Chapter_1_Introduction

April 2, 2024

[2]:
```
print?
```

A string is actually a type of sequence: this is a generic term for an ordered sequence list. The three most important types of sequences are lists, tuples, and strings

A package is a collection of modules that numpy package are not necessarily included in the base Python distribution.

[3]:
```
import numpy as np
x = np.array([[1, 2], [3, 4]])
x
```

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

The object x has several attributes, or associated objects. To access an attribute attribute of x, we type x.attribute, where we replace attribute with the name of the attribute. For instance, we can access the ndim attribute of x ndim as follows

[4]:
```
x.ndim
```

[4]:
```
2
```

[5]:
```
x.dtype
```

[5]:
```
dtype('int32')
```

While it is also possible to create matrices using np.matrix(), we will use np.array() throughout the labs in this book

[6]:
```
np.array([[1, 2], [3.0, 4]]).dtype
```

[6]:
```
dtype('float64')
```

[7]:
```
np.array?
```

[8]:
```
np.array([[1, 2], [3, 4]], float).dtype
```

[8]:
```
dtype('float64')
```

[9]:
```
x.shape
```

[9]:
```
(2, 2)
```

A method is a function that is associated with an object. For instance, method given an array x, the expression x.sum() sums all of its elements, using the sum() method for arrays. The call x.sum() automatically provides x as the .sum() frst argument to its sum() method.

[10]:
```
x = np.array([1, 2, 3, 4])
x.sum()
```

[10]:
```
10
```

[11]:
```
x = np.array([1, 2, 3, 4])
np.sum(x)
```

[11]:
```
10
```

As another example, the reshape() method returns a new array with the .reshape() same elements as x, but a diferent shape. We do this by passing in a tuple in our call to reshape(), in this case (2, 3). This tuple specifes that we would like to create a two-dimensional array with 2 rows and 3 columns

[12]:
```
x = np.array([1, 2, 3, 4, 5, 6])
print('beginning x:\n', x)
x_reshape = x.reshape((2, 3))
print('reshaped x:\n', x_reshape)
```

```
beginning x:
 [1 2 3 4 5 6]
reshaped x:
 [[1 2 3]
 [4 5 6]]
```

The previous output reveals that numpy arrays are specifed as a sequence of rows. This is called row-major ordering, as opposed to column-major ordering.

Python (and hence numpy) uses 0-based indexing. This means that to access the top left element of x_reshape, we type in x_reshape[0,0].

[13]:
```
x_reshape[0, 0]
```

[13]:
```
1
```

Similarly, x_reshape[1,2] yields the element in the second row and the third column of x_reshape.

[14]:
```
x_reshape[1, 2]
```

[14]:
```
6
```

[15]:
```
x[2]
```

[15]: 3

Now, let's modify the top left element of x_reshape. To our surprise, we discover that the frst element of x has been modifed as well!

[16]:
```
print('x before we modify x_reshape:\n', x)
print('x_reshape before we modify x_reshape:\n', x_reshape)
x_reshape[0, 0] = 5
print('x_reshape after we modify its top left element:\n',
x_reshape)
print('x after we modify top left element of x_reshape:\n', x)
```

```
x before we modify x_reshape:
 [1 2 3 4 5 6]
x_reshape before we modify x_reshape:
 [[1 2 3]
 [4 5 6]]
x_reshape after we modify its top left element:
 [[5 2 3]
 [4 5 6]]
x after we modify top left element of x_reshape:
 [5 2 3 4 5 6]
```

Modifying x_reshape also modifed x because the two objects occupy the same space in memory.

We now briefy mention some attributes of arrays that will come in handy. An array's shape attribute contains its dimension; this is always a tuple. The ndim attribute yields the number of dimensions, and T provides its transpose

[17]:
```
x_reshape.shape, x_reshape.ndim, x_reshape.T
```

[17]:
```
((2, 3),
 2,
 array([[5, 4],
        [2, 5],
        [3, 6]]))
```

We will often want to apply functions to arrays. For instance, we can compute the square root of the entries using the np.sqrt() function:

[18]:
```
np.sqrt(x)
```

[18]:
```
array([2.23606798, 1.41421356, 1.73205081, 2.        , 2.23606798,
       2.44948974])
```

[19]:
```
x**2
```

[19]:
```
array([25,  4,  9, 16, 25, 36])
```

The np.random.normal() function generates a vector of random normal variables. np.random. We can learn more about this function by looking at the help page, via a call normal() to np.random.normal?. The frst line of the help page reads normal(loc=0.0, scale=1.0, size=None). This signature line tells us that the function's ar- signature arguments are loc, scale, and size. These are keyword arguments, which keyword means that when they are passed into the function, they can be referred to by name (in any order).3 By default, this function will generate random normal variable(s) with mean (loc) 0 and standard deviation (scale) 1; furthermore, a single random variable will be generated unless the argument to size is changed. We now generate 50 independent random variables from a N(0, 1) distribution.

[20]:
```
x = np.random.normal(size=50)
x
```

[20]:
```
array([-0.62264   ,  0.54217042,  0.63082209, -1.21356244,  0.16755297,
       -0.08965368, -0.9578536 ,  0.56445544,  0.24335614, -0.12957577,
       -0.89732196, -0.28537959, -0.73370082,  2.18104527,  0.9560208 ,
       -0.65983881, -0.31004284,  1.20654063,  0.08146026, -0.33307018,
        2.07304985, -1.12650102, -0.43777087, -0.43950841, -0.44471984,
        0.68201395, -0.4526087 ,  0.05948541,  0.50430984, -0.77282011,
        0.69658225, -0.56909323,  0.02652412,  1.03021127,  0.42711163,
        0.12809508, -1.99835941, -1.40588098,  0.37389455,  0.36389951,
        0.34246731, -1.28801594, -1.06040585, -0.20500475,  0.52731695,
        0.49374442, -0.24007398,  0.63201259,  0.61218675, -0.91679842])
```

[21]:
```
y = x + np.random.normal(loc=50, scale=1, size=50)
```

The np.corrcoef() function computes the correlation matrix between x and y. The of-diagonal elements give the correlation between x and y.

[23]:
```
np.corrcoef(x, y)
```

[23]:
```
array([[1.        , 0.48201619],
       [0.48201619, 1.        ]])
```

If you're following along in your own Jupyter notebook, then you probably noticed that you got a diferent set of results when you ran the past few commands. In particular, each time we call np.random.normal(), we will get a diferent answer, as shown in the following example

[24]:
```
print(np.random.normal(scale=5, size=2))
print(np.random.normal(scale=5, size=2))
```

```
[-0.74746642  1.97596639]
[-8.18650997 -1.13252245]
```

In order to ensure that our code provides exactly the same results each time it is run, we can set a random seed using the np.random.default_rng() random seed function. This function takes an arbitrary, user-specifed integer argument. If we set a random seed before generating random data, then re-running our code will yield the same results. The object rng has essentially all the random number generating methods found in np.random. Hence, to generate normal data we use rng.normal().

[25]:
```python
rng = np.random.default_rng(1303)
print(rng.normal(scale=5, size=2))
rng2 = np.random.default_rng(1303)
print(rng2.normal(scale=5, size=2))
```

```
[ 4.09482632 -1.07485605]
[ 4.09482632 -1.07485605]
```

The np.mean(), np.var(), and np.std() functions can be used to compute the mean, variance, and standard deviation of arrays. These functions are also available as methods on the arrays.

[26]:
```python
rng = np.random.default_rng(3)
y = rng.standard_normal(10)
np.mean(y), y.mean()
```

[26]:
```
(-0.1126795190952861, -0.1126795190952861)
```

[27]:
```python
np.var(y), y.var(), np.mean((y - y.mean())**2)
```

[27]:
```
(2.7243406406465125, 2.7243406406465125, 2.7243406406465125)
```

Notice that by default np.var() divides by the sample size n rather than n − 1; see the ddof argument in np.var?.

[28]:
```python
np.sqrt(np.var(y)), np.std(y)
```

[28]:
```
(1.6505576756498128, 1.6505576756498128)
```

The np.mean(), np.var(), and np.std() functions can also be applied to the rows and columns of a matrix. To see this, we construct a 10×3 matrix of $N(0, 1)$ random variables, and consider computing its row sums.

[29]:
```python
X = rng.standard_normal((10, 3))
X
```

[29]:
```
array([[ 0.22578661, -0.35263079, -0.28128742],
       [-0.66804635, -1.05515055, -0.39080098],
       [ 0.48194539, -0.23855361,  0.9577587 ],
       [-0.19980213,  0.02425957,  1.54582085],
       [ 0.54510552, -0.50522874, -0.18283897],
       [ 0.54052513,  1.93508803, -0.26962033],
       [-0.24355868,  1.0023136 , -0.88645994],
       [-0.29172023,  0.88253897,  0.58035002],
       [ 0.0915167 ,  0.67010435, -2.82816231],
       [ 1.02130682, -0.95964476, -1.66861984]])
```

Since arrays are row-major ordered, the frst axis, i.e. axis=0, refers to its rows. We pass this argument into the mean() method for the object X.

[30]:
```python
X.mean(axis=0)
```

[30]: array([0.15030588, 0.14030961, -0.34238602])

[31]:
```
X.mean(0)
```

[31]: array([0.15030588, 0.14030961, -0.34238602])

0.1 2.3.4 Graphics

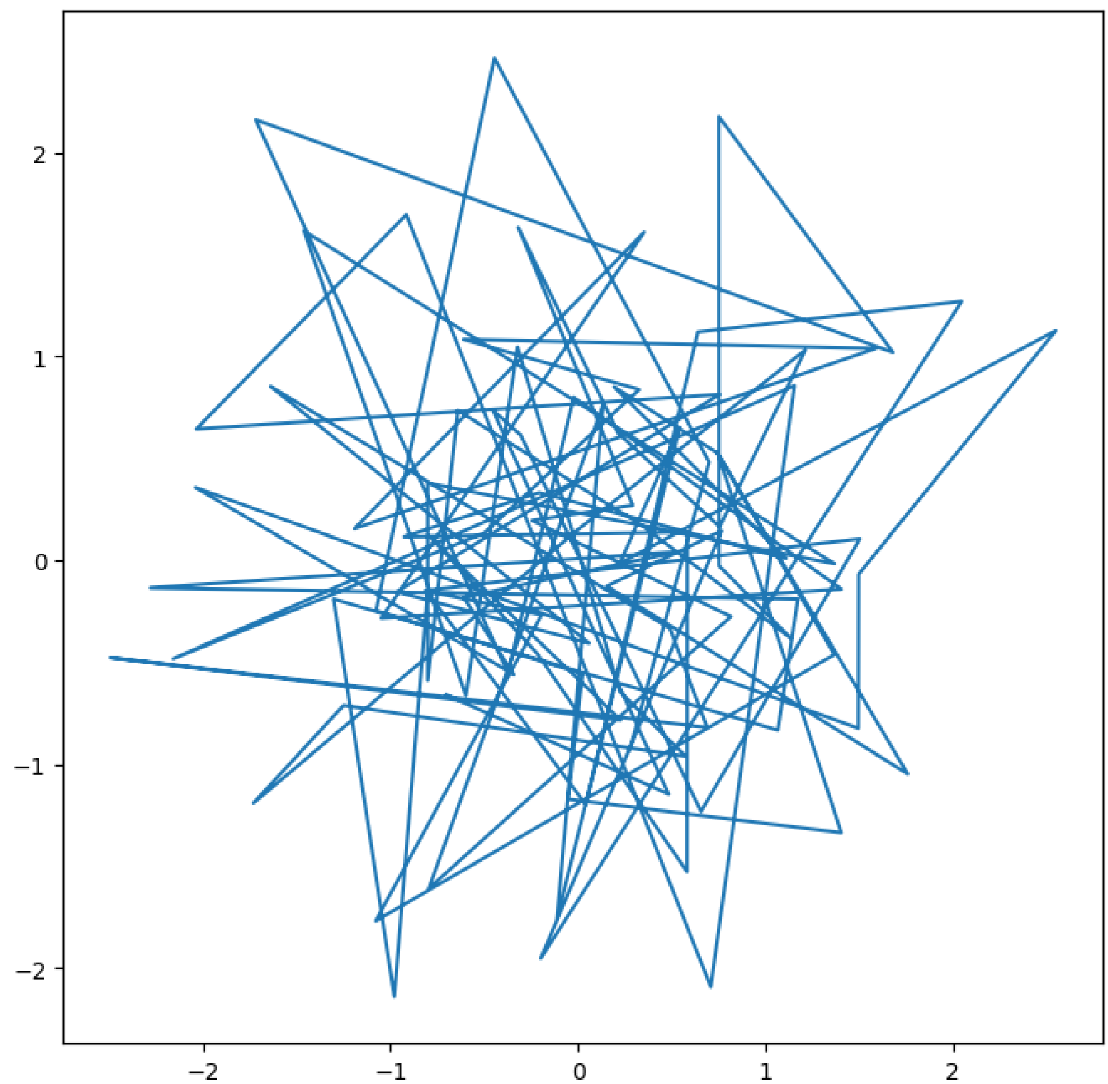
In Python, common practice is to use the library matplotlib for graphics. matplotlib However, since Python was not written with data analysis in mind, the notion of plotting is not intrinsic to the language. We will use the subplots() function from matplotlib.pyplot to create a fgure and the axes onto which we plot our data.

In matplotlib, a plot consists of a fgure and one or more axes. You can fgure axes think of the fgure as the blank canvas upon which one or more plots will be displayed: it is the entire plotting window. The axes contain important information about each plot, such as its x- and y-axis labels, title, and more. (Note that in matplotlib, the word axes is not the plural of axis: a plot's axes contains much more information than just the x-axis and the y-axis.)

We begin by importing the subplots() function from matplotlib. We subplots() use this function throughout when creating fgures. The function returns a tuple of length two: a fgure object as well as the relevant axes object. We will typically pass figsize as a keyword argument. Having created our axes, we attempt our frst plot using its plot() method. To learn more .plot() about it, type ax.plot?

