02_python_pandas

January 21, 2021

1 Pandas

1.1 Introduction

`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.

1.2 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 workflows.

[1]:
```
import numpy as np
import pandas as pd
```

1.3 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. The most common of these are listed below:

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

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

Note: You will need to have the data located in a file system that is exactly the same as mine for this to work. The `!ls`, which means list, line located bellow can be used to understand where you are located and navigate through your file system to get to where the directory called `data` is located.

[5]:
```
!ls
```

```
00_python_primer.Rmd                08_genomics_project.ipynb
00_python_primer.ipynb              08_genomics_project_filledin.ipynb
01_python_tools_ds.Rmd              LICENSE
01_python_tools_ds.ipynb            README.md
02_python_pandas.ipynb              data
03_python_vis.ipynb                 docs
04_python_stat.ipynb                graphs
05_practice_stats_filled.ipynb      homeworks
05_stats_python_practice.ipynb      live_coding
06_python_learning.ipynb            temporary.csv
07_python_appl.ipynb                workshop_documents
```

[6]:
```
pd.read_csv('data/mtcars.csv')
```

[6]:
```
                   make   mpg  cyl   disp   hp  drat     wt   qsec  vs  am  \
0             Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0   1
1         Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0   1
2            Datsun 710  22.8    4  108.0   93  3.85  2.320  18.61   1   1
3        Hornet 4 Drive  21.4    6  258.0  110  3.08  3.215  19.44   1   0
4     Hornet Sportabout  18.7    8  360.0  175  3.15  3.440  17.02   0   0
5               Valiant  18.1    6  225.0  105  2.76  3.460  20.22   1   0
6            Duster 360  14.3    8  360.0  245  3.21  3.570  15.84   0   0
7             Merc 240D  24.4    4  146.7   62  3.69  3.190  20.00   1   0
8              Merc 230  22.8    4  140.8   95  3.92  3.150  22.90   1   0
9              Merc 280  19.2    6  167.6  123  3.92  3.440  18.30   1   0
10            Merc 280C  17.8    6  167.6  123  3.92  3.440  18.90   1   0
11           Merc 450SE  16.4    8  275.8  180  3.07  4.070  17.40   0   0
12           Merc 450SL  17.3    8  275.8  180  3.07  3.730  17.60   0   0
13          Merc 450SLC  15.2    8  275.8  180  3.07  3.780  18.00   0   0
14   Cadillac Fleetwood  10.4    8  472.0  205  2.93  5.250  17.98   0   0
15  Lincoln Continental  10.4    8  460.0  215  3.00  5.424  17.82   0   0
16    Chrysler Imperial  14.7    8  440.0  230  3.23  5.345  17.42   0   0
17             Fiat 128  32.4    4   78.7   66  4.08  2.200  19.47   1   1
18          Honda Civic  30.4    4   75.7   52  4.93  1.615  18.52   1   1
19       Toyota Corolla  33.9    4   71.1   65  4.22  1.835  19.90   1   1
20        Toyota Corona  21.5    4  120.1   97  3.70  2.465  20.01   1   0
21     Dodge Challenger  15.5    8  318.0  150  2.76  3.520  16.87   0   0
22          AMC Javelin  15.2    8  304.0  150  3.15  3.435  17.30   0   0
23           Camaro Z28  13.3    8  350.0  245  3.73  3.840  15.41   0   0
```

```
24     Pontiac Firebird  19.2    8  400.0  175  3.08  3.845  17.05   0   0
25            Fiat X1-9  27.3    4   79.0   66  4.08  1.935  18.90   1   1
26        Porsche 914-2  26.0    4  120.3   91  4.43  2.140  16.70   0   1
27         Lotus Europa  30.4    4   95.1  113  3.77  1.513  16.90   1   1
28       Ford Pantera L  15.8    8  351.0  264  4.22  3.170  14.50   0   1
29         Ferrari Dino  19.7    6  145.0  175  3.62  2.770  15.50   0   1
30        Maserati Bora  15.0    8  301.0  335  3.54  3.570  14.60   0   1
31           Volvo 142E  21.4    4  121.0  109  4.11  2.780  18.60   1   1

    gear  carb
0      4     4
1      4     4
2      4     1
3      3     1
4      3     2
5      3     1
6      3     4
7      4     2
8      4     2
9      4     4
10     4     4
11     3     3
12     3     3
13     3     3
14     3     4
15     3     4
16     3     4
17     4     1
18     4     2
19     4     1
20     3     1
21     3     2
22     3     2
23     3     4
24     3     2
25     4     1
26     5     2
27     5     2
28     5     4
29     5     6
30     5     8
31     4     2
```

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

[7]:
```python
mtcars = pd.read_csv('data/mtcars.csv')
```

One of the big differences between a spreadsheet program and a programming language from the data science perspective is that you have to load data into the programming language. It's not "just there" like Excel. This is a good thing, since it allows the common functionality of the programming language to work across multiple data sets, and also keeps the original data set pristine. Excel users can run into problems and corrupt their data if they are not careful.

If we wanted to write this data set back out into an Excel file, say, we could do

[8]:
```
mtcars.to_excel('data/mtcars.xlsx')
```

You may get an error if you don't have the `openpyxl` package installed. You can easily install it from the Anaconda prompt using `conda install openpyxl` and following the prompts.

1.4 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

[9]:
```
mtcars.head(8)
```

[9]:
```
                make   mpg  cyl   disp   hp  drat     wt   qsec  vs  am  gear  \
0          Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0   1     4
1      Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0   1     4
2         Datsun 710  22.8    4  108.0   93  3.85  2.320  18.61   1   1     4
3     Hornet 4 Drive  21.4    6  258.0  110  3.08  3.215  19.44   1   0     3
4  Hornet Sportabout  18.7    8  360.0  175  3.15  3.440  17.02   0   0     3
5            Valiant  18.1    6  225.0  105  2.76  3.460  20.22   1   0     3
6         Duster 360  14.3    8  360.0  245  3.21  3.570  15.84   0   0     3
7          Merc 240D  24.4    4  146.7   62  3.69  3.190  20.00   1   0     4

   carb
0     4
1     4
2     1
3     1
4     2
5     1
6     4
7     2
```

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

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

[10]:
```
mtcars.dtypes
```

```
[10]: 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.

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

```
[11]: 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. Each row has an index value ranging from 0 to 11. 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.

