Week 4: Brandon Mather DSC550-T301

In [40]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.datasets import make_regression
from sklearn.model_selection import cross_val_score
import sklearn.metrics as metrics
from sklearn.metrics import make_scorer, r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

In [2]:
```
#1:Load the data as a Pandas data frame and ensure that it imported correctly.
data = pd.read_csv('auto-mpg.csv')
```

In [4]:
```
data
```

Out[4]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
...	...	...	...	...	...	...	...	...	...
393	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
394	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
395	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
396	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
397	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

398 rows × 9 columns

In [3]:
```
#2: Begin by prepping the data for modeling: Remove the car name column.
data.drop('car name', inplace=True, axis=1)
data
```

Out[3]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1
2	18.0	8	318.0	150	3436	11.0	70	1
3	16.0	8	304.0	150	3433	12.0	70	1
4	17.0	8	302.0	140	3449	10.5	70	1
...	...	...	...	...	...	...	...	...
393	27.0	4	140.0	86	2790	15.6	82	1
394	44.0	4	97.0	52	2130	24.6	82	2
395	32.0	4	135.0	84	2295	11.6	82	1
396	28.0	4	120.0	79	2625	18.6	82	1
397	31.0	4	119.0	82	2720	19.4	82	1

398 rows × 8 columns

In [4]:
```
#The horsepower column values likely imported as a string data type. Figure out why ar
data['horsepower'] = data['horsepower'].replace('?',
    np.mean(pd.to_numeric(data['horsepower'], errors='coerce')))
```

In [5]:
```
#Create dummy variables for the origin column
dummies = pd.get_dummies(data['origin'])
data = pd.concat([data, dummies], axis=1)
data.drop('origin', inplace=True, axis=1)
data
```

Out[5]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	1	2	3
0	18.0	8	307.0	130	3504	12.0	70	1	0	0
1	15.0	8	350.0	165	3693	11.5	70	1	0	0
2	18.0	8	318.0	150	3436	11.0	70	1	0	0
3	16.0	8	304.0	150	3433	12.0	70	1	0	0
4	17.0	8	302.0	140	3449	10.5	70	1	0	0
...	...	...	...	...	...	...	...	...	...	...
393	27.0	4	140.0	86	2790	15.6	82	1	0	0
394	44.0	4	97.0	52	2130	24.6	82	0	1	0
395	32.0	4	135.0	84	2295	11.6	82	1	0	0
396	28.0	4	120.0	79	2625	18.6	82	1	0	0
397	31.0	4	119.0	82	2720	19.4	82	1	0	0

398 rows × 10 columns

In [27]:
```
#3: Create a correlation coefficient matrix and/or visualization. Are there features h
matrix = data.corr()
matrix
```

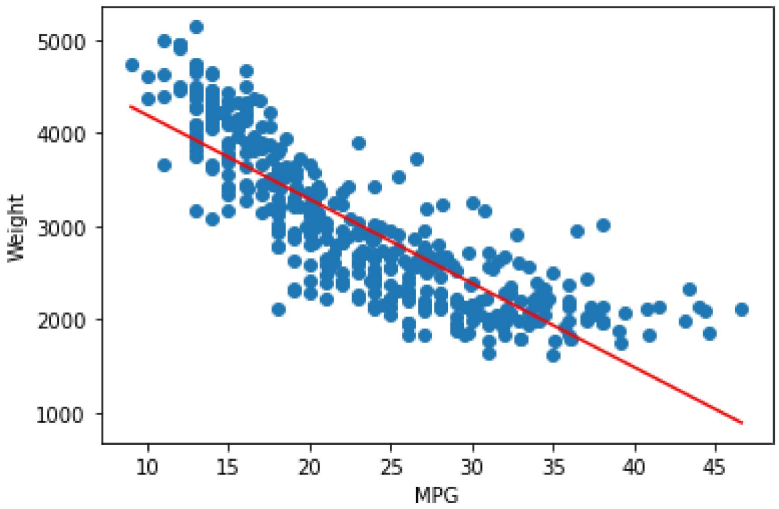
Out[27]:

	mpg	cylinders	displacement	weight	acceleration	model year	1	
mpg	1.000000	-0.775396	-0.804203	-0.831741	0.420289	0.579267	-0.568192	0.259
cylinders	-0.775396	1.000000	0.950721	0.896017	-0.505419	-0.348746	0.604351	-0.352
displacement	-0.804203	0.950721	1.000000	0.932824	-0.543684	-0.370164	0.651407	-0.373
weight	-0.831741	0.896017	0.932824	1.000000	-0.417457	-0.306564	0.598398	-0.298
acceleration	0.420289	-0.505419	-0.543684	-0.417457	1.000000	0.288137	-0.250806	0.204
model year	0.579267	-0.348746	-0.370164	-0.306564	0.288137	1.000000	-0.139883	-0.024
1	-0.568192	0.604351	0.651407	0.598398	-0.250806	-0.139883	1.000000	-0.597
2	0.259022	-0.352861	-0.373886	-0.298843	0.204473	-0.024489	-0.597198	1.000
3	0.442174	-0.396479	-0.433505	-0.440817	0.109144	0.193101	-0.643317	-0.229

Based off these numbers, it looks like Weight, Displacement, and cylinders has a negative correlation with MPG, and acceleration and model year have a slight positive correlation with MPG. The negative correlations are much stronger. Weight has the largest correlation either direction.

In [30]:
```
#4: Plot mpg versus weight. Analyze this graph and explain how it relates to the corre
plt.scatter(data['mpg'], data['weight'])
plt.plot(np.unique(data['mpg']), np.poly1d(np.polyfit(data['mpg'], data['weight'], 1))
         (np.unique(data['mpg'])), color='red')
plt.xlabel('MPG')
plt.ylabel('Weight')
```

Out[30]:
```
Text(0, 0.5, 'Weight')
```



This shows that the correlation that the lower the weight, the higher the MPG, showing a negative correlation.

In [6]:
```
#5: Randomly split the data into 80% training data and 20% test data, where your targe
y = data.mpg
```

In [7]:
```
x = data.drop('mpg',axis=1)
```

In [24]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=
```

In [25]:
```
#6: Train an ordinary linear regression on the training data.
reg = LinearRegression().fit(x, y)
```

```
C:\Users\brand\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
rning: Feature names only support names that are all strings. Got feature names with
dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

In [27]:
```
reg.coef_
```

Out[27]:
```
array([-0.42081606,  0.02361652, -0.01335768, -0.00696597,  0.09957094,
        0.78421339, -1.87009498,  0.91246382,  0.95763116])
```

In [28]:
```
#7: Calculate R2, RMSE, and MAE on both the training and test sets and interpret your
reg.score(x, y)
```

```
C:\Users\brand\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
rning: Feature names only support names that are all strings. Got feature names with
dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

Out[28]:
```
0.8244697856581006
```

In [35]:
```
pred = reg.predict(x_test)
```

```
C:\Users\brand\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
rning: Feature names only support names that are all strings. Got feature names with
dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

In [36]:
```
mean = mean_squared_error(y_test, pred)
```

In [38]:
```
rmse = np.sqrt(mean_squared_error(y_test,pred))
```

In [39]:
```
rmse
```

Out[39]:
```
2.8021694138181528
```

In [41]:
```
mae = np.sqrt(mean_absolute_error(y_test,pred))
```

In [42]:
```
mae
```

Out[42]:
```
1.4936686534205834
```

In [ ]:
```
#8:Pick another regression model and repeat the previous two steps. Note: Do NOT choos
#like a classification model.
```

In [43]:
```
#Lasso Regression model
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
```

In [44]:
```
scaler = StandardScaler()
features_standardized = scaler.fit_transform(features)
```

In [45]:
```
regression = Lasso(alpha=0.5)
```

In [48]:
```
model = regression.fit(x, y)
```

```
C:\Users\brand\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
rning: Feature names only support names that are all strings. Got feature names with
dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

In [49]:
```
model.coef_
```

Out[49]:
```
array([-0.00000000e+00,  6.29633864e-04, -3.99125373e-03, -6.64144517e-03,
        0.00000000e+00,  7.11084623e-01, -0.00000000e+00,  0.00000000e+00,
        0.00000000e+00])
```

In [50]:
```
model.score(x, y)
```

```
C:\Users\brand\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
rning: Feature names only support names that are all strings. Got feature names with
dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

Out[50]:
```
0.8075956913714164
```

In [ ]: