Assignment 3: Predicting Fuel Efficiency with Linear Regression

Objective: The objective of this assignment is to use the "mtcars" dataset to perform linear regression analysis and predict the fuel efficiency (miles per gallon) of car models based on their specifications.

Dataset: "mtcars" Dataset

Description: The "mtcars" dataset contains data on various car models from the 1970s, including 32 observations and 11 variables. The variables include characteristics like horsepower, weight, and number of cylinders, as well as the target variable, miles per gallon (mpg), which represents the car's fuel efficiency

Module: CS401 Machine Learning

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```
%matplotlib inline

import pandas as pd
import seaborn as sns
import matplotlib as m
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as stats
import sys
```

Data Exploration and Preparation (10 points):

1.1 Load the "mtcars" dataset and describe its structure, including the number of observations and variables.

I downloaded the dataset from a github repository as there was no indication of importing it from a library like with the iris dataset. I also found the datset on kaggle for comparision and they were the same so I am hoping this is the right setthe assignment is based on.

```
mtcars_dataset = pd.read_csv('mtcars.csv')

mtcars_dataset
```

```
                  model   mpg  cyl   disp   hp  drat     wt   qsec  vs
am  \
0             Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0
1
1         Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0
1
```

2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0
5	Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0
6	Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0
7	Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0
8	Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0
9	Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0
10	Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0
11	Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0
12	Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0
13	Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0
14	Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0
15	Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0
16	Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0
17	Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1
18	Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1
19	Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1
20	Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0
21	Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0
22	AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0
23	Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0
24	Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0
25	Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1
26	Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	

```
1
27         Lotus Europa  30.4    4   95.1  113  3.77  1.513  16.90   1
1
28       Ford Pantera L  15.8    8  351.0  264  4.22  3.170  14.50   0
1
29         Ferrari Dino  19.7    6  145.0  175  3.62  2.770  15.50   0
1
30        Maserati Bora  15.0    8  301.0  335  3.54  3.570  14.60   0
1
31           Volvo 142E  21.4    4  121.0  109  4.11  2.780  18.60   1
1

    gear  carb
0      4     4
1      4     4
2      4     1
3      3     1
4      3     2
5      3     1
6      3     4
7      4     2
8      4     2
9      4     4
10     4     4
11     3     3
12     3     3
13     3     3
14     3     4
15     3     4
16     3     4
17     4     1
18     4     2
19     4     1
20     3     1
21     3     2
22     3     2
23     3     4
24     3     2
25     4     1
26     5     2
27     5     2
28     5     4
29     5     6
30     5     8
31     4     2
```

This is an explanation I found online for what all the variables stand for and mean. Link is in references.

Format A data frame with 32 observations on 11 (numeric) variables.

[, 1] mpg => Miles/(US) gallon

[, 2] cyl => Number of cylinders

[, 3] disp => Displacement (cu.in.)

[, 4] hp => Gross horsepower

[, 5] drat => Rear axle ratio

[, 6] wt => Weight (1000 lbs)

[, 7] qsec => 1/4 mile time

[, 8] vs => Engine (0 = V-shaped, 1 = straight)

[, 9] am => Transmission (0 = automatic, 1 = manual)

[, 10] gear => Number of forward gears

[, 11] carb => no. of carburetors.

1.2 Explore the dataset by calculating summary statistics and visualizing the data. Create scatter plots to examine the relationships between the independent variables and the target variable (mpg).

```
mtcars_dataset.describe()
```

```
             mpg        cyl        disp          hp        drat
wt  \
count  32.000000  32.000000   32.000000   32.000000  32.000000
32.000000
mean   20.090625   6.187500  230.721875  146.687500   3.596563
3.217250
std     6.026948   1.785922  123.938694   68.562868   0.534679
0.978457
min    10.400000   4.000000   71.100000   52.000000   2.760000
1.513000
25%    15.425000   4.000000  120.825000   96.500000   3.080000
2.581250
50%    19.200000   6.000000  196.300000  123.000000   3.695000
3.325000
75%    22.800000   8.000000  326.000000  180.000000   3.920000
3.610000
max    33.900000   8.000000  472.000000  335.000000   4.930000
5.424000

            qsec         vs         am       gear     carb
count  32.000000  32.000000  32.000000  32.000000  32.0000
mean   17.848750   0.437500   0.406250   3.687500   2.8125
std     1.786943   0.504016   0.498991   0.737804   1.6152
min    14.500000   0.000000   0.000000   3.000000   1.0000
25%    16.892500   0.000000   0.000000   3.000000   2.0000
```