[12]:
```
mtcars.shape
```

[12]:
```
(32, 12)
```

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

[13]:
```
mtcars.describe()
```

[13]:
```
             mpg        cyl        disp          hp       drat         wt  \
count  32.000000  32.000000   32.000000   32.000000  32.000000  32.000000
mean   20.090625   6.187500  230.721875  146.687500   3.596563   3.217250
std     6.026948   1.785922  123.938694   68.562868   0.534679   0.978457
min    10.400000   4.000000   71.100000   52.000000   2.760000   1.513000
25%    15.425000   4.000000  120.825000   96.500000   3.080000   2.581250
50%    19.200000   6.000000  196.300000  123.000000   3.695000   3.325000
75%    22.800000   8.000000  326.000000  180.000000   3.920000   3.610000
max    33.900000   8.000000  472.000000  335.000000   4.930000   5.424000

            qsec         vs         am       gear     carb
count  32.000000  32.000000  32.000000  32.000000  32.0000
mean   17.848750   0.437500   0.406250   3.687500   2.8125
std     1.786943   0.504016   0.498991   0.737804   1.6152
min    14.500000   0.000000   0.000000   3.000000   1.0000
25%    16.892500   0.000000   0.000000   3.000000   2.0000
50%    17.710000   0.000000   0.000000   4.000000   2.0000
75%    18.900000   1.000000   1.000000   4.000000   4.0000
max    22.900000   1.000000   1.000000   5.000000   8.0000
```

These are usually the first steps in exploring the data.

1.5 Data structures and types

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.

1.5.1 pandas.Series

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

[14]:
```
s = pd.Series([1,3,5,np.nan, 9, 13])
s
```

[14]:
```
0     1.0
1     3.0
2     5.0
3     NaN
4     9.0
5    13.0
```

```
dtype: float64
```

[15]:
```python
s2 = pd.Series(np.arange(1,20))
s2
```

[15]:
```
0      1
1      2
2      3
3      4
4      5
5      6
6      7
7      8
8      9
9     10
10    11
11    12
12    13
13    14
14    15
15    16
16    17
17    18
18    19
dtype: int64
```

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

[16]:
```python
s2[4]
```

[16]:
```
5
```

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

[17]:
```python
s3 = pd.Series(np.random.normal(0,1, (5,)), index = ['a','b','c','d','e'])
s3
```

[17]:
```
a    0.495129
b   -0.123514
c    0.779712
d   -1.216104
e    0.910280
dtype: float64
```

[18]:
```python
s3['d']
```

[18]:
```
-1.216103950445352
```

[19]:
```python
s3['a':'d']
```

[19]:
```
a    0.495129
b   -0.123514
c    0.779712
d   -1.216104
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

[20]:
```python
s3.to_numpy()
```

[20]:
```
array([ 0.49512917, -0.1235141 ,  0.77971247, -1.21610395,  0.91027988])
```

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.

Making the point about slicing again,

[21]:
```python
s3.to_numpy()[0:3]
```

[21]:
```
array([ 0.49512917, -0.1235141 ,  0.77971247])
```

This is different from index-based slicing done earlier.

1.5.2 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.

[22]:
```python
rng = np.random.RandomState(25)
d1 = pd.DataFrame(rng.normal(0,1, (4,5)))
d1
```

[22]:
```
          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.

[23]:
```
d2 = pd.DataFrame(rng.normal(0,1, (4, 5)),
                  columns = ['A','B','C','D','E'],
                  index = ['a','b','c','d'])
d2
```

[23]:
```
          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 below, make more sense.

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

[24]:
```
d2.columns
```

[24]:
```
Index(['A', 'B', 'C', 'D', 'E'], dtype='object')
```

[25]:
```
d2.columns = pd.Index(['V'+str(i) for i in range(1,6)]) # Index creates the␣
↪right objects for both column names and row names, which can be extracted␣
↪and changed with the `index` attribute
d2
```

[25]:
```
         V1        V2        V3        V4        V5
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
```

Exercise: Can you explain what I did in the list comprehension above? The key points are understanding `str` and how I constructed the `range`.

[26]:
```
d2.index = ['o1','o2','o3','o4']
d2
```

[26]:
```
          V1        V2        V3        V4        V5
o1  2.294842 -2.594487  2.822756  0.680889 -1.577693
o2 -1.976254  0.533340 -0.290870 -0.513520  1.982626
o3  0.226001 -1.839905  1.607671  0.388292  0.399732
o4  0.405477  0.217002 -0.633439  0.246622 -1.939546
```

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

[27]:
```
d1.to_numpy()
```

[27]:
```
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. There is some more detail about the `object` data type in the Python Tools for Data Science (notebook, PDF) document.

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

[28]:
```
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
```

[28]:
```
     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
```

[29]:
```
df.info()
```

```
<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(2), int64(1), object(1)
memory usage: 429.0+ bytes
```

We note that C is a date object, E is a category object, and F is a text/string object. pandas has excellent time series capabilities (having origins in FinTech), and the `TimeStamp` function creates datetime objects which can be queried and manipulated in Python. We'll describe category data in the next section.

You can also create a `DataFrame` where each column is composed of composite objects, like lists and dicts, as well. This might have limited value in some settings, but may be useful in others. In particular, this allows capabilities like the *list-column* construct in R tibbles. For example,

[30]:
```
pd.DataFrame({'list' :[[1,2],[3,4],[5,6]],
             'tuple' : [('a','b'), ('c','d'), ('e','f')],
              'set' : [{'A','B','C'}, {'D','E'}, {'F'}],
            'dicts' : [{'A': [1,2,3]}, {'B':[5,6,8]}, {'C': [3,9]}]})
```

[30]:
```
     list   tuple        set               dicts
0  [1, 2]  (a, b)  {A, C, B}  {'A': [1, 2, 3]}
1  [3, 4]  (c, d)     {E, D}  {'B': [5, 6, 8]}
2  [5, 6]  (e, f)        {F}     {'C': [3, 9]}
```

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

[31]:
```
df['E']
```

[31]:
```
0    yes
1     no
2     no
3    yes
4     no
Name: E, dtype: category
Categories (2, object): [no, yes]
```

[32]:
```
df['B']
```

[32]:
```
0    0.958092
1    0.883201
2    0.295432
3    0.512376
4    0.088702
Name: B, dtype: float64
```

There is also a shortcut for accessing single columns, using Python's dot (`.`) notation. Just note that this notation does not work for all column names. Columns which have spaces in the name or dashes (`-`) cannot be read with this method. For example `B-1` would not be possible like this.

[33]:
```
df.B
```

[33]:
```
0    0.958092
1    0.883201
2    0.295432
3    0.512376
4    0.088702
Name: B, dtype: float64
```

This 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.

Let's look at slicing a `DataFrame`

Extracting rows and columns There are two extractor functions in `pandas`:

- `loc` extracts by label (index label, column label, slice of labels, etc.
- `iloc` extracts by index (integers, slice objects, etc.

[34]:
```
df2 = pd.DataFrame(rng.randint(0,10, (5,4)),
                   index = ['a','b','c','d','e'],
                   columns = ['one','two','three','four'])
df2
```

[34]:

	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

First, let's see what naively slicing this `DataFrame` does.

[35]:
```
df2['one']
```

[35]:
```
a    5
b    9
c    8
d    5
e    6
Name: one, dtype: int64
```

Ok, that works. It grabs one column from the dataset. How about the dot notation?

[36]:
```
df2.one
```

[36]:
```
a    5
b    9
c    8
d    5
e    6
Name: one, dtype: int64
```

Let's see what this produces.

[37]:
```
type(df2.one)
```

[37]:
```
pandas.core.series.Series
```

So this is a series, so we can potentially do slicing of this series.

[38]:
```
df2.one['b']
```

[38]:
```
9
```

[39]:
```
df2.one['b':'d']
```

[39]:
```
b    9
c    8
d    5
Name: one, dtype: int64
```

[40]:
```
df2.one[:3]
```

[40]:
```
a    5
b    9
c    8
Name: one, dtype: int64
```

Ok, so we have all the `Series` slicing available. The problem here is in semantics, in that we are grabbing one column and then slicing the rows. That doesn't quite work with our sense that a `DataFrame` is a rectangle with rows and columns, and we tend to think of rows, then columns.

Let's see if we can do column slicing with this.

[41]:
```
df2[:'two']
```

[41]:
```
   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
```

That's not what we want, of course. It's giving back the entire data frame. We'll come back to this.

[42]:
```
df2[['one','three']]
```

[42]:

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

That works correctly though. We can give a list of column names. Ok.

How about row slices?

[43]:
```
#df2['a'] # Doesn't work
df2['a':'c']
```

[43]:

	one	two	three	four
a	5	3	2	8
b	9	3	0	5
c	8	4	3	3

Ok, that works. It slices rows, but includes the largest index, like a `Series` but unlike `numpy` arrays.

[44]:
```
df2[0:2]
```

[44]:

	one	two	three	four
a	5	3	2	8
b	9	3	0	5

Slices by location work too, but use the `numpy` slicing rules.

This entire extraction method becomes confusing. 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

[45]:
```
df2.loc[:,'one':'three']
```

[45]:

	one	two	three
a	5	3	2
b	9	3	0

```
c    8    4      3
d    5    2      7
e    6    7      8
```

[46]:
```
df2.loc['a':'d',:]
```

[46]:

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

[47]:
```
df2.loc['b', 'three']
```

[47]: 0

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

[48]:
```
df2.iloc[:,1:4]
```

[48]:

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

[49]:
```
df2.iloc[1:3,:]
```

[49]:

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

[50]:
```
df2.iloc[1:3, 1:4]
```

[50]:

	two	three	four
b	3	0	5
c	4	3	3

`iloc` slices like a matrix, but uses `numpy` slicing conventions (does **not** include highest index)

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.

[51]:
```
df2.iat[2,3]
```

[51]: 3

[52]:
```
df2.at['b','three']
```

[52]: 0

Boolean selection 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.

[53]:
```
df2[df2.one > 3]
```

[53]:

	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

[54]:
```
df2[(df2.one > 3) & (df2.three < 9)]
```

[54]:

	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

`query` (this section will not be covered in its entirety during the lecture) `DataFrame`'s have a `query` method allowing selection using a Python expression

[55]:
```
n = 10
df = pd.DataFrame(np.random.rand(n, 3), columns = list('abc'))
df
```

[55]:

	a	b	c
0	0.815508	0.028886	0.785901
1	0.300541	0.338317	0.641448
2	0.505391	0.112547	0.185908
3	0.400225	0.931705	0.094609
4	0.981477	0.008321	0.880875
5	0.876385	0.144667	0.768066
6	0.000640	0.269403	0.649907
7	0.250573	0.479758	0.654926
8	0.358420	0.624067	0.374675
9	0.686182	0.661075	0.398815

[56]:
```
df[(df.a < df.b) & (df.b < df.c)]
```

[56]:

	a	b	c
1	0.300541	0.338317	0.641448
6	0.000640	0.269403	0.649907
7	0.250573	0.479758	0.654926

We can equivalently write this query as

[57]:
```
df.query('(a < b) & (b < c)')
```

[57]:

	a	b	c
1	0.300541	0.338317	0.641448
6	0.000640	0.269403	0.649907
7	0.250573	0.479758	0.654926

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

[58]:
```
df2
```

[58]:

	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

[59]:
```
df2['one'] = [2,5,2,5,2]
df2
```

[59]:

	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

[60]:
```
df2.iat[2,3] = -9 # missing value
df2
```

[60]:

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

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

[61]:
```
df2.replace(0, -9) # replace 0 with -9
```

[61]:
```
   one  two  three  four
a    2    3      2     8
b    5    3     -9     5
c    2    4      3    -9
d    5    2      7     1
e    2    7      8     7
```

[62]:
```
df2.replace({2: 2.5, 8: 6.5}) # multiple replacements
```

[62]:
```
   one  two  three  four
a  2.5  3.0    2.5   6.5
b  5.0  3.0    0.0   5.0
c  2.5  4.0    3.0  -9.0
d  5.0  2.5    7.0   1.0
e  2.5  7.0    6.5   7.0
```

[63]:
```
df2.replace({'one': {5: 500}, 'three': {0: -9, 8: 800}})
# different replacements in different columns
```

[63]:
```
   one  two  three  four
a    2    3      2     8
b  500    3     -9     5
c    2    4      3    -9
d  500    2      7     1
e    2    7    800     7
```

See more examples in the documentation

1.5.3 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:

[64]:
```
s = pd.Series(['a','b','c'], dtype='category')
```

[65]:
```
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')
```

[65]:
```
0    NIH
1    NIH
2    NIH
3    NIH
4    NIH
Name: F, dtype: category
Categories (1, object): [NIH]
```

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

[66]:
```
df = pd.DataFrame({'A': list('abcd'), 'B': list('bdca')})
df_cat = df.astype('category')
df_cat.dtypes
```

[66]:
```
A    category
B    category
dtype: object
```

You can explore categorical data in a variety of ways

[67]:
```
df_cat['A'].describe()
```

[67]:
```
count     4
unique    4
top       d
freq      1
Name: A, dtype: object
```

[68]:
```
df['A'].value_counts()
```

[68]:
```
a    1
b    1
c    1
d    1
Name: A, dtype: int64
```

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

[69]:
```
df_cat['B'] = pd.Categorical(list('aabb'), categories = ['a','b','c','d'])
df_cat['B'].value_counts()
```

[69]:
```
b    2
a    2
d    0
```

```
c    0
Name: B, dtype: int64
```

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 both visualization as well as in regression modeling. 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".

