9   d9
2  a2  b2  c2  d2  a6  b6  c6  d6  a10  b10  c10  d10
3  a3  b3  c3  d3  a7  b7  c7  d7  a11  b11  c11  d11
```

The option `axis=1` ensures that concatenation happens by columns. The default value `axis = 0` concatenates by rows.

Concatenation of data sets

Let's play a little game. Let's change the column names of `df2` and `df3` so they are not the same as `df1`.

```
df2.columns = ['E','F','G','H']
df3.columns = ['A','D','F','H']
pd.concat([df1,df2,df3])
```

```
     A    B    C    D    E    F    G    H
0   a0   b0   c0   d0  NaN  NaN  NaN  NaN
1   a1   b1   c1   d1  NaN  NaN  NaN  NaN
2   a2   b2   c2   d2  NaN  NaN  NaN  NaN
3   a3   b3   c3   d3  NaN  NaN  NaN  NaN
0  NaN  NaN  NaN  NaN   a4   b4   c4   d4
1  NaN  NaN  NaN  NaN   a5   b5   c5   d5
2  NaN  NaN  NaN  NaN   a6   b6   c6   d6
3  NaN  NaN  NaN  NaN   a7   b7   c7   d7
0   a8  NaN  NaN   b8  NaN   c8  NaN   d8
1   a9  NaN  NaN   b9  NaN   c9  NaN   d9
2  a10  NaN  NaN  b10  NaN  c10  NaN  d10
3  a11  NaN  NaN  b11  NaN  c11  NaN  d11
```

Now pandas ensures that all column names are represented in the new data frame, but with missing values where the row indices and column indices are mismatched.

Merging data sets

For this section we'll use a set of data from a survey, also used by Daniel Chen in "Pandas for Everyone"

```
person = pd.read_csv('data/survey_person.csv')
site = pd.read_csv('data/survey_site.csv')
survey = pd.read_csv('data/survey_survey.csv')
visited = pd.read_csv('data/survey_visited.csv')
```

Merging data sets

```
print(person)
```

```
      ident   personal    family
0      dyer    William      Dyer
1        pb      Frank   Pabodie
2      lake   Anderson      Lake
3       roe  Valentina   Roerich
4  danforth      Frank  Danforth
```

```
print(site)
```

```
    name    lat    long
0   DR-1 -49.85 -128.57
1   DR-3 -47.15 -126.72
2  MSK-4 -48.87 -123.40
```

```
print(survey.head())
```

```
   taken person quant  reading
0    619   dyer   rad     9.82
1    619   dyer   sal     0.13
2    622   dyer   rad     7.80
3    622   dyer   sal     0.09
4    734     pb   rad     8.41
```

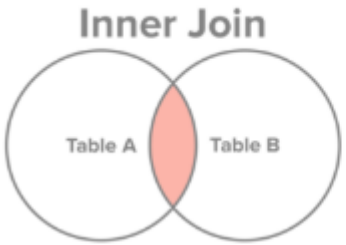
```
print(visited.head())
```