```
50%    17.710000   0.000000   0.000000   4.000000   2.0000
75%    18.900000   1.000000   1.000000   4.000000   4.0000
max    22.900000   1.000000   1.000000   5.000000   8.0000
```

```
mtcars_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   model   32 non-null     object
 1   mpg     32 non-null     float64
 2   cyl     32 non-null     int64
 3   disp    32 non-null     float64
 4   hp      32 non-null     int64
 5   drat    32 non-null     float64
 6   wt      32 non-null     float64
 7   qsec    32 non-null     float64
 8   vs      32 non-null     int64
 9   am      32 non-null     int64
 10  gear    32 non-null     int64
 11  carb    32 non-null     int64
dtypes: float64(5), int64(6), object(1)
memory usage: 3.1+ KB
```

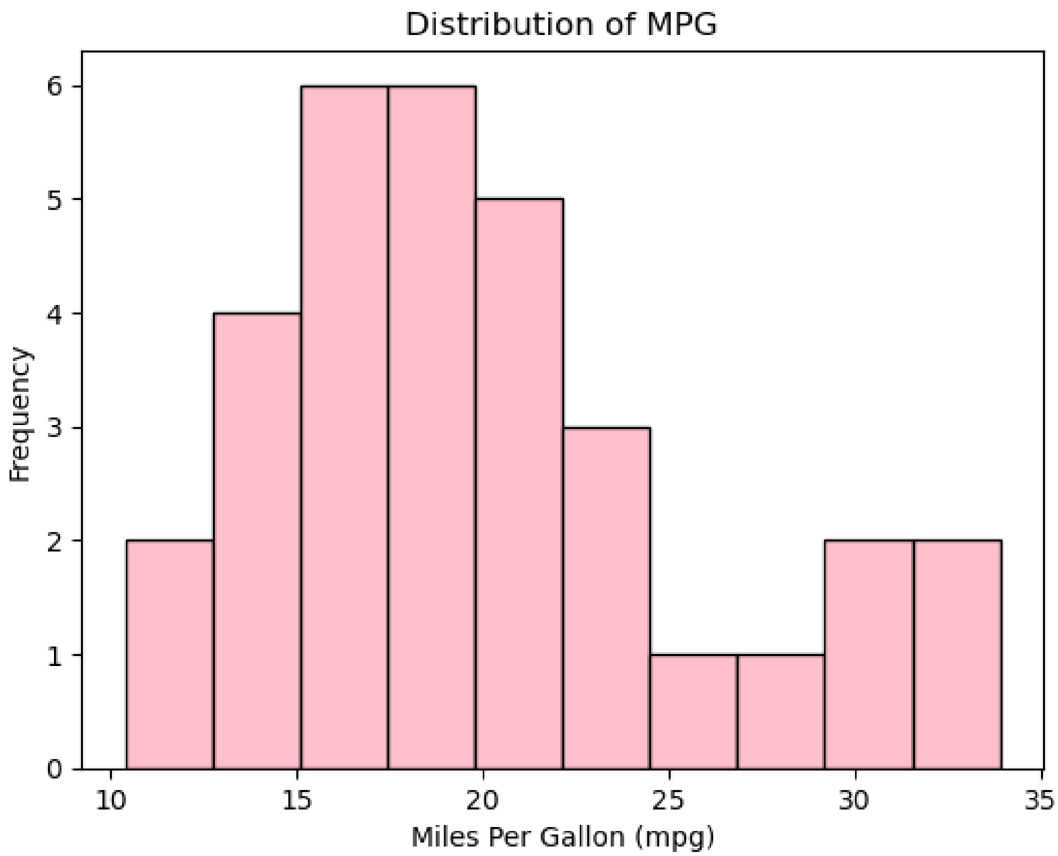
```
print(f"There are {len(mtcars_dataset)} rows and
{len(mtcars_dataset.columns)} columns in the mtcars_dataset.")
```

```
There are 32 rows and 12 columns in the mtcars_dataset.
```

A majority of the data seems lie in the 15-20 range when it comes to miles per gallon (mpg). According to the mean value, the mean value of mpg is 20.