[32]:
```
from matplotlib.pyplot import subplots
fig, ax = subplots(figsize=(8, 8))
x = rng.standard_normal(100)
y = rng.standard_normal(100)
ax.plot(x, y)
```

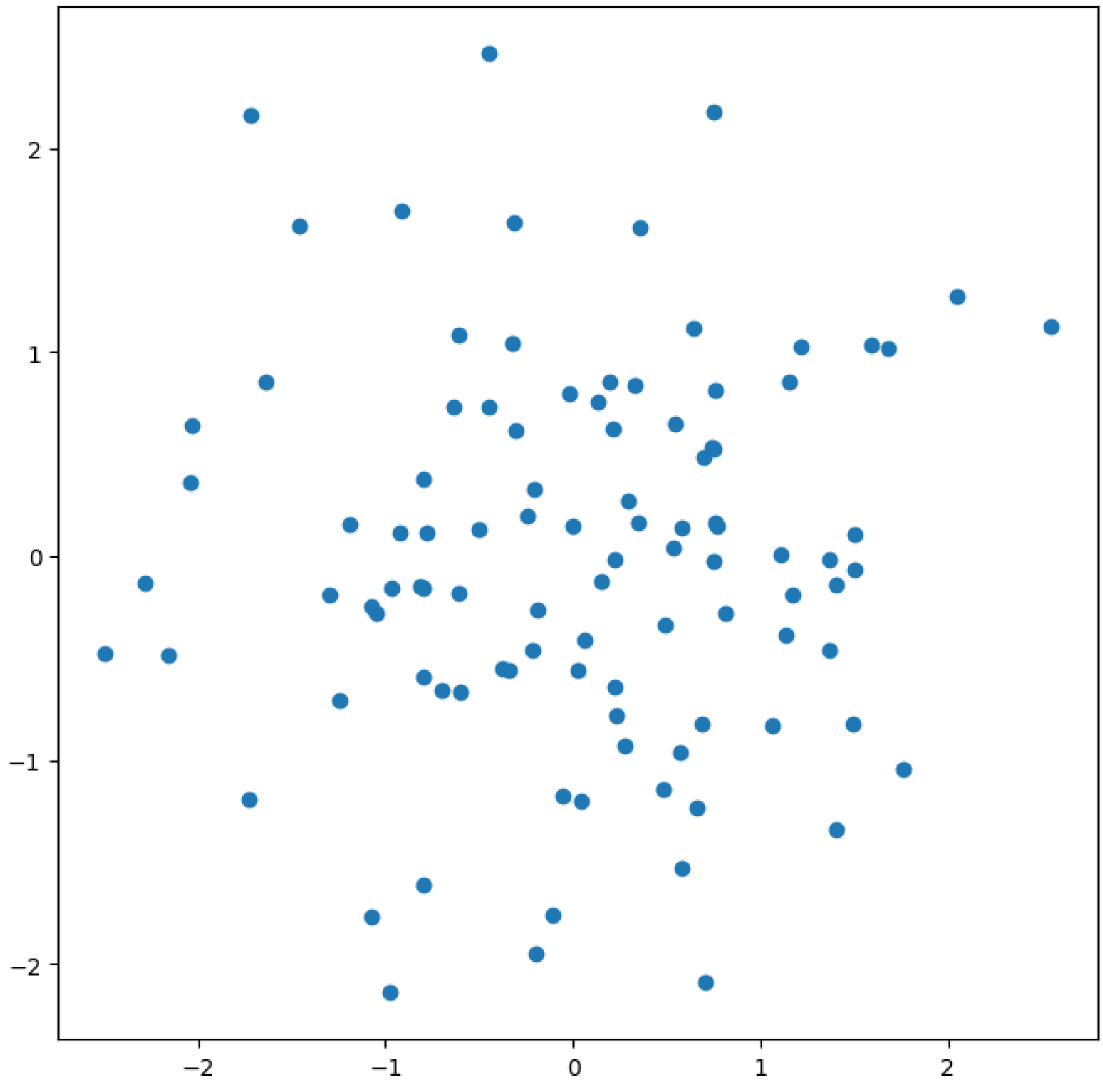
[32]: [<matplotlib.lines.Line2D at 0x173237dae80>]



We see that our earlier cell produced a line plot, which is the default. To create a scatterplot, we provide an additional argument to ax.plot(), indicating that circles should be displayed.

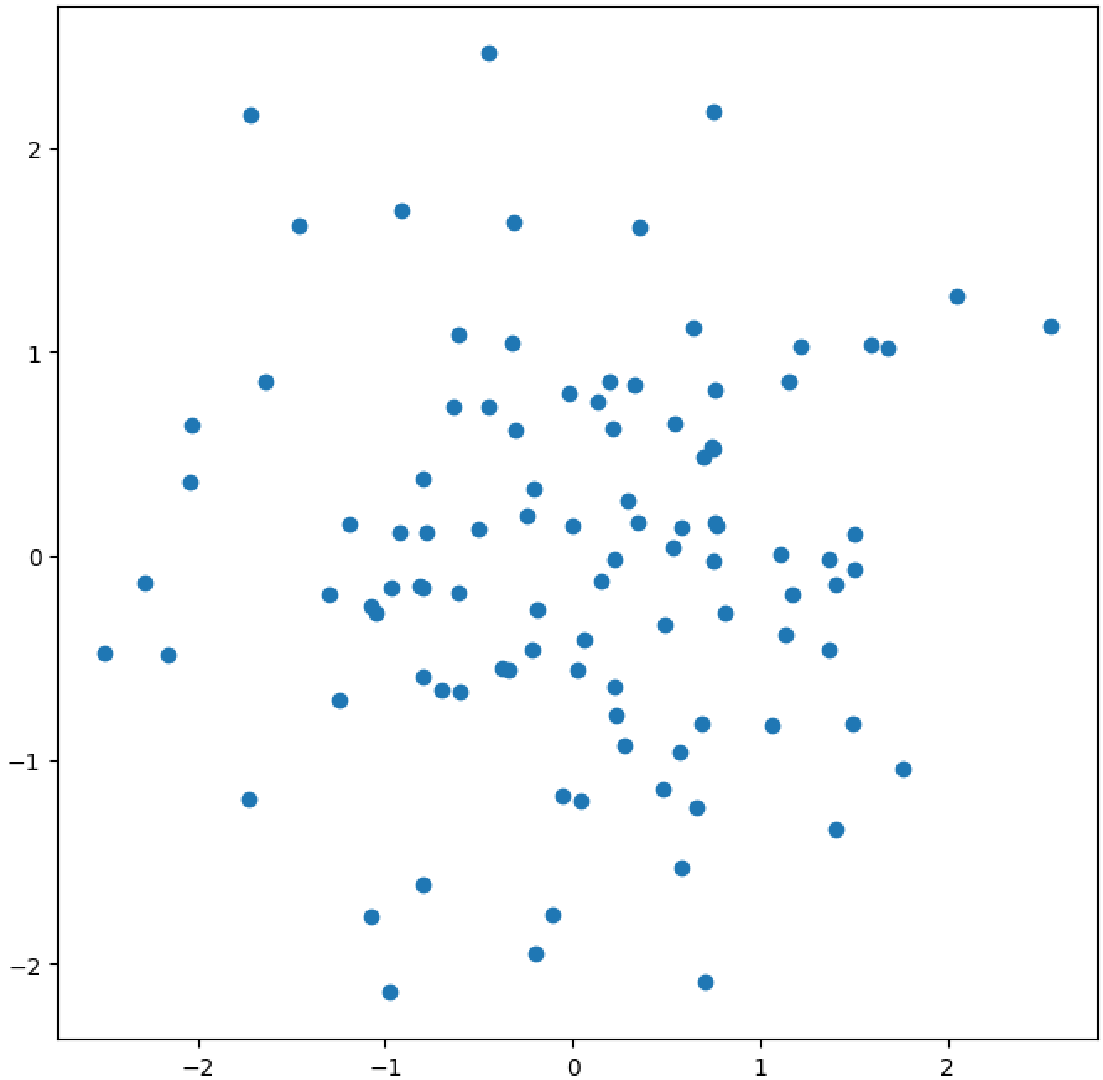
[33]:
```
fig, ax = subplots(figsize=(8, 8))
ax.plot(x, y, 'o')
```

[33]:
```
[<matplotlib.lines.Line2D at 0x173238165e0>]
```



As an alternative, we could use the ax.scatter() function to create a .scatter() scatterplot.

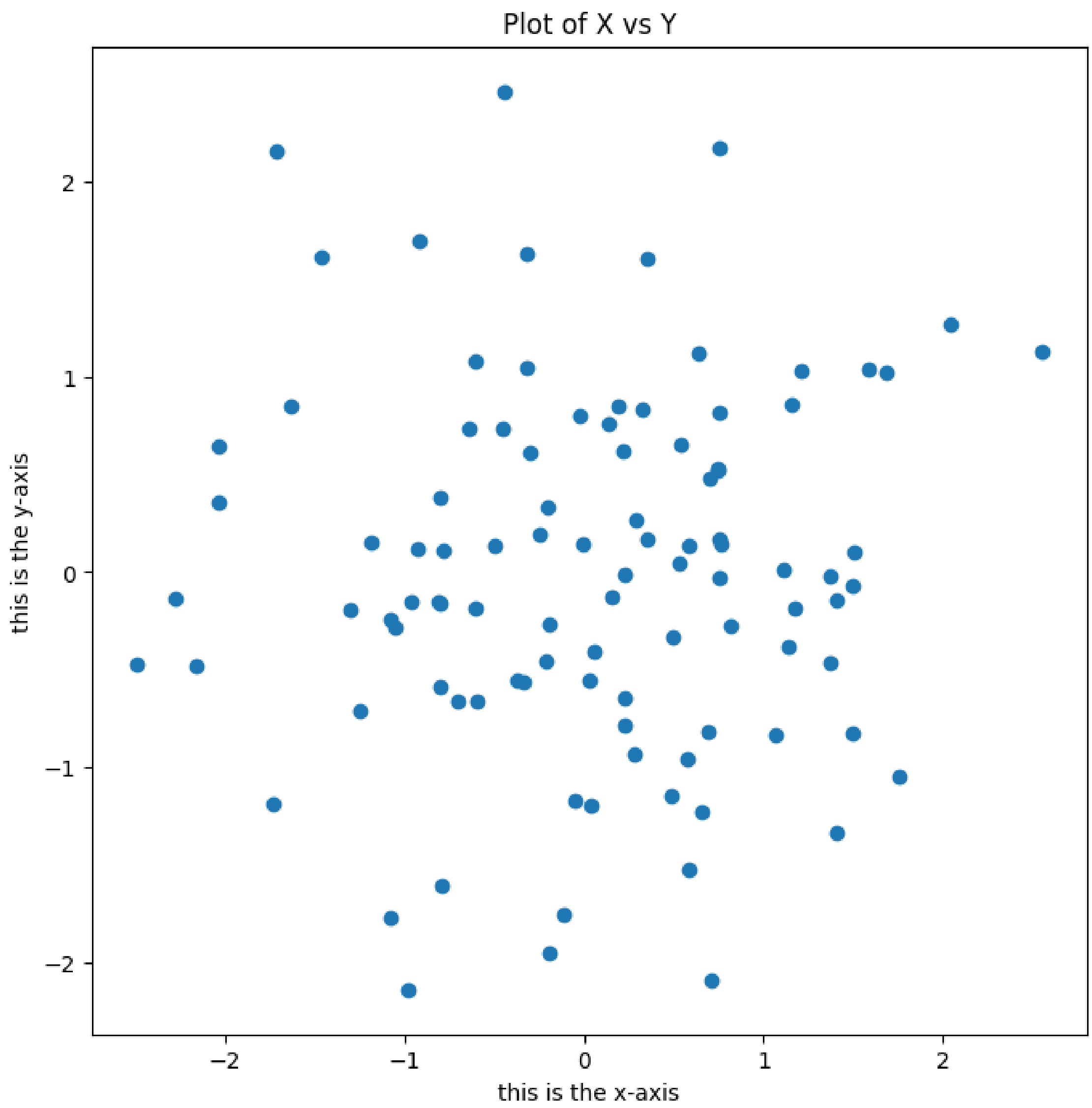
[34]:
```
fig, ax = subplots(figsize=(8, 8))
ax.scatter(x, y, marker='o');
```



Notice that in the code blocks above, we have ended the last line with a semicolon. This prevents ax.plot(x, y) from printing text to the notebook. However, it does not prevent a plot from being produced. If we omit the trailing semi-colon, then we obtain the following output:

To label our plot, we make use of the set_xlabel(), set_ylabel(), and .set_xlabel() methods of ax

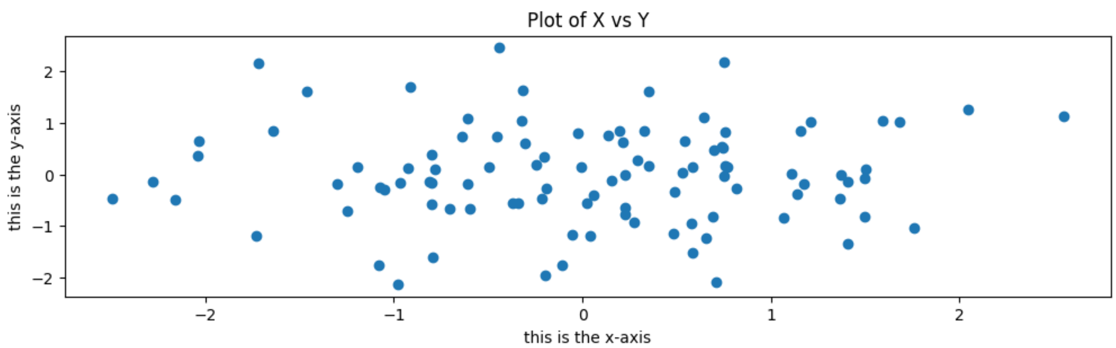
[36]:
```
fig, ax = subplots(figsize=(8, 8))
ax.scatter(x, y, marker='o')
ax.set_xlabel("this is the x-axis")
ax.set_ylabel("this is the y-axis")
ax.set_title("Plot of X vs Y");
```



Having access to the fgure object fig itself means that we can go in and change some aspects and then redisplay it. Here, we change the size from (8, 8) to (12, 3).

