1-ExploringTheAutomobileMpgDataset

October 16, 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  \
161  16.0          6         250.0        105    3897          18.5
96   13.0          8         360.0        175    3821          11.0
57   24.0          4         113.0         95    2278          15.5
220  33.5          4          85.0         70    1945          16.8
13   14.0          8         455.0        225    3086          10.0

     model year  origin                    car name
161          75       1  chevroelt chevelle malibu
96           73       1    amc ambassador brougham
57           72       3      toyota corona hardtop
220          77       3      datsun f-10 hatchback
13           70       1    buick estate wagon (sw)
```

[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  \
104  12.0          8         400.0        167    4906          12.5
66   17.0          8         304.0        150    3672          11.5
154  15.0          6         250.0         72    3432          21.0
271  23.2          4         156.0        105    2745          16.7
77   22.0          4         121.0         76    2511          18.0

     model year  origin              car name
104          73       1          ford country
66           72       1    amc ambassador sst
154          75       1       mercury monarch
271          78       1      plymouth sapporo
77           72       2  volkswagen 411 (sw)
```

[8]:
```python
'''

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]:
```python
'''

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]:
```python
'''

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]:
```python
'''
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.
'''
```

```python
automobile_df.shape
```

[11]: (392, 9)

[12]:
```python
'''
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]:
```python
'''

  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]:

```python
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
33	19.0	6	232.0	100	2634	13.0	1971
223	15.5	8	318.0	145	4140	13.7	1977
341	23.5	6	173.0	110	2725	12.6	1981
282	22.3	4	140.0	88	2890	17.3	1979
94	13.0	8	440.0	215	4735	11.0	1973

[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
134	16.0	6	258.0	110	3632	18.0	47
26	10.0	8	307.0	200	4376	15.0	51
378	38.0	4	105.0	63	2125	14.7	39
141	29.0	4	98.0	83	2219	16.5	47
246	32.8	4	78.0	52	1985	19.4	43

[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()
```

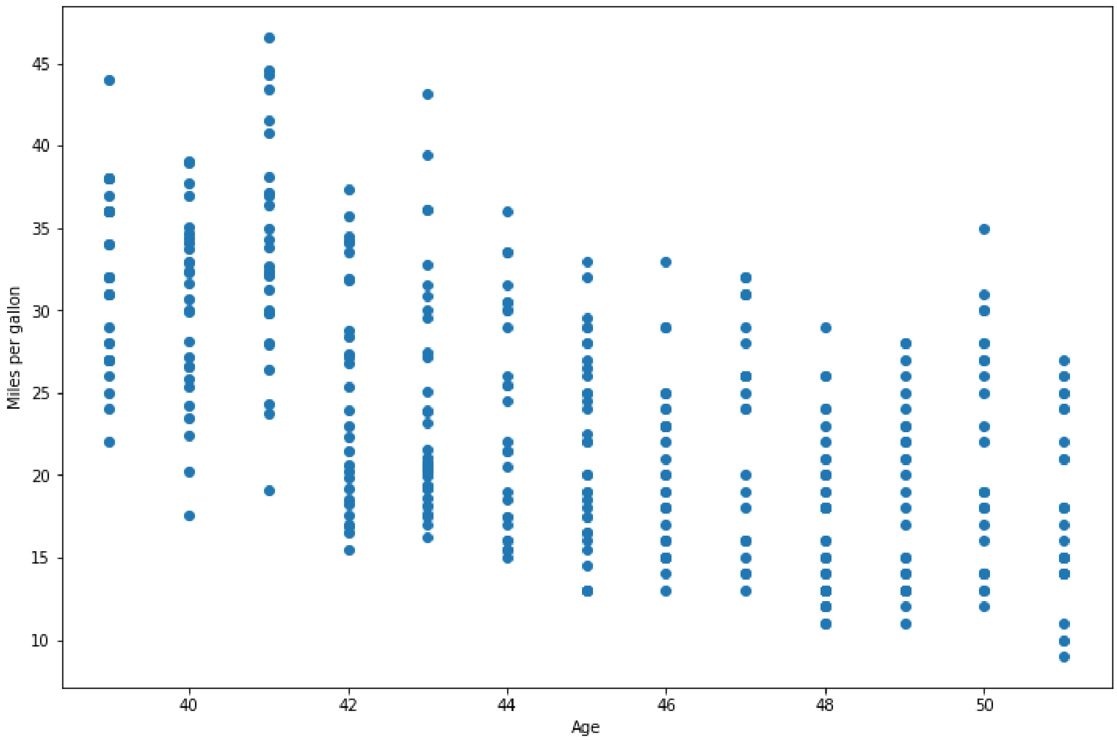
[21]:

```
              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
```

[26]:

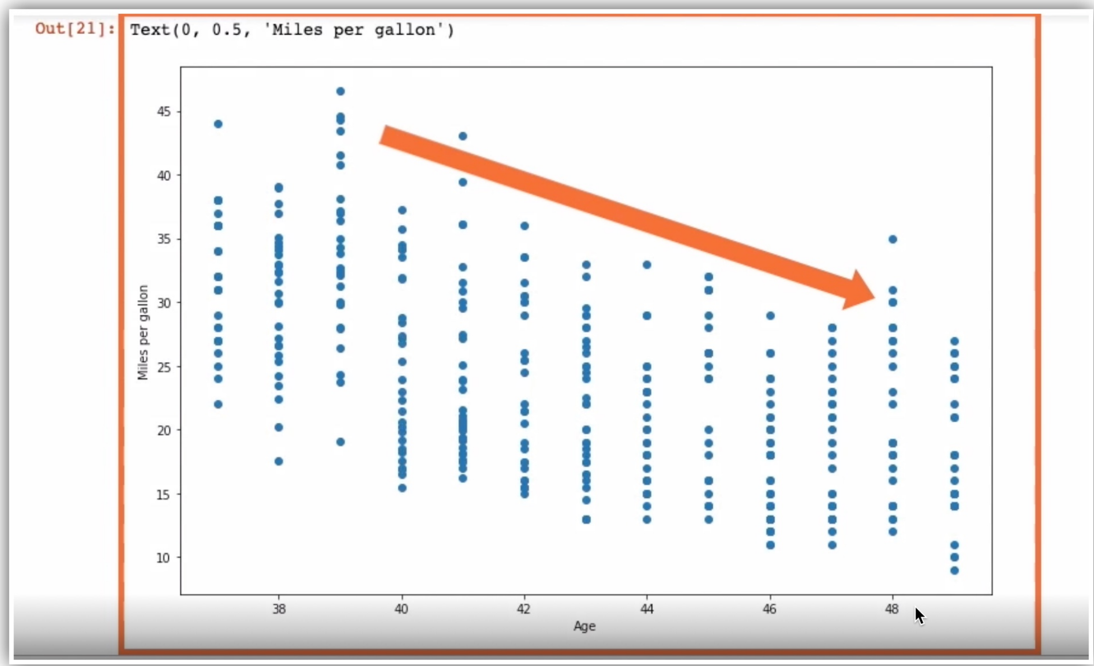
```
'''
Understanding the features of our dataset and what we're trying to predict is␣
 ↪the first step.
The next step is to explore the data using visualizations.

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')
```

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



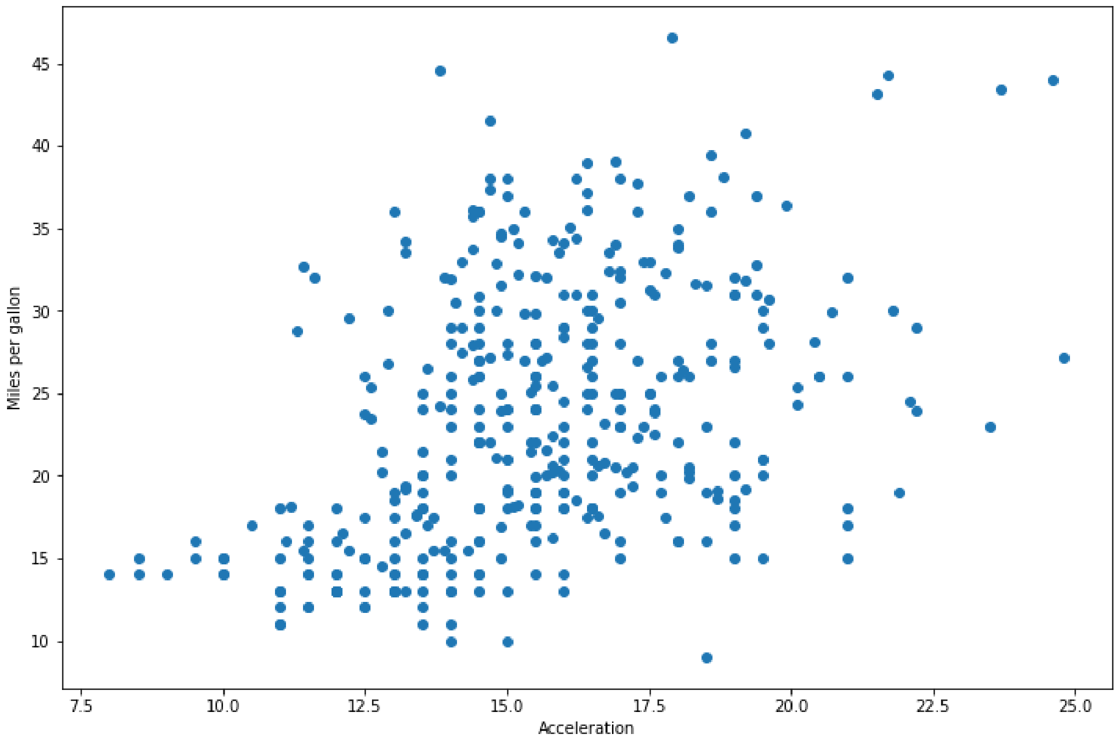
[28]:
```
'''
And you can see that there is a definite downward trend here.
Now this doesn't necessarily mean that a relationship does exist that needs␣
↪more statistical analysis,
but this visualization seems to tell us that older cars have lower mileage.