[70]:
```
df_cat.A
```

[70]:
```
0    a
1    b
2    c
3    d
Name: A, dtype: category
Categories (4, object): [a, b, c, d]
```

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

[71]:
```
df_cat['A'] = df_cat.A.cat.reorder_categories(['d','c','b','a'])
df_cat.A
```

[71]:
```
0    a
1    b
2    c
3    d
Name: A, dtype: category
Categories (4, object): [d, c, b, a]
```

1.5.4 Missing data (will not be covered in its entirety)

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

[72]:
```
df = pd.DataFrame(np.random.randn(5, 3), index = ['a','c','e', 'f','g'],␣
↪columns = ['one','two','three']) # pre-specify index and column names
df['four'] = 20 # add a column named "four", which will all be 20
df['five'] = df['one'] > 0
df
```

[72]:
```
        one       two     three  four   five
a -0.461526  0.100114  1.203480    20  False
c  0.895374  0.411451 -0.090356    20   True
e  0.411101  1.047826 -1.688879    20   True
```

```
f  1.083412 -1.034765  0.002112    20   True
g  1.974888  0.255597 -0.949174    20   True
```

[73]:
```
df2 = df.reindex(['a','b','c','d','e','f','g'])
df2.style.applymap(lambda x: 'background-color:yellow', subset = pd.
 ↪IndexSlice[['b','d'],:])
```

[73]:
```
<pandas.io.formats.style.Styler at 0x7feba82e1310>
```

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.

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

[74]:
```
df2.isna()
```

[74]:
```
     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
```

[75]:
```
df2['one'].notna()
```

[75]:
```
a     True
b    False
c     True
d    False
e     True
f     True
g     True
Name: one, dtype: bool
```

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.

[76]:
```
df2.dropna(how='any')
```

[76]:
```
        one       two     three  four   five
a -0.461526  0.100114  1.203480  20.0  False
c  0.895374  0.411451 -0.090356  20.0   True
e  0.411101  1.047826 -1.688879  20.0   True
f  1.083412 -1.034765  0.002112  20.0   True
```

```
g  1.974888  0.255597 -0.949174  20.0   True
```

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

```
[77]: out1 = df2.fillna(value = 5)

      out1.style.applymap(lambda x: 'background-color:yellow', subset = pd.
       ↪IndexSlice[['b','d'],:])
```

```
[77]: <pandas.io.formats.style.Styler at 0x7feba8e3b290>
```

or a computed value like a column mean

```
[78]: df3 = df2.copy()
      df3 = df3.select_dtypes(exclude=[object])   # remove non-numeric columns
      out2 = df3.fillna(df3.mean())  # df3.mean() computes column-wise means

      out2.style.applymap(lambda x: 'background-color:yellow', subset = pd.
       ↪IndexSlice[['b','d'],:])
```

```
[78]: <pandas.io.formats.style.Styler at 0x7feba82dd110>
```

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.

```
[79]: out3 = df2.fillna(method = 'ffill') # Fill forward

      out3.style.applymap(lambda x: 'background-color:yellow', subset = pd.
       ↪IndexSlice[['b','d'],:])
```

```
[79]: <pandas.io.formats.style.Styler at 0x7feba9382390>
```

```
[80]: out4 = df2.fillna(method = 'bfill') # Fill backward

      out4.style.applymap(lambda x: 'background-color:yellow', subset = pd.
       ↪IndexSlice[['b','d'],:])
```

```
[80]: <pandas.io.formats.style.Styler at 0x7feba9398e10>
```

1.6 End live coding portion

The rest of this material is covered during the Asyncronous section, but the information is also here for your future use

1.7 Data transformation

1.7.1 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.

[81]:
```
A = pd.DataFrame(np.random.randn(4,5))
print(A)
```

```
          0         1         2         3         4
0  0.670003  0.252635  0.440303  1.015211  2.682897
1 -0.255074 -1.039442  0.586182 -0.160948 -1.552889
2 -0.609655  0.540724  1.277570 -0.583918 -0.260800
3  2.814046  0.303757  0.170083  0.090630  0.568430
```

[82]:
```
print(A + 6)
```

```
          0         1         2         3         4
0  6.670003  6.252635  6.440303  7.015211  8.682897
1  5.744926  4.960558  6.586182  5.839052  4.447111
2  5.390345  6.540724  7.277570  5.416082  5.739200
3  8.814046  6.303757  6.170083  6.090630  6.568430
```

[83]:
```
print(A * -10)
```

```
           0          1          2          3          4
0  -6.700033  -2.526347  -4.403026 -10.152107 -26.828973
1   2.550739  10.394422  -5.861815   1.609480  15.528886
2   6.096548  -5.407241 -12.775704   5.839178   2.608003
3 -28.140456  -3.037571  -1.700833  -0.906296  -5.684301
```

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

[84]:
```
B = pd.DataFrame(np.random.randn(4,5) + 4)
print(A + B)
```

```
          0         1         2         3         4
0  4.168630  3.687596  3.975981  5.392280  7.763671
1  3.658142  1.958768  5.279375  5.128594  0.011606
2  1.991331  5.950211  8.031543  2.998088  5.140077
3  7.058083  5.038382  2.142168  3.489493  5.321225
```

[85]:
```
print(A * B)
```

```
          0         1         2         3          4
0  2.344091  0.867790  1.556768  4.443648  13.631194
1 -0.998160 -3.116466  2.751063 -0.851341  -2.429485
```

```
2  -1.585703  2.925040  8.628675 -2.091597  -1.408551
3  11.942915  1.438176  0.335419  0.308038   2.701632
```

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`

[86]:
```
c = pd.Series([1,2,3,4,5])
print(A + c)
```

```
          0         1         2         3         4
0  1.670003  2.252635  3.440303  5.015211  7.682897
1  0.744926  0.960558  3.586182  3.839052  3.447111
2  0.390345  2.540724  4.277570  3.416082  4.739200
3  3.814046  2.303757  3.170083  4.090630  5.568430
```

[87]:
```
print(A * c)
```

```
          0         1         2         3          4
0  0.670003  0.505269  1.320908  4.060843  13.414487
1 -0.255074 -2.078884  1.758545 -0.643792  -7.764443
2 -0.609655  1.081448  3.832711 -2.335671  -1.304001
3  2.814046  0.607514  0.510250  0.362519   2.842150
```

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

[88]:
```
means = A.mean(axis=0)
stds = A.std(axis = 0)

(A - means)/stds
```

[88]:
```
          0         1         2         3         4
0  0.009870  0.333779 -0.377639  1.367184  1.306800
1 -0.591909 -1.476625 -0.068550 -0.371284 -1.075535
2 -0.822570  0.737437  1.396369 -0.996471 -0.348825
3  1.404608  0.405409 -0.950181  0.000571  0.117559
```

1.7.2 Concatenation of data sets

Let's create some example data sets

[89]:
```
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)]})
```

We can concatenate these `DataFrame` objects by row

[90]:
```
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.

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

[91]:
```
df1.append(df2).append(df3)
```

[91]:
```
     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
```

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

[92]:
```
new_row = pd.Series(['n1','n2','n3','n4'])
pd.concat([df1, new_row])
```

[92]:

	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. The solution is to make it a `DataFrame`.

[93]:
```
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
```

[94]:
```
pd.concat([df1, new_row])
```

[94]:

	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

or

[95]:
```
df1.append(new_row)
```

[95]:

	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

[96]:
```
pd.concat([df1,df2,df3], axis = 1)
```

[96]:

	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.

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

[97]:

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

[97]:

	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. Some of this can be avoided by only joining on common columns. This is done using the `join` option ir `concat`. The default value is 'outer', which is what you see. above

[98]:

```
pd.concat([df1, df3], join = 'inner')
```

[98]:

	A	D
0	a0	d0
1	a1	d1
2	a2	d2
3	a3	d3
0	a8	b8
1	a9	b9
2	a10	b10
3	a11	b11

You can do the same thing when joining by rows, using `axis = 0` and `join="inner"` to only join on rows with matching indices. Reminder that the indices are just labels and happen to be the row numbers by default.

1.7.3 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"

[99]:
```python
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')
```

[100]:
```python
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
```

[101]:
```python
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
```

[129]:
```python
print(survey)
```

```
    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
5     734   lake   sal     0.05
6     734     pb  temp   -21.50
7     735     pb   rad     7.22
8     735    NaN   sal     0.06
9     735    NaN  temp   -26.00
10    751     pb   rad     4.35
11    751     pb  temp   -18.50
12    751   lake   sal     0.10
13    752   lake   rad     2.19
14    752   lake   sal     0.09
15    752   lake  temp   -16.00
16    752    roe   sal    41.60
17    837   lake   rad     1.46
```

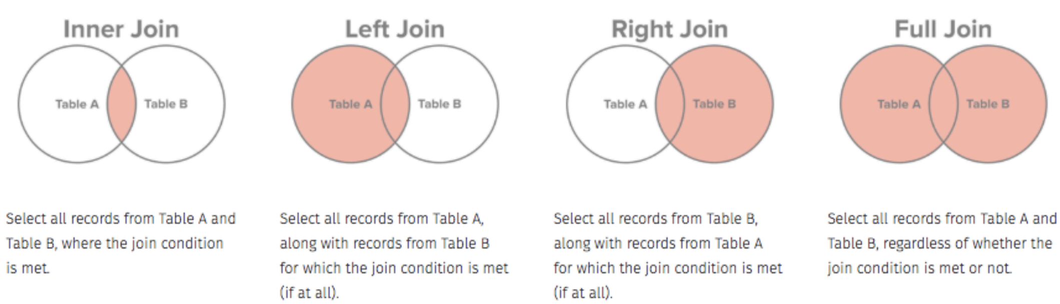
```
18    837   lake   sal    0.21
19    837    roe   sal   22.50
20    844    roe   rad   11.25
```

[102]:
```python
print(visited)
```

```
   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
5    752   DR-3         NaN
6    837  MSK-4  1932-01-14
7    844   DR-1  1932-03-22
```

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



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

We start with an left join

[103]:
```python
s2v_merge = survey.merge(visited, left_on = 'taken',right_on = 'ident', how =␣
↪'left')
```

[104]:
```python
print(s2v_merge)
```

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

```
5     734  lake   sal    0.05   734   DR-3  1939-01-07
6     734    pb  temp  -21.50   734   DR-3  1939-01-07
7     735    pb   rad    7.22   735   DR-3  1930-01-12
8     735   NaN   sal    0.06   735   DR-3  1930-01-12
9     735   NaN  temp  -26.00   735   DR-3  1930-01-12
10    751    pb   rad    4.35   751   DR-3  1930-02-26
11    751    pb  temp  -18.50   751   DR-3  1930-02-26
12    751  lake   sal    0.10   751   DR-3  1930-02-26
13    752  lake   rad    2.19   752   DR-3         NaN
14    752  lake   sal    0.09   752   DR-3         NaN
15    752  lake  temp  -16.00   752   DR-3         NaN
16    752   roe   sal   41.60   752   DR-3         NaN
17    837  lake   rad    1.46   837  MSK-4  1932-01-14
18    837  lake   sal    0.21   837  MSK-4  1932-01-14
19    837   roe   sal   22.50   837  MSK-4  1932-01-14
20    844   roe   rad   11.25   844   DR-1  1932-03-22
```

Here, the left dataset is `survey` and the right one is `visited`. Since we're doing a left join, we keed 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.

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

[105]:
```
s2v2loc_merge = s2v_merge.merge(site, how = 'left', left_on = 'site', right_on = 'name')
print(s2v2loc_merge)
```

```
    taken person quant  reading  ident   site       dated   name    lat  \
0     619   dyer   rad     9.82    619   DR-1  1927-02-08   DR-1 -49.85
1     619   dyer   sal     0.13    619   DR-1  1927-02-08   DR-1 -49.85
2     622   dyer   rad     7.80    622   DR-1  1927-02-10   DR-1 -49.85
3     622   dyer   sal     0.09    622   DR-1  1927-02-10   DR-1 -49.85
4     734     pb   rad     8.41    734   DR-3  1939-01-07   DR-3 -47.15
5     734   lake   sal     0.05    734   DR-3  1939-01-07   DR-3 -47.15
6     734     pb  temp   -21.50    734   DR-3  1939-01-07   DR-3 -47.15
7     735     pb   rad     7.22    735   DR-3  1930-01-12   DR-3 -47.15
8     735    NaN   sal     0.06    735   DR-3  1930-01-12   DR-3 -47.15
9     735    NaN  temp   -26.00    735   DR-3  1930-01-12   DR-3 -47.15
10    751     pb   rad     4.35    751   DR-3  1930-02-26   DR-3 -47.15
11    751     pb  temp   -18.50    751   DR-3  1930-02-26   DR-3 -47.15
12    751   lake   sal     0.10    751   DR-3  1930-02-26   DR-3 -47.15
13    752   lake   rad     2.19    752   DR-3         NaN   DR-3 -47.15
14    752   lake   sal     0.09    752   DR-3         NaN   DR-3 -47.15
15    752   lake  temp   -16.00    752   DR-3         NaN   DR-3 -47.15
16    752    roe   sal    41.60    752   DR-3         NaN   DR-3 -47.15
17    837   lake   rad     1.46    837  MSK-4  1932-01-14  MSK-4 -48.87
18    837   lake   sal     0.21    837  MSK-4  1932-01-14  MSK-4 -48.87
19    837    roe   sal    22.50    837  MSK-4  1932-01-14  MSK-4 -48.87
```

```
20    844    roe    rad    11.25    844   DR-1  1932-03-22   DR-1 -49.85

      long
0   -128.57
1   -128.57
2   -128.57
3   -128.57
4   -126.72
5   -126.72
6   -126.72
7   -126.72
8   -126.72
9   -126.72
10  -126.72
11  -126.72
12  -126.72
13  -126.72
14  -126.72
15  -126.72
16  -126.72
17  -123.40
18  -123.40
19  -123.40
20  -128.57
```

Lastly, we add the person information to this dataset.

[106]:
```
merged = s2v2loc_merge.merge(person, how = 'left', left_on = 'person', right_on␣
↪= 'ident')
print(merged.head())
```

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

     long ident_y personal   family
0 -128.57    dyer  William     Dyer
1 -128.57    dyer  William     Dyer
2 -128.57    dyer  William     Dyer
3 -128.57    dyer  William     Dyer
4 -126.72      pb    Frank  Pabodie
```

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

[107]:
```python
ps = person.merge(survey, left_on = 'ident', right_on = 'person')
vs = visited.merge(survey, left_on = 'ident', right_on = 'taken')
print(ps)
```

```
   ident   personal   family  taken person quant  reading
0   dyer    William     Dyer    619   dyer   rad     9.82
1   dyer    William     Dyer    619   dyer   sal     0.13
2   dyer    William     Dyer    622   dyer   rad     7.80
3   dyer    William     Dyer    622   dyer   sal     0.09
4     pb      Frank  Pabodie    734     pb   rad     8.41
5     pb      Frank  Pabodie    734     pb  temp   -21.50
6     pb      Frank  Pabodie    735     pb   rad     7.22
7     pb      Frank  Pabodie    751     pb   rad     4.35
8     pb      Frank  Pabodie    751     pb  temp   -18.50
9   lake   Anderson     Lake    734   lake   sal     0.05
10  lake   Anderson     Lake    751   lake   sal     0.10
11  lake   Anderson     Lake    752   lake   rad     2.19
12  lake   Anderson     Lake    752   lake   sal     0.09
13  lake   Anderson     Lake    752   lake  temp   -16.00
14  lake   Anderson     Lake    837   lake   rad     1.46
15  lake   Anderson     Lake    837   lake   sal     0.21
16   roe  Valentina  Roerich    752    roe   sal    41.60
17   roe  Valentina  Roerich    837    roe   sal    22.50
18   roe  Valentina  Roerich    844    roe   rad    11.25
```

[108]:
```python
print(vs)
```

```
    ident   site       dated  taken person quant  reading
0     619   DR-1  1927-02-08    619   dyer   rad     9.82
1     619   DR-1  1927-02-08    619   dyer   sal     0.13
2     622   DR-1  1927-02-10    622   dyer   rad     7.80
3     622   DR-1  1927-02-10    622   dyer   sal     0.09
4     734   DR-3  1939-01-07    734     pb   rad     8.41
5     734   DR-3  1939-01-07    734   lake   sal     0.05
6     734   DR-3  1939-01-07    734     pb  temp   -21.50
7     735   DR-3  1930-01-12    735     pb   rad     7.22
8     735   DR-3  1930-01-12    735    NaN   sal     0.06
9     735   DR-3  1930-01-12    735    NaN  temp   -26.00
10    751   DR-3  1930-02-26    751     pb   rad     4.35
11    751   DR-3  1930-02-26    751     pb  temp   -18.50
12    751   DR-3  1930-02-26    751   lake   sal     0.10
13    752   DR-3         NaN    752   lake   rad     2.19
14    752   DR-3         NaN    752   lake   sal     0.09
15    752   DR-3         NaN    752   lake  temp   -16.00
16    752   DR-3         NaN    752    roe   sal    41.60
17    837  MSK-4  1932-01-14    837   lake   rad     1.46
18    837  MSK-4  1932-01-14    837   lake   sal     0.21
19    837  MSK-4  1932-01-14    837    roe   sal    22.50
```

```
20    844   DR-1  1932-03-22    844     roe    rad     11.25
```

[109]:
```
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()
```

[109]:
```
  ident_x personal   family  taken_x person_x quant  reading  ident_y  site  \
0    dyer  William     Dyer      619     dyer   rad     9.82      619  DR-1
1    dyer  William     Dyer      619     dyer   sal     0.13      619  DR-1
2    dyer  William     Dyer      622     dyer   rad     7.80      622  DR-1
3    dyer  William     Dyer      622     dyer   sal     0.09      622  DR-1
4      pb    Frank  Pabodie      734       pb   rad     8.41      734  DR-3

        dated  taken_y person_y
0  1927-02-08      619     dyer
1  1927-02-08      619     dyer
2  1927-02-10      622     dyer
3  1927-02-10      622     dyer
4  1939-01-07      734       pb
```

Note that since there are common column names, the merge appends `_x` and `_y` to denote which column came from the left and right, respectively.

1.7.4 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.

[110]:
```
from glob import glob
filenames = sorted(glob('data/table*.csv')) # find files matching pattern. I␣
 ↪know there are 6 of them
table1, table2, table3, table4a, table4b, table5 = [pd.read_csv(f) for f in␣
 ↪filenames] # Use a list comprehension
```

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.

