Week 4.2 Assignment

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- DSC550 Data Mining
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In [ ]:
```
import pandas as pd
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from math import sqrt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
import matplotlib.pyplot as plt
```

Load the data as a Pandas data frame and ensure that it imported correctly.

In [ ]:
```
df = pd.read_csv('./DATA/auto-mpg.csv')
df.head()
```

Out[ ]:

	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

Begin by prepping the data for modeling:

- #### Remove the car name column.
- #### The horsepower column values likely imported as a string data type. Figure out why and replace any strings with the column mean.
- #### Create dummy variables for the origin column.

In [ ]:
```
# Drop the column
df = df.drop('car name', 1)
```

```
# Validate the drop worked correctly
df.head()
```

```
C:\Users\Joshu\AppData\Local\Temp\ipykernel_8236\1306409664.py:2: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only.
  df = df.drop('car name', 1)
```

Out[ ]:

	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

In [ ]:

```
# Obtain the counts of each value in the hosepower column
df.groupby('horsepower').count()
```

Out[ ]:

	mpg	cylinders	displacement	weight	acceleration	model year	origin
horsepower							
100	17	17	17	17	17	17	17
102	1	1	1	1	1	1	1
103	1	1	1	1	1	1	1
105	12	12	12	12	12	12	12
107	1	1	1	1	1	1	1
...	...	...	...	...	...	...	...
95	14	14	14	14	14	14	14
96	3	3	3	3	3	3	3
97	9	9	9	9	9	9	9
98	2	2	2	2	2	2	2
?	6	6	6	6	6	6	6

94 rows × 7 columns

In [ ]:

```
# Replace the ? with NaN
df = df.apply(pd.to_numeric, errors='coerce')

# Show NaN values for horsepower
df[df['horsepower'].isna()]
```

Out[ ]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
32	25.0	4	98.0	NaN	2046	19.0	71	1
126	21.0	6	200.0	NaN	2875	17.0	74	1
330	40.9	4	85.0	NaN	1835	17.3	80	2
336	23.6	4	140.0	NaN	2905	14.3	80	1
354	34.5	4	100.0	NaN	2320	15.8	81	2
374	23.0	4	151.0	NaN	3035	20.5	82	1

In [ ]:

```
# Calculate the mean horsepower
hp_mean = df['horsepower'].mean()

# Replace NaN with the mean
df['horsepower'] = df['horsepower'].fillna(hp_mean)

# View row 32 to validate horsepower replacement with mean
df.iloc[[32]]
```

Out[ ]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
32	25.0	4	98.0	104.469388	2046	19.0	71	1

In [ ]:

```
# Add dummy variables for origin column to original dataframe
df = pd.concat([df, pd.get_dummies(df['origin'])], axis=1)

# View dataframe
df.head()
```

Out[ ]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	1	2	3
0	18.0	8	307.0	130.0	3504	12.0	70	1	1	0	0
1	15.0	8	350.0	165.0	3693	11.5	70	1	1	0	0
2	18.0	8	318.0	150.0	3436	11.0	70	1	1	0	0
3	16.0	8	304.0	150.0	3433	12.0	70	1	1	0	0
4	17.0	8	302.0	140.0	3449	10.5	70	1	1	0	0

Create a correlation coefficient matrix and/or visualization. Are there features highly correlated with mpg?

In [ ]:

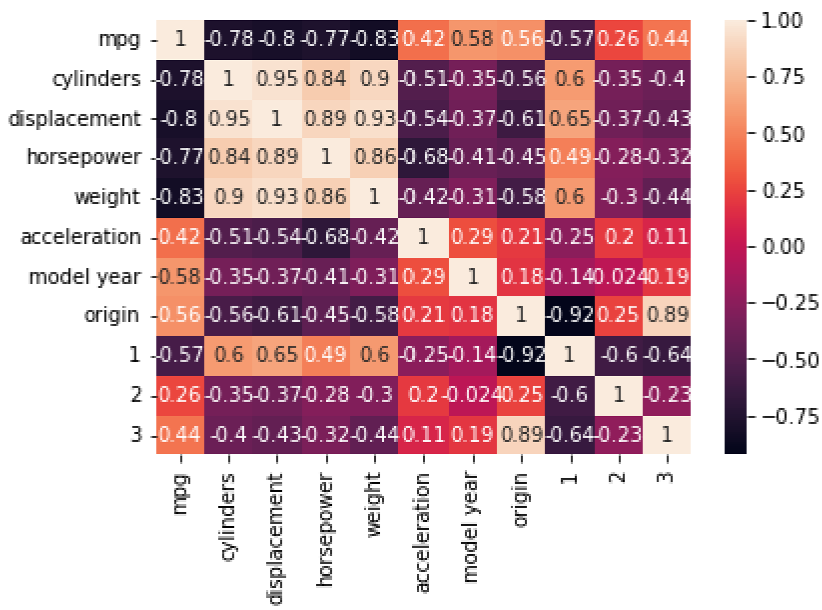
```
# Build correlation matrix
corrM = df.corr()

# Display correlation matrix
corrM
```

Out[ ]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	
mpg	1.000000	-0.775396	-0.804203	-0.771437	-0.831741	0.420289	0.579267	0.5
cylinders	-0.775396	1.000000	0.950721	0.838939	0.896017	-0.505419	-0.348746	-0.5
displacement	-0.804203	0.950721	1.000000	0.893646	0.932824	-0.543684	-0.370164	-0.6
horsepower	-0.771437	0.838939	0.893646	1.000000	0.860574	-0.684259	-0.411651	-0.4
weight	-0.831741	0.896017	0.932824	0.860574	1.000000	-0.417457	-0.306564	-0.5
acceleration	0.420289	-0.505419	-0.543684	-0.684259	-0.417457	1.000000	0.288137	0.2
model year	0.579267	-0.348746	-0.370164	-0.411651	-0.306564	0.288137	1.000000	0.1
origin	0.563450	-0.562543	-0.609409	-0.453669	-0.581024	0.205873	0.180662	1.0
1	-0.568192	0.604351	0.651407	0.486083	0.598398	-0.250806	-0.139883	-0.9
2	0.259022	-0.352861	-0.373886	-0.281258	-0.298843	0.204473	-0.024489	0.2
3	0.442174	-0.396479	-0.433505	-0.321325	-0.440817	0.109144	0.193101	0.8

In [ ]:

```python
# using the correlation_mat above, create a visualization using a heatmap
sns.heatmap(corrM, annot = True)
plt.show()
```

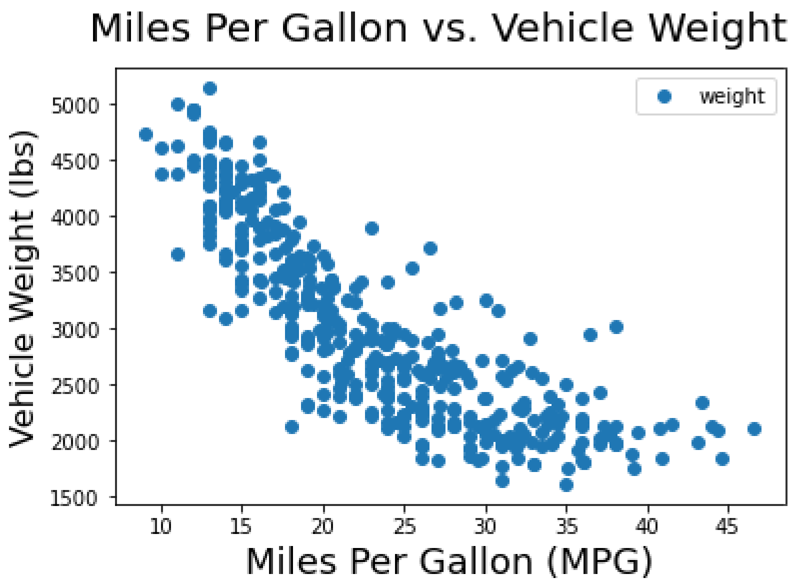


Plot mpg versus weight. Analyze this graph and explain how it relates to the corresponding correlation coefficient.

