1-ExploringTheAutomobileMpgDataset

October 17, 2021

[1]:
```
import sklearn

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import datetime
```

[2]:
```
print(sklearn.__version__)
```

```
0.24.1
```

[3]:
```
print(np.__version__)
```

```
1.20.1
```

[4]:
```
print(pd.__version__)
```

```
1.2.4
```

[5]:
```
'''
This is a dataset that contains a number of different automobile features,␣
 ↪which we use to predict how many
miles that automobile runs per gallon of fuel.
'''
automobile_df=pd.read_csv('data/auto-mpg.csv')
```

[6]:
```
'''
 If you want to view a sample of records in your data frame so that you can␣
 ↪explore the dataset,
 you can call the df.sample function. The parameter 5 indicates that five␣
 ↪records should be displayed.
 And here are five records chosen at random from our dataset.
'''
automobile_df.sample(5)
```

[6]:
```
      mpg  cylinders  displacement horsepower  weight  acceleration  \
247  39.4          4          85.0         70    2070          18.6
74   13.0          8         302.0        140    4294          16.0
233  29.0          4          97.0         78    1940          14.5
327  36.4          5         121.0         67    2950          19.9
129  31.0          4          79.0         67    1950          19.0

     model year  origin                    car name
247          78       3             datsun b210 gx
74           72       1      ford gran torino (sw)
233          77       2  volkswagen rabbit custom
327          80       2        audi 5000s (diesel)
129          74       3                datsun b210
```

[7]:
```
'''
The columns at the very right make up the features of our machine learning model.

The regression models that we're going to build will use these columns in order to make predictions
about the miles per gallon for that car.

There are features such as the number of cylinders the car has, the displacement of the car from the bottom,
the horsepower, the weight, the acceleration, model, year, the origin of the car, and the name of the car.

The first column off to the left, the mpg column, gives us the miles per gallon for that particular car,
and this is what we'll try and predict using regression.
'''
automobile_df.sample(5)
```

[7]:
```
      mpg  cylinders  displacement horsepower  weight  acceleration  \
131  32.0          4          71.0         65    1836          21.0
121  15.0          8         318.0        150    3399          11.0
318  29.8          4         134.0         90    2711          15.5
204  32.0          4          85.0         70    1990          17.0
238  33.5          4          98.0         83    2075          15.9

     model year  origin                car name
131          74       3     toyota corolla 1200
121          73       1       dodge dart custom
318          80       3  toyota corona liftback
204          76       3            datsun b-210
238          77       1          dodge colt m/m
```

[8]:

```
'''

The shape variable for any dataset gives us how many records are in the dataset␣
 ↪and how many columns.
So we have 398 records and 9 columns of data.


These 9 columns include 8 columns of features and 1 column that forms our␣
 ↪machine learning target,
the value we are trying to predict, the mpg.
'''
automobile_df.shape
```

[8]:

```
(398, 9)
```

[9]:

```
'''

Now, datasets that we work with in the real world often contain missing fields␣
 ↪or values, and these records need to be handled and cleaned in some way.
This is part of the data wrangling or preprocessing that will apply to our data.


Now this particular dataset contains question marks(?) in place of missing␣
 ↪fields;
we'll replace all of those question marks with NaNs, or not a numbers.
Call the automobile_df.replace function in order to perform this replacement.
'''

automobile_df=automobile_df.replace("?",np.nan)
```

[10]:

```
'''

And once you have NaNs in place of missing values, it's very easy to clean your␣
 ↪data frame.
The drop any function on your pandas DataFrame will simply drop all of those␣
 ↪records which have any fields missing.
'''

automobile_df=automobile_df.dropna()
```

[11]:

```
'''
And if you take a look at the shape of your data frame now, you see that we␣
 ↪have 392 records.
We originally had 398 records, and now it's 392.
6 records had missing fields, they were dropped.
'''
```

```
automobile_df.shape
```

[11]:

```
(392, 9)
```

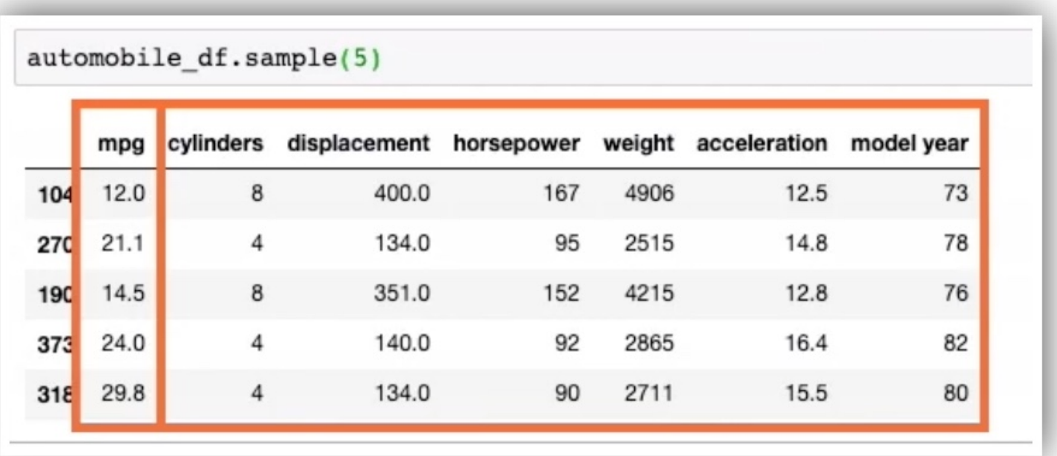
[12]:

```
'''
While we are building up the features for our linear regression model,
it's pretty clear that the origin of the car and the name of the car has no␣
 ↪impact on its mileage.
This is something that we can determine just by a cursory look at the columns␣
 ↪in our data frame,
so go ahead and drop the origin and car name columns in place.

These features, we know by using our common sense and logic, have no predictive␣
 ↪powers.
'''
automobile_df.drop(['origin','car name'],axis=1,inplace=True)
```

[13]:

```
'''

  I'm going to call automobile_df.sample to sample five records from our data␣
 ↪frames.
  And here are the features that we're going to work with: cylinders,␣
 ↪displacement, horsepower, weight,
  acceleration, and model year, and the miles per gallon is our target, what␣
 ↪you're going to try and predict.
'''
automobile_df.sample(5)
from IPython.display import Image
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
 ↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_01-21-45.jpg')
```

[13]:



```
automobile_df.sample(5)
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year
104	12.0	8	400.0	167	4906	12.5	73
270	21.1	4	134.0	95	2515	14.8	78
190	14.5	8	351.0	152	4215	12.8	76
373	24.0	4	140.0	92	2865	16.4	82
318	29.8	4	134.0	90	2711	15.5	80

[14]:

```
'''

 Now this dataset is from the '90s, and you can see that all of the model years␣
 ↪are basically 1973, 78, 82, and so on.
 Now the model year by itself is just an object. Let's make this useful by␣
 ↪converting this to be the age of the car.

 It's quite possible that we don't know for sure that the age of the car might␣
 ↪have some impact on its mileage.
 Before we get to the age, let's convert the year to its full form, 1973, 1980,␣
 ↪and so on,

 so I'm going to prepend the string 19 to the model year. So 19 + model year as␣
 ↪string,
 will give us the resultant model year.

 Assign this new format to the model year column and let's sample our data␣
 ↪frame and take a look at the result.
 The model year now has the full year, 1982, 1972, and so on.
'''
automobile_df['model year'] = '19' + automobile_df['model year'].astype(str)
```

[15]:

```
'''

 Assign this new format to the model year column and let's sample our data␣
 ↪frame and take a look at the result.
 The model year now has the full year, 1982, 1972, and so on.



 Now with this, we can calculate how old this particular car is.
'''
automobile_df.sample(5)
```

[15]:

```
      mpg  cylinders  displacement horsepower  weight  acceleration model year
108  20.0          4          97.0         88    2279          19.0       1973
222  17.0          8         260.0        110    4060          19.0       1977
329  44.6          4          91.0         67    1850          13.8       1980
129  31.0          4          79.0         67    1950          19.0       1974
191  22.0          6         225.0        100    3233          15.4       1976
```

[16]:

```
'''
 You can choose any reference date to calculate the age, as long as it's later␣
 ↪than the last year that the
 car was made.
 In order to keep things simple, we'll calculate each field by subtracting from␣
 ↪the current year.

 I'll use the datetime library to access the current year we're at; this year␣
 ↪will be in numeric form.

 And I'll convert the data in the model year column to numeric form by calling␣
 ↪pd.to_numeric.

 The result will be a number that will represent the age of a particular car.

'''


automobile_df['age']=datetime.datetime.now().year-pd.
 ↪to_numeric(automobile_df['model year'])
```

[17]:

```
'''
 Go ahead and drop the original model year field, we no longer needed because␣
 ↪we have the age column.
'''
automobile_df.drop(['model year'], axis=1, inplace=True)
```

[18]:

```
'''
 Let's view a sample of this data frame.
 Once again, you can see we now have each column which tells you how old this␣
 ↪particular car is.

 The absolute values for these ages don't really matter so much.
 It is their relative values that are more significant.
 If a car is older than another, it's possible that its mileage goes down.
'''


automobile_df.sample(5)
```

[18]:

```
      mpg  cylinders  displacement horsepower  weight  acceleration  age
252  19.2          6         231.0        105    3535          19.2   43
104  12.0          8         400.0        167    4906          12.5   48
72   15.0          8         304.0        150    3892          12.5   49
267  27.5          4         134.0         95    2560          14.2   43
8    14.0          8         455.0        225    4425          10.0   51
```

[19]:

```
'''


If you're building and training a machine learning model, all of the inputs to␣
 ↪your model need to be numeric.
```

```
Take a look at the data types of the different columns.
You'll find that all of them are numeric except for one, that is the horsepower␣
 ↪column.

The horsepower is a numeric field, but its data type in our data frame is␣
 ↪object.
We need to fix this. This is very easily done using pandas.






'''
automobile_df.dtypes
```

[19]:

```
mpg             float64
cylinders         int64
displacement    float64
horsepower       object
weight            int64
acceleration    float64
age               int64
dtype: object
```

[20]:

```
'''
Simply call pd.to_numeric to convert horsepower to a numeric field and assign␣
 ↪it to the horsepower column once again.

'''
automobile_df['horsepower']=pd.
 ↪to_numeric(automobile_df['horsepower'],errors='coerce')
```

[21]:

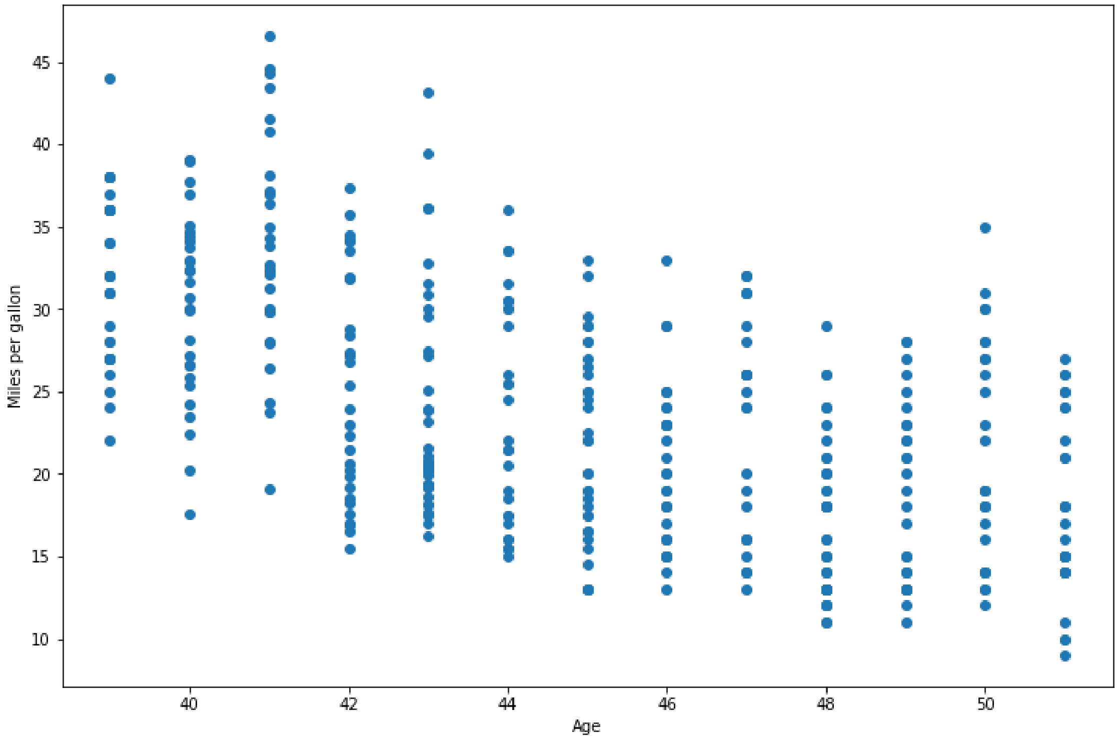
```
'''
Let's now call describe on our dataset in order to get a few statistical bits␣
 ↪of information about all of our
numerical features.

You can see that all of the features in our dataset are now numeric.

We have mean value, standard deviations, and the different percentiles␣
 ↪displayed here.