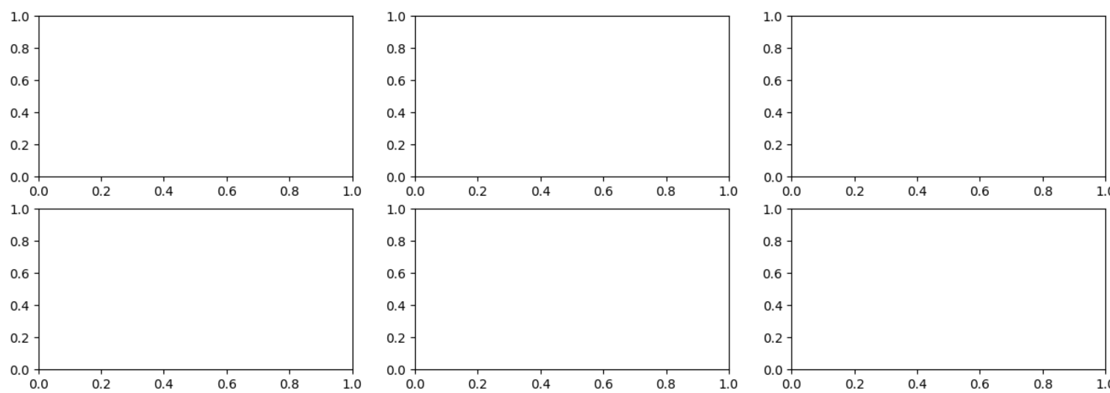
[37]:
```
fig.set_size_inches(12,3)
fig
```

[37]:



Occasionally we will want to create several plots within a fgure. This can be achieved by passing additional arguments to subplots(). Below, we create a 2 × 3 grid of plots in a fgure of size determined by the figsize argument. In such situations, there is often a relationship between the axes in the plots. For example, all plots may have a common x-axis. The subplots() function can automatically handle this situation when passed the keyword argument sharex=True. The axes object below is an array pointing to diferent plots in the fgure.

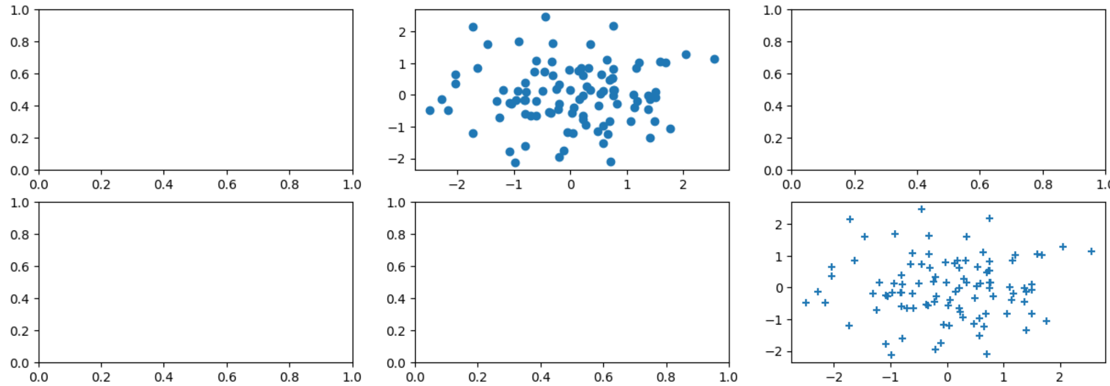
[38]:
```
fig, axes = subplots(nrows=2,
ncols=3,
figsize=(15, 5))
```



We now produce a scatter plot with 'o' in the second column of the frst row and a scatter plot with '+' in the third column of the second row.

[39]:
```
axes[0,1].plot(x, y, 'o')
axes[1,2].scatter(x, y, marker='+')
fig
```

[39]:

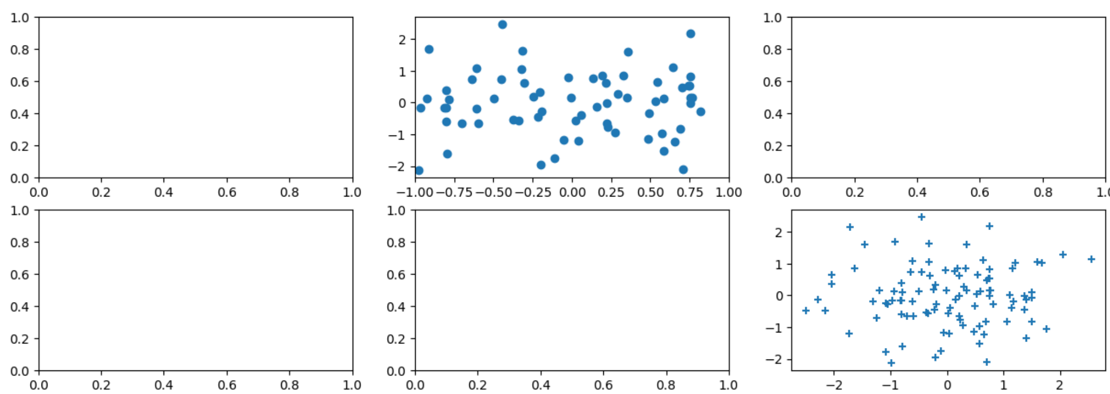


Type subplots? to learn more about subplots(). To save the output of fig, we call its savefig() method. The argument dpi is the dots per inch, used to determine how large the fgure will be in pixels.

[40]:
```
fig.savefig("Figure.png", dpi=400)
fig.savefig("Figure.pdf", dpi=200);
```

[41]:
```
axes[0,1].set_xlim([-1,1])
fig.savefig("Figure_updated.jpg")
fig
```

[41]:

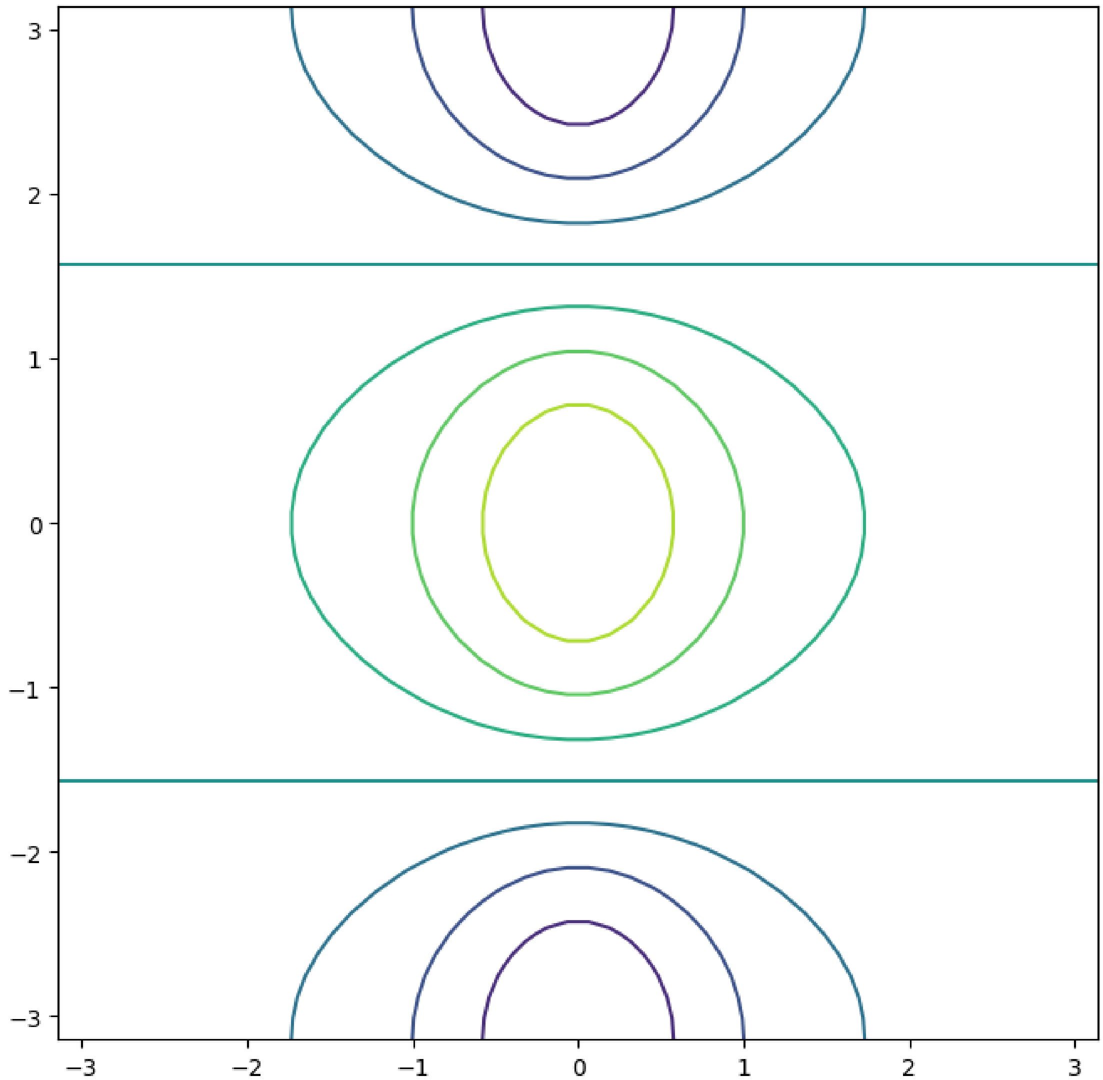


We now create some more sophisticated plots. The ax.contour() method produces a contour plot in order to represent three-dimensional data, similar contour plot to a topographical map. It takes three arguments:

- A vector of x values (the frst dimension),
- A vector of y values (the second dimension), and
- A matrix whose elements correspond to the z value (the third dimension) for each pair of (x,y) coordinates.

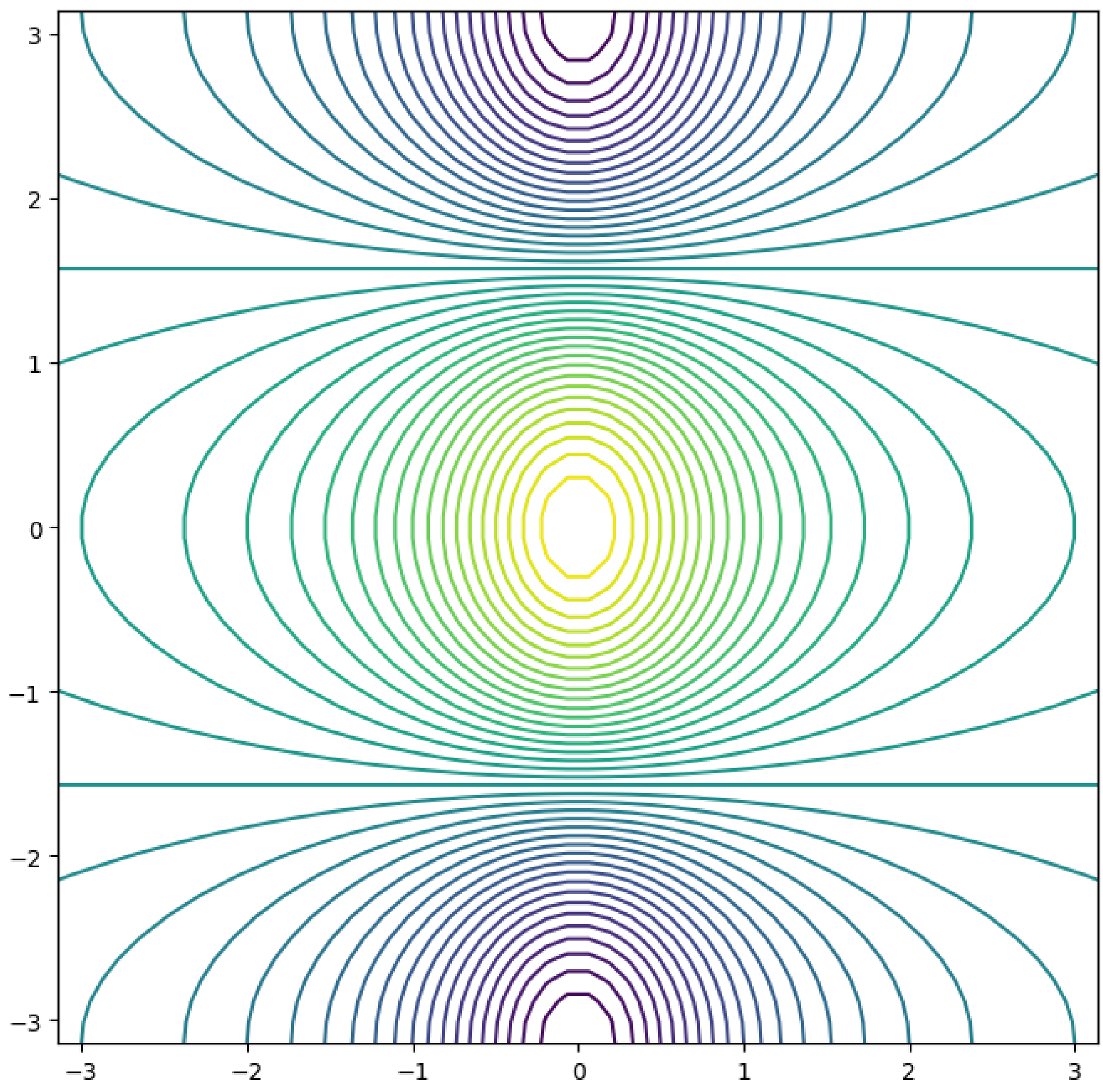
To create x and y, we'll use the command np.linspace(a, b, n), which returns a vector of n numbers starting at a and ending at b.

[42]:
```
fig, ax = subplots(figsize=(8, 8))
x = np.linspace(-np.pi, np.pi, 50)
y=x
f = np.multiply.outer(np.cos(y), 1 / (1 + x**2))
ax.contour(x, y, f);
```



We can increase the resolution by adding more levels to the image.