```
   ident  site       dated
0    619  DR-1  1927-02-08
1    622  DR-1  1927-02-10
2    734  DR-3  1939-01-07
3    735  DR-3  1930-01-12
4    751  DR-3  1930-02-26
```

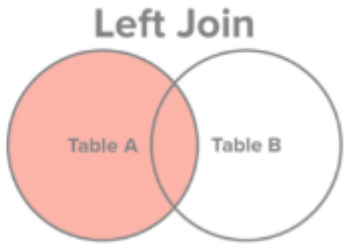
Merging data sets

There are basically four kinds of joins:

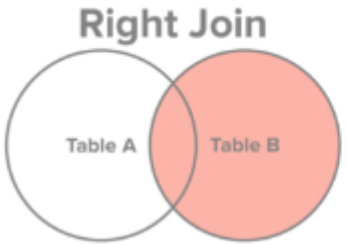
pandas	R	SQL	Description
left	left_join	left outer	keep all rows on left
right	right_join	right outer	keep all rows on right
outer	outer_join	full outer	keep all rows from both
inner	inner_join	inner	keep only rows with common keys



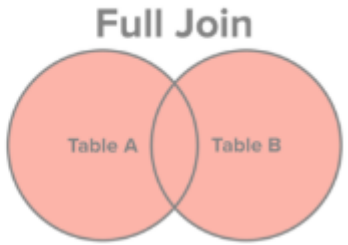
Select all records from Table A and Table B, where the join condition is met.



Select all records from Table A, along with records from Table B for which the join condition is met (if at all).



Select all records from Table B, along with records from Table A for which the join condition is met (if at all).



Select all records from Table A and Table B, regardless of whether the join condition is met or not.

Merging data sets

The terms `left` and `right` refer to which data set you call first and second respectively.

We start with an left join

```
s2v_merge = survey.merge(visited, left_on = 'taken',right_on = 'ident', how = 'left')
```

```
print(s2v_merge.head())
```

```
   taken person quant  reading  ident  site
0    619   dyer   rad     9.82    619  DR-1  19
1    619   dyer   sal     0.13    619  DR-1  19
2    622   dyer   rad     7.80    622  DR-1  19
3    622   dyer   sal     0.09    622  DR-1  19
4    734     pb   rad     8.41    734  DR-3  19
```

Here, the left dataset is `survey` and the right one is `visited`. Since we're doing a left join, we keep all the rows from `survey` and add columns from `visited`, matching on the common key, called "taken" in one dataset and "ident" in the other. Note that the rows of `visited` are repeated as needed to line up with all the rows with common "taken" values.

Merging data sets

We can now add location information, where the common key is the site code

```
s2v2loc_merge = s2v_merge.merge(site, how = 'left', left_on = 'site', right_on = 'name')
print(s2v2loc_merge.head())
```

```
   taken person quant  reading  ident  site       dated  name    lat    long
0    619   dyer   rad     9.82    619  DR-1  1927-02-08  DR-1 -49.85 -128.57
1    619   dyer   sal     0.13    619  DR-1  1927-02-08  DR-1 -49.85 -128.57
2    622   dyer   rad     7.80    622  DR-1  1927-02-10  DR-1 -49.85 -128.57
3    622   dyer   sal     0.09    622  DR-1  1927-02-10  DR-1 -49.85 -128.57
4    734     pb   rad     8.41    734  DR-3  1939-01-07  DR-3 -47.15 -126.72
```

Merging data sets

Lastly, we add the person information to this dataset.

```
merged = s2v2loc_merge.merge(person, how = 'left', left_on = 'person', right_on = 'ident')
print(merged.head())
```

```
   taken person quant  reading  ...    long ident_y personal   family
0    619   dyer   rad     9.82  ... -128.57    dyer  William    Dyer
1    619   dyer   sal     0.13  ... -128.57    dyer  William    Dyer
2    622   dyer   rad     7.80  ... -128.57    dyer  William    Dyer
3    622   dyer   sal     0.09  ... -128.57    dyer  William    Dyer
4    734     pb   rad     8.41  ... -126.72      pb    Frank  Pabodie

[5 rows x 13 columns]
```

Merging data sets

You can merge based on multiple columns as long as they match up.