In [ ]:

```python
# Create a plot of mpg vs. weight
df.plot(x='mpg', y='weight', style='o')
plt.suptitle('Miles Per Gallon vs. Vehicle Weight', fontsize=20)
plt.xlabel('Miles Per Gallon (MPG)', fontsize=18)
```

```
plt.ylabel('Vehicle Weight (lbs)', fontsize=16)
plt.savefig('MPGWeight.jpg')
```



Randomly split the data into 80% training data and 20% test data, where your target is mpg.

In [ ]:
```
# Create x & y arrays
x = df[['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration', 'model ye
y = df['mpg']

# Create training & test datasets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2)
```

Train an ordinary linear regression on the training data.

In [ ]:
```
# Import libraries
from sklearn.linear_model import LinearRegression

# create a model
model = LinearRegression()
model.fit(x_train, y_train)

# View model coefficients
pd.DataFrame(model.coef_, x.columns, columns = ['Coeff'])
```

```
c:\Users\Joshu\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[ ]:

	Coeff
cylinders	-0.176464
displacement	0.014260
horsepower	-0.006971
weight	-0.006684
acceleration	0.100501
model year	0.750472
1	-1.796449
2	0.494659
3	1.301790

Calculate R2, RMSE, and MAE on both the training and test sets and interpret your results.

In [ ]:

```
test_predictions = model.predict(x_test)
train_predictions = model.predict(x_train)
# Printout Testing set relevant metrics
print('Test Metrics:')
print('R2', metrics.r2_score(y_test, test_predictions))
print('RMSE', metrics.mean_squared_error(y_test, test_predictions, squared=False))
print('MAE', metrics.mean_absolute_error(y_test, test_predictions))
print('\nTrain Metrics:')
print('R2', metrics.r2_score(y_train, train_predictions))
print('RMSE', metrics.mean_squared_error(y_train, train_predictions, squared=False))
print('MAE', metrics.mean_absolute_error(y_train, train_predictions))
```

```
Test Metrics:
R2 0.8215130267474595
RMSE 3.298002705627301
MAE 2.5388842703161845

Train Metrics:
R2 0.8225545944035954
RMSE 3.2827691321671137
MAE 2.485044460966265
```

```
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```

- R2: A little over 80% of the variability in mpg can be explained with our model.
- MAE: On average we can expect our model to be ~2.6 mpg off from actual values. There are not significant changes to RMSE and MAE from the training dataset to the test dataset meaning our model does have some predictive value.

Pick another regression model and repeat the previous two steps. Note: Do NOT choose logistic regression as it is more like a classification model.

In [ ]:
```
from sklearn.preprocessing import PolynomialFeatures

# Create polynomial features x^2 and x^3
polynomial = PolynomialFeatures(degree=3, include_bias=False)
x_train_p = polynomial.fit_transform(x_train)
x_test_p = polynomial.fit_transform(x_test)

# Build the model
regression = LinearRegression()
p_model = regression.fit(x_train_p, y_train)



# Build predictions
p_test_predictions = p_model.predict(x_test_p)
p_train_predictions = p_model.predict(x_train_p)

# Calculate metrics
print('Test Metrics:')
print('R2', metrics.r2_score(y_test, p_test_predictions))
print('RMSE', metrics.mean_squared_error(y_test, p_test_predictions, squared=False))
print('MAE', metrics.mean_absolute_error(y_test, p_test_predictions))
print('\nTrain Metrics:')
print('R2', metrics.r2_score(y_train, p_train_predictions))
print('RMSE', metrics.mean_squared_error(y_train, p_train_predictions, squared=False))
print('MAE', metrics.mean_absolute_error(y_train, p_train_predictions))
```

```
Test Metrics:
R2 -13.50348853505353
RMSE 29.72925205522567
MAE 7.81398982401659

Train Metrics:
R2 0.9628045914143147
RMSE 1.5029780166565232
MAE 1.1066642142738823
```

```
c:\Users\Joshu\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688: FutureWa
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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(
```

The polynomial model does well on the training data. However, when the model is used on the test data the model does not succeed based on the R2, RMSE, and MAE.