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

[28]:



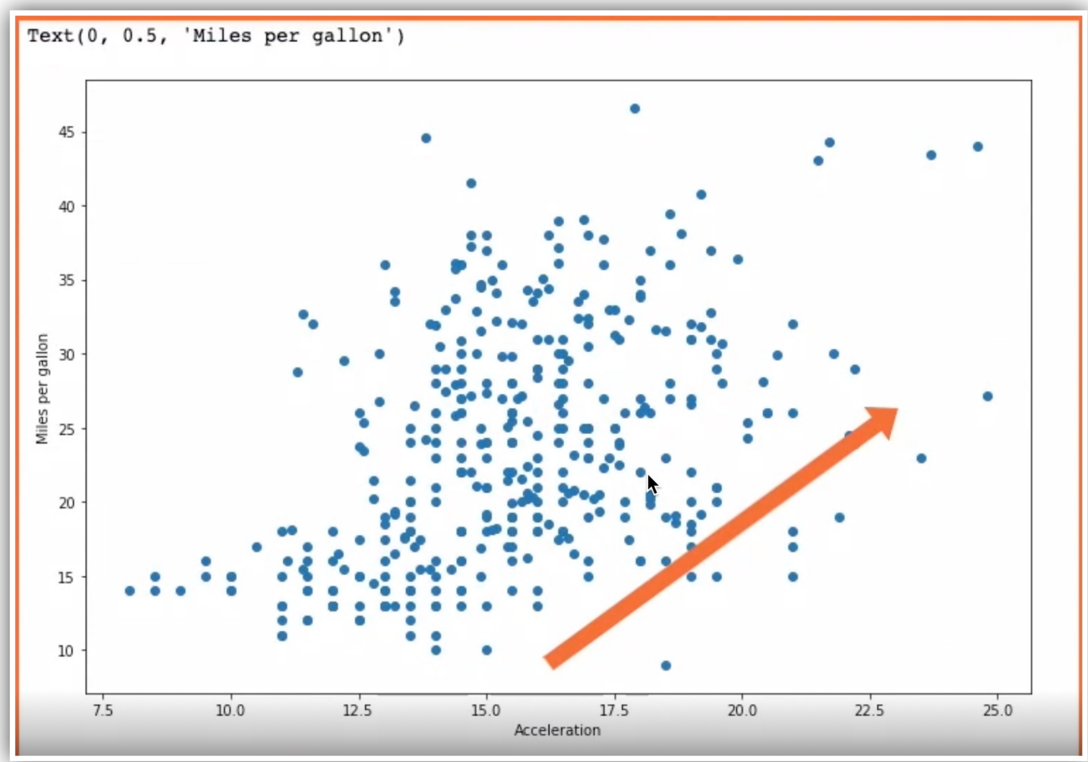
[29]:
```
fig,ax=plt.subplots(figsize=(12,8))
plt.scatter(automobile_df['acceleration'],automobile_df['mpg'])
plt.xlabel('Acceleration')
plt.ylabel('Miles per gallon')
```