```
ps = person.merge(survey, left_on = 'ident',
  right_on = 'person')
print(ps.head(4))
```

```
  ident personal family  taken person quant  re
0  dyer  William   Dyer    619   dyer   rad
1  dyer  William   Dyer    619   dyer   sal
2  dyer  William   Dyer    622   dyer   rad
3  dyer  William   Dyer    622   dyer   sal
```

```
vs = visited.merge(survey, left_on = 'ident',
  right_on = 'taken')
print(vs.head(4))
```

```
   ident  site       dated  taken person quant
0    619  DR-1  1927-02-08    619   dyer   rad
1    619  DR-1  1927-02-08    619   dyer   sal
2    622  DR-1  1927-02-10    622   dyer   rad
3    622  DR-1  1927-02-10    622   dyer   sal
```

```
ps_vs = ps.merge(vs,
                 left_on = ['ident','taken', 'quant','reading'],
                 right_on = ['person','ident','quant','reading']) # The keys need to correspond
ps_vs.head()
```

```
  ident_x personal   family  taken_x  ...  site       dated  taken_y  person_y
0    dyer  William     Dyer      619  ...  DR-1  1927-02-08      619      dyer
1    dyer  William     Dyer      619  ...  DR-1  1927-02-08      619      dyer
2    dyer  William     Dyer      622  ...  DR-1  1927-02-10      622      dyer
3    dyer  William     Dyer      622  ...  DR-1  1927-02-10      622      dyer
```

Tidy data principles and reshaping datasets

The tidy data principle is a principle espoused by Dr. Hadley Wickham, one of the foremost R developers. Tidy data is a structure for datasets to make them more easily analyzed on computers. The basic principles are

- Each row is an observation
- Each column is a variable
- Each type of observational unit forms a table

> Tidy data is tidy in one way. Untidy data can be untidy in many ways

Let's look at some examples.

```
from glob import glob
filenames = sorted(glob('data/table*.csv')) # find files matching pattern. I know there are 6 of th
table1, table2, table3, table4a, table4b, table5 = [pd.read_csv(f) for f in filenames] # Use a list
```

This code imports data from 6 files matching a pattern. Python allows multiple assignments on the left of the `=`, and as each dataset is imported, it gets assigned in order to the variables on the left. In the second line I sort the file names so that they match the order in which I'm storing them in the 3rd line. The function `glob` does pattern-matching of file names.

Tidy data principles and reshaping datasets

The following tables refer to the number of TB cases and population in Afghanistan, Brazil and China in 1999 and 2000

```
print(table1)
```

```
       country  year   cases  population
0  Afghanistan  1999     745    19987071
1  Afghanistan  2000    2666    20595360
2       Brazil  1999   37737   172006362
3       Brazil  2000   80488   174504898
4        China  1999  212258  1272915272
5        China  2000  213766  1280428583
```

```
print(table2)
```

```
       country  year        type       count
0  Afghanistan  1999       cases         745
1  Afghanistan  1999  population    19987071
2  Afghanistan  2000       cases        2666
3  Afghanistan  2000  population    20595360
4       Brazil  1999       cases       37737
5       Brazil  1999  population   172006362
6       Brazil  2000       cases       80488
```

```
print(table3)
```

```
       country  year              rate
0  Afghanistan  1999       745/19987071
1  Afghanistan  2000      2666/20595360
2       Brazil  1999    37737/172006362
3       Brazil  2000    80488/174504898
4        China  1999  212258/1272915272
5        China  2000  213766/1280428583
```

```
print(table4a) # cases
```

```
       country    1999    2000
0  Afghanistan     745    2666
1       Brazil   37737   80488
2        China  212258  213766
```

Tidy data principles and reshaping datasets

```
print(table4b) # population
```

```
       country        1999        2000
0  Afghanistan    19987071    20595360
1       Brazil   172006362   174504898
2        China  1272915272  1280428583
```

```
print(table5)
```

```
       country  century  year               rate
0  Afghanistan       19    99       745/19987071
1  Afghanistan       20     0      2666/20595360
2       Brazil       19    99    37737/172006362
3       Brazil       20     0    80488/174504898
4        China       19    99  212258/1272915272
5        China       20     0  213766/1280428583
```

Exercise: Describe why and why not each of these datasets are tidy.

Melting (unpivoting) data

Melting is the operation of collapsing multiple columns into 2 columns,

- where one column is formed by the old column names,
- and the other by the corresponding values.

Some columns may be kept fixed and their data are repeated to maintain the interrelationships between the variables.

Melting (unpivoting) data

We'll start with loading some data on income and religion in the US from the Pew Research Center.