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

[111]:
```
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
```

[112]:
```
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
7        Brazil  2000  population   174504898
8         China  1999       cases      212258
9         China  1999  population  1272915272
10        China  2000       cases      213766
11        China  2000  population  1280428583
```

[113]:
```
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
```

[114]:
```
print(table4a) # cases
```

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

[115]:
```
print(table4b) # population
```

```
       country        1999        2000
```

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

[116]:
```python
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.

1.7.5 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.

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

[117]:
```python
pew = pd.read_csv('data/pew.csv')
print(pew.head())
```

```
             religion  <$10k  $10-20k  $20-30k  $30-40k  $40-50k  $50-75k  \
0            Agnostic     27       34       60       81       76      137
1             Atheist     12       27       37       52       35       70
2            Buddhist     27       21       30       34       33       58
3            Catholic    418      617      732      670      638     1116
4  Don’t know/refused     15       14       15       11       10       35

   $75-100k  $100-150k  >150k  Don't know/refused
0       122        109     84                  96
1        73         59     74                  76
2        62         39     53                  54
3       949        792    633                1489
4        21         17     18                 116
```

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.

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`)

[118]:
```python
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
```

1.7.6 Separating columns containing multiple variables

We will use an Ebola dataset to illustrate this principle

[119]:
```python
ebola = pd.read_csv('data/country_timeseries.csv')
print(ebola.head())
```

```
         Date  Day  Cases_Guinea  Cases_Liberia  Cases_SierraLeone  \
0    1/5/2015  289        2776.0            NaN            10030.0
1    1/4/2015  288        2775.0            NaN             9780.0
2    1/3/2015  287        2769.0         8166.0             9722.0
3    1/2/2015  286           NaN         8157.0                NaN
4  12/31/2014  284        2730.0         8115.0             9633.0

   Cases_Nigeria  Cases_Senegal  Cases_UnitedStates  Cases_Spain  Cases_Mali  \
0            NaN            NaN                 NaN          NaN         NaN
1            NaN            NaN                 NaN          NaN         NaN
2            NaN            NaN                 NaN          NaN         NaN
3            NaN            NaN                 NaN          NaN         NaN
4            NaN            NaN                 NaN          NaN         NaN

   Deaths_Guinea  Deaths_Liberia  Deaths_SierraLeone  Deaths_Nigeria  \
0         1786.0             NaN              2977.0             NaN
1         1781.0             NaN              2943.0             NaN
2         1767.0          3496.0              2915.0             NaN
3            NaN          3496.0                 NaN             NaN
4         1739.0          3471.0              2827.0             NaN

   Deaths_Senegal  Deaths_UnitedStates  Deaths_Spain  Deaths_Mali
0             NaN                  NaN           NaN          NaN
1             NaN                  NaN           NaN          NaN
2             NaN                  NaN           NaN          NaN
```

```
3               NaN                     NaN            NaN            NaN
4               NaN                     NaN            NaN            NaN
```

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.

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.

[120]:
```
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
```

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.

[121]:
```
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

[122]:
```
type(variable_split)
```

[122]:
```
pandas.core.frame.DataFrame
```

We can now concatenate this to the original data

[123]:
```
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 replace the old data with the new one in the same location

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
```

1.7.7 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.

[124]:
```
ebola_parsed.pivot_table(index = ['Date','Day', 'country'], columns = 'status',␣
↪values = 'value')
```

[124]:
```
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
…                             …       …
9/7/2014 169 Liberia       2081.0  1137.0
             Nigeria         21.0     8.0
             Senegal          3.0     0.0
             SierraLeone   1424.0   524.0
9/9/2014 171 Liberia       2407.0     NaN

[375 rows x 2 columns]
```

This creates something called `MultiIndex` in the `pandas` `DataFrame`. This is useful in some advanced cases, but here, we just want a normal `DataFrame` back. We can achieve that by using the `reset_index` function.

[125]:
```
ebola_parsed.pivot_table(index = ['Date','Day','country'], columns = 'status',␣
↪values = 'value').reset_index()
```

[125]:
```
status       Date  Day      country   Cases  Deaths
0        1/2/2015  286      Liberia  8157.0  3496.0
1        1/3/2015  287       Guinea  2769.0  1767.0
2        1/3/2015  287      Liberia  8166.0  3496.0
3        1/3/2015  287  SierraLeone  9722.0  2915.0
4        1/4/2015  288       Guinea  2775.0  1781.0
```

```
..         …   …          …      …      …
370      9/7/2014  169       Liberia  2081.0  1137.0
371      9/7/2014  169       Nigeria    21.0     8.0
372      9/7/2014  169       Senegal     3.0     0.0
373      9/7/2014  169   SierraLeone  1424.0   524.0
374      9/9/2014  171       Liberia  2407.0     NaN

[375 rows x 5 columns]
```

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`

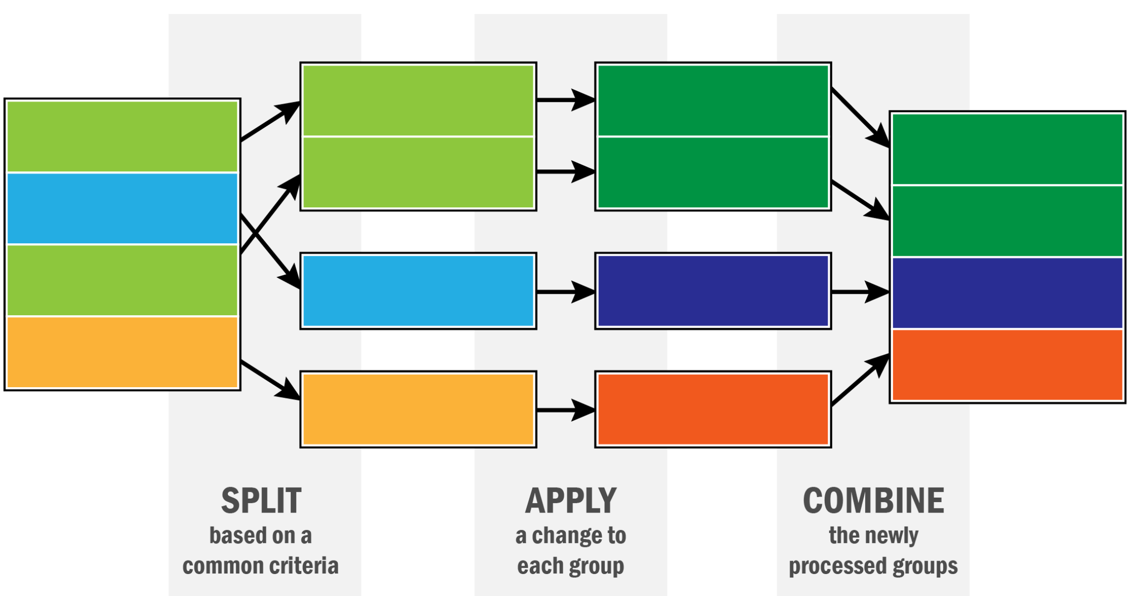
Exercise: Load the file `weather.csv` into Python and work on making it a tidy dataset. It requires melting and pivoting. The dataset comprises of the maximun and minimum temperatures recorded each day in 2010. There are lots of missing value. Ultimately we want columns for days of the month, maximum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

1.8 Data aggregation and split-apply-combine

We'll use the Gapminder dataset for this section

[126]:
```
df = pd.read_csv('data/gapminder.tsv', sep = '\t') # data is tab-separated, so␣
↪we use `\t` to specify that
```

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.



`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.

[127]:
```
df.head()
```

[127]:
```
       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
```

[128]:
```
f"This dataset has {len(df['country'].unique())} countries in it"
```

[128]:
```
'This dataset has 142 countries in it'
```

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.

[129]:
```
df.groupby('country')['lifeExp'].mean()
```

[129]:
```
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
```

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`.

[130]:
```
df.groupby('country')
```

[130]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7feba93dc590>
```

`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.

[131]:
```
df.groupby('country').ngroups
```

[131]:
```
142
```

[132]:
```
df.groupby('country').get_group('United Kingdom')
```

[132]:

```
              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
```

[133]:

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

[133]:

```
pandas.core.frame.DataFrame
```

[134]:

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

[134]:

```
73.92258333333332
```

[135]:

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

[135]:

```
73.92258333333332
```

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

[136]:

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

[136]:

```
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
           1992    69.568360
           1997    71.150480
           2002    72.422040
           2007    73.608120
Asia       1952    46.314394
           1957    49.318544
           1962    51.563223
           1967    54.663640
           1972    57.319269
           1977    59.610556
           1982    62.617939
           1987    64.851182
           1992    66.537212
           1997    68.020515
           2002    69.233879
           2007    70.728485
Europe     1952    64.408500
           1957    66.703067
           1962    68.539233
           1967    69.737600
           1972    70.775033
           1977    71.937767
           1982    72.806400
           1987    73.642167
           1992    74.440100
           1997    75.505167
           2002    76.700600
           2007    77.648600
Oceania    1952    69.255000
           1957    70.295000
           1962    71.085000
           1967    71.310000
           1972    71.910000
           1977    72.855000
           1982    74.290000
           1987    75.320000
           1992    76.945000
           1997    78.190000
           2002    79.740000
           2007    80.719500
Name: lifeExp, dtype: float64
```

[137]:
```
avg_lifeexp_continent_yr = df.groupby(['continent','year']).lifeExp.mean().
  ↪reset_index()
avg_lifeexp_continent_yr
```

[137]:

	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
21	Americas	1997	71.150480
22	Americas	2002	72.422040
23	Americas	2007	73.608120
24	Asia	1952	46.314394
25	Asia	1957	49.318544
26	Asia	1962	51.563223
27	Asia	1967	54.663640
28	Asia	1972	57.319269
29	Asia	1977	59.610556
30	Asia	1982	62.617939
31	Asia	1987	64.851182
32	Asia	1992	66.537212
33	Asia	1997	68.020515
34	Asia	2002	69.233879
35	Asia	2007	70.728485
36	Europe	1952	64.408500
37	Europe	1957	66.703067
38	Europe	1962	68.539233
39	Europe	1967	69.737600
40	Europe	1972	70.775033
41	Europe	1977	71.937767

```
42     Europe  1982  72.806400
43     Europe  1987  73.642167
44     Europe  1992  74.440100
45     Europe  1997  75.505167
46     Europe  2002  76.700600
47     Europe  2007  77.648600
48    Oceania  1952  69.255000
49    Oceania  1957  70.295000
50    Oceania  1962  71.085000
51    Oceania  1967  71.310000
52    Oceania  1972  71.910000
53    Oceania  1977  72.855000
54    Oceania  1982  74.290000
55    Oceania  1987  75.320000
56    Oceania  1992  76.945000
57    Oceania  1997  78.190000
58    Oceania  2002  79.740000
59    Oceania  2007  80.719500
```

[138]:
```
type(avg_lifeexp_continent_yr)
```

[138]:
```
pandas.core.frame.DataFrame
```

The aggregation function, in this case `mean`, does both the "apply" and "combine" parts of the process.

We can do quick aggregations with `pandas`

[139]:
```
df.groupby('continent').lifeExp.describe()
```

[139]:
```
           count       mean        std     min       25%      50%       75%  \
continent
Africa     624.0  48.865330   9.150210  23.599  42.37250  47.7920  54.41150
Americas   300.0  64.658737   9.345088  37.579  58.41000  67.0480  71.69950
Asia       396.0  60.064903  11.864532  28.801  51.42625  61.7915  69.50525
Europe     360.0  71.903686   5.433178  43.585  69.57000  72.2410  75.45050
Oceania     24.0  74.326208   3.795611  69.120  71.20500  73.6650  77.55250

              max
continent
Africa     76.442
Americas   80.653
Asia       82.603
Europe     81.757
Oceania    81.235
```

[140]:
```
df.groupby('continent').nth(10) # Tenth observation in each group
```

[140]:
```
                  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
```

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

[141]:
```
df.groupby('continent').lifeExp.agg(np.mean)
```

[141]:
```
continent
Africa      48.865330
Americas    64.658737
Asia        60.064903
Europe      71.903686
Oceania     74.326208
Name: lifeExp, dtype: float64
```

[142]:
```
def my_mean(values):
    n = len(values)
    sum = 0
    for value in values:
        sum += value
    return(sum/n)

df.groupby('continent').lifeExp.agg(my_mean)
```

[142]:
```
continent
Africa      48.865330
Americas    64.658737
Asia        60.064903
Europe      71.903686
Oceania     74.326208
Name: lifeExp, dtype: float64
```

You can do many functions at once

[143]:
```
df.groupby('year').lifeExp.agg([np.count_nonzero, np.mean, np.std])
```

[143]:
```
      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
```

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

[144]:
```
df.groupby('year').agg({'lifeExp': np.mean,'pop': np.median,'gdpPercap': np.
 ↪median}).reset_index()
```

[144]:
```
    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  2678.334741
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  6124.371109
```

Transformation You can do grouped transformations using this same method. We will compute the z-score for each year, i.e. we will substract the average life expectancy and divide by the standard deviation

[145]:
```
def my_zscore(values):
    m = np.mean(values)
    s = np.std(values)
    return((values - m)/s)
```

[146]:
```
df.groupby('year').lifeExp.transform(my_zscore)
```

[146]:
```
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
Name: lifeExp, Length: 1704, dtype: float64
```

[147]:
```
df['lifeExp_z'] = df.groupby('year').lifeExp.transform(my_zscore)
```

[148]:
```
df.groupby('year').lifeExp_z.mean()
```

[148]:
```
year
1952   -1.103089e-15
1957    1.802842e-15
1962    1.464400e-15
1967   -1.935072e-17
1972   -1.057448e-15
1977    2.447182e-16
1982    1.122928e-15
1987   -2.045899e-15
1992    5.773942e-16
1997   -1.590277e-15
2002    5.254013e-16
2007    5.035096e-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

[149]:
```
df.groupby('country').filter(lambda d: d['pop'].max() > 10000000)
```

[149]:

	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]