The describe function in pandas is an easy way for you to get a quick feel for␣
 ↪your numeric data.
'''

```

```
automobile_df.describe()
```

```
[21]:               mpg   cylinders  displacement  horsepower       weight  \
      count  392.000000  392.000000    392.000000  392.000000   392.000000
      mean    23.445918    5.471939    194.411990  104.469388  2977.584184
      std      7.805007    1.705783    104.644004   38.491160   849.402560
      min      9.000000    3.000000     68.000000   46.000000  1613.000000
      25%     17.000000    4.000000    105.000000   75.000000  2225.250000
      50%     22.750000    4.000000    151.000000   93.500000  2803.500000
      75%     29.000000    8.000000    275.750000  126.000000  3614.750000
      max     46.600000    8.000000    455.000000  230.000000  5140.000000

             acceleration         age
      count    392.000000  392.000000
      mean      15.541327   45.020408
      std        2.758864    3.683737
      min        8.000000   39.000000
      25%       13.775000   42.000000
      50%       15.500000   45.000000
      75%       17.025000   48.000000
      max       24.800000   51.000000
```

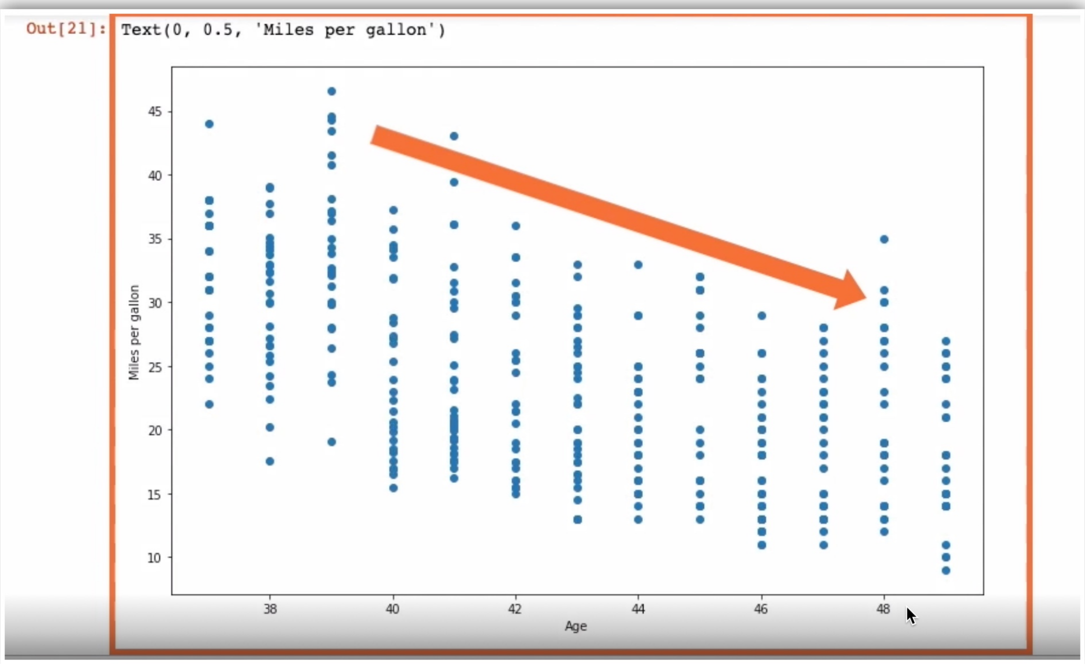
```
[22]: '''
      Understanding the features of our dataset and what we're trying to predict is␣
       ↪the first step.
      The next step is to explore the data using visualizations.

      I'm going to use Matplotlib to plot a few scatter plots in order to understand␣
       ↪the
      pairwise relationships that exists in my data.


       here I'm going to plot age versus the automobile's miles per gallon.
       We thought it might be possible that the older car is, the lower its mileage.
       Let's see if that's true using our visualization.
      '''

      fig,ax=plt.subplots(figsize=(12,8))
      plt.scatter(automobile_df['age'],automobile_df['mpg'])
      plt.xlabel('Age')
      plt.ylabel('Miles per gallon')
```

```
[22]: Text(0, 0.5, 'Miles per gallon')
```



[23]:
```
'''
And you can see that there is a definite downward trend here.
Now this doesn't necessarily mean that a relationship does exist that needs␣
 ↪more statistical analysis,
but this visualization seems to tell us that older cars have lower mileage.

'''
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
 ↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-20-04.jpg')
```

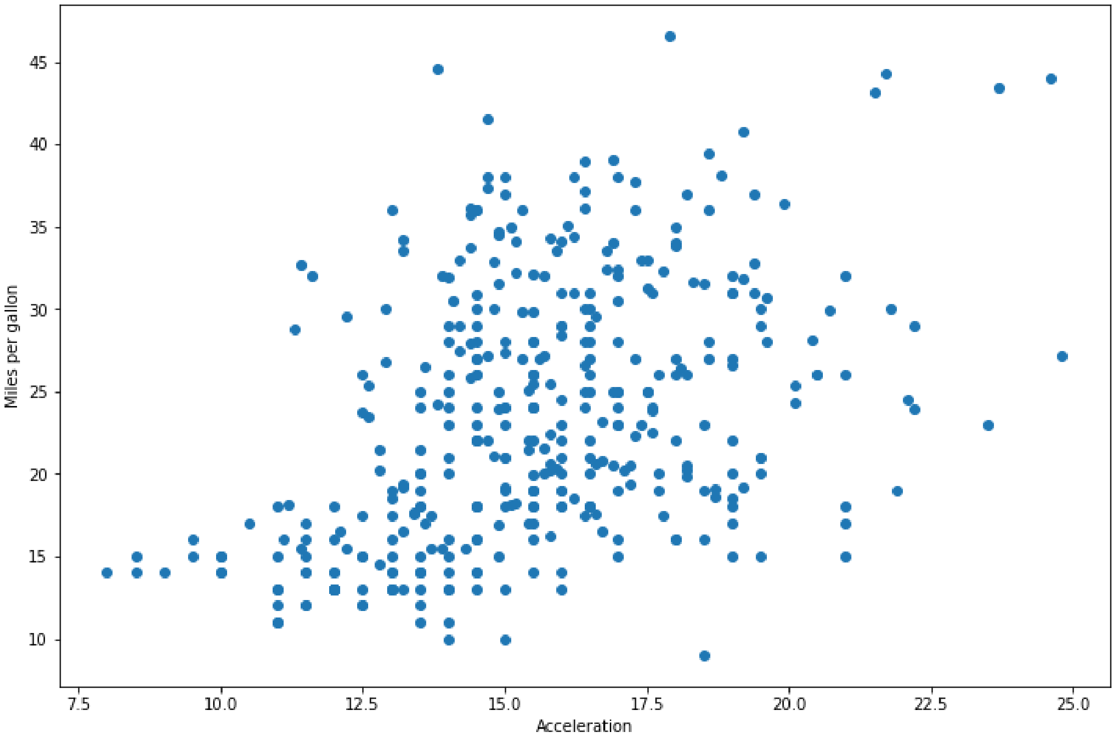
[23]:



```
Out[21]: Text(0, 0.5, 'Miles per gallon')
```

```
[24]: fig,ax=plt.subplots(figsize=(12,8))
      plt.scatter(automobile_df['acceleration'],automobile_df['mpg'])
      plt.xlabel('Acceleration')
      plt.ylabel('Miles per gallon')
```

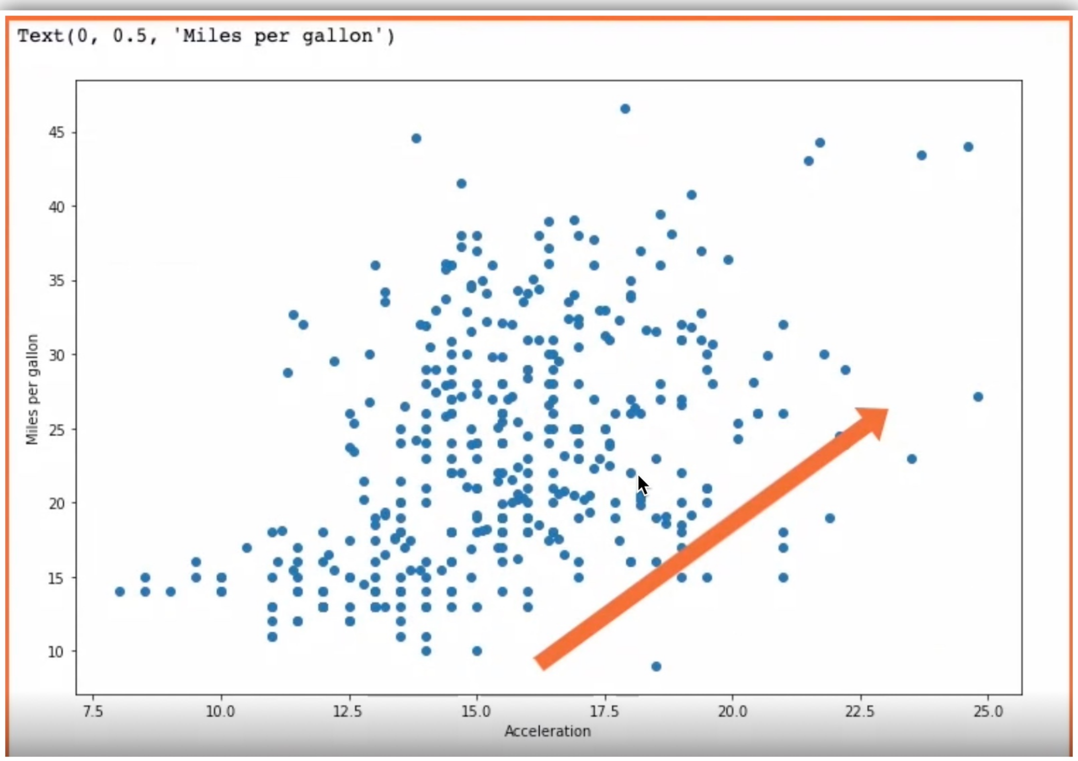
```
[24]: Text(0, 0.5, 'Miles per gallon')
```



[25]:

```
'''

Let's plot another scatter plot here.
This time we'll try and see whether the acceleration of a particular car has␣
↪any impact on mileage.
Here is our resulting scatter plot, and you can see with acceleration on the x␣
↪axis and miles per gallon
on the y axis, there's a definite upward slope to the scatter plot.

So maybe there is a relationship here.
'''
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-28-30.jpg')
```

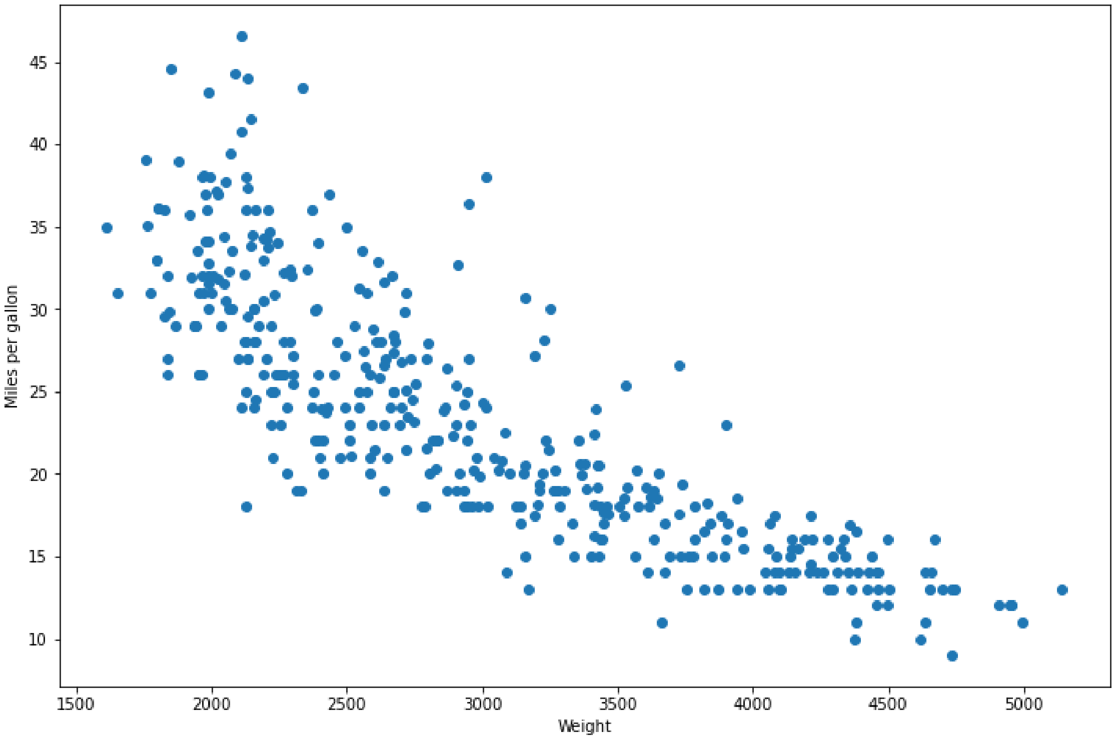
[25]:



```
Text(0, 0.5, 'Miles per gallon')
```

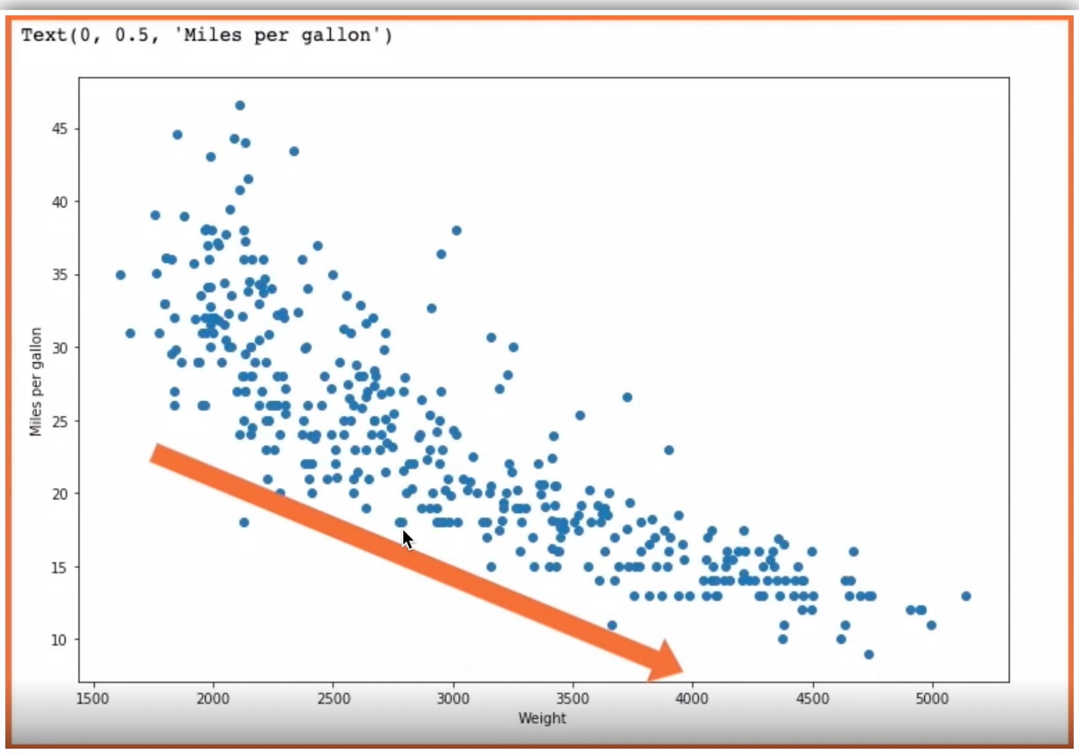
```
[26]: '''
I'm curious about another one of our input features, that is the weight of the␣
 ↪car.
Does the weight of the automobile have any significant impact on its mileage?
Maybe this scatter plot will give us some information.
And yes, definitely there is a downward trend here.
It seems like greater the weight of the car, lower its mileage, which makes␣
 ↪sense to us intuitively.
'''
fig,ax=plt.subplots(figsize=(12,8))
plt.scatter(automobile_df['weight'],automobile_df['mpg'])
plt.xlabel('Weight')
plt.ylabel('Miles per gallon')
```

```
[26]: Text(0, 0.5, 'Miles per gallon')
```



```
[27]: Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
      ↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-31-31.jpg')
```

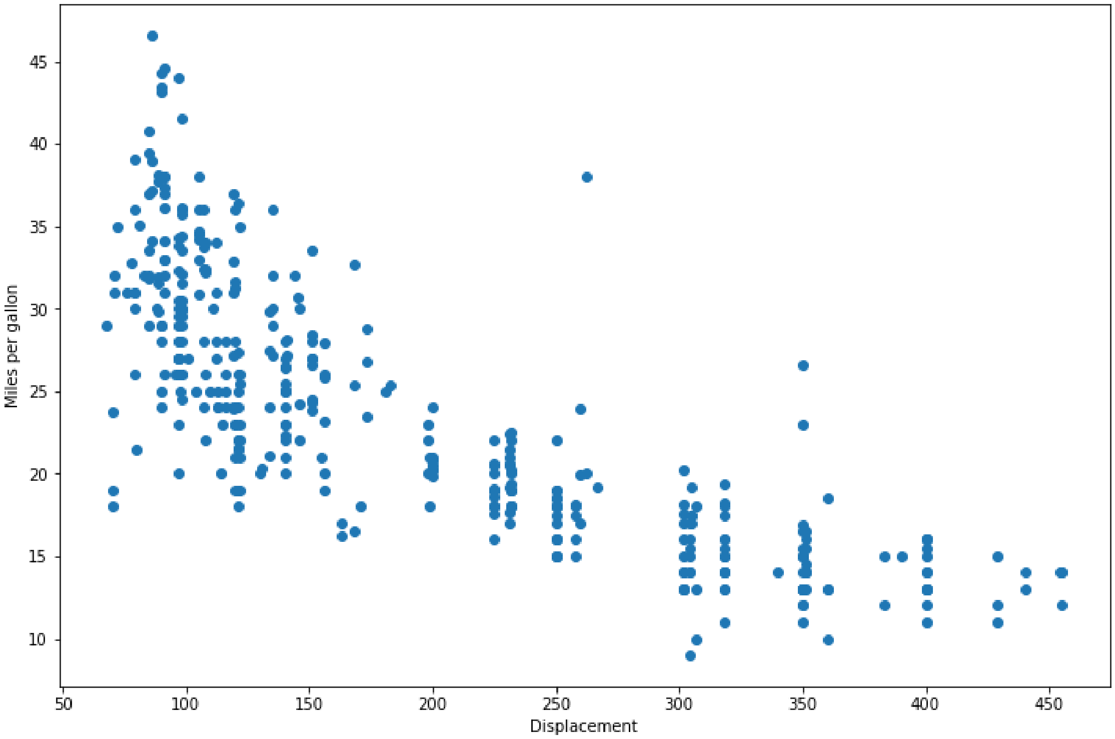
[27]:



```
Text(0, 0.5, 'Miles per gallon')
```

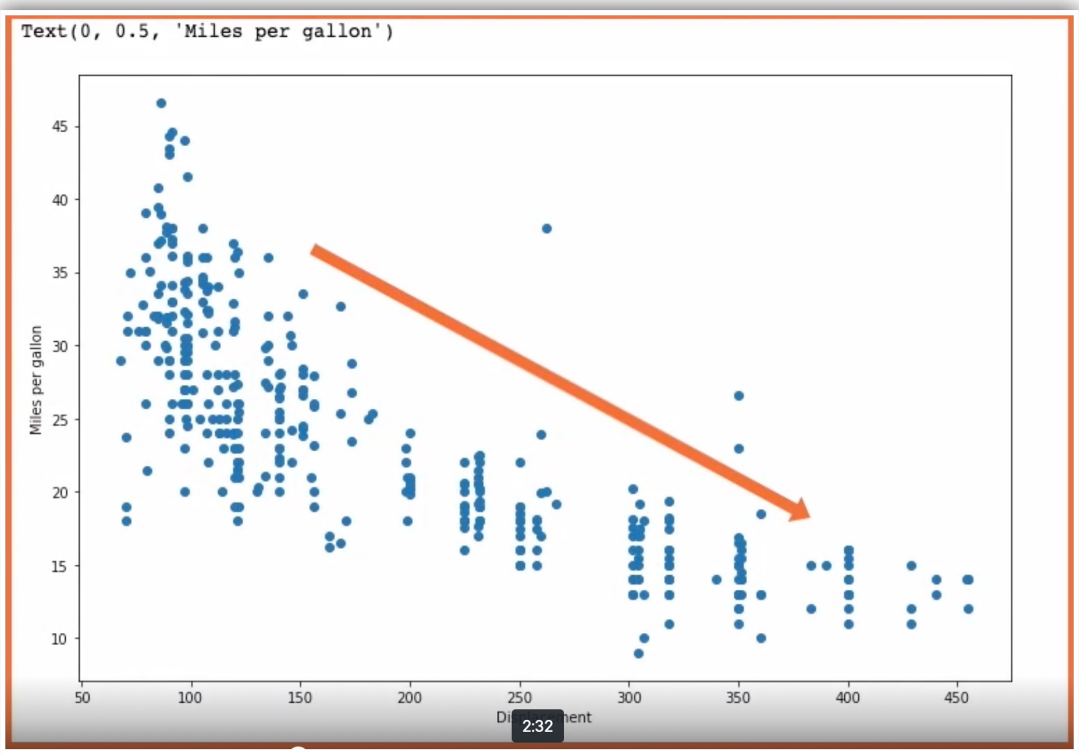
[28]:
```
'''

What about how the car is positioned relative to the ground, the displacement of the car versus mileage,
is there any relationship?

And once again, the visualization seems to say yes.
It seems like greater the displacement of the car off the ground, lower the miles per gallon it travels.
'''
fig,ax=plt.subplots(figsize=(12,8))
plt.scatter(automobile_df['displacement'],automobile_df['mpg'])
plt.xlabel('Displacement')
plt.ylabel('Miles per gallon')
```

[28]:
```
Text(0, 0.5, 'Miles per gallon')
```



[29]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-33-37.jpg')
```

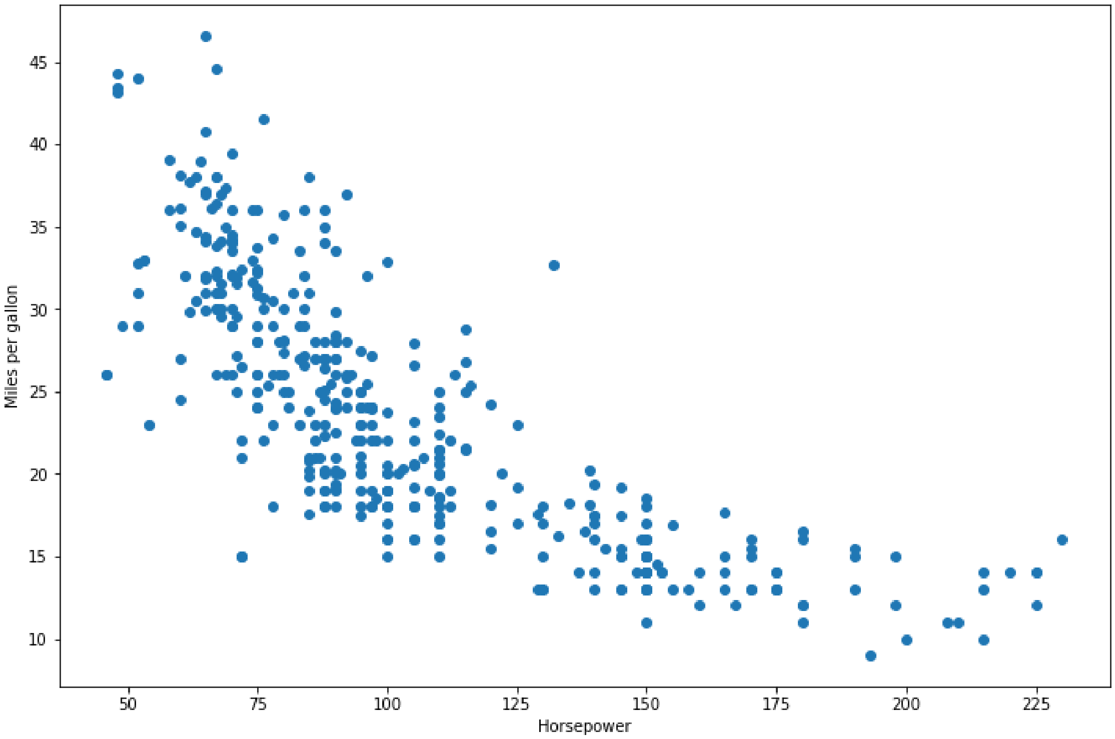
[29]:



```
Text(0, 0.5, 'Miles per gallon')
```

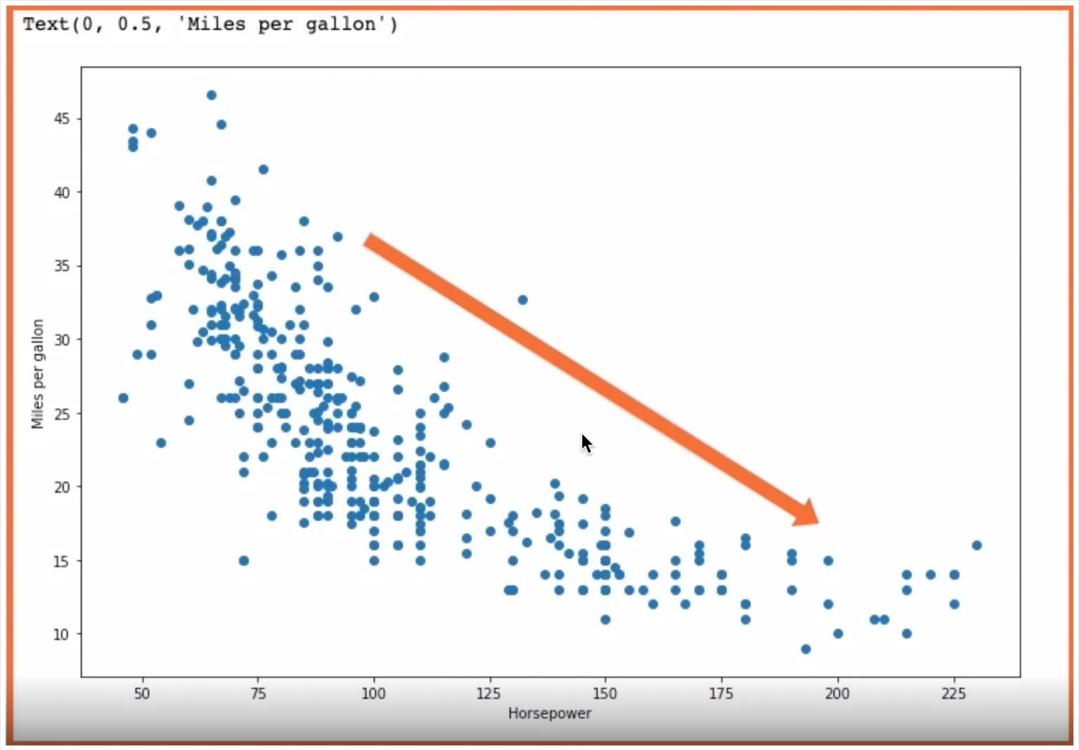
```
[30]: '''

      This pairwise exploration of variables really helps us cement our understanding␣
       ↪of the underlying dataset.
      What about horsepower, does it affect the miles per gallon?
      Yes, indeed, it does.
      '''
      fig,ax=plt.subplots(figsize=(12,8))
      plt.scatter(automobile_df['horsepower'],automobile_df['mpg'])
      plt.xlabel('Horsepower')
      plt.ylabel('Miles per gallon')
```

```
[30]: Text(0, 0.5, 'Miles per gallon')
```



[31]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-35-22.jpg')
```

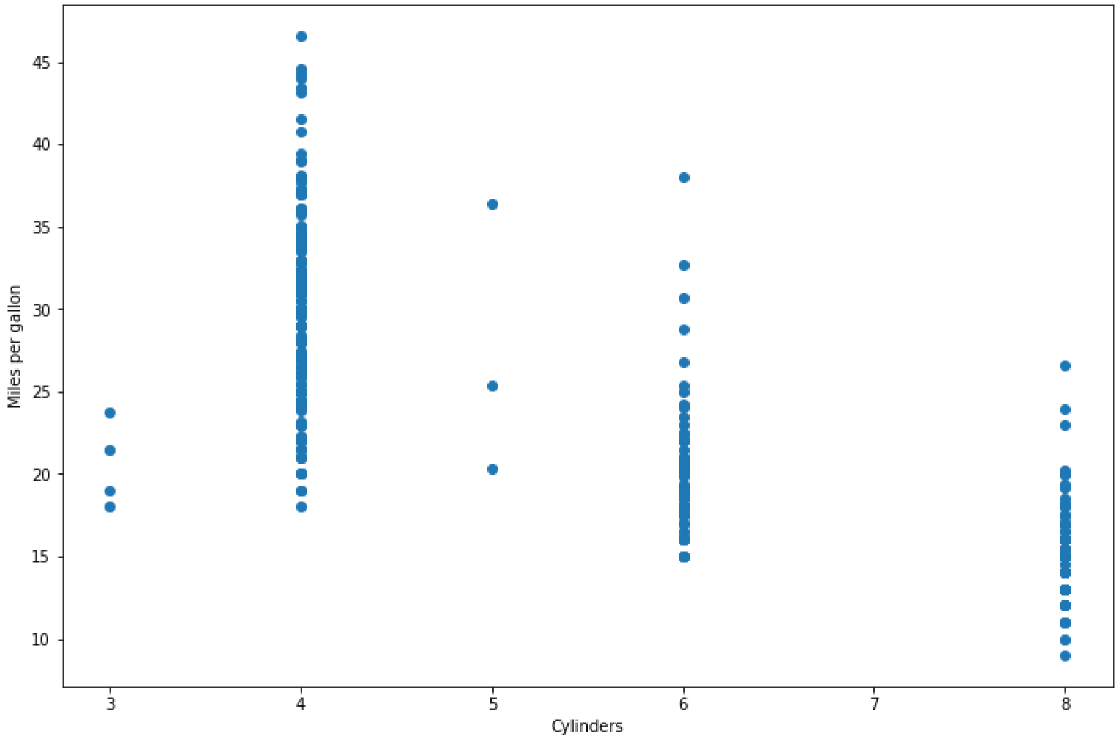
[31]:



```
Text(0, 0.5, 'Miles per gallon')
```

```
[32]: '''
      Let's consider one last visualization here, cylinders versus mpg.

      And this scatter plot definitely seems to be a little harder to pass as␣
       ↪compared with others.
      Cars with four cylinders overall seem to have the best miles per gallon.

      When you train your machine learning model, you feed it features that you think␣
       ↪are significant.
      '''
      fig, ax = plt.subplots(figsize=(12, 8))

      plt.scatter(automobile_df['cylinders'], automobile_df['mpg'])

      plt.xlabel('Cylinders')
      plt.ylabel('Miles per gallon')
```

```
[32]: Text(0, 0.5, 'Miles per gallon')
```



[33]:
```
'''
Now it's quite possible that your features themselves have interrelationships or correlations with one another.

Correlations is a statistical measure that tells you whether and how strongly pairs of variables are related.

Data frames offer this nifty little core function that will list out pairwise correlations between every pair
of variables in your dataset.

Correlation values are floating point numbers between -1 and 1.

1 implies a perfect positive correlation between two variables.

You can see here that every variable is perfectly positively correlated with itself.

Positive correlation implies that two variables move together in the same direction.
A negative correlation implies that the two variables move in different directions.
```

```
 The raw correlation numbers tell us that acceleration is positively correlated␣
 ↪with the mileage per gallon.
 You can also see that weight is negatively correlated with miles per gallon.

 In fact, weight is highly negatively correlated, - 0.83.
'''
automobile_corr=automobile_df.corr()
automobile_corr
```

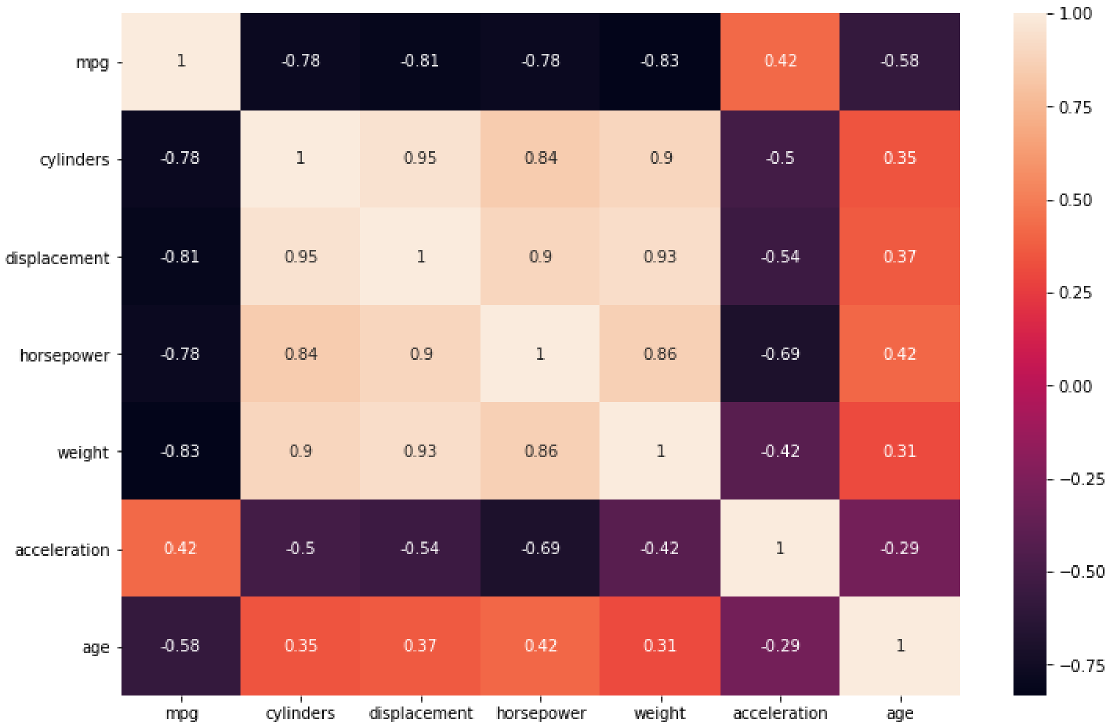
[33]:

```
                   mpg  cylinders  displacement  horsepower    weight  \
mpg           1.000000  -0.777618     -0.805127   -0.778427 -0.832244
cylinders    -0.777618   1.000000      0.950823    0.842983  0.897527
displacement -0.805127   0.950823      1.000000    0.897257  0.932994
horsepower   -0.778427   0.842983      0.897257    1.000000  0.864538
weight       -0.832244   0.897527      0.932994    0.864538  1.000000
acceleration  0.423329  -0.504683     -0.543800   -0.689196 -0.416839
age          -0.580541   0.345647      0.369855    0.416361  0.309120

              acceleration       age
mpg               0.423329 -0.580541
cylinders        -0.504683  0.345647
displacement     -0.543800  0.369855
horsepower       -0.689196  0.416361
weight           -0.416839  0.309120
acceleration      1.000000 -0.290316
age              -0.290316  1.000000
```

[34]:

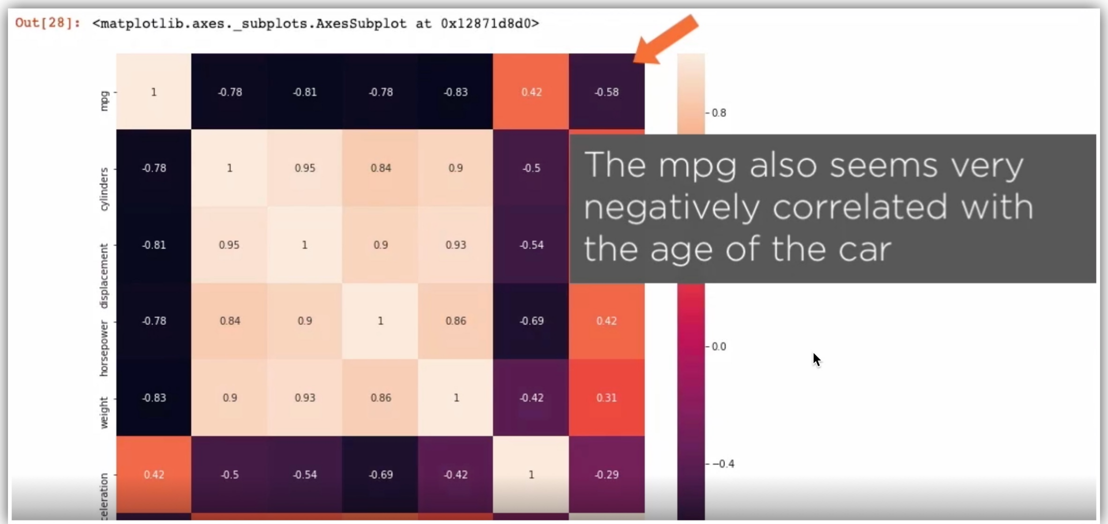
```
'''
 Viewing correlations with the raw numbers is hard, which is why we use a␣
 ↪visualization technique
 called the heatmap in order to view correlations in our data.

 When we pass in annot is equal to True to the heatmap in Seaborn, it will␣
 ↪print out the actual
 correlation number along with the color-coded grid.

 And this is what a heatmap looks like. Lighter colors tending towards cream␣
 ↪denote positive correlation,
 darker colors tending towards black denote negative correlation.

 This value of - 0.58 is in the mpg row and the age column.
 This shows that the miles per gallon seems very negatively correlated with the␣
 ↪age of the car.
'''
fig, ax = plt.subplots(figsize=(12, 8))
sns.heatmap(automobile_corr,annot=True)
```

[34]: <AxesSubplot:>



[35]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-49-07.jpg')
```

[35]:



```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x12871d8d0>
```

The mpg also seems very negatively correlated with the age of the car

mpg 1 -0.78 -0.81 -0.78 -0.83 0.42 -0.58
cylinders -0.78 1 0.95 0.84 0.9 -0.5
displacement -0.81 0.95 1 0.9 0.93 -0.54
horsepower -0.78 0.84 0.9 1 0.86 -0.69 0.42
weight -0.83 0.9 0.93 0.86 1 -0.42 0.31
celeration 0.42 -0.5 -0.54 -0.69 -0.42 1 -0.29
0.8
0.0
−0.4

[36]:

```
'''

 We've done a bunch of preprocessing on our dataset, we've also viewed the␣
 ↪relationships in our data.

 Now let's take this updated data frame and shuffle it so that we feed and␣
 ↪shuffle data to our
 machine learning models.

 I'll use the sample function on our data frame to shuffle my dataset,
 I'm keeping all of the original samples, frac is equal to 1, and I'm resetting␣
 ↪the indices.

 Drop is equal to True, passed into reset_index will drop the original index␣
 ↪values that existed in our data frame.

 Here is our shuffled and cleaned up data frame.

 Now, shuffling data before feeding into an ML model is important so that our␣
 ↪model doesn't
 inadvertently pick up patterns that do not exist.


 so it's important that your data be shuffled.

 model.
'''

automobile_df = automobile_df.sample(frac=1).reset_index(drop=True)

automobile_df.head()
```

[36]:

```
    mpg  cylinders  displacement  horsepower  weight  acceleration  age
0  19.0          4         121.0         112    2868          15.5   48
1  46.6          4          86.0          65    2110          17.9   41
2  25.0          4         140.0          75    2542          17.0   47
3  15.0          6         258.0         110    3730          19.0   46
4  31.0          4          91.0          68    1970          17.6   39
```

[37]:

```
'''
I'm going to save my shuffled and cleaned up dataset to a new CSV file,␣
 ↪auto-mpg- processed.csv.
This is the CSV file that I'll use to build my regression models.
'''
automobile_df.to_csv('data/auto-mpg-processed.csv', index=False)
```

```
[38]: '''
      Here is what the dataset looks like. The features are cylinders, displacement,␣
       ↪horsepower, weight,
      acceleration, and age, and we'll use these features in a linear regression␣
       ↪model in order
      to predict the mileage of the car.
      '''
      automobile_df=pd.read_csv('data/auto-mpg-processed.csv')
      automobile_df.sample(5)
```

```
[38]:       mpg  cylinders  displacement  horsepower  weight  acceleration  age
      114  18.0          3          70.0          90    2124          13.5   48
      321  15.0          8         390.0         190    3850           8.5   51
      16   32.9          4         119.0         100    2615          14.8   40
      196  20.0          6         232.0         100    2914          16.0   46
      79   13.0          8         400.0         190    4422          12.5   49
```

```
[39]: '''
      When you are building and training a machine learning model,
      how do you know that the model that you've built is a good one?

      Well, you'll evaluate your model on test data.
      Test data are basically a holdout from your training dataset.
      These are instances your model hasn't seen before, and you'll see how well your␣
       ↪model predicts
      using those instances.

      Scikit-learn offers a useful train_test_split function in order to split your␣
       ↪data into training and test sets.
      '''

      from sklearn.model_selection import train_test_split
```

```
[40]: '''
       Let's first perform a linear regression using just one feature;
       that is, we'll see how the horsepower of a particular car can be used to␣
       ↪predict its mileage.

       So your X variable is going to be just horsepower, and the Y variable is going␣
       ↪to be MPG.

       The Y variables are what we'll try and predict using our machine learning␣
       ↪model.
      '''
      X=automobile_df[['horsepower']]
      Y=automobile_df['mpg']
```

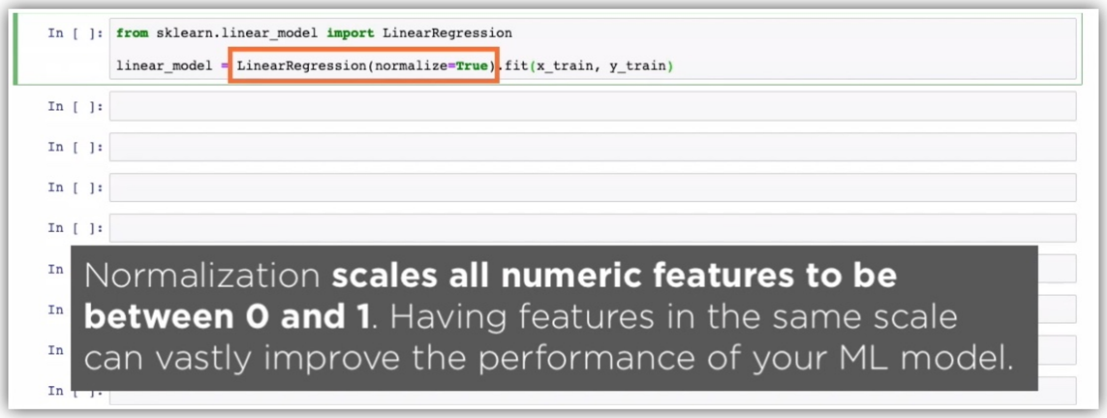
[41]:
```
'''
Let's split our data into training and test sets.

It's pretty common to use 20% of your data as test data used to measure and␣
↪evaluate the model that you build
using your training data, which is 80% of your dataset.

We've already shuffled our dataset earlier;
however, you should know that the train test split function in scikit-learn␣
↪automatically shuffles
your data as well.
'''
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
```

[42]:
```
'''
Let's take a look at a sample from our training dataset.
We've used just one feature here, we have just one column for horsepower.
'''
x_train.sample(5)
```

[42]:
```
     horsepower
252         150
81           78
122         165
194          96
389         110
```

[43]:
```
'''
Scikit-learn offers us high-level estimator objects that we can use to build␣
↪and train our machine learning model.

In order to perform linear regression, we'll use the LinearRegression estimator␣
↪object.

Import this object and let's instantiate a linear model.
'''


from sklearn.linear_model import LinearRegression
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_21-13-03.jpg')
```

[43]:

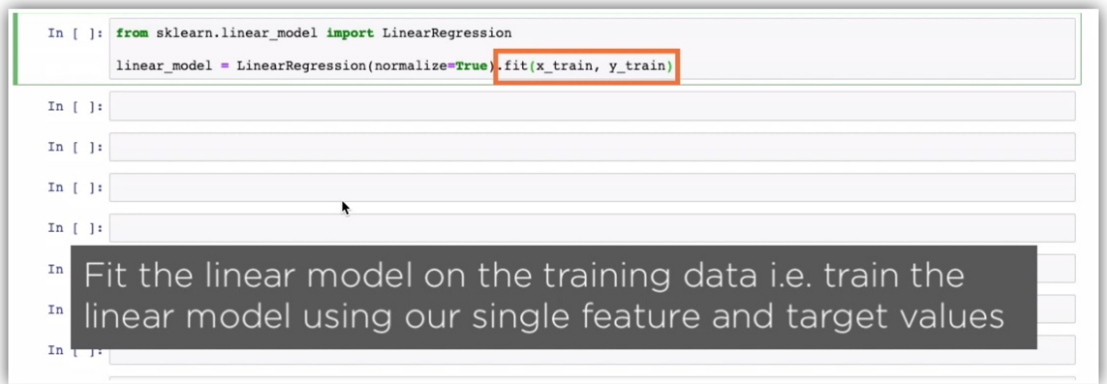


```
In [ ]: from sklearn.linear_model import LinearRegression

        linear_model = LinearRegression(normalize=True).fit(x_train, y_train)
```

Normalization **scales all numeric features to be between 0 and 1**. Having features in the same scale can vastly improve the performance of your ML model.

```
[44]: Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
       ↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_21-16-23.jpg')
```

[44]:



```
In [ ]: from sklearn.linear_model import LinearRegression

        linear_model = LinearRegression(normalize=True).fit(x_train, y_train)
```

Fit the linear model on the training data i.e. train the linear model using our single feature and target values

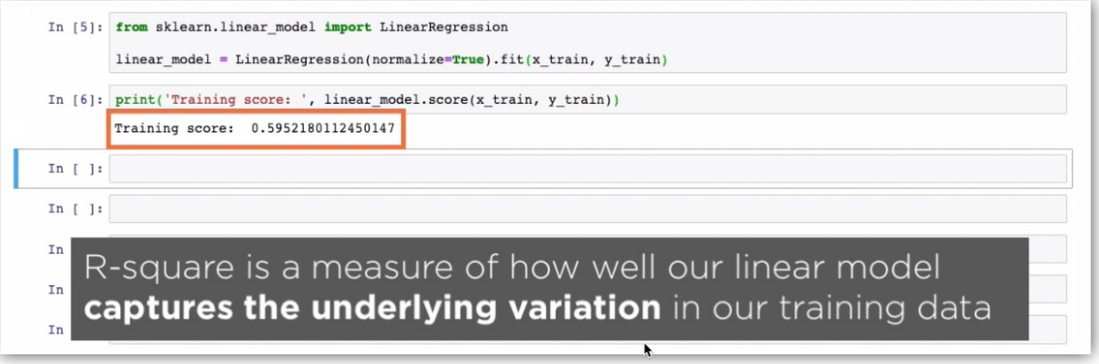
```
[45]: '''
      The features that you feed into your machine learning model are numeric and␣
       ↪typically when you're working with
      numbers, your ML model performs far better if you normalize your data.

      If you pass in the parameter normalize is equal to True to your␣
       ↪LinearRegression estimator object,
      this will scale all your numeric features to be between 0 and 1.

      For a simple model, such as the ones that we'll build in this particular␣
       ↪course,
      you'll find that normalizing your dataset may or may not make a difference,
      but for more complex models in the real world, normalizing your numeric data is␣
       ↪a standard preprocessing
```

```
technique for machine learning.

The fit function on an estimator object is what you call to train your machine␣
↪learning model.

This fits the linear model on the training data, so it trains the linear model␣
↪using our single feature,
the horsepower, and it uses the target values to adjust the model parameters.



'''
linear_model = LinearRegression(normalize=True).fit(x_train, y_train)
```

[46]:

```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_21-22-19.jpg')
```

[46]:



```
In [5]: from sklearn.linear_model import LinearRegression

        linear_model = LinearRegression(normalize=True).fit(x_train, y_train)

In [6]: print('Training score: ', linear_model.score(x_train, y_train))

        Training score:  0.5952180112450147

In [ ]:

In [ ]:

In

In

In
```

R-square is a measure of how well our linear model **captures the underlying variation** in our training data

[47]:

```
'''
A way to measure how well your model has performed on the training data is to␣
↪score your model using the
R squared score.

The score function on your linear regression model will return the R square␣
↪value for your training data.

As we discussed, this R square value is a measure of how well our linear model␣
↪captures the underlying
variation in our training data.

And you can see here that with just a single feature, horsepower, our model has␣
↪an R square of 60%.
It isn't great, but it isn't terrible either.

'''
```

```
print('Training score: ', linear_model.score(x_train, y_train))
```

```
Training score:  0.6040260228388256
```

[48]:

```
'''
Now that we have a fully trained model built using a single feature, let's use␣
 ↪this model for prediction.

Call linear_model.predict and pass in our test data, as in only X values are␣
 ↪the features to predict.
And here are our predictions, saved in y_pred.
'''
y_pred=linear_model.predict(x_test)
```

[49]:

```
'''
A way to objectively measure how well your linear model performed on instances␣
 ↪it
hasn't seen before is to calculate the R square score on your test data.

The sklearn.metrics namespace offers a number of useful metrics to use with␣
 ↪your ML models.

Import the r2_score function here from the sklearn.metrics namespace, and use␣
 ↪that to score how your
model performed on the test data.

Pass in the predicted values from your model, and compare them with the actual␣
 ↪values in your test data.
'''

from sklearn.metrics import r2_score
print('Testing score: ', r2_score(y_test, y_pred))
```

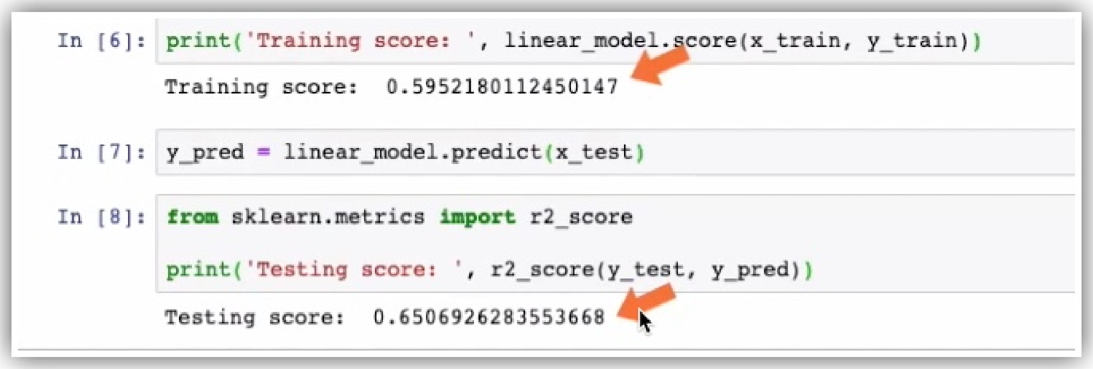
```
Testing score:  0.6134703584934424
```

[50]:

```
'''
And with just one feature, our linear regression model has an R squared score␣
 ↪of 60%.

Compare that with the R square score of the training data.
The R square on test data is better than on training data, which means that our␣
 ↪model is a good, robust model,
not overfitted on the training data.

An overfitted model is one that does well on the training data, but does poorly␣
 ↪when used for prediction or on
test data.
```

```
'''
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_21-29-24.jpg')
```

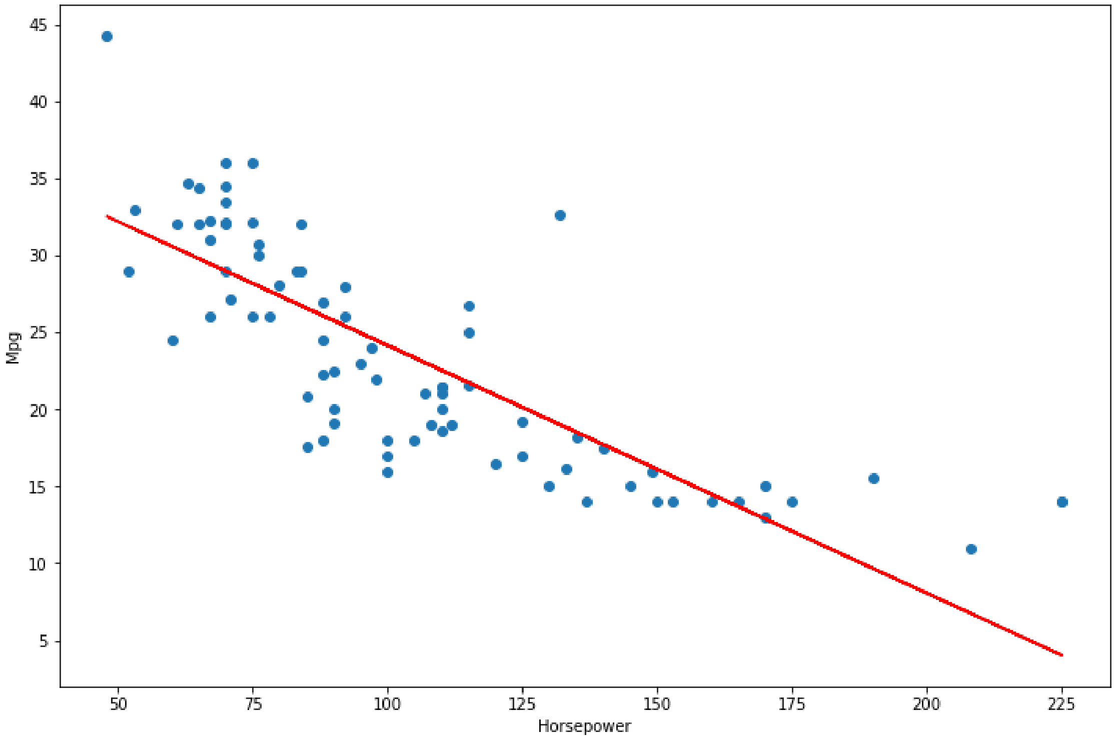
[50]:



```
In [6]: print('Training score: ', linear_model.score(x_train, y_train))

        Training score:  0.5952180112450147

In [7]: y_pred = linear_model.predict(x_test)

In [8]: from sklearn.metrics import r2_score

        print('Testing score: ', r2_score(y_test, y_pred))

        Testing score:  0.6506926283553668
```

[51]:

```
'''
Let's use a little visualization to see how well our linear model fits on the␣
↪underlying data.

I'll first plot a scatterplot of horsepower versus miles per gallon.
This scatterplot represents the test dataset and the actual Y values.

I'll then plot a line representing the horsepower and predictions from our␣
↪linear model in the red color.

And here is what the resulting visualization looks like.

The scatterplot represents the test data, the red line represents the predicted␣
↪values from our model.
This is our linear model.
'''

fig, ax = plt.subplots(figsize=(12, 8))

plt.scatter(x_test, y_test)
plt.plot(x_test, y_pred, color='r')

plt.xlabel('Horsepower')
plt.ylabel('Mpg')
plt.show()
```



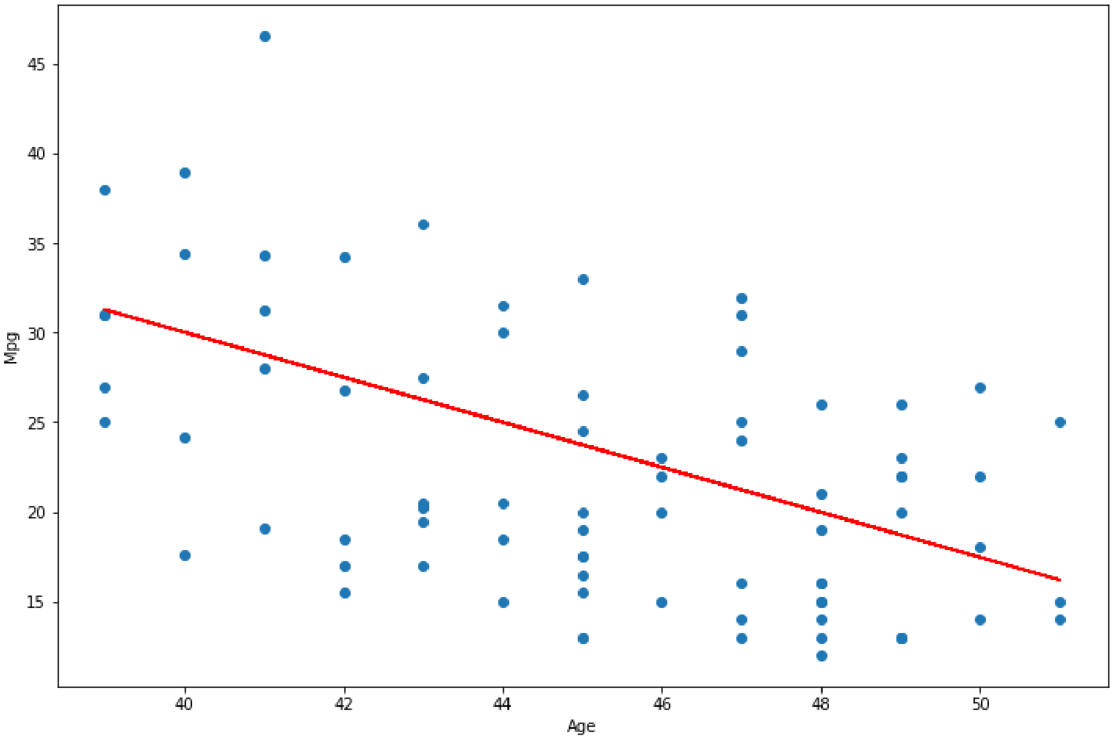
[52]:
```
'''
Let's build one more linear model.
The feature that we'll use this time to train our model is the age of the car.

The features from our X variables and our Y values are the target, what we want␣
↪to predict, miles per gallon.

Split our dataset into training and test data, initialize a LinearRegression␣
↪estimator object,
make sure you normalize your numeric features, and call fit on the training␣
↪data.

Once we have a fully trained linear regression model, print out the R square␣
↪score for this model on the
training data, use this model for prediction on the test data, and print out␣
↪the R square score on the
test data as well.

And here is how the two scores compare when we use age as our feature.
The training R square score is 36%, and the test score is 19%, so this is a␣
↪pretty poor model.
'''
X=automobile_df[['age']]
```

```
Y=automobile_df['mpg']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
linear_model = LinearRegression(normalize=True).fit(x_train, y_train)
print('Training score: ', linear_model.score(x_train, y_train))

y_pred = linear_model.predict(x_test)

print('Testing score: ', r2_score(y_test, y_pred))
```

```
Training score:  0.36112880608556863
Testing score:  0.19827232820453733
```