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



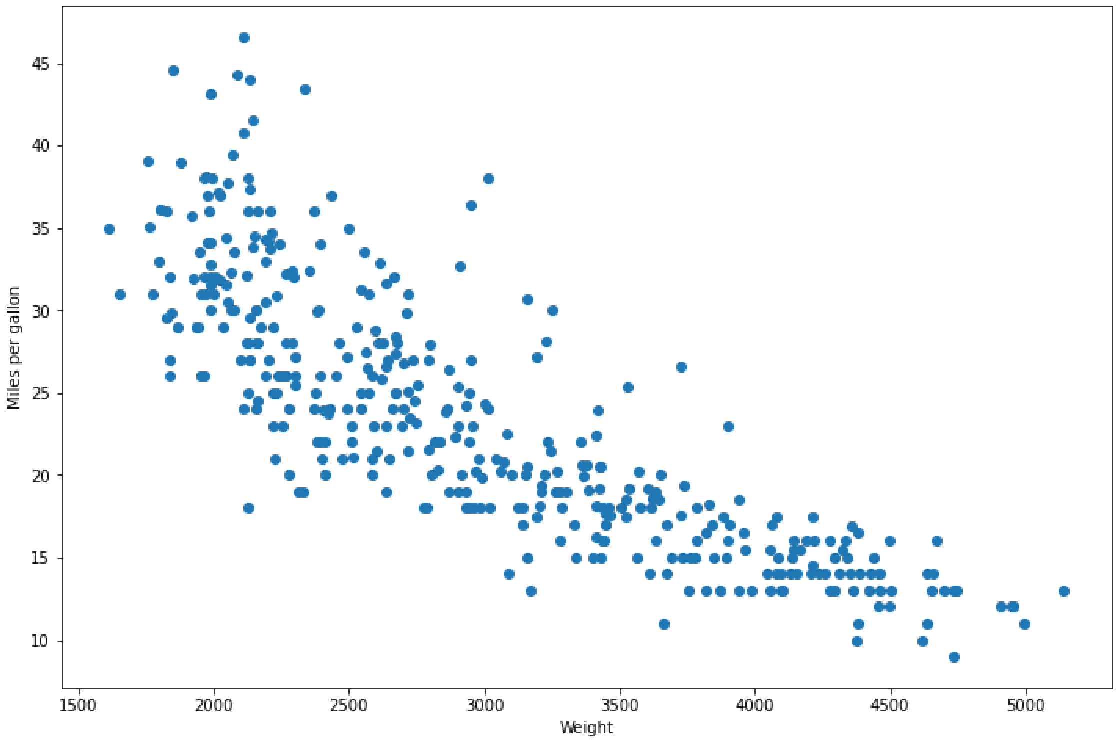
[32]:
```
'''

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')
```

[32]:



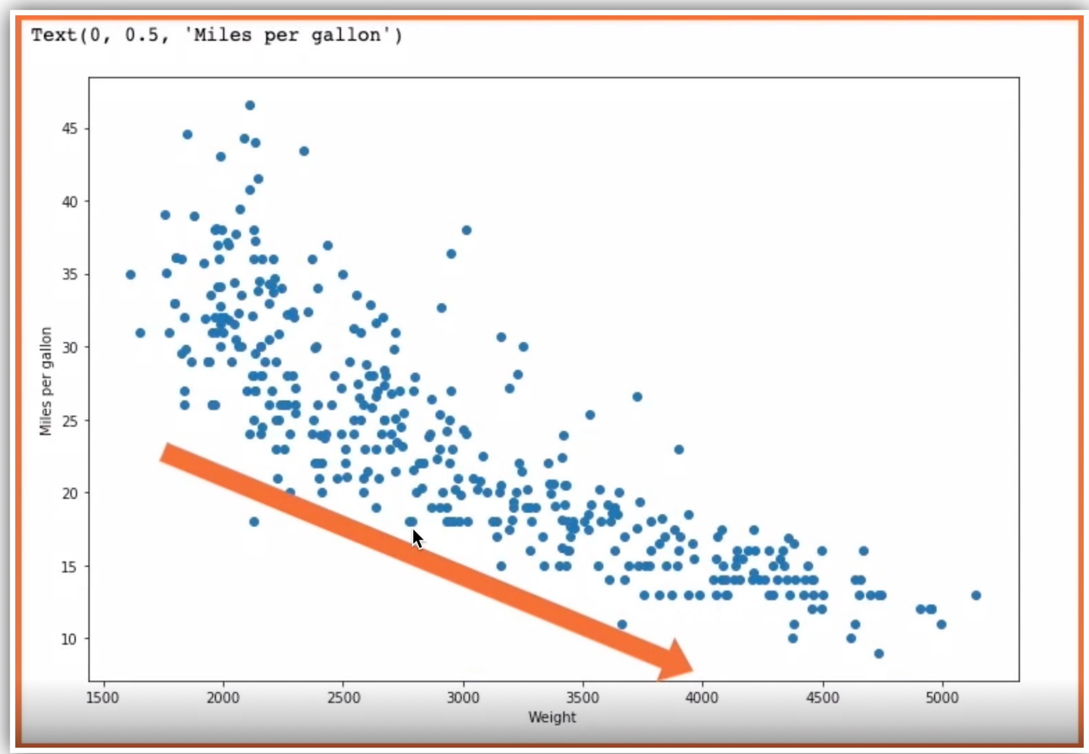
[33]:
```
'''
I'm curious about another one of our input features, that is the weight of the␣
↪car.
Does the weight of the automobile have any significant impact on its mileage?
Maybe this scatter plot will give us some information.
And yes, definitely there is a downward trend here.
It seems like greater 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')
```