```
mtcars_dataset['mpg'].hist(color='pink', grid=False,
edgecolor='black')
plt.xlabel('Miles Per Gallon (mpg)')
plt.ylabel('Frequency')
plt.title('Distribution of MPG')
```

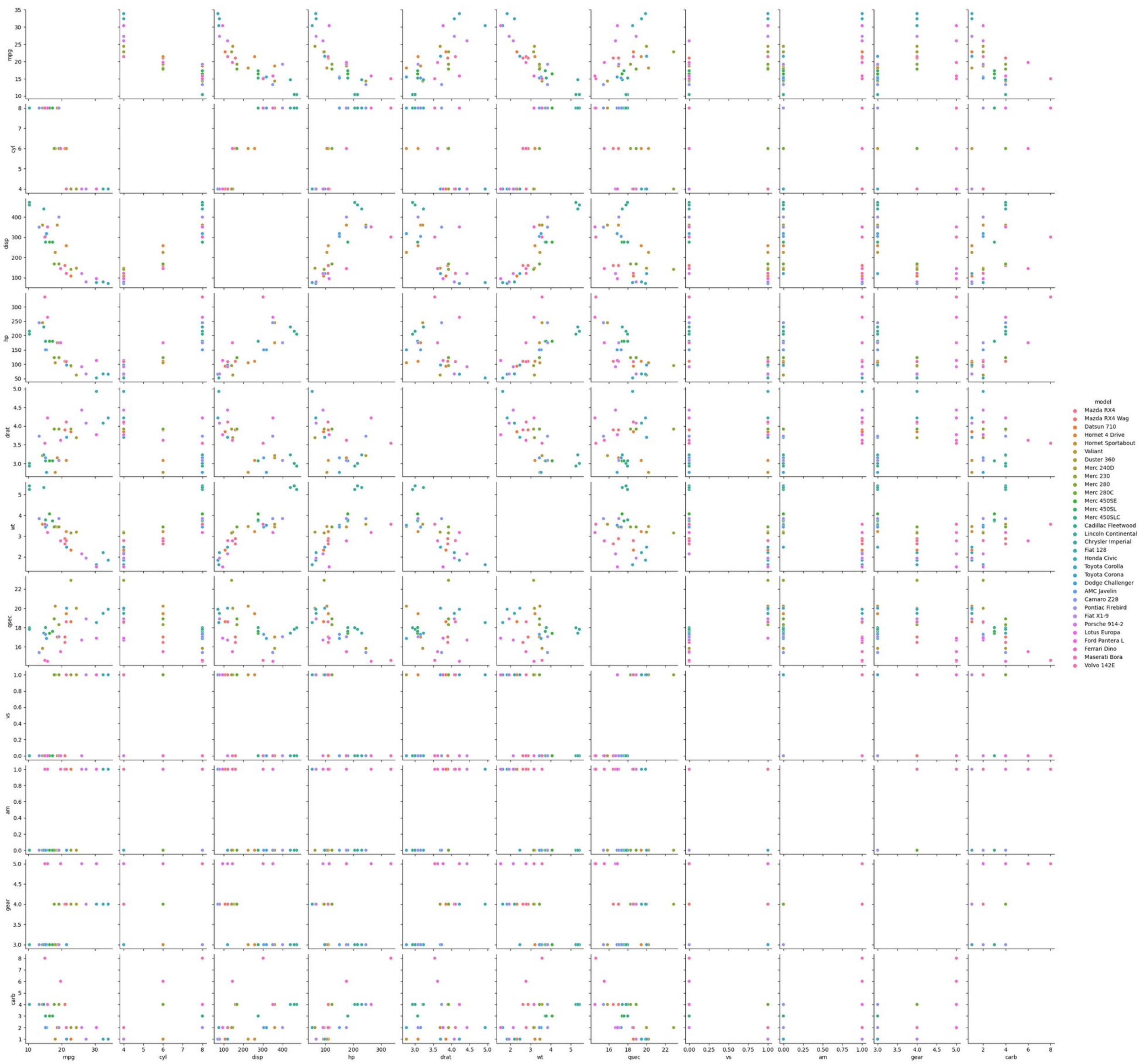
```
Text(0.5, 1.0, 'Distribution of MPG')
```