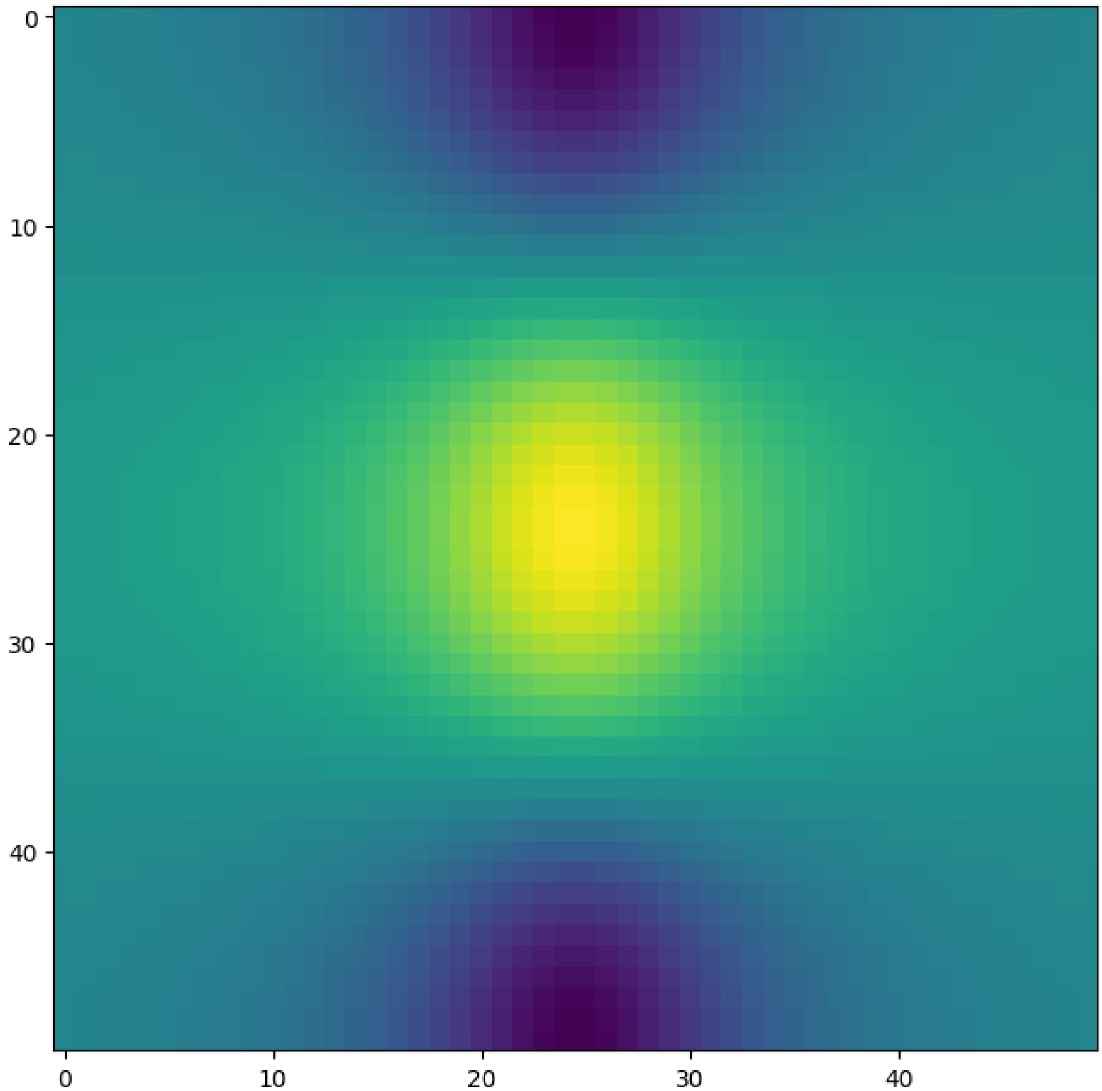
[43]:
```
fig, ax = subplots(figsize=(8, 8))
ax.contour(x, y, f, levels=45);
```



To fne-tune the output of the ax.contour() function, take a look at the help fle by typing ?plt.contour.

The ax.imshow() method is similar to ax.contour(), except that it produces a color-coded plot whose colors depend on the z value. This is known as a heatmap, and is sometimes used to plot temperature in weather fore casts.

[45]:
```
fig, ax = subplots(figsize=(8, 8))
ax.imshow(f);
```



0.2 2.3.5 Sequences and Slice Notation

As seen above, the function np.linspace() can be used to create a sequence of numbers.

[46]:
```
seq1 = np.linspace(0, 10, 11)
seq1
```

[46]:
```
array([ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10.])
```

The function np.arange() returns a sequence of numbers spaced out by step. If step is not specifed, then a default value of 1 is used. Let's create a sequence that starts at 0 and ends at 10.

[47]:
```
seq2 = np.arange(0, 10)
seq2
```

[47]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

[48]:
```
"hello world"[3:6]
```

[48]: 'lo '

In the code block above, the notation 3:6 is shorthand for slice(3,6) when used inside [].

[49]:
```
"hello world"[slice(3,6)]
```

[49]: 'lo '

See the documentation slice? for useful options in creating slices.

0.3 2.3.6 Indexing Data

[50]:
```
A = np.array(np.arange(16)).reshape((4, 4))
A
```

[50]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15]])
```

0.3.1 Indexing Rows, Columns, and Submatrices

To select multiple rows at a time, we can pass in a list specifying our selection. For instance, [1,3] will retrieve the second and fourth rows:

[51]:
```
A[[1,3]]
```

[51]:
```
array([[ 4,  5,  6,  7],
       [12, 13, 14, 15]])
```

To select the frst and third columns, we pass in [0,2] as the second argument in the square brackets. In this case we need to supply the frst argument : which selects all rows.

[52]:
```
A[:,[0,2]]
```

[52]:
```
array([[ 0,  2],
       [ 4,  6],
       [ 8, 10],
       [12, 14]])
```

Now, suppose that we want to select the submatrix made up of the second and fourth rows as well as the frst and third columns. This is where indexing gets slightly tricky. It is natural to try to use lists to retrieve the rows and columns:

[53]:
```
A[[1,3],[0,2]]
```

[53]: array([4, 14])

Oops — what happened? We got a one-dimensional array of length two identical to

[54]:
```
np.array([A[1,0],A[3,2]])
```

[54]: array([4, 14])

Similarly, the following code fails to extract the submatrix comprised of the second and fourth rows and the frst, third, and fourth columns:

[55]:
```
A[[1,3],[0,2,3]]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[55], line 1
----> 1 A[[1,3],[0,2,3]]

IndexError: shape mismatch: indexing arrays could not be broadcast together with
  ↪shapes (2,) (3,)
```

We can see what has gone wrong here. When supplied with two indexing lists, the numpy interpretation is that these provide pairs of i, j indices for a series of entries. That is why the pair of lists must have the same length. However, that was not our intent, since we are looking for a submatrix.

One easy way to do this is as follows. We frst create a submatrix by subsetting the rows of A, and then on the fy we make a further submatrix by subsetting its columns.

[56]:
```
A[[1,3]][:,[0,2]]
```

[56]:
```
array([[ 4,  6],
       [12, 14]])
```

There are more efcient ways of achieving the same result.

The convenience function np.ix_() allows us to extr act a submatrix using lists, by creating an intermediate object.

[57]:
```
idx = np.ix_([1,3],[0,2,3])
A[idx]
```

[57]:
```
array([[ 4,  6,  7],
       [12, 14, 15]])
```

Alternatively, we can subset matrices efciently using slices. The slice 1:4:2 captures the second and fourth items of a sequence, while the slice 0:3:2 captures the frst and third items (the third element in a slice sequence is the step size).

[58]:
```
A[1:4:2,0:3:2]
```

[58]: array([[4, 6],
        [12, 14]])

Why are we able to retrieve a submatrix directly using slices but not using lists? Its because they are diferent Python types, and are treated diferently by numpy. Slices can be used to extract objects from arbitrary sequences, such as strings, lists, and tuples, while the use of lists for indexing is more limited.

0.3.2 Boolean Indexing

In numpy, a Boolean is a type that equals either True or False (also represented as 1 and 0, respectively). The next line creates a vector of 0's, represented as Booleans, of length equal to the frst dimension of A.

[59]:
```
keep_rows = np.zeros(A.shape[0], bool)
keep_rows
```

[59]: array([False, False, False, False])

We now set two of the elements to True.

[60]:
```
keep_rows[[1,3]] = True
keep_rows
```

[60]: array([False, True, False, True])

Note that the elements of keep_rows, when viewed as integers, are the same as the values of np.array([0,1,0,1]). Below, we use == to verify their equality. When applied to two arrays, the == operation is applied elementwise.

[61]:
```
np.all(keep_rows == np.array([0,1,0,1]))
```

[61]: True

(Here, the function np.all() has checked whether all entries of an array are True. A similar function, np.any(), can be used to check whether any np.any() entries of an array are True.)

However, even though np.array([0,1,0,1]) and keep_rows are equal according to ==, they index diferent sets of rows! The former retrieves the frst, second, frst, and second rows of A.

[62]:
```
A[np.array([0,1,0,1])]
```

[62]: array([[0, 1, 2, 3],
        [4, 5, 6, 7],
        [0, 1, 2, 3],
        [4, 5, 6, 7]])

By contrast, keep_rows retrieves only the second and fourth rows of A — i.e. the rows for which the Boolean equals TRUE.

[63]:
```
A[keep_rows]
```

[63]:
```
array([[ 4,  5,  6,  7],
       [12, 13, 14, 15]])
```

This example shows that Booleans and integers are treated diferently by numpy.

We again make use of the np.ix_() function to create a mesh containing the second and fourth rows, and the frst, third, and fourth columns. This time, we apply the function to Booleans, rather than lists.

[64]:
```
keep_cols = np.zeros(A.shape[1], bool)
keep_cols[[0, 2, 3]] = True
idx_bool = np.ix_(keep_rows, keep_cols)
A[idx_bool]
```

[64]:
```
array([[ 4,  6,  7],
       [12, 14, 15]])
```

We can also mix a list with an array of Booleans in the arguments to np.ix_():

[66]:
```
idx_mixed = np.ix_([1,3], keep_cols)
A[idx_mixed]
```

[66]:
```
array([[ 4,  6,  7],
       [12, 14, 15]])
```

0.4 2.3.7 Loading Data

Data sets often contain diferent types of data, and may have names associated with the rows or columns. For these reasons, they typically are best accommodated using a data frame. We can think of a data frame as data frame a sequence of arrays of identical length; these are the columns. Entries in the diferent arrays can be combined to form a row. The pandas library can be used to create and work with data frame objects.

0.4.1 Reading in a Data Set

[69]:
```
import pandas as pd
Auto = pd.read_csv('ISLP_labs/Auto.csv')
Auto
```

[69]:
```
      mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0    18.0          8         307.0         130    3504          12.0    70
1    15.0          8         350.0         165    3693          11.5    70
2    18.0          8         318.0         150    3436          11.0    70
3    16.0          8         304.0         150    3433          12.0    70
4    17.0          8         302.0         140    3449          10.5    70
..    …        …           …        …     …            …   …
387  27.0          4         140.0          86    2790          15.6    82
388  44.0          4          97.0          52    2130          24.6    82
389  32.0          4         135.0          84    2295          11.6    82
```

```
390  28.0          4        120.0          79    2625             18.6    82
391  31.0          4        119.0          82    2720             19.4    82

     origin                       name
0         1  chevrolet chevelle malibu
1         1          buick skylark 320
2         1         plymouth satellite
3         1              amc rebel sst
4         1                ford torino
..      …                         …
387       1            ford mustang gl
388       2                  vw pickup
389       1              dodge rampage
390       1                ford ranger
391       1                 chevy s-10

[392 rows x 9 columns]
```

The book website also has a whitespace-delimited version of this data, called Auto.data. This can be read in as follows:

[70]:
```python
Auto = pd.read_csv('ISLP_labs/Auto.data', delim_whitespace=True)
```

[72]:
```python
Auto
```

[72]:
```
      mpg  cylinders  displacement horsepower  weight  acceleration  year  \
0    18.0          8         307.0      130.0  3504.0          12.0    70
1    15.0          8         350.0      165.0  3693.0          11.5    70
2    18.0          8         318.0      150.0  3436.0          11.0    70
3    16.0          8         304.0      150.0  3433.0          12.0    70
4    17.0          8         302.0      140.0  3449.0          10.5    70
..    …        …          …         …      …            …    …
392  27.0          4         140.0      86.00  2790.0          15.6    82
393  44.0          4          97.0      52.00  2130.0          24.6    82
394  32.0          4         135.0      84.00  2295.0          11.6    82
395  28.0          4         120.0      79.00  2625.0          18.6    82
396  31.0          4         119.0      82.00  2720.0          19.4    82

     origin                       name
0         1  chevrolet chevelle malibu
1         1          buick skylark 320
2         1         plymouth satellite
3         1              amc rebel sst
4         1                ford torino
..      …                         …
392       1            ford mustang gl
393       2                  vw pickup
394       1              dodge rampage
```

```
395       1                 ford ranger
396       1                  chevy s-10

[397 rows x 9 columns]
```

Both Auto.csv and Auto.data are simply text fles. Before loading data into Python, it is a good idea to view it using a text editor or other software, such as Microsoft Excel. We now take a look at the column of Auto corresponding to the variable horsepower:

[73]:
```
Auto['horsepower']
```

[73]:
```
0      130.0
1      165.0
2      150.0
3      150.0
4      140.0
       …
392    86.00
393    52.00
394    84.00
395    79.00
396    82.00
Name: horsepower, Length: 397, dtype: object
```

We see that the dtype of this column is object. It turns out that all values of the horsepower column were interpreted as strings when reading in the data. We can fnd out why by looking at the unique values.

[74]:
```
np.unique(Auto['horsepower'])
```

[74]:
```
array(['100.0', '102.0', '103.0', '105.0', '107.0', '108.0', '110.0',
       '112.0', '113.0', '115.0', '116.0', '120.0', '122.0', '125.0',
       '129.0', '130.0', '132.0', '133.0', '135.0', '137.0', '138.0',
       '139.0', '140.0', '142.0', '145.0', '148.0', '149.0', '150.0',
       '152.0', '153.0', '155.0', '158.0', '160.0', '165.0', '167.0',
       '170.0', '175.0', '180.0', '190.0', '193.0', '198.0', '200.0',
       '208.0', '210.0', '215.0', '220.0', '225.0', '230.0', '46.00',
       '48.00', '49.00', '52.00', '53.00', '54.00', '58.00', '60.00',
       '61.00', '62.00', '63.00', '64.00', '65.00', '66.00', '67.00',
       '68.00', '69.00', '70.00', '71.00', '72.00', '74.00', '75.00',
       '76.00', '77.00', '78.00', '79.00', '80.00', '81.00', '82.00',
       '83.00', '84.00', '85.00', '86.00', '87.00', '88.00', '89.00',
       '90.00', '91.00', '92.00', '93.00', '94.00', '95.00', '96.00',
       '97.00', '98.00', '?'], dtype=object)
```

To save space, we have omitted the output of the previous code block. We see the culprit is the value ?, which is being used to encode missing values. To fx the problem, we must provide pd.read_csv() with an argument called na_values. Now, each instance of ? in the fle is replaced with the value np.nan, which means not a number:

[76]:
```
Auto = pd.read_csv('ISLP_labs/Auto.data',na_values=['?'],delim_whitespace=True)
Auto['horsepower'].sum()
```

[76]:
```
40952.0
```

The Auto.shape attribute tells us that the data has 397 observations, or rows, and nine variables, or columns

[77]:
```
Auto.shape
```

[77]:
```
(397, 9)
```

There are various ways to deal with missing data. In this case, since only fve of the rows contain missing observations, we choose to use the Auto.dropna() method to simply remove these rows.

[78]:
```
Auto_new = Auto.dropna()
Auto_new.shape
```

[78]:
```
(392, 9)
```

0.4.2 Basics of Selecting Rows and Columns

[79]:
```
Auto = Auto_new # overwrite the previous value
Auto.columns
```

[79]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'year', 'origin', 'name'],
      dtype='object')
```