[53]:

```
'''
So, age by itself is not really a good predictor for the car's mileage, and␣
 ↪this will be born out using our
visualization as well.

Plot a scatter plot of X versus actual Y and X versus Y predicted, and here is␣
 ↪what the result looks like.
You can see that the line that we've drawn here really doesn't capture the␣
 ↪underlying variation in the data well,
which is why this model has a low R square score.

The points are too scattered, too far apart, the line really doesn't represent␣
 ↪them well.

'''

fig, ax = plt.subplots(figsize=(12, 8))

plt.scatter(x_test, y_test)
plt.plot(x_test, y_pred, color='r')

plt.xlabel('Age')
plt.ylabel('Mpg')
plt.show()
```



[54]:
```
'''
This time, instead of using a single feature to train our model, we'll use more␣
 ↪than one feature.
 Create our X variables that we'll use to train our model using displacement,␣
 ↪horsepower, and weight.
 We'll use these three features to predict the miles per gallon for the cars in␣
 ↪our dataset.
 MPG is our Y variable assigned to the Y data frame.
'''

X=automobile_df[['displacement','horsepower','weight']]
Y=automobile_df['mpg']
```

[55]:
```
'''
With our data all set up, let's call the train_test_split function to split␣
 ↪into training data that we'll use to build our model,
and test data that we'll use to measure our model.
'''
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2)
```

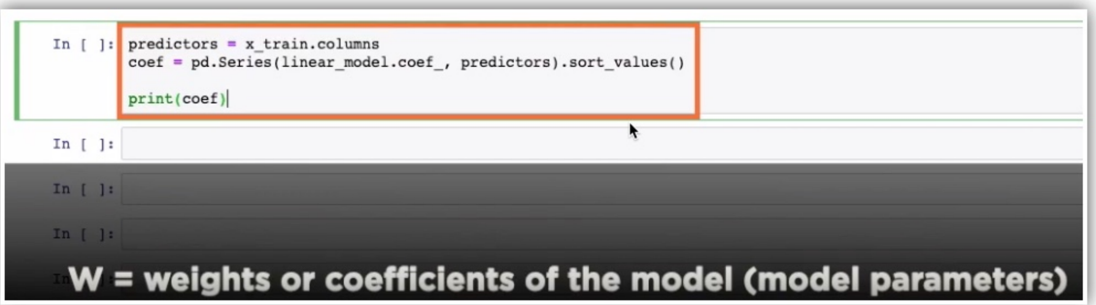
[56]:
```
'''
 We'll continue to work with the LinearRegression estimator object, and we'll␣
 ↪normalize all of the numeric features
 that we pass in to train our model.

 Call the fit function on your estimator object to start the training process,␣
 ↪and pass in the training
 data and the corresponding training Y values.
'''
linear_model=LinearRegression(normalize=True).fit(x_train,y_train)
```

[58]:
```
'''
 Once the model has completed training, call the linear_model.score function to␣
 ↪calculate the R square score on the training data.
 You can see from this R square score here that the additional features that␣
 ↪we've used to train our model have real predictive power.
 Our R square has improved, it's now 71 %.
 Earlier when we used just a single feature, horsepower, our R square was␣
 ↪around 59% on the training data, so this is a definite improvement.
'''


print("Training Score : ", linear_model.score(x_train,y_train))
```

```
Training Score :  0.7170149678642119
```

[59]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
 ↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_11-17-07.jpg')
'''
 A linear model assumes a linear relationship between your input features and␣
 ↪the output that
 you're trying to predict, and this linear relationship can be represented as Y␣
 ↪is equal to WX + B,
 where W is the weight, or the coefficients that you use to multiply your X␣
 ↪variables, the features.

 W is also referred to as the model weight or model parameters.
'''
```

[59]:



```
In [ ]: predictors = x_train.columns
        coef = pd.Series(linear_model.coef_, predictors).sort_values()

        print(coef)

In [ ]:

In [ ]:

In [ ]:
```

W = weights or coefficients of the model (model parameters)

[62]:
```
'''

 You can use the linear model instance in order to get the coefficients for␣
 ↪your X variables or the predictors.

 Get the predictors from your x_train data frame, these are the columns of your␣
 ↪data frame,
 and we'll instantiate a pandas series with a coefficient for each predictor.

 And let's print out these coefficients and see what they are.

 The coefficients of your linear model for horsepower, displacement, and weight␣
 ↪are all negative.

 This indicates that as the values for these features increase, the mileage of␣
 ↪the car tends to go down.
'''

predictors=x_train.columns
coef=pd.Series(linear_model.coef_,predictors).sort_values()
coef
```

[62]:
```
horsepower     -0.031554
displacement   -0.008993
weight         -0.005457
dtype: float64
```

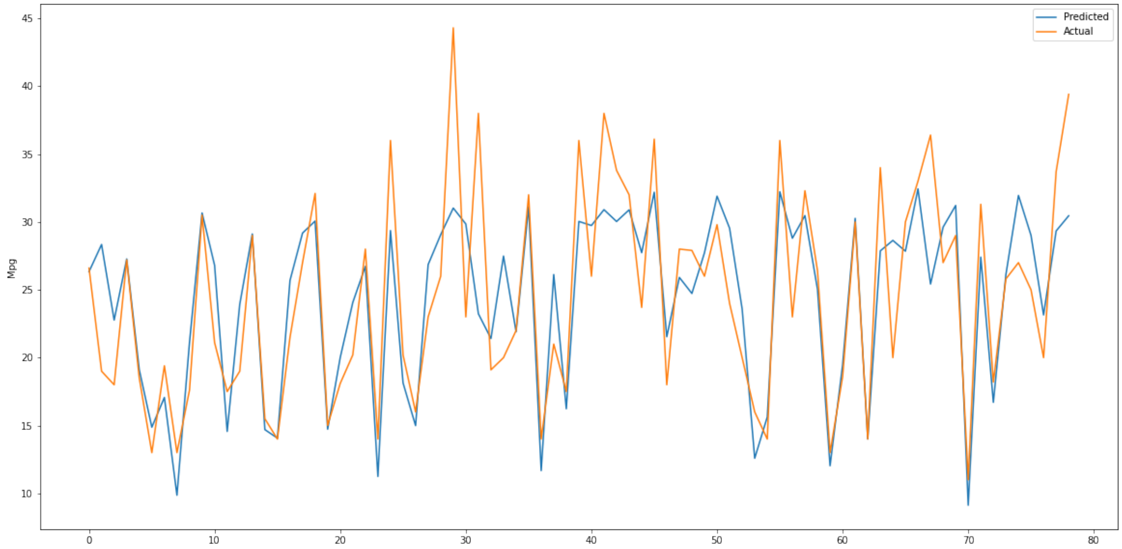
[63]:
```
'''
The R square on the training data for this model with additional features was␣
 ↪much better.
Let's use this model for prediction and store the predicted values in y_pred.
'''
y_pred=linear_model.predict(x_test)
```

[64]:
```
'''
Let's now calculate the R square score for the test data.
And you can see that there is a significant improvement here as well.

The R square score on test data is almost 76%. Once again, the R square␣
 ↪calculated on test data is better than the
R square on training data, indicating that it's a robust model.

The overall higher R square that we get with three features instead of one␣
 ↪means that this model has better predictive power.
'''
print("Testing Score : ", r2_score(y_test,y_pred))
```

```
Testing Score :  0.6562725029103171
```

[65]:

```
'''
It's always fun to visualize our results. Let's plot the predicted values␣
 ↪versus actual values from our dataset using a line chart,
and see how closely they track one another.
And here's what the result looks like. The values predicted by our model are in␣
 ↪blue, and actual values are in orange.
You can see that these two lines track each other pretty closely.
'''

plt.figure(figsize = (20,10))

plt.plot(y_pred, label='Predicted')
plt.plot(y_test.values, label='Actual')

plt.ylabel('Mpg')

plt.legend()
plt.show()
```



[67]:

```
'''
    Well, we added more features, we got a better model.
    What if we add even more features? Displacement, horsepower, and weight are␣
 ↪the features that we're using currently.

    I'm going to include acceleration, as well as the number of cylinders.
    For now, I'm going to go over these five features to train our machine␣
 ↪learning model.
```

```
    We'll instantiate a new LinearRegression estimator object and fit on this␣
 ↪new training data.
    Once this new model has been trained, let's calculate its R squared.

    Let's see what kind of a model it is. Now, the original R square that we␣
 ↪got earlier with three features was around 69%.
    Hit Shift+Enter to calculate the new R squared, and you might say wow, it's␣
 ↪73%, this is definitely a better model.

    Use the linear model to predict on our x_test dataset, save the predictions␣
 ↪in y_pred, and let's calculate the r2_score for our test data.

    The R square on test data is 60.9 %, almost as low as the R square that we␣
 ↪got when we trained a model using just a single feature, the horsepower.

    So a lesson learned here. More features do not necessarily make a better␣
 ↪model.

    What we just performed is what is sometimes called kitchen sink regression␣
 ↪where we throw all of the features that we have into our model.
    Kitchen sink regression does not necessarily perform well because all of␣
 ↪our model features may not have good predictive power.
'''



X=automobile_df[['displacement','horsepower','weight','acceleration','cylinders']]
Y=automobile_df['mpg']
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2)
linear_model=LinearRegression(normalize=True).fit(x_train,y_train)
print("Training Score : ", linear_model.score(x_train,y_train))
y_pred=linear_model.predict(x_test)
print("Testing Score : ", r2_score(y_test,y_pred))
```

```
Training Score :  0.713982761241602
Testing Score :  0.6721641982553026
```

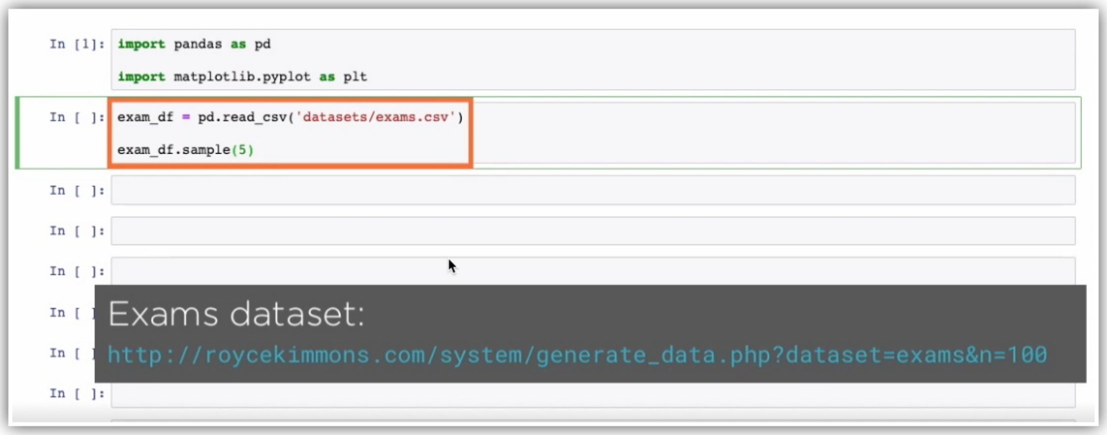
[68]:

```
'''
once again to get the coefficients of all of the features that we've included.
We get five coefficients corresponding to the five features that we used to␣
 ↪train our model.
'''
predictors=x_train.columns
coef=pd.Series(linear_model.coef_,predictors).sort_values()
coef
```

[68]:
```
cylinders      -0.350272
horsepower     -0.038871
displacement   -0.007406
weight         -0.004643
acceleration    0.041235
dtype: float64
```

[71]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-02-56.jpg')
```

[71]:



```
In [1]: import pandas as pd

        import matplotlib.pyplot as plt

In [ ]: exam_df = pd.read_csv('datasets/exams.csv')

        exam_df.sample(5)

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:
```

Exams dataset:
http://roycekimmons.com/system/generate_data.php?dataset=exams&n=100

[72]:
```
'''
 This is a dataset that contains categorical values, and we'll see how we can␣
 ↪convert these to
 numeric form so that we can use them to train our machine learning model.

 That's the dataset we're going to use, exam scores dataset.

 We know the gender of the student, the race or ethnicity he or she belongs to,␣
 ↪the parental level of education,
 whether the student has standard or subsidized lunch, and whether the student␣
 ↪has joined a test preparation course.

 You can see that these personal details are categorical, or discrete values.
 They're not numeric either, they're represented as string values in our␣
 ↪dataset.

 We also have a few features describing the scores for that student in math,␣
 ↪reading, as well as writing.
 All of these scores are out of a hundred. These are the only numeric features␣
 ↪in our dataset with continuous values.
'''
```

```
exam_df=pd.read_csv('data/exams.csv')
exam_df.sample(5)
```

[72]:

```
    gender race/ethnicity parental level of education     lunch  \
53  female        group B          associate's degree  standard
39  female        group D                some college  standard
25  female        group C            some high school  standard
30    male        group C                some college  standard
24  female        group D                 high school  standard

   test preparation course  math score  reading score  writing score
53                    none          86             91             82
39                    none          75             92             89
25               completed          29             38             43
30               completed          77             73             73
24                    none          66             69             67
```

[73]:

```
'''
The describe function on a pandas DataFrame will give us brief statistics about␣
 ↪all of the numeric values in our data frame.
This dataset has a total of 100 records for 100 students.
You can see the average scores for these students in math, reading, and writing.
You can see that math scores are a little lower than their reading and writing␣
 ↪scores.
The standard deviation of these scores, how these scores vary across students,␣
 ↪is also different.
'''
exam_df.describe()
```

[73]:

```
       math score  reading score  writing score
count  100.000000     100.000000     100.000000
mean    66.730000      69.980000      69.140000
std     15.631395      13.732642      14.886792
min     18.000000      25.000000      20.000000
25%     58.000000      61.000000      62.000000
50%     69.000000      71.500000      69.000000
75%     78.250000      80.000000      81.000000
max     96.000000      94.000000      93.000000
```

[76]:

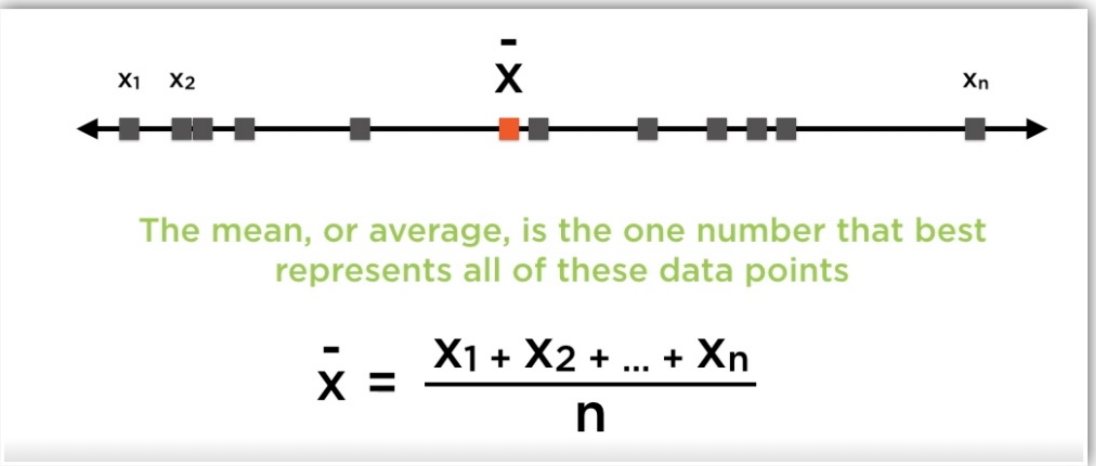
```
'''
This dataset is interesting because the data needs a lot of preprocessing␣
 ↪before we can feed it into a linear model.
And scikit-learn makes it very easy for you to preprocess data using the␣
 ↪preprocessing module from sklearn.
Go ahead and import preprocessing.
We're going to use the preprocessing.scale function to standardize all of the␣
 ↪scores in our dataset.
```

```
Standardizing a dataset means that these column values will now have 0 mean and␣
↪unit variance. We'll have a variance of 1.

Standardizing values is extremely useful because it gives you an easy way to␣
↪compare values which are part of different distributions.
Standardization is also a common preprocessing technique for machine learning␣
↪algorithms to build more robust models.
We call preprocessing.scale to standardize the math score, reading score, and␣
↪writing score of all of our students.

Standardization is done by subtracting the mean, or average, value of a column␣
↪of values from each value in that column and dividing the number by the␣
↪standard deviation of the column.
'''

from sklearn import preprocessing
exam_df[['math score']]=preprocessing.scale(exam_df[['math score']]).
↪astype('float64')
exam_df[['reading score']]=preprocessing.scale(exam_df[['reading score']]).
↪astype('float64')
exam_df[['writing score']]=preprocessing.scale(exam_df[['writing score']]).
↪astype('float64')
```

[79]:

```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-19-03.jpg')
```

[79]:



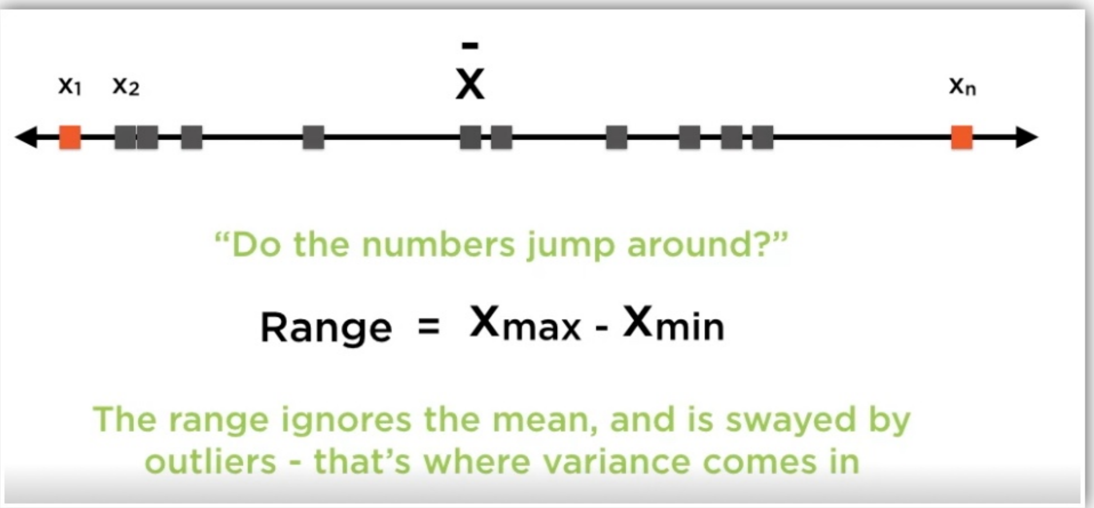
The mean, or average, is the one number that best represents all of these data points

$$\bar{x} = \frac{x_1 + x_2 + \ldots + x_n}{n}$$

[80]:

```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-19-58.jpg')
```

[80]:



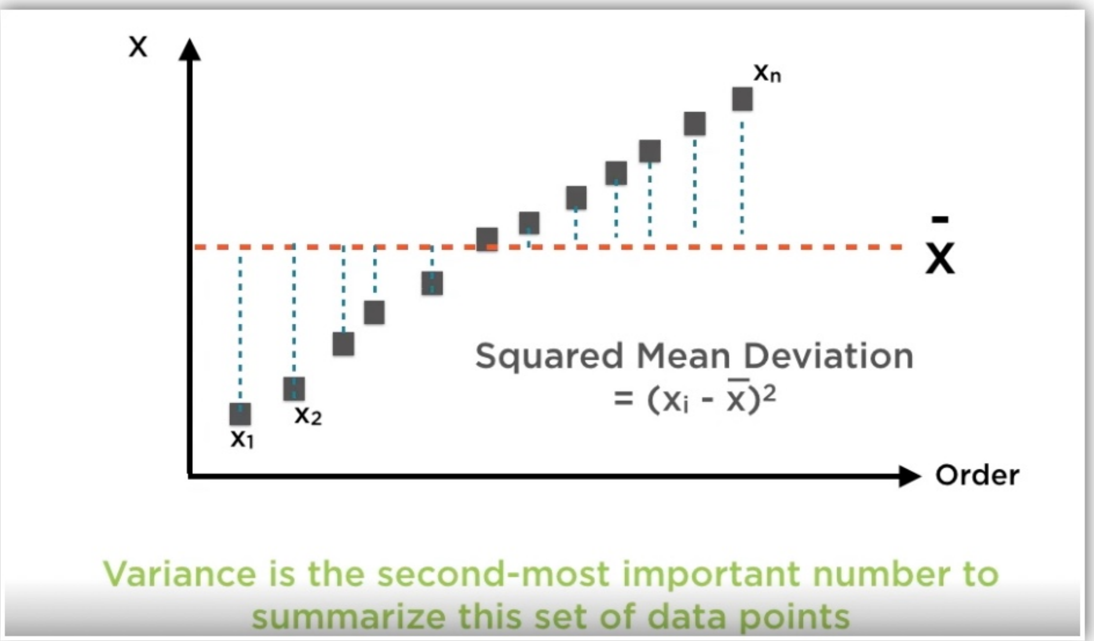
"Do the numbers jump around?"

$$\text{Range} = X_{max} - X_{min}$$

The range ignores the mean, and is swayed by outliers - that's where variance comes in

[81]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-20-48.jpg')
```

[81]:



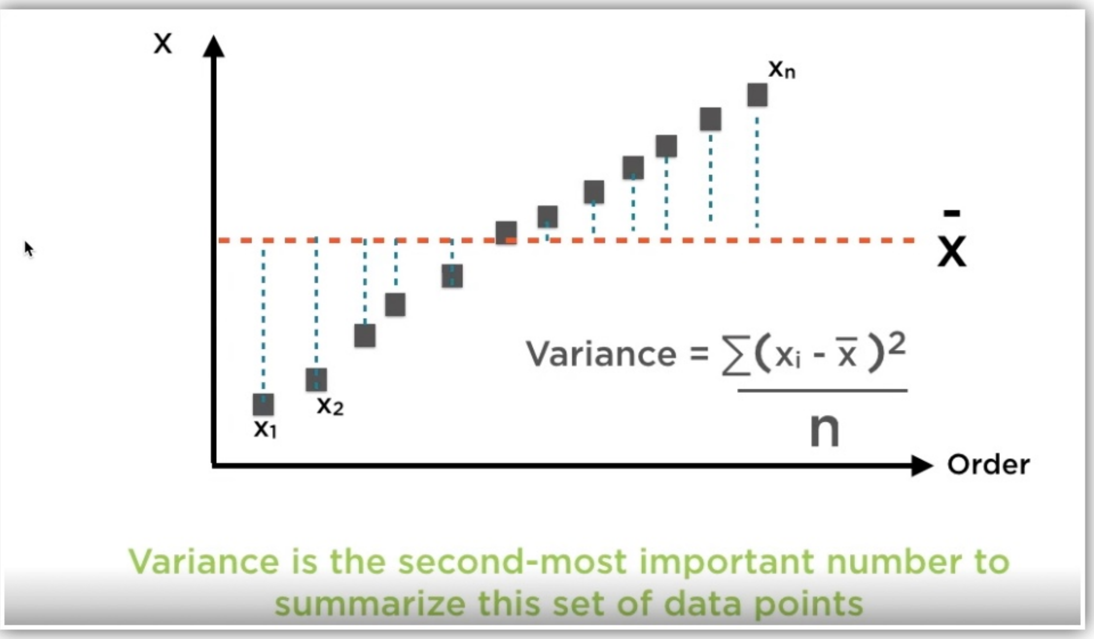
Squared Mean Deviation

$$= (x_i - \bar{x})^2$$

Variance is the second-most important number to summarize this set of data points

[82]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-21-32.jpg')
```

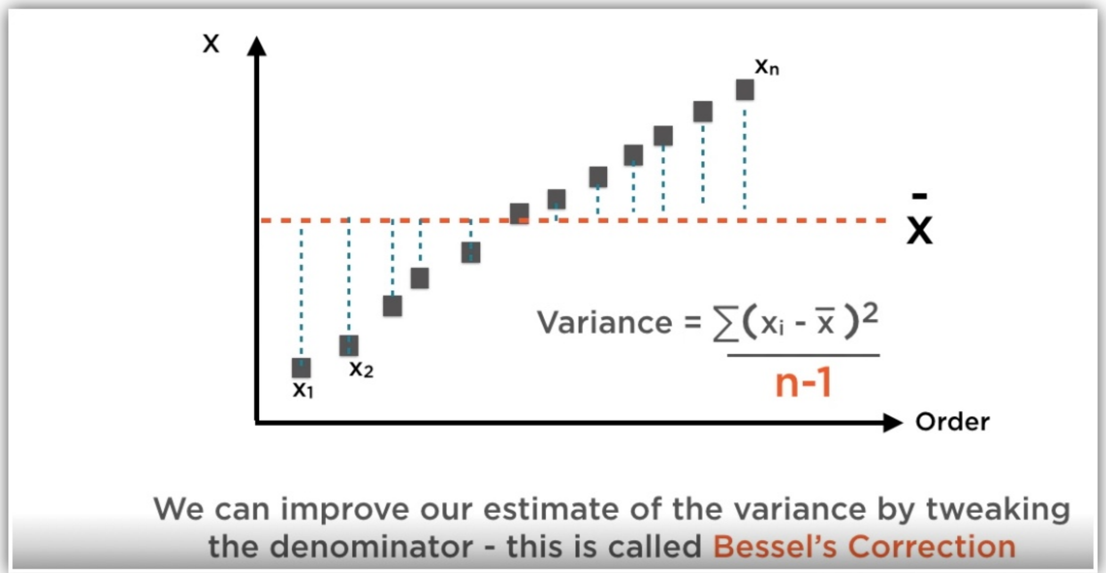
[82]:



Variance is the second-most important number to summarize this set of data points

[83]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-22-14.jpg')
```

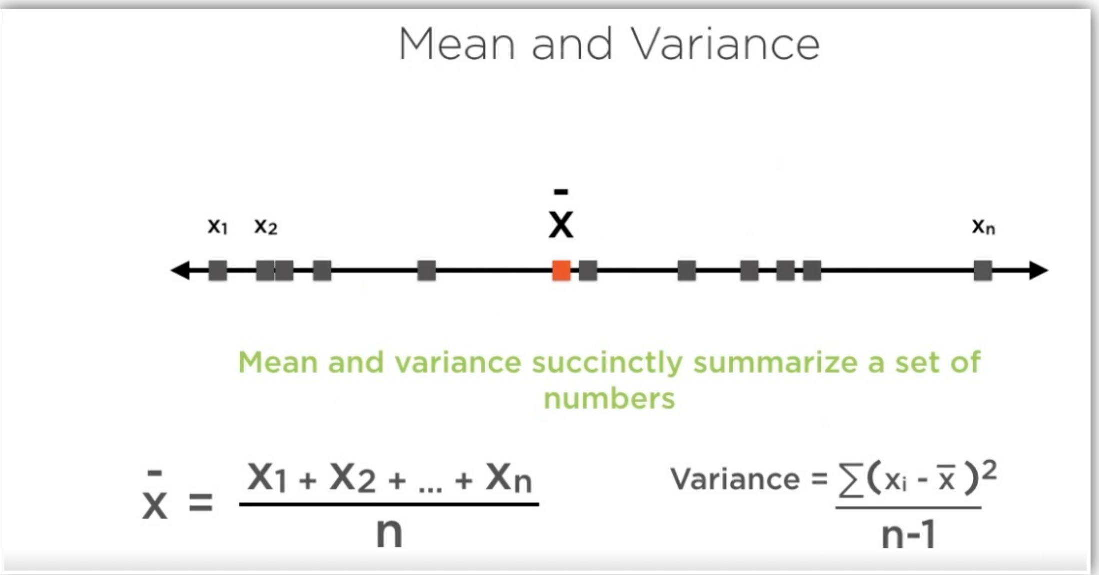
[83]:



We can improve our estimate of the variance by tweaking the denominator - this is called Bessel's Correction

[84]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-22-46.jpg')
```

[84]:



Mean and Variance

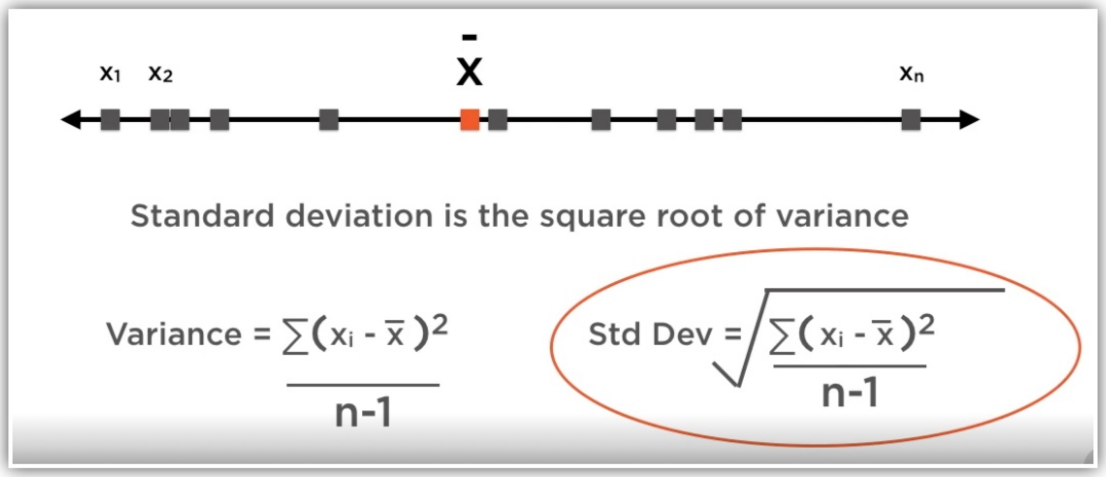
Mean and variance succinctly summarize a set of numbers

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

$$\text{Variance} = \frac{\sum(x_i - \bar{x})^2}{n-1}$$

[85]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-23-21.jpg')
```

[85]:



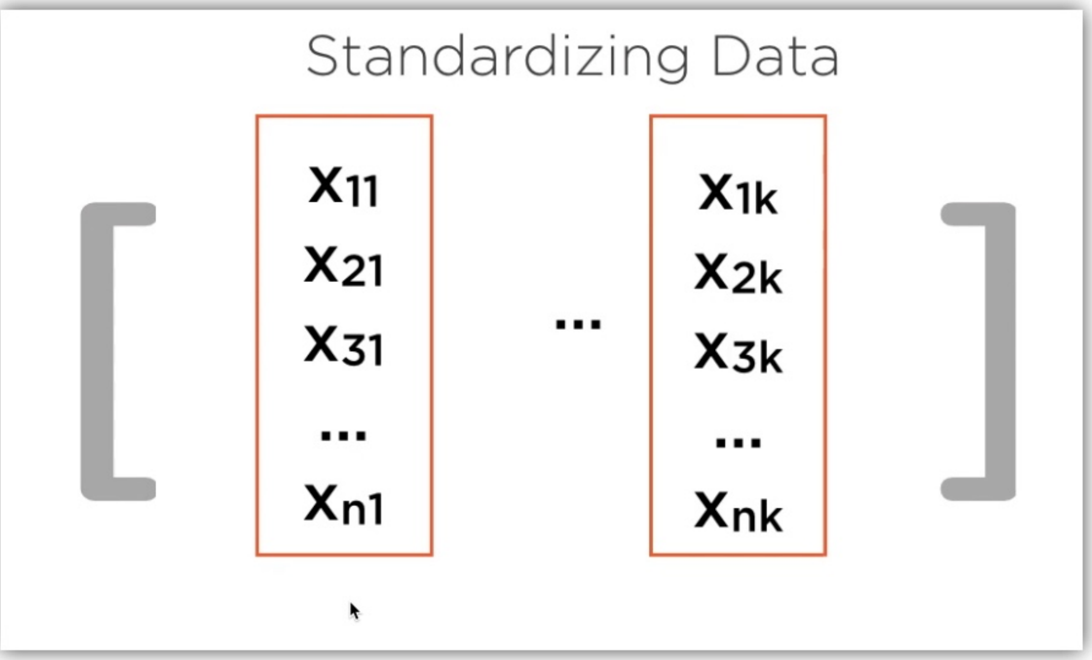
Standard deviation is the square root of variance

$$\text{Variance} = \frac{\sum(x_i - \bar{x})^2}{n-1}$$

$$\text{Std Dev} = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$$

[86]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-23-59.jpg')
```

[86]:

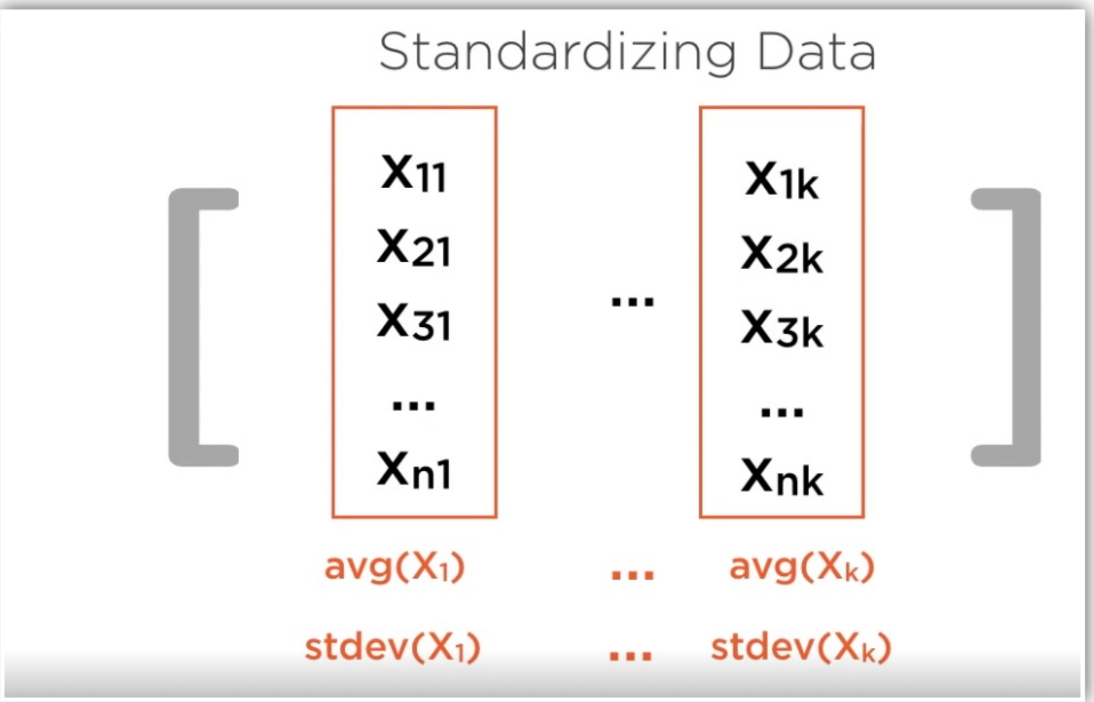


Standardizing Data

$$\left[\begin{array}{ccc} x_{11} & & x_{1k} \\ x_{21} & & x_{2k} \\ x_{31} & \cdots & x_{3k} \\ \cdots & & \cdots \\ x_{n1} & & x_{nk} \end{array}\right]$$

[87]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-24-34.jpg')
```

[87]:

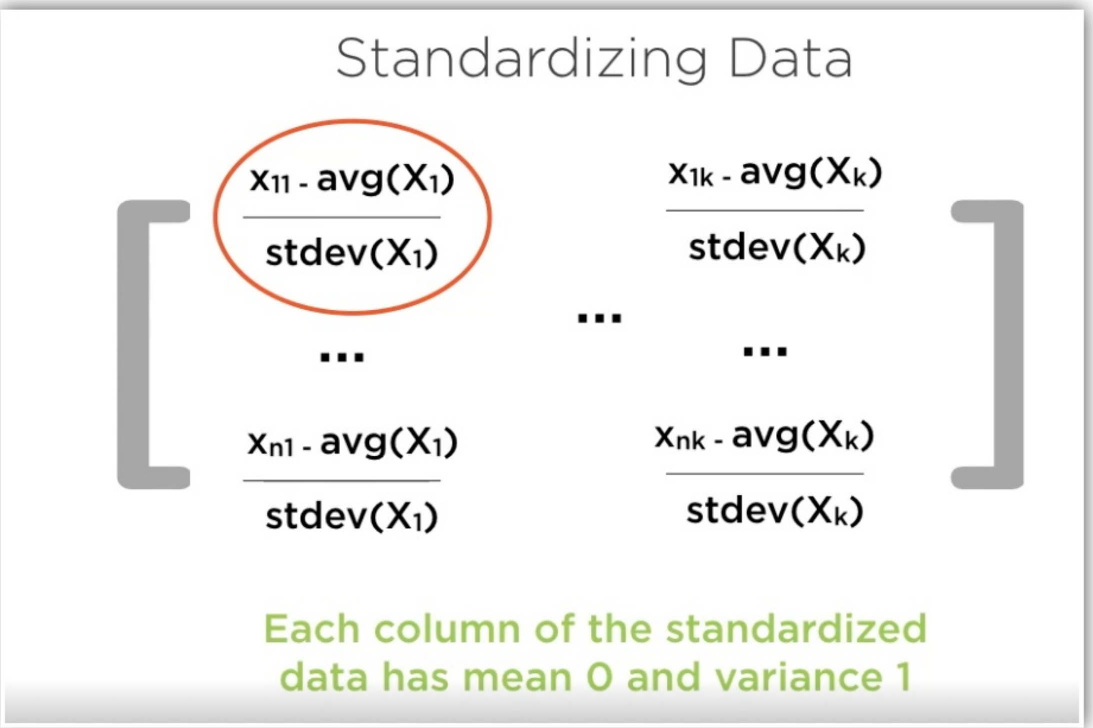


Standardizing Data

$$\begin{array}{ccc} x_{11} & & x_{1k} \\ x_{21} & & x_{2k} \\ x_{31} & \cdots & x_{3k} \\ \cdots & & \cdots \\ x_{n1} & & x_{nk} \\ \text{avg}(X_1) & \cdots & \text{avg}(X_k) \\ \text{stdev}(X_1) & \cdots & \text{stdev}(X_k) \end{array}$$

[88]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-17_18-25-14.jpg')
```

[88]:



Standardizing Data

$$\begin{bmatrix} \frac{x_{11} - avg(X_1)}{stdev(X_1)} & & \frac{x_{1k} - avg(X_k)}{stdev(X_k)} \\ \cdots & \cdots & \cdots \\ \frac{x_{n1} - avg(X_1)}{stdev(X_1)} & & \frac{x_{nk} - avg(X_k)}{stdev(X_k)} \end{bmatrix}$$

Each column of the standardized data has mean 0 and variance 1

[77]:
```
'''
If you sample your data frame now with the standardized values for the␣
↪different scores,
you can see that the scores are now very small numbers. Negative scores are␣
↪those which are below the mean,
and positive scores are those that are above the mean.

Standardizing a dataset allows you to see this at a single glance. You don't␣
↪need to know the actual numbers, actual mean values, nothing.

You can see that this particular student has been doing pretty poorly in her␣
↪exams. All of her scores are more than one standard deviation below the mean.
'''
exam_df.head()
```

[77]:
```
   gender race/ethnicity parental level of education         lunch  \
0  female        group E          associate's degree      standard
1  female        group C                some college      standard
2    male        group E                 high school      standard
3  female        group B                some college  free/reduced
```

```
4  female        group B           bachelor's degree      standard

  test preparation course  math score  reading score  writing score
0                    none    0.210248       0.440580      -0.009452
1                    none   -1.268562      -1.315885      -1.292181
2                    none    0.531729       0.147836      -0.076964
3               completed   -1.461450      -1.315885      -1.022132
4               completed    0.017360       0.440580       0.733181
```

[78]:

```
'''
Let's call describe on our data frame once again. Our data frame now contains␣
 ↪standardized values for scores.
You can see that mean values are very, very close to 0, and the standard␣
 ↪deviations for all three scores are very, very close to 1.
This is what standardization has done.
'''
exam_df.describe()
```

[78]:

```
         math score  reading score  writing score
count  1.000000e+02   1.000000e+02   1.000000e+02
mean  -8.881784e-18  -3.048950e-16  -4.468648e-17
std    1.005038e+00   1.005038e+00   1.005038e+00
min   -3.133149e+00  -3.291909e+00  -3.317542e+00
25%   -5.613050e-01  -6.572107e-01  -4.820360e-01
50%    1.459522e-01   1.112428e-01  -9.451687e-03
75%    7.406911e-01   7.333242e-01   8.006929e-01
max    1.881947e+00   1.757929e+00   1.610838e+00
```