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



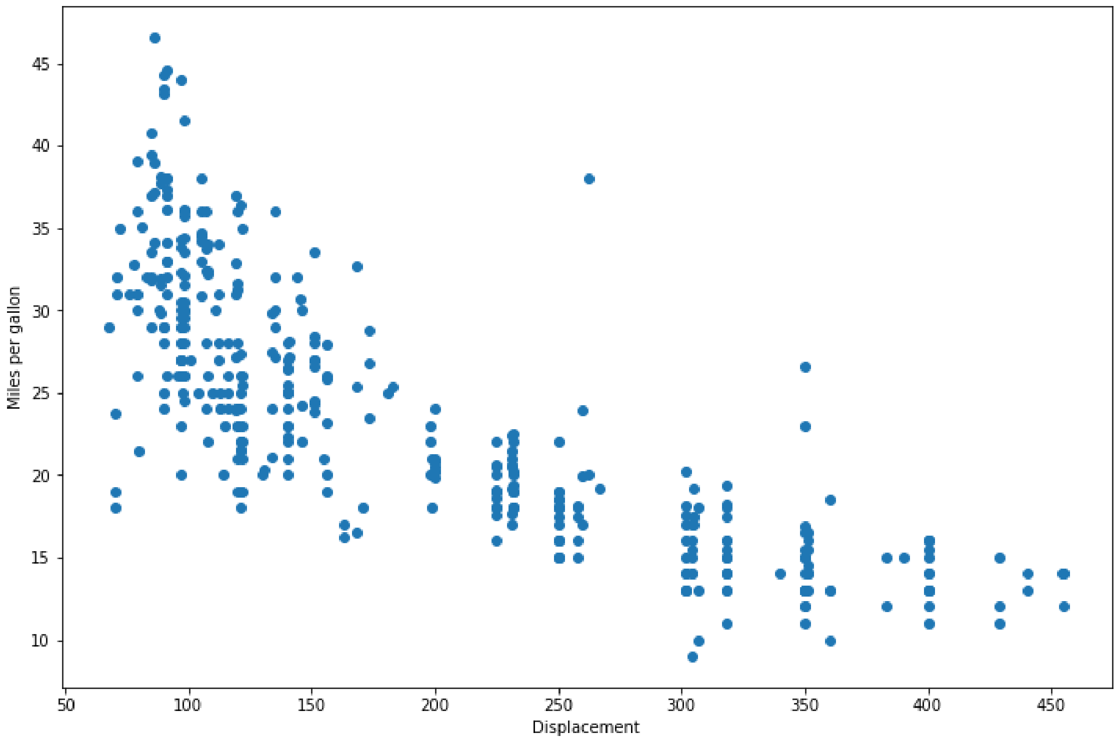
[34]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-31-31.jpg')
```

[34]:



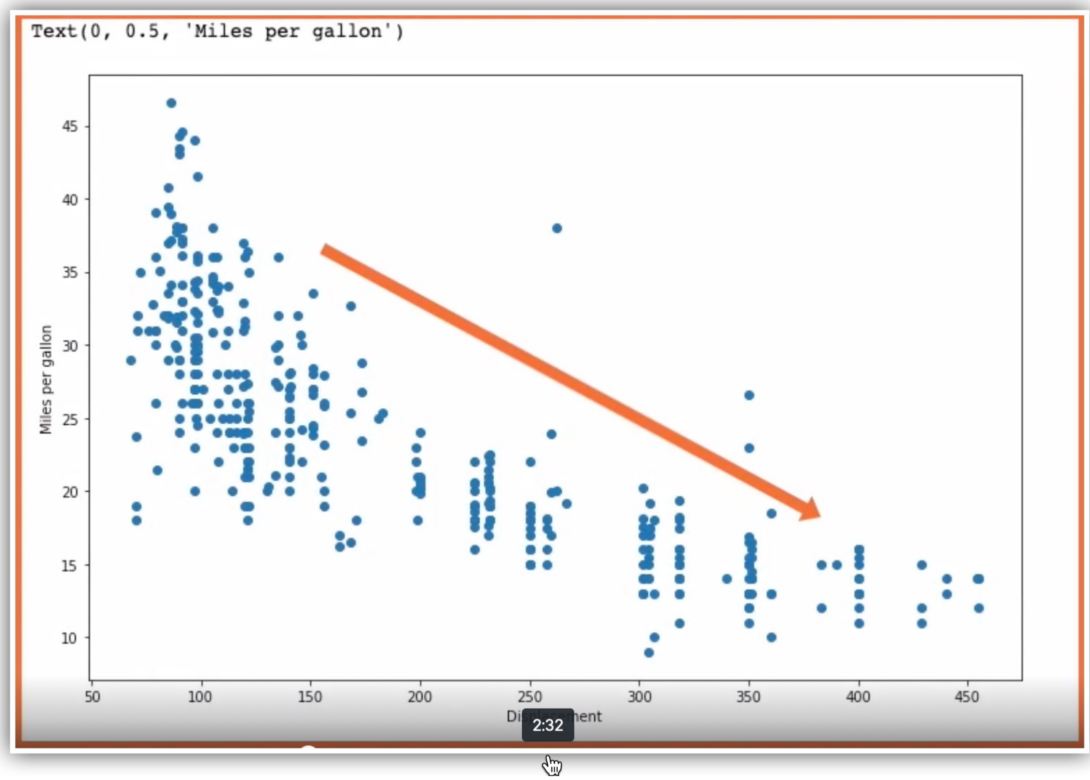
[35]:
```
'''