Accessing the rows and columns of a data frame is similar, but not identical, to accessing the rows and columns of an array. Recall that the frst argument to the [] method is always applied to the rows of the array. Similarly, passing in a slice to the [] method creates a data frame whose rows are determined by the slice:

[80]:
```
Auto[:3]
```

[80]:
```
    mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0  18.0          8         307.0       130.0  3504.0          12.0    70
1  15.0          8         350.0       165.0  3693.0          11.5    70
2  18.0          8         318.0       150.0  3436.0          11.0    70

   origin                       name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
```

Similarly, an array of Booleans can be used to subset the rows:

[81]:
```
idx_80 = Auto['year'] > 80
Auto[idx_80]
```

[81]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
338	27.2	4	135.0	84.0	2490.0	15.7	81	
339	26.6	4	151.0	84.0	2635.0	16.4	81	
340	25.8	4	156.0	92.0	2620.0	14.4	81	
341	23.5	6	173.0	110.0	2725.0	12.6	81	
342	30.0	4	135.0	84.0	2385.0	12.9	81	
343	39.1	4	79.0	58.0	1755.0	16.9	81	
344	39.0	4	86.0	64.0	1875.0	16.4	81	
345	35.1	4	81.0	60.0	1760.0	16.1	81	
346	32.3	4	97.0	67.0	2065.0	17.8	81	
347	37.0	4	85.0	65.0	1975.0	19.4	81	
348	37.7	4	89.0	62.0	2050.0	17.3	81	
349	34.1	4	91.0	68.0	1985.0	16.0	81	
350	34.7	4	105.0	63.0	2215.0	14.9	81	
351	34.4	4	98.0	65.0	2045.0	16.2	81	
352	29.9	4	98.0	65.0	2380.0	20.7	81	
353	33.0	4	105.0	74.0	2190.0	14.2	81	
355	33.7	4	107.0	75.0	2210.0	14.4	81	
356	32.4	4	108.0	75.0	2350.0	16.8	81	
357	32.9	4	119.0	100.0	2615.0	14.8	81	
358	31.6	4	120.0	74.0	2635.0	18.3	81	
359	28.1	4	141.0	80.0	3230.0	20.4	81	
360	30.7	6	145.0	76.0	3160.0	19.6	81	
361	25.4	6	168.0	116.0	2900.0	12.6	81	
362	24.2	6	146.0	120.0	2930.0	13.8	81	
363	22.4	6	231.0	110.0	3415.0	15.8	81	
364	26.6	8	350.0	105.0	3725.0	19.0	81	
365	20.2	6	200.0	88.0	3060.0	17.1	81	
366	17.6	6	225.0	85.0	3465.0	16.6	81	
367	28.0	4	112.0	88.0	2605.0	19.6	82	
368	27.0	4	112.0	88.0	2640.0	18.6	82	
369	34.0	4	112.0	88.0	2395.0	18.0	82	
370	31.0	4	112.0	85.0	2575.0	16.2	82	
371	29.0	4	135.0	84.0	2525.0	16.0	82	
372	27.0	4	151.0	90.0	2735.0	18.0	82	
373	24.0	4	140.0	92.0	2865.0	16.4	82	
374	36.0	4	105.0	74.0	1980.0	15.3	82	
375	37.0	4	91.0	68.0	2025.0	18.2	82	
376	31.0	4	91.0	68.0	1970.0	17.6	82	
377	38.0	4	105.0	63.0	2125.0	14.7	82	
378	36.0	4	98.0	70.0	2125.0	17.3	82	
379	36.0	4	120.0	88.0	2160.0	14.5	82	
380	36.0	4	107.0	75.0	2205.0	14.5	82	
381	34.0	4	108.0	70.0	2245.0	16.9	82	
382	38.0	4	91.0	67.0	1965.0	15.0	82	
383	32.0	4	91.0	67.0	1965.0	15.7	82	
384	38.0	4	91.0	67.0	1995.0	16.2	82	

385	25.0	6	181.0	110.0	2945.0	16.4	82
386	38.0	6	262.0	85.0	3015.0	17.0	82
387	26.0	4	156.0	92.0	2585.0	14.5	82
388	22.0	6	232.0	112.0	2835.0	14.7	82
389	32.0	4	144.0	96.0	2665.0	13.9	82
390	36.0	4	135.0	84.0	2370.0	13.0	82
391	27.0	4	151.0	90.0	2950.0	17.3	82
392	27.0	4	140.0	86.0	2790.0	15.6	82
393	44.0	4	97.0	52.0	2130.0	24.6	82
394	32.0	4	135.0	84.0	2295.0	11.6	82
395	28.0	4	120.0	79.0	2625.0	18.6	82
396	31.0	4	119.0	82.0	2720.0	19.4	82

	origin	name
338	1	plymouth reliant
339	1	buick skylark
340	1	dodge aries wagon (sw)
341	1	chevrolet citation
342	1	plymouth reliant
343	3	toyota starlet
344	1	plymouth champ
345	3	honda civic 1300
346	3	subaru
347	3	datsun 210 mpg
348	3	toyota tercel
349	3	mazda glc 4
350	1	plymouth horizon 4
351	1	ford escort 4w
352	1	ford escort 2h
353	2	volkswagen jetta
355	3	honda prelude
356	3	toyota corolla
357	3	datsun 200sx
358	3	mazda 626
359	2	peugeot 505s turbo diesel
360	2	volvo diesel
361	3	toyota cressida
362	3	datsun 810 maxima
363	1	buick century
364	1	oldsmobile cutlass ls
365	1	ford granada gl
366	1	chrysler lebaron salon
367	1	chevrolet cavalier
368	1	chevrolet cavalier wagon
369	1	chevrolet cavalier 2-door
370	1	pontiac j2000 se hatchback
371	1	dodge aries se

```
372       1                 pontiac phoenix
373       1            ford fairmont futura
374       2             volkswagen rabbit l
375       3              mazda glc custom l
376       3                mazda glc custom
377       1          plymouth horizon miser
378       1                  mercury lynx l
379       3                nissan stanza xe
380       3                    honda accord
381       3                  toyota corolla
382       3                     honda civic
383       3              honda civic (auto)
384       3                   datsun 310 gx
385       1           buick century limited
386       1  oldsmobile cutlass ciera (diesel)
387       1         chrysler lebaron medallion
388       1                  ford granada l
389       3                toyota celica gt
390       1               dodge charger 2.2
391       1                chevrolet camaro
392       1                 ford mustang gl
393       2                       vw pickup
394       1                   dodge rampage
395       1                     ford ranger
396       1                      chevy s-10
```

However, if we pass in a list of strings to the [] method, then we obtain a data frame containing the corresponding set of columns.

[82]:
```python
Auto[['mpg', 'horsepower']]
```

[82]:
```
      mpg  horsepower
0    18.0       130.0
1    15.0       165.0
2    18.0       150.0
3    16.0       150.0
4    17.0       140.0
..    …          …
392  27.0        86.0
393  44.0        52.0
394  32.0        84.0
395  28.0        79.0
396  31.0        82.0

[392 rows x 2 columns]
```

Since we did not specify an index column when we loaded our data frame, the rows are labeled using integers 0 to 396.

[83]:
```
Auto.index
```

[83]:
```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
             …
             387, 388, 389, 390, 391, 392, 393, 394, 395, 396],
           dtype='int64', length=392)
```

We can use the set_index() method to re-name the rows using the contents of Auto['name']

[84]:
```
Auto_re = Auto.set_index('name')
Auto_re
```

[84]:
```
                            mpg  cylinders  displacement  horsepower  weight  \
name
chevrolet chevelle malibu  18.0          8         307.0       130.0  3504.0
buick skylark 320          15.0          8         350.0       165.0  3693.0
plymouth satellite         18.0          8         318.0       150.0  3436.0
amc rebel sst              16.0          8         304.0       150.0  3433.0
ford torino                17.0          8         302.0       140.0  3449.0
…                           …         …            …          …       …
ford mustang gl            27.0          4         140.0        86.0  2790.0
vw pickup                  44.0          4          97.0        52.0  2130.0
dodge rampage              32.0          4         135.0        84.0  2295.0
ford ranger                28.0          4         120.0        79.0  2625.0
chevy s-10                 31.0          4         119.0        82.0  2720.0

                           acceleration  year  origin
name
chevrolet chevelle malibu          12.0    70       1
buick skylark 320                  11.5    70       1
plymouth satellite                 11.0    70       1
amc rebel sst                      12.0    70       1
ford torino                        10.5    70       1
…                                   …   …     …
ford mustang gl                    15.6    82       1
vw pickup                          24.6    82       2
dodge rampage                      11.6    82       1
ford ranger                        18.6    82       1
chevy s-10                         19.4    82       1

[392 rows x 8 columns]
```

[85]:
```
Auto_re.columns
```

[85]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'year', 'origin'],
      dtype='object')
```

We see that the column 'name' is no longer there. Now that the index has been set to name, we can access rows of the data frame by name using the loc[] method of Auto:

[86]:
```python
rows = ['amc rebel sst', 'ford torino']
Auto_re.loc[rows]
```

[86]:
```
                mpg  cylinders  displacement  horsepower  weight  \
name
amc rebel sst  16.0          8         304.0       150.0  3433.0
ford torino    17.0          8         302.0       140.0  3449.0

               acceleration  year  origin
name
amc rebel sst          12.0    70       1
ford torino            10.5    70       1
```

As an alternative to using the index name, we could retrieve the 4th and 5th rows of Auto using the iloc[] method:

[87]:
```python
Auto_re.iloc[[3,4]]
```

[87]:
```
                mpg  cylinders  displacement  horsepower  weight  \
name
amc rebel sst  16.0          8         304.0       150.0  3433.0
ford torino    17.0          8         302.0       140.0  3449.0

               acceleration  year  origin
name
amc rebel sst          12.0    70       1
ford torino            10.5    70       1
```

We can also use it to retrieve the 1st, 3rd and and 4th columns of Auto_re:

[88]:
```python
Auto_re.iloc[:,[0,2,3]]
```

[88]:
```
                            mpg  displacement  horsepower
name
chevrolet chevelle malibu  18.0         307.0       130.0
buick skylark 320          15.0         350.0       165.0
plymouth satellite         18.0         318.0       150.0
amc rebel sst              16.0         304.0       150.0
ford torino                17.0         302.0       140.0
…                           …            …           …
ford mustang gl            27.0         140.0        86.0
vw pickup                  44.0          97.0        52.0
dodge rampage              32.0         135.0        84.0
ford ranger                28.0         120.0        79.0
chevy s-10                 31.0         119.0        82.0

[392 rows x 3 columns]
```

We can extract the 4th and 5th rows, as well as the 1st, 3rd and 4th columns, using a single call to iloc[]:

```
[89]: Auto_re.iloc[[3,4],[0,2,3]]
```

```
[89]:                 mpg  displacement  horsepower
      name
      amc rebel sst  16.0         304.0       150.0
      ford torino    17.0         302.0       140.0
```

Index entries need not be unique: there are several cars in the data frame named ford galaxie 500.