```
pew = pd.read_csv('data/pew.csv')
print(pew.head())
```

```
              religion  <$10k  $10-20k  ...  $100-150k  >150k  Don't know/refused
0             Agnostic     27       34  ...        109     84                  96
1              Atheist     12       27  ...         59     74                  76
2             Buddhist     27       21  ...         39     53                  54
3             Catholic    418      617  ...        792    633                1489
4  Don’t know/refused     15       14  ...         17     18                 116

[5 rows x 11 columns]
```

This dataset is considered in "wide" format. There are several issues with it, including the fact that column headers have data. Those column headers are income groups, that should be a column by tidy principles. Our job is to turn this dataset into "long" format with a column for income group.

Melting (unpivoting) data

We will use the function `melt` to achieve this. This takes a few parameters:

- id_vars is a list of variables that will remain as is
- value_vars is a list of column nmaes that we will melt (or unpivot). By default, it will melt all columns not mentioned in id_vars
- var_name is a string giving the name of the new column created by the headers (default: `variable`)
- value_name is a string giving the name of the new column created by the values (default: `value`)

```
pew_long = pew.melt(id_vars = ['religion'], var_name = 'income_group', value_name = 'count')
print(pew_long.head())
```

```
              religion income_group  count
0             Agnostic        <$10k     27
1              Atheist        <$10k     12
2             Buddhist        <$10k     27
3             Catholic        <$10k    418
4  Don't know/refused        <$10k     15
```

Separating columns containing multiple variables

We will use an Ebola dataset to illustrate this principle

```
ebola = pd.read_csv('data/country_timeseries.csv')
print(ebola.head())
```

```
         Date  Day  ...  Deaths_Spain  Deaths_Mali
0    1/5/2015  289  ...           NaN          NaN
1    1/4/2015  288  ...           NaN          NaN
2    1/3/2015  287  ...           NaN          NaN
3    1/2/2015  286  ...           NaN          NaN
4  12/31/2014  284  ...           NaN          NaN

[5 rows x 18 columns]
```

Note that for each country we have two columns -- one for cases (number infected) and one for deaths. Ideally we want one column for country, one for cases and one for deaths.

Separating columns containing multiple variables

The first step will be to melt this data sets so that the column headers in question from a column and the corresponding data forms a second column.

```
ebola_long = ebola.melt(id_vars = ['Date','Day'])
print(ebola_long.head())
```

```
         Date  Day      variable   value
0    1/5/2015  289  Cases_Guinea  2776.0
1    1/4/2015  288  Cases_Guinea  2775.0
2    1/3/2015  287  Cases_Guinea  2769.0
3    1/2/2015  286  Cases_Guinea     NaN
4  12/31/2014  284  Cases_Guinea  2730.0
```

Separating columns containing multiple variables

We now need to split the data in the `variable` column to make two columns. One will contain the country name and the other either Cases or Deaths. We will use some string manipulation functions that we will see later to achieve this.

```
variable_split = ebola_long['variable'].str.split('_', expand=True) # split on the `_` character
print(variable_split[:5])
```

```
      0       1
0  Cases  Guinea
1  Cases  Guinea
2  Cases  Guinea
3  Cases  Guinea
4  Cases  Guinea
```

The `expand=True` option forces the creation of an `DataFrame` rather than a list

```
type(variable_split)
```

```
<class 'pandas.core.frame.DataFrame'>
```

Separating columns containing multiple variables

We can now concatenate this to the original data

```
variable_split.columns = ['status','country']

ebola_parsed = pd.concat([ebola_long, variable_split], axis = 1)

ebola_parsed.drop('variable', axis = 1, inplace=True) # Remove the column named "variable" and repla

print(ebola_parsed.head())
```

```
         Date  Day   value status country
0    1/5/2015  289  2776.0  Cases  Guinea
1    1/4/2015  288  2775.0  Cases  Guinea
2    1/3/2015  287  2769.0  Cases  Guinea
3    1/2/2015  286     NaN  Cases  Guinea
4  12/31/2014  284  2730.0  Cases  Guinea
```

Pivot/spread datasets

If we wanted to, we could also make two columns based on cases and deaths, so for each country and date you could easily read off the cases and deaths. This is achieved using the `pivot_table` function.

In the `pivot_table` syntax, `index` refers to the columns we don't want to change, `columns` refers to the column whose values will form the column names of the new columns, and `values` is the name of the column that will form the values in the pivoted dataset.

Pivot/spread datasets

```
ebola_parsed.pivot_table(index = ['Date','Day'
  columns = 'status', values = 'value').head()
```

```
status                      Cases  Deaths
Date     Day country
1/2/2015 286 Liberia       8157.0  3496.0
1/3/2015 287 Guinea        2769.0  1767.0
             Liberia       8166.0  3496.0
             SierraLeone   9722.0  2915.0
1/4/2015 288 Guinea        2775.0  1781.0
```

This creates something called `MultiIndex` in the `pandas DataFrame`

```
ebola_parsed.pivot_table(index = ['Date','Day'
  columns = 'status',
  values = 'value').reset_index().head()
```

```
status       Date  Day       country   Cases  Dea
0       1/2/2015  286       Liberia  8157.0  349
1       1/3/2015  287        Guinea  2769.0  176
2       1/3/2015  287       Liberia  8166.0  349
3       1/3/2015  287  SierraLeone  9722.0  291
4       1/4/2015  288        Guinea  2775.0  178
```

We can get a normal DataFrame by using the `reset_index` function.

Pivot/spread datasets

Pivoting is a 2-column to many-column operation, with the number of columns formed depending on the number of unique values present in the column of the original data that is entered into the `columns` argument of `pivot_table`

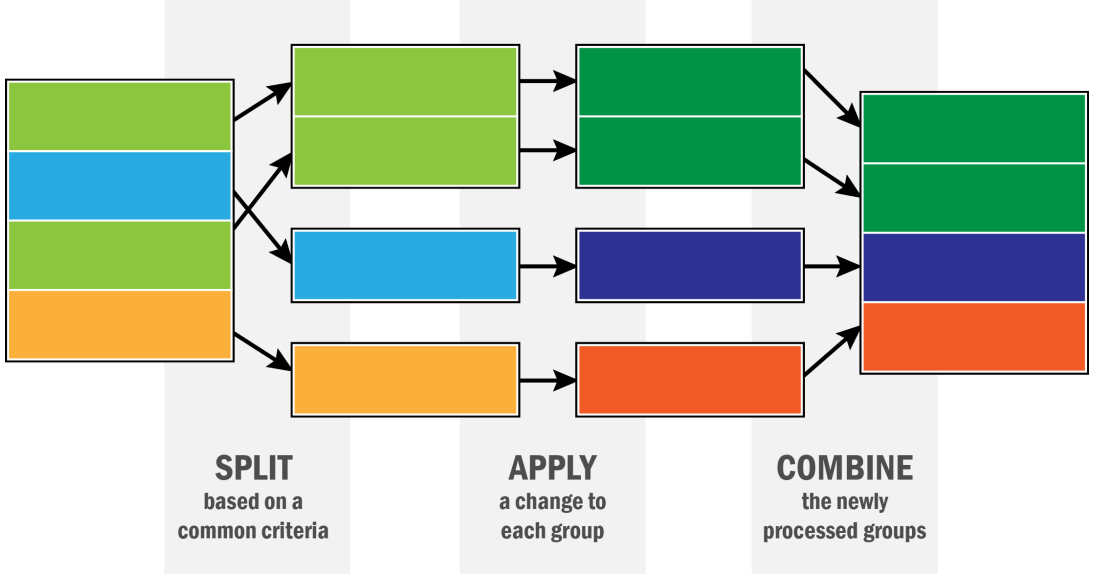
Exercise: Load the file `weather.csv` into Python and work on making it a tidy dataset. It requires melting and pivoting. The dataset comprises of the maximum and minimum temperatures recorded each day in 2010. There are lots of missing value. Ultimately we want columns for days of the month, maximum temperature and minimum temperature along with the location ID, the year and the month.

Data aggregation and split-apply-combine

We'll use the Gapminder dataset for this section

```
df = pd.read_csv('data/gapminder.tsv', sep = '\t') # data is tab-separated, so we use `\t` to speci
```

The paradigm we will be exploring is often called *split-apply-combine* or MapReduce or grouped aggregation. The basic idea is that you split a data set up by some feature, apply a recipe to each piece, compute the result, and then put the results back together into a dataset. This can be described in teh following schematic.



Data aggregation and split-apply-combine

`pandas` is set up for this. It features the `groupby` function that allows the "split" part of the operation. We can then apply a function to each part and put it back together. Let's see how.

```
df.head()
```

```
       country continent  year  lifeExp       pop   gdpPercap
0  Afghanistan      Asia  1952   28.801   8425333  779.445314
1  Afghanistan      Asia  1957   30.332   9240934  820.853030
2  Afghanistan      Asia  1962   31.997  10267083  853.100710
3  Afghanistan      Asia  1967   34.020  11537966  836.197138
4  Afghanistan      Asia  1972   36.088  13079460  739.981106
```

```
f"This dataset has {len(df['country'].unique())} countries in it"
```

```
'This dataset has 142 countries in it'
```

Data aggregation and split-apply-combine

One of the variables in this dataset is life expectancy at birth, `lifeExp`. Suppose we want to find the average life expectancy of each country over the period of study.

```
df.groupby('country')['lifeExp'].mean()
```

```
country
Afghanistan            37.478833
Albania                68.432917
Algeria                59.030167
Angola                 37.883500
Argentina              69.060417
                          ...
Vietnam                57.479500
West Bank and Gaza     60.328667
Yemen, Rep.            46.780417
Zambia                 45.996333
Zimbabwe               52.663167
Name: lifeExp, Length: 142, dtype: float64
```

Data aggregation and split-apply-combine

So what's going on here? First, we use the `groupby` function, telling `pandas` to split the dataset up by values of the column `country`.

```
df.groupby('country')
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7fe3d3901bb0>
```

`pandas` won't show you the actual data, but will tell you that it is a grouped dataframe object. This means that each element of this object is a `DataFrame` with data from one country.

Data aggregation and split-apply-combine

```
df.groupby('country').ngroups
```

```
142
```

```
df.groupby('country').get_group('United Kingdom')
```

```
             country continent  year  lifeExp       pop     gdpPercap
1596  United Kingdom    Europe  1952   69.180  50430000   9979.508487
1597  United Kingdom    Europe  1957   70.420  51430000  11283.177950
1598  United Kingdom    Europe  1962   70.760  53292000  12477.177070
1599  United Kingdom    Europe  1967   71.360  54959000  14142.850890
1600  United Kingdom    Europe  1972   72.010  56079000  15895.116410
1601  United Kingdom    Europe  1977   72.760  56179000  17428.748460
1602  United Kingdom    Europe  1982   74.040  56339704  18232.424520
1603  United Kingdom    Europe  1987   75.007  56981620  21664.787670
1604  United Kingdom    Europe  1992   76.420  57866349  22705.092540
1605  United Kingdom    Europe  1997   77.218  58808266  26074.531360
1606  United Kingdom    Europe  2002   78.471  59912431  29478.999190
1607  United Kingdom    Europe  2007   79.425  60776238  33203.261280
```

Data aggregation and split-apply-combine

```
avg_lifeexp_country = df.groupby('country').lifeExp.mean()
avg_lifeexp_country['United Kingdom']
```

```
73.92258333333332
```

Data aggregation and split-apply-combine

```
df.groupby('country').get_group('United Kingdom').lifeExp.mean()
```

```
73.92258333333332
```

Data aggregation and split-apply-combine

Let's look at if life expectancy has gone up over time, by continent

```
df.groupby(['continent','year']).lifeExp.mean()
```

```
continent  year
Africa     1952    39.135500
           1957    41.266346
           1962    43.319442
           1967    45.334538
           1972    47.450942
           1977    49.580423
           1982    51.592865
           1987    53.344788
           1992    53.629577
           1997    53.598269
           2002    53.325231
           2007    54.806038
Americas   1952    53.279840
           1957    55.960280
           1962    58.398760
           1967    60.410920
           1972    62.394920
           1977    64.391560
           1982    66.228840
           1987    68.090720
```

Data aggregation and split-apply-combine

```
avg_lifeexp_continent_yr = df.groupby(['continent','year']).lifeExp.mean().reset_index()
avg_lifeexp_continent_yr
```

	continent	year	lifeExp
0	Africa	1952	39.135500
1	Africa	1957	41.266346
2	Africa	1962	43.319442
3	Africa	1967	45.334538
4	Africa	1972	47.450942
5	Africa	1977	49.580423
6	Africa	1982	51.592865
7	Africa	1987	53.344788
8	Africa	1992	53.629577
9	Africa	1997	53.598269
10	Africa	2002	53.325231
11	Africa	2007	54.806038
12	Americas	1952	53.279840
13	Americas	1957	55.960280
14	Americas	1962	58.398760
15	Americas	1967	60.410920
16	Americas	1972	62.394920
17	Americas	1977	64.391560
18	Americas	1982	66.228840
19	Americas	1987	68.090720
20	Americas	1992	69.568360

Data aggregation and split-apply-combine

We can do quick aggregations with `pandas`

```
df.groupby('continent').lifeExp.describe()
```

```
           count       mean        std  ...      50%       75%     max
continent                               ...
Africa     624.0  48.865330   9.150210  ...  47.7920  54.41150  76.442
Americas   300.0  64.658737   9.345088  ...  67.0480  71.69950  80.653
Asia       396.0  60.064903  11.864532  ...  61.7915  69.50525  82.603
Europe     360.0  71.903686   5.433178  ...  72.2410  75.45050  81.757
Oceania     24.0  74.326208   3.795611  ...  73.6650  77.55250  81.235

[5 rows x 8 columns]
```

Data aggregation and split-apply-combine

```
df.groupby('continent').nth(10) # Tenth observation in each group
```

```
               country  year  lifeExp       pop     gdpPercap
continent
Africa         Algeria  2002   70.994  31287142   5288.040382
Americas     Argentina  2002   74.340  38331121   8797.640716
Asia       Afghanistan  2002   42.129  25268405    726.734055
Europe         Albania  2002   75.651   3508512   4604.211737
Oceania      Australia  2002   80.370  19546792  30687.754730
```

Data aggregation and split-apply-combine

You can also use functions from other modules, or your own functions in this aggregation work.

```
df.groupby('continent').lifeExp.agg(np.mean)
```

```
continent
Africa      48.865330
Americas    64.658737
Asia        60.064903
Europe      71.903686
Oceania     74.326208
Name: lifeExp, dtype: float64
```

Data aggregation and split-apply-combine

You can do many functions at once