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')
```

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



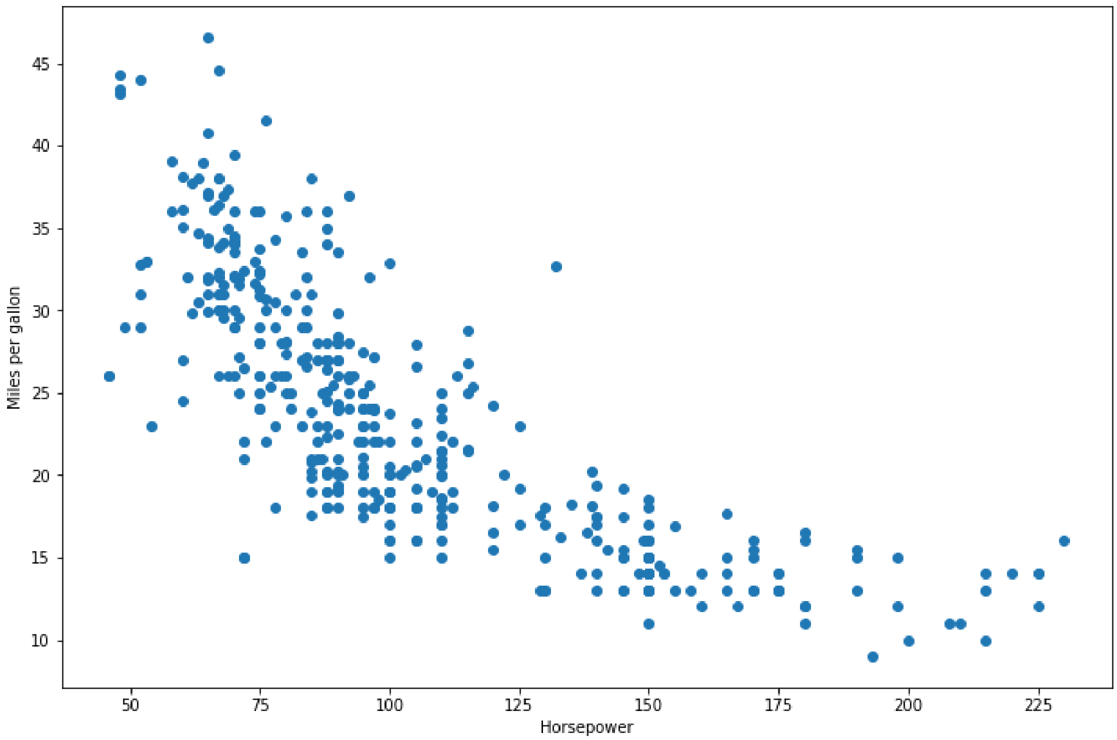
[36]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-33-37.jpg')
```

[36]:



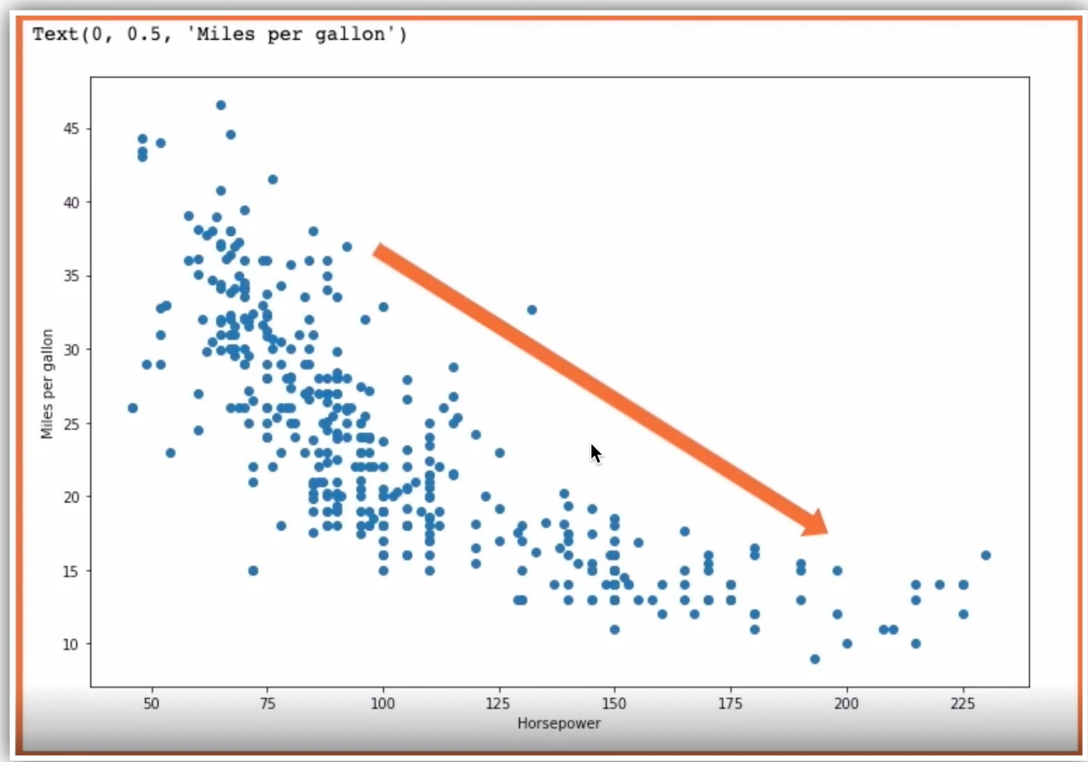
[37]:
```
'''

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')
```

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



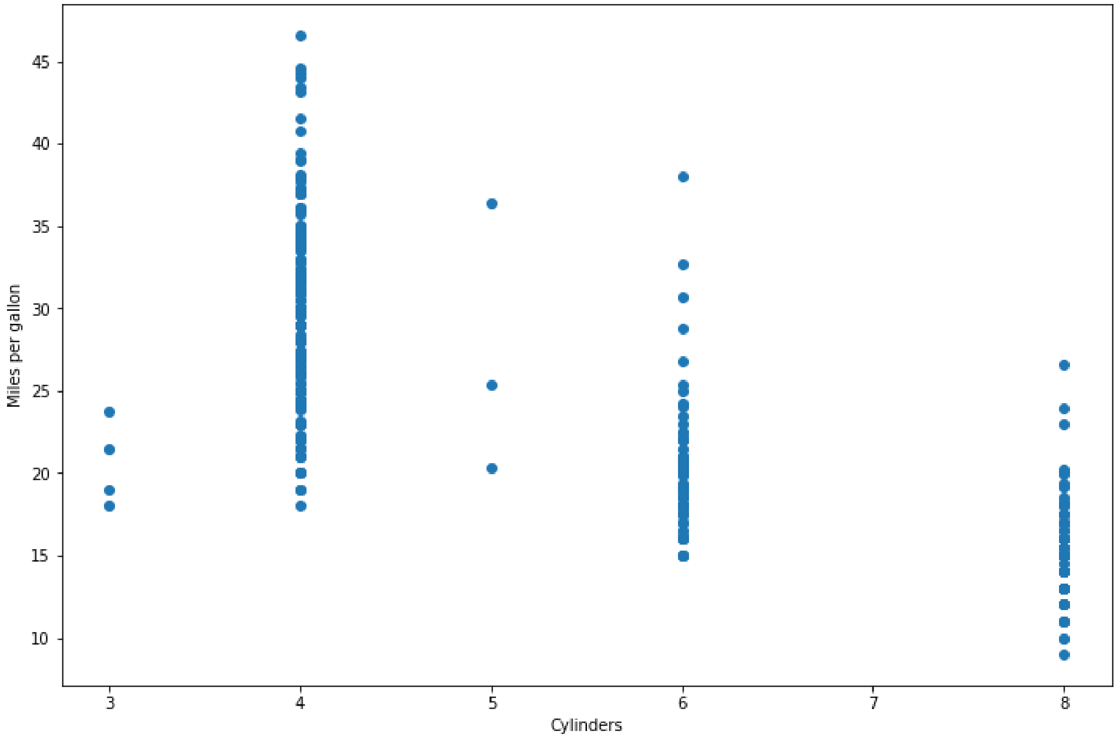
[39]:
```
Image('/Users/subhasish/Documents/APPLE/SUBHASISH/Development/GIT/Interstellar/
↪SB-AI-DEV/ML/SB/LinerRegression/Images/2021-10-16_02-35-22.jpg')
```

[39]:




```
[41]: '''
      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')
```

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



[43]:
```
'''
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
```

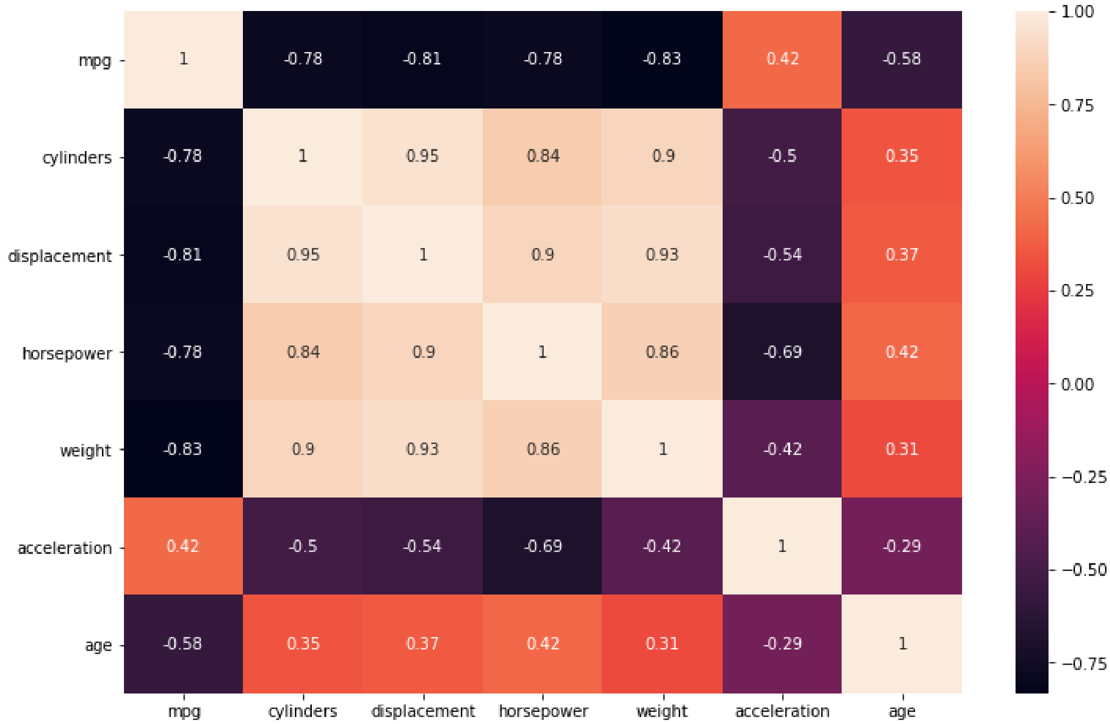
[43]:

```
                   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
```

[44]:

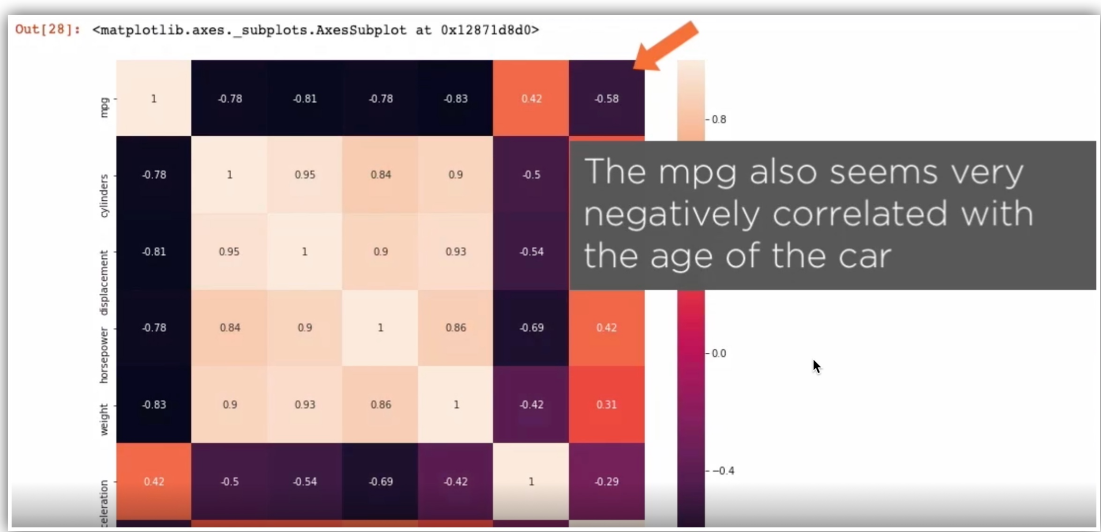
```
'''
 Viewing correlations with the raw numbers is hard, which is why we use a␣
↪visualization technique
 called the heatmap in order to view correlations in our data.

 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)
```

[44]: <AxesSubplot:>




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

[45]:



[46]:

```python
'''

 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()
```

[46]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	age
0	18.1	6	258.0	120	3410	15.1	43
1	19.2	8	267.0	125	3605	15.0	42
2	15.0	8	350.0	165	3693	11.5	51
3	26.0	4	96.0	69	2189	18.0	49
4	18.5	6	250.0	110	3645	16.2	45

[48]:

```python
'''
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)
```

[ ]:

```python

```