```
[90]: Auto_re.loc['ford galaxie 500', ['mpg', 'origin']]
```

```
[90]:                    mpg  origin
      name
      ford galaxie 500  15.0       1
      ford galaxie 500  14.0       1
      ford galaxie 500  14.0       1
```

0.4.3 More on Selecting Rows and Columns

Suppose now that we want to create a data frame consisting of the weight and origin of the subset of cars with year greater than 80 — i.e. those built after 1980. To do this, we frst create a Boolean array that indexes the rows. The loc[] method allows for Boolean entries as well as strings:

```
[91]: idx_80 = Auto_re['year'] > 80
      Auto_re.loc[idx_80, ['weight', 'origin']]
```

```
[91]:                                  weight  origin
      name
      plymouth reliant                 2490.0       1
      buick skylark                    2635.0       1
      dodge aries wagon (sw)           2620.0       1
      chevrolet citation               2725.0       1
      plymouth reliant                 2385.0       1
      toyota starlet                   1755.0       3
      plymouth champ                   1875.0       1
      honda civic 1300                 1760.0       3
      subaru                           2065.0       3
      datsun 210 mpg                   1975.0       3
      toyota tercel                    2050.0       3
      mazda glc 4                      1985.0       3
      plymouth horizon 4               2215.0       1
      ford escort 4w                   2045.0       1
      ford escort 2h                   2380.0       1
      volkswagen jetta                 2190.0       2
      honda prelude                    2210.0       3
      toyota corolla                   2350.0       3
```

```
datsun 200sx                        2615.0       3
mazda 626                           2635.0       3
peugeot 505s turbo diesel           3230.0       2
volvo diesel                        3160.0       2
toyota cressida                     2900.0       3
datsun 810 maxima                   2930.0       3
buick century                       3415.0       1
oldsmobile cutlass ls               3725.0       1
ford granada gl                     3060.0       1
chrysler lebaron salon              3465.0       1
chevrolet cavalier                  2605.0       1
chevrolet cavalier wagon            2640.0       1
chevrolet cavalier 2-door           2395.0       1
pontiac j2000 se hatchback          2575.0       1
dodge aries se                      2525.0       1
pontiac phoenix                     2735.0       1
ford fairmont futura                2865.0       1
volkswagen rabbit l                 1980.0       2
mazda glc custom l                  2025.0       3
mazda glc custom                    1970.0       3
plymouth horizon miser              2125.0       1
mercury lynx l                      2125.0       1
nissan stanza xe                    2160.0       3
honda accord                        2205.0       3
toyota corolla                      2245.0       3
honda civic                         1965.0       3
honda civic (auto)                  1965.0       3
datsun 310 gx                       1995.0       3
buick century limited               2945.0       1
oldsmobile cutlass ciera (diesel)   3015.0       1
chrysler lebaron medallion          2585.0       1
ford granada l                      2835.0       1
toyota celica gt                    2665.0       3
dodge charger 2.2                   2370.0       1
chevrolet camaro                    2950.0       1
ford mustang gl                     2790.0       1
vw pickup                           2130.0       2
dodge rampage                       2295.0       1
ford ranger                         2625.0       1
chevy s-10                          2720.0       1
```

To do this more concisely, we can use an anonymous function called a lambda:

[92]:
```python
Auto_re.loc[lambda df: df['year'] > 80, ['weight', 'origin']]
```

[92]:
```
                                   weight  origin
name
plymouth reliant                    2490.0       1
```

buick skylark	2635.0	1
dodge aries wagon (sw)	2620.0	1
chevrolet citation	2725.0	1
plymouth reliant	2385.0	1
toyota starlet	1755.0	3
plymouth champ	1875.0	1
honda civic 1300	1760.0	3
subaru	2065.0	3
datsun 210 mpg	1975.0	3
toyota tercel	2050.0	3
mazda glc 4	1985.0	3
plymouth horizon 4	2215.0	1
ford escort 4w	2045.0	1
ford escort 2h	2380.0	1
volkswagen jetta	2190.0	2
honda prelude	2210.0	3
toyota corolla	2350.0	3
datsun 200sx	2615.0	3
mazda 626	2635.0	3
peugeot 505s turbo diesel	3230.0	2
volvo diesel	3160.0	2
toyota cressida	2900.0	3
datsun 810 maxima	2930.0	3
buick century	3415.0	1
oldsmobile cutlass ls	3725.0	1
ford granada gl	3060.0	1
chrysler lebaron salon	3465.0	1
chevrolet cavalier	2605.0	1
chevrolet cavalier wagon	2640.0	1
chevrolet cavalier 2-door	2395.0	1
pontiac j2000 se hatchback	2575.0	1
dodge aries se	2525.0	1
pontiac phoenix	2735.0	1
ford fairmont futura	2865.0	1
volkswagen rabbit l	1980.0	2
mazda glc custom l	2025.0	3
mazda glc custom	1970.0	3
plymouth horizon miser	2125.0	1
mercury lynx l	2125.0	1
nissan stanza xe	2160.0	3
honda accord	2205.0	3
toyota corolla	2245.0	3
honda civic	1965.0	3
honda civic (auto)	1965.0	3
datsun 310 gx	1995.0	3
buick century limited	2945.0	1
oldsmobile cutlass ciera (diesel)	3015.0	1

```
chrysler lebaron medallion        2585.0       1
ford granada l                    2835.0       1
toyota celica gt                  2665.0       3
dodge charger 2.2                 2370.0       1
chevrolet camaro                  2950.0       1
ford mustang gl                   2790.0       1
vw pickup                         2130.0       2
dodge rampage                     2295.0       1
ford ranger                       2625.0       1
chevy s-10                        2720.0       1
```

[93]:
```
Auto_re.loc[lambda df: (df['year'] > 80) & (df['mpg'] > 30),
['weight', 'origin']
]
```

[93]:
```
                                  weight  origin
name
toyota starlet                    1755.0       3
plymouth champ                    1875.0       1
honda civic 1300                  1760.0       3
subaru                            2065.0       3
datsun 210 mpg                    1975.0       3
toyota tercel                     2050.0       3
mazda glc 4                       1985.0       3
plymouth horizon 4                2215.0       1
ford escort 4w                    2045.0       1
volkswagen jetta                  2190.0       2
honda prelude                     2210.0       3
toyota corolla                    2350.0       3
datsun 200sx                      2615.0       3
mazda 626                         2635.0       3
volvo diesel                      3160.0       2
chevrolet cavalier 2-door         2395.0       1
pontiac j2000 se hatchback        2575.0       1
volkswagen rabbit l               1980.0       2
mazda glc custom l                2025.0       3
mazda glc custom                  1970.0       3
plymouth horizon miser            2125.0       1
mercury lynx l                    2125.0       1
nissan stanza xe                  2160.0       3
honda accord                      2205.0       3
toyota corolla                    2245.0       3
honda civic                       1965.0       3
honda civic (auto)                1965.0       3
datsun 310 gx                     1995.0       3
oldsmobile cutlass ciera (diesel) 3015.0       1
toyota celica gt                  2665.0       3
```

```
dodge charger 2.2                  2370.0       1
vw pickup                          2130.0       2
dodge rampage                      2295.0       1
chevy s-10                         2720.0       1
```

As another example, suppose that we want to retrieve all Ford and Datsun cars with displacement less than 300. We check whether each name entry contains either the string ford or datsun using the str.contains() method of the .str. contains() index attribute of of the dataframe:

[94]:
```python
Auto_re.loc[lambda df: (df['displacement'] < 300)
& (df.index.str.contains('ford')
| df.index.str.contains('datsun')),
['weight', 'origin']
]
```

[94]:
```
                       weight  origin
name
ford maverick          2587.0       1
datsun pl510           2130.0       3
datsun pl510           2130.0       3
ford torino 500        3302.0       1
ford mustang           3139.0       1
datsun 1200            1613.0       3
ford pinto runabout    2226.0       1
ford pinto (sw)        2395.0       1
datsun 510 (sw)        2288.0       3
ford maverick          3021.0       1
datsun 610             2379.0       3
ford pinto             2310.0       1
datsun b210            1950.0       3
ford pinto             2451.0       1
datsun 710             2003.0       3
ford maverick          3158.0       1
ford pinto             2639.0       1
datsun 710             2545.0       3
ford pinto             2984.0       1
ford maverick          3012.0       1
ford granada ghia      3574.0       1
datsun b-210           1990.0       3
ford pinto             2565.0       1
datsun f-10 hatchback  1945.0       3
ford granada           3525.0       1
ford mustang ii 2+2    2755.0       1
datsun 810             2815.0       3
ford fiesta            1800.0       1
datsun b210 gx         2070.0       3
ford fairmont (auto)   2965.0       1
ford fairmont (man)    2720.0       1
```

```
datsun 510              2300.0       3
datsun 200-sx           2405.0       3
ford fairmont 4         2890.0       1
datsun 210              2020.0       3
datsun 310              2019.0       3
ford fairmont           2870.0       1
datsun 510 hatchback    2434.0       3
datsun 210              2110.0       3
datsun 280-zx           2910.0       3
datsun 210 mpg          1975.0       3
ford escort 4w          2045.0       1
ford escort 2h          2380.0       1
datsun 200sx            2615.0       3
datsun 810 maxima       2930.0       3
ford granada gl         3060.0       1
ford fairmont futura    2865.0       1
datsun 310 gx           1995.0       3
ford granada l          2835.0       1
ford mustang gl         2790.0       1
ford ranger             2625.0       1
```

In summary, a powerful set of operations is available to index the rows and columns of data frames. For integer based queries, use the iloc[] method. For string and Boolean selections, use the loc[] method. For functional queries that flter rows, use the loc[] method with a function (typically a lambda) in the rows argument.

the expression a += b increment is equivalent to a=a+b. Besides being a convenient notation, this can save time in computationally heavy tasks in which the intermediate value of a+b need not be explicitly created.

[96]:
```
total = 0
for value, weight in zip([2,3,19],[0.2,0.3,0.5]):
    total += weight * value
print('Weighted average is: {0}'.format(total))
```

```
Weighted average is: 10.8
```

For example we may want to loop over the columns of a data frame and print the percent missing in each column. Let's create a data frame D with columns in which 20% of the entries are missing i.e. set to np.nan. np.nan We'll create the values in D from a normal distribution with mean 0 and variance 1 using rng.standard_normal() and then overwrite some random entries using rng.choice().

[97]:
```
rng = np.random.default_rng(1)
A = rng.standard_normal((127, 5))
M = rng.choice([0, np.nan], p=[0.8,0.2], size=A.shape)
A += M
D = pd.DataFrame(A, columns=['food',
'bar',
'pickle',
```

```
'snack',
'popcorn'])
D[:3]
```

[97]:

```
       food       bar    pickle     snack   popcorn
0  0.345584  0.821618  0.330437 -1.303157       NaN
1       NaN -0.536953  0.581118  0.364572  0.294132
2       NaN  0.546713       NaN -0.162910 -0.482119
```

[98]:

```
for col in D.columns:
    template = 'Column "{0}" has {1:.2%} missing values'
    print(template.format(col,np.isnan(D[col]).mean()))
```

```
Column "food" has 16.54% missing values
Column "bar" has 25.98% missing values
Column "pickle" has 29.13% missing values
Column "snack" has 21.26% missing values
Column "popcorn" has 22.83% missing values
```

We see that the template.format() method expects two arguments {0} and {1:.2%}, and the latter includes some formatting information. In particular, it specifes that the second argument should be expressed as a percent with two decimal digits.

0.5 2.3.9 Additional Graphical and Numerical Summaries

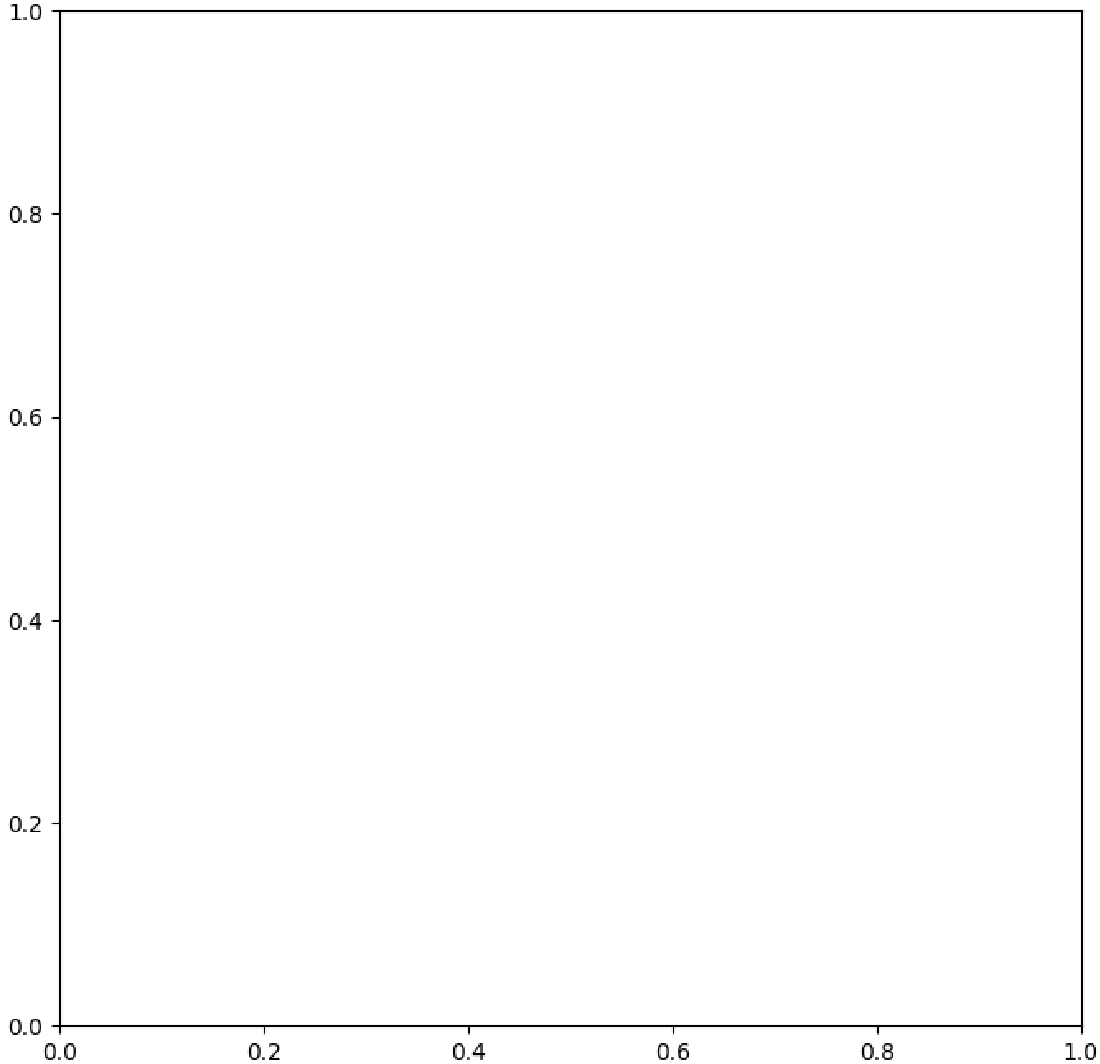
We can use the ax.plot() or ax.scatter() functions to display the quantitative variables. However, simply typing the variable names will produce an error message, because Python does not know to look in the Auto data set for those variables.

[99]:

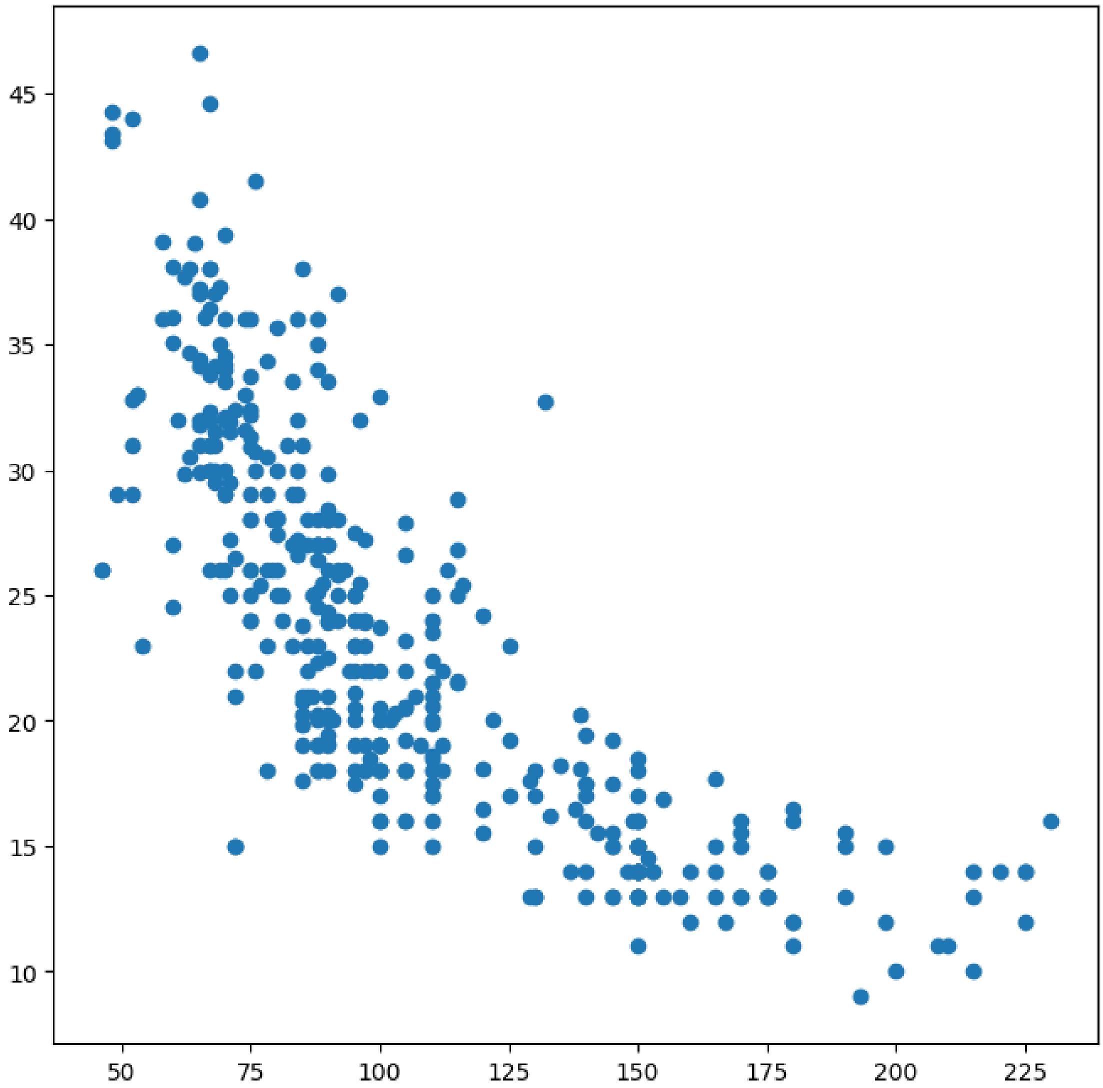
```
fig, ax = subplots(figsize=(8, 8))
ax.plot(horsepower , mpg, 'o');
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[99], line 2
      1 fig, ax = subplots(figsize=(8, 8))
----> 2 ax.plot(horsepower , mpg, 'o');