```
df.groupby('year').lifeExp.agg([np.count_nonzero, np.mean, np.std])
```

```
      count_nonzero       mean        std
year
1952          142.0  49.057620  12.225956
1957          142.0  51.507401  12.231286
1962          142.0  53.609249  12.097245
1967          142.0  55.678290  11.718858
1972          142.0  57.647386  11.381953
1977          142.0  59.570157  11.227229
1982          142.0  61.533197  10.770618
1987          142.0  63.212613  10.556285
1992          142.0  64.160338  11.227380
1997          142.0  65.014676  11.559439
2002          142.0  65.694923  12.279823
2007          142.0  67.007423  12.073021
```

Data aggregation and split-apply-combine

You can also aggregate on different columns at the same time by passing a `dict` to the `agg` function

```
df.groupby('year').agg({'lifeExp': np.mean,'pop': np.median,'gdpPercap': np.median}).reset_index()
```

```
    year    lifeExp         pop    gdpPercap
0   1952  49.057620   3943953.0  1968.528344
1   1957  51.507401   4282942.0  2173.220291
2   1962  53.609249   4686039.5  2335.439533
3   1967  55.678290   5170175.5  2678.334740
4   1972  57.647386   5877996.5  3339.129407
5   1977  59.570157   6404036.5  3798.609244
6   1982  61.533197   7007320.0  4216.228428
7   1987  63.212613   7774861.5  4280.300366
8   1992  64.160338   8688686.5  4386.085502
9   1997  65.014676   9735063.5  4781.825478
10  2002  65.694923  10372918.5  5319.804524
11  2007  67.007423  10517531.0  6124.371108
```

Transformation

You can do grouped transformations using this same method. Transformations are 1-1 functions, so you get back the same number of observations instead of getting aggregations.

We will compute the z-score for each year, i.e. we will subtract the average life expectancy and divide by the standard deviation

```
def my_zscore(values):
    m = np.mean(values)
    s = np.std(values)
    return((values - m)/s)
```

```
df.groupby('year').lifeExp.transform(my_zscore)
```

```
0      -1.662719
1      -1.737377
2      -1.792867
3      -1.854699
4      -1.900878
          ...
1699   -0.081910
1700   -0.338167
1701   -1.580537
1702   -2.100756
1703   -1.955077
```

Transformation

```
df['lifeExp_z'] = df.groupby('year').lifeExp.transform(my_zscore)
```

```
df.groupby('year').lifeExp_z.mean()
```

```
year
1952   -1.123368e-15
1957    2.392843e-15
1962    1.432149e-15
1967    5.668392e-18
1972   -4.251294e-16
1977    3.004248e-16
1982    1.118237e-15
1987   -2.030262e-15
1992    5.273559e-16
1997   -1.590277e-15
2002    4.691083e-16
2007    4.550351e-16
Name: lifeExp_z, dtype: float64
```

Filter

We can split the dataset by values of one variable, and filter out those splits that fail some criterion. The following code only keeps countries with a population of at least 10 million at some point during the study period

```
df.groupby('country').filter(lambda d: d['pop'].max() > 10000000)
```

```
         country continent  year  lifeExp       pop   gdpPercap  lifeExp_z
0    Afghanistan      Asia  1952   28.801   8425333  779.445314  -1.662719
1    Afghanistan      Asia  1957   30.332   9240934  820.853030  -1.737377
2    Afghanistan      Asia  1962   31.997  10267083  853.100710  -1.792867
3    Afghanistan      Asia  1967   34.020  11537966  836.197138  -1.854699
4    Afghanistan      Asia  1972   36.088  13079460  739.981106  -1.900878
...          ...       ...   ...      ...       ...         ...        ...
1699    Zimbabwe    Africa  1987   62.351   9216418  706.157306  -0.081910
1700    Zimbabwe    Africa  1992   60.377  10704340  693.420786  -0.338167
1701    Zimbabwe    Africa  1997   46.809  11404948  792.449960  -1.580537
1702    Zimbabwe    Africa  2002   39.989  11926563  672.038623  -2.100756
1703    Zimbabwe    Africa  2007   43.487  12311143  469.709298  -1.955077

[924 rows x 7 columns]
```