NameError: name 'horsepower' is not defined
```



[100]:
```
fig, ax = subplots(figsize=(8, 8))
ax.plot(Auto['horsepower'], Auto['mpg'], 'o');
```

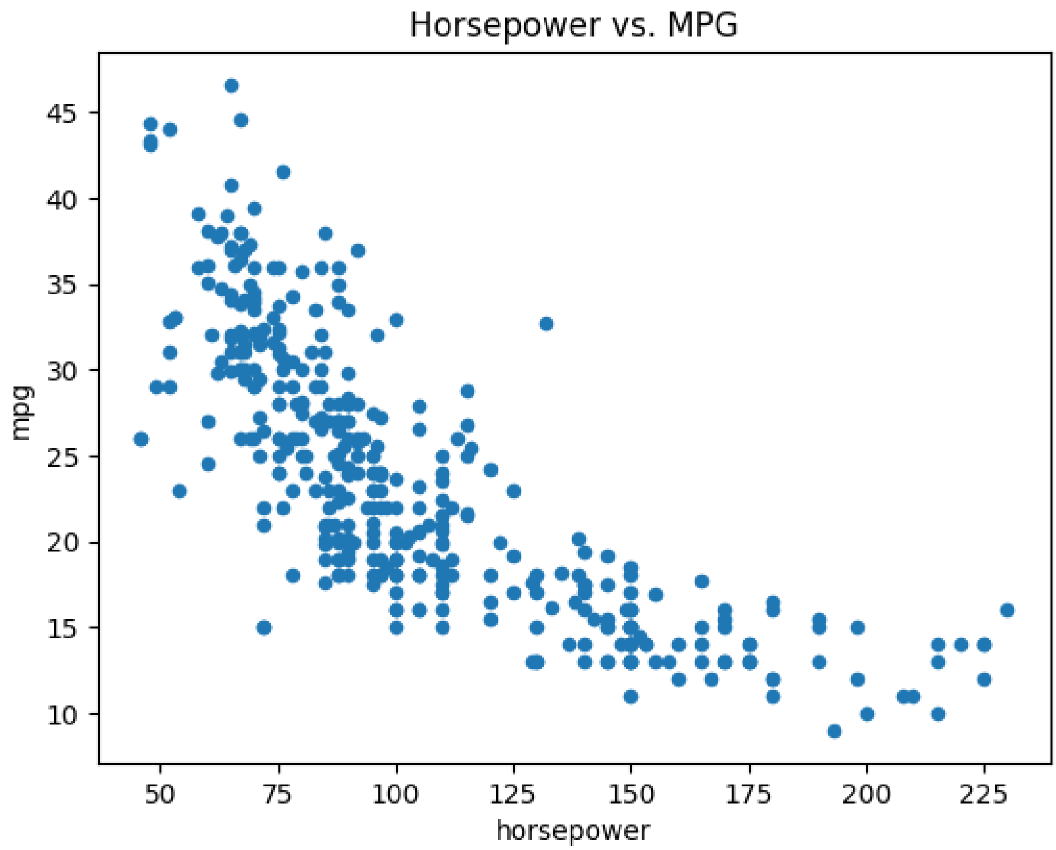


Alternatively, we can use the plot() method with the call Auto.plot(). Us- .plot() ing this method, the variables can be accessed by name. The plot methods of a data frame return a familiar object: an axes. We can use it to update the plot as we did previously:

[101]:
```
ax = Auto.plot.scatter('horsepower', 'mpg');
ax.set_title('Horsepower vs. MPG')
```

```
C:\Users\ankit19.gupta\AppData\Roaming\Python\Python38\site-
packages\pandas\plotting\_matplotlib\core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```

[101]:
```
Text(0.5, 1.0, 'Horsepower vs. MPG')
```



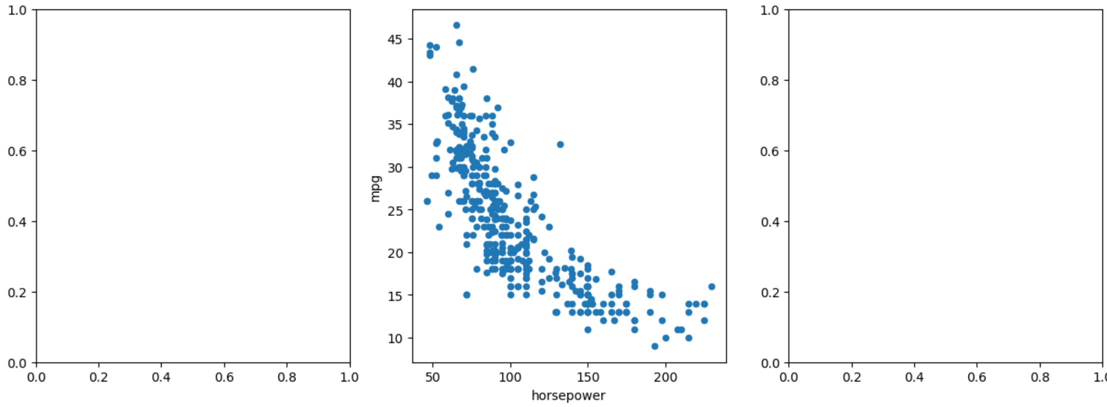
If we want to save the fgure that contains a given axes, we can fnd the relevant fgure by accessing the figure attribute:

[102]:
```
fig = ax.figure
fig.savefig('horsepower_mpg.png');
```

We can further instruct the data frame to plot to a particular axes object. In this case the corresponding plot() method will return the modifed axes we passed in as an argument. Note that when we request a one-dimensional grid of plots, the object axes is similarly one-dimensional. We place our scatter plot in the middle plot of a row of three plots within a fgure

[103]:
```
fig, axes = subplots(ncols=3, figsize=(15, 5))
Auto.plot.scatter('horsepower', 'mpg', ax=axes[1]);
```

```
C:\Users\ankit19.gupta\AppData\Roaming\Python\Python38\site-
packages\pandas\plotting\_matplotlib\core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```



Note also that the columns of a data frame can be accessed as attributes: try typing in Auto.horsepower.

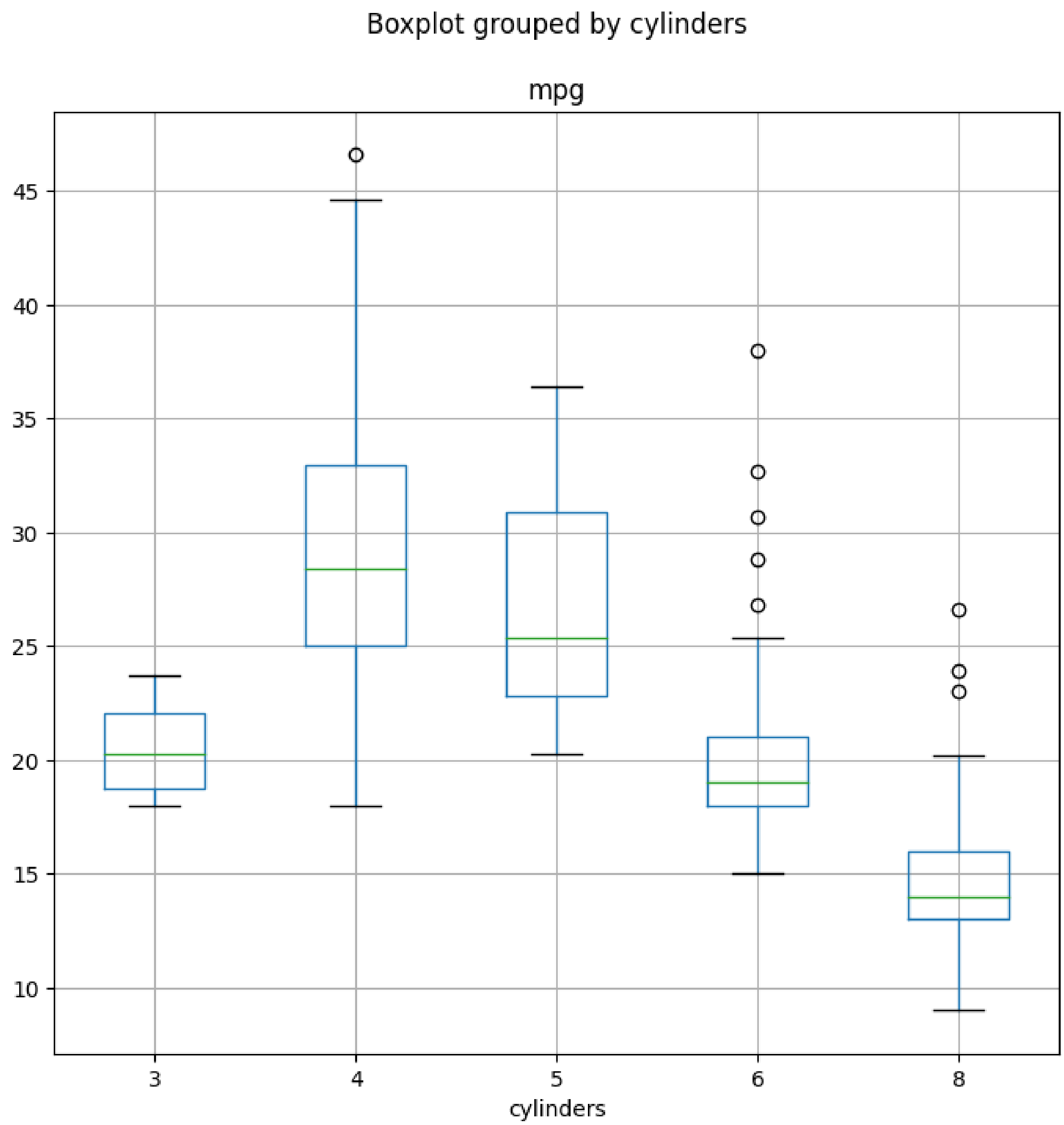
We now consider the cylinders variable. Typing in Auto.cylinders.dtype reveals that it is being treated as a quantitative variable. However, since there is only a small number of possible values for this variable, we may wish to treat it as qualitative. Below, we replace the cylinders column with a categorical version of Auto.cylinders. The function pd.Series() owes its name to the fact that pandas is often used in time series applications

[104]:
```
Auto.cylinders = pd.Series(Auto.cylinders, dtype='category')
Auto.cylinders.dtype
```

[104]:
```
CategoricalDtype(categories=[3, 4, 5, 6, 8], ordered=False)
```

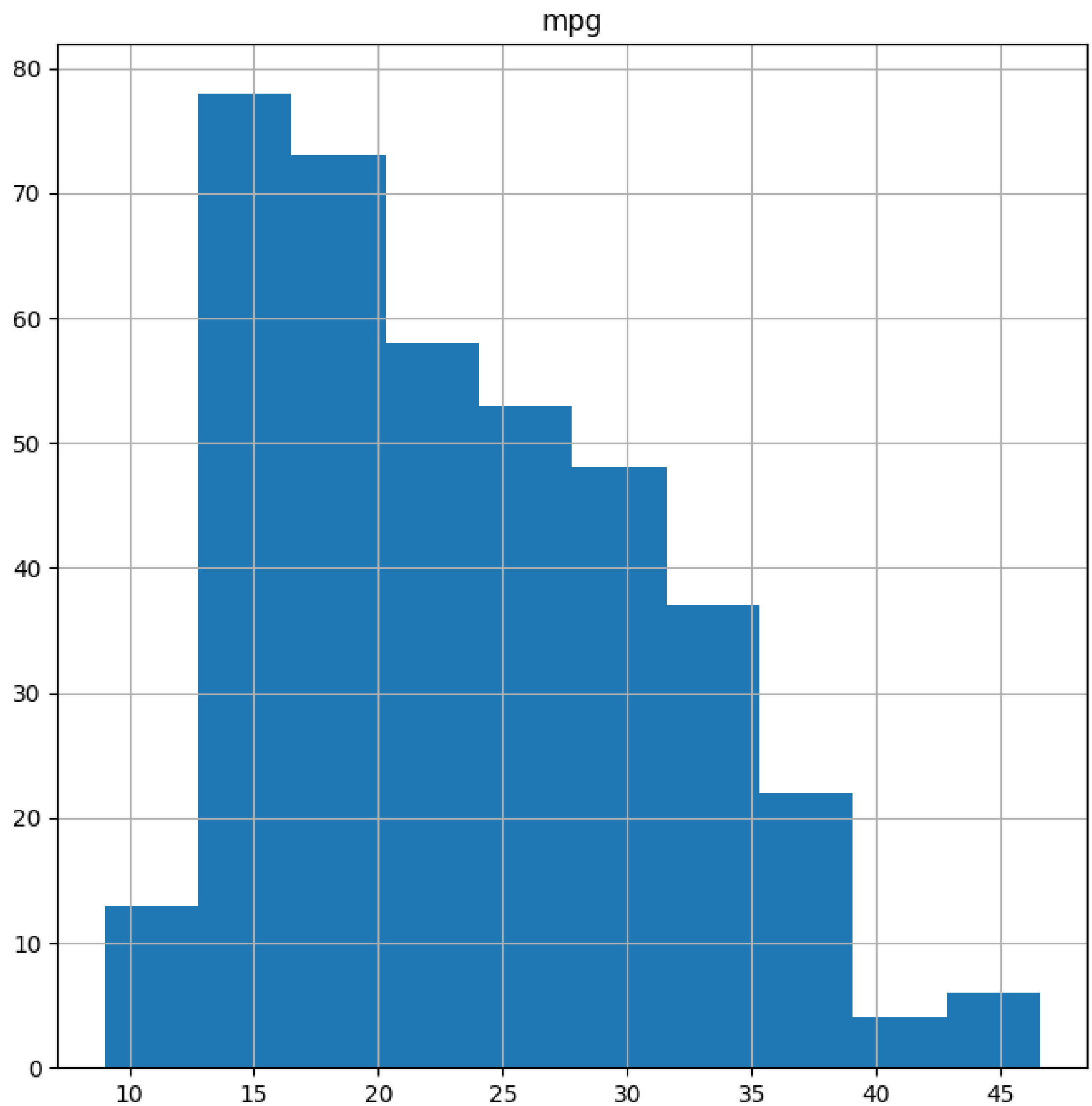
Now that cylinders is qualitative, we can display it using the boxplot() .boxplot() method.

[105]:
```
fig, ax = subplots(figsize=(8, 8))
Auto.boxplot('mpg', by='cylinders', ax=ax);
```



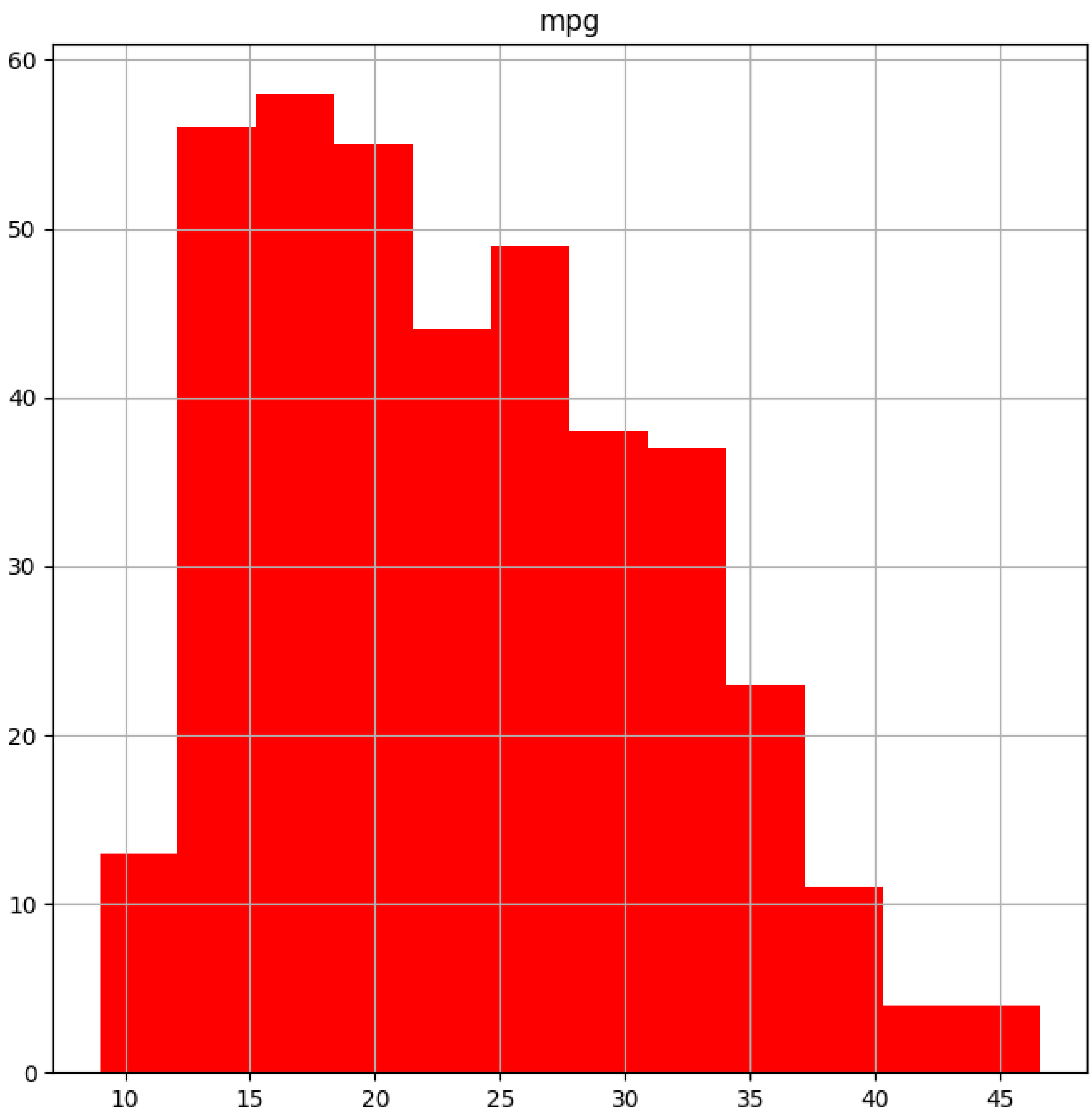
The hist() method can be used to plot a histogram.

[106]:
```
fig, ax = subplots(figsize=(8, 8))
Auto.hist('mpg', ax=ax);
```



The color of the bars and the number of bins can be changed:

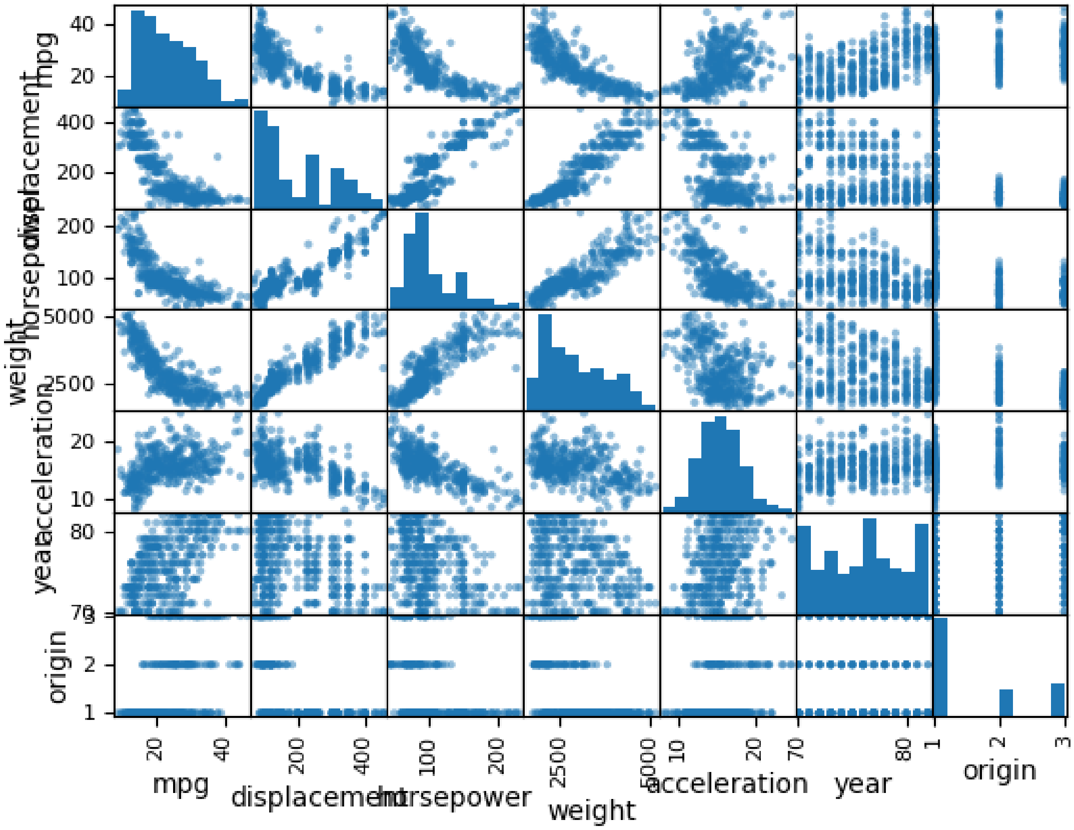
[107]:
```
fig, ax = subplots(figsize=(8, 8))
Auto.hist('mpg', color='red', bins=12, ax=ax);
```



See Auto.hist? for more plotting options.

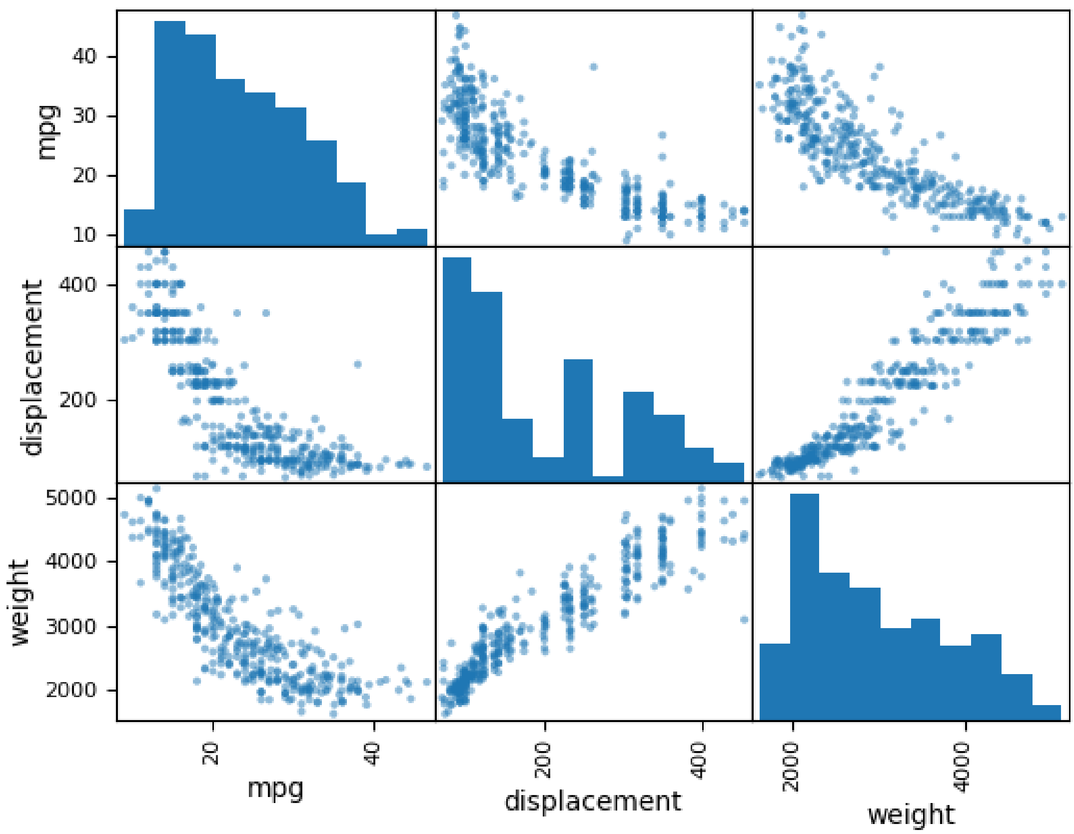
We can use the pd.plotting.scatter_matrix() function to create a scatterplot matrix to visualize all of the pairwise relationships between the columns in a data frame.

[108]:
```
pd.plotting.scatter_matrix(Auto);
```



We can also produce scatterplots for a subset of the variables.

[109]:
```
pd.plotting.scatter_matrix(Auto[['mpg',
'displacement',
'weight']]);
```



The describe() method produces a numerical summary of each column in .describe() a data frame

[110]:
```
Auto[['mpg', 'weight']].describe()
```

[110]:
```
             mpg       weight
count  392.000000   392.000000
mean    23.445918  2977.584184
std      7.805007   849.402560
min      9.000000  1613.000000
25%     17.000000  2225.250000
50%     22.750000  2803.500000
75%     29.000000  3614.750000
max     46.600000  5140.000000
```

We can also produce a summary of just a single column.

[111]:
```
Auto['cylinders'].describe()
Auto['mpg'].describe()
```

[111]:
```
count    392.000000
mean      23.445918
```

```
std       7.805007
min       9.000000
25%      17.000000
50%      22.750000
75%      29.000000
max      46.600000
Name: mpg, dtype: float64
```

[ ]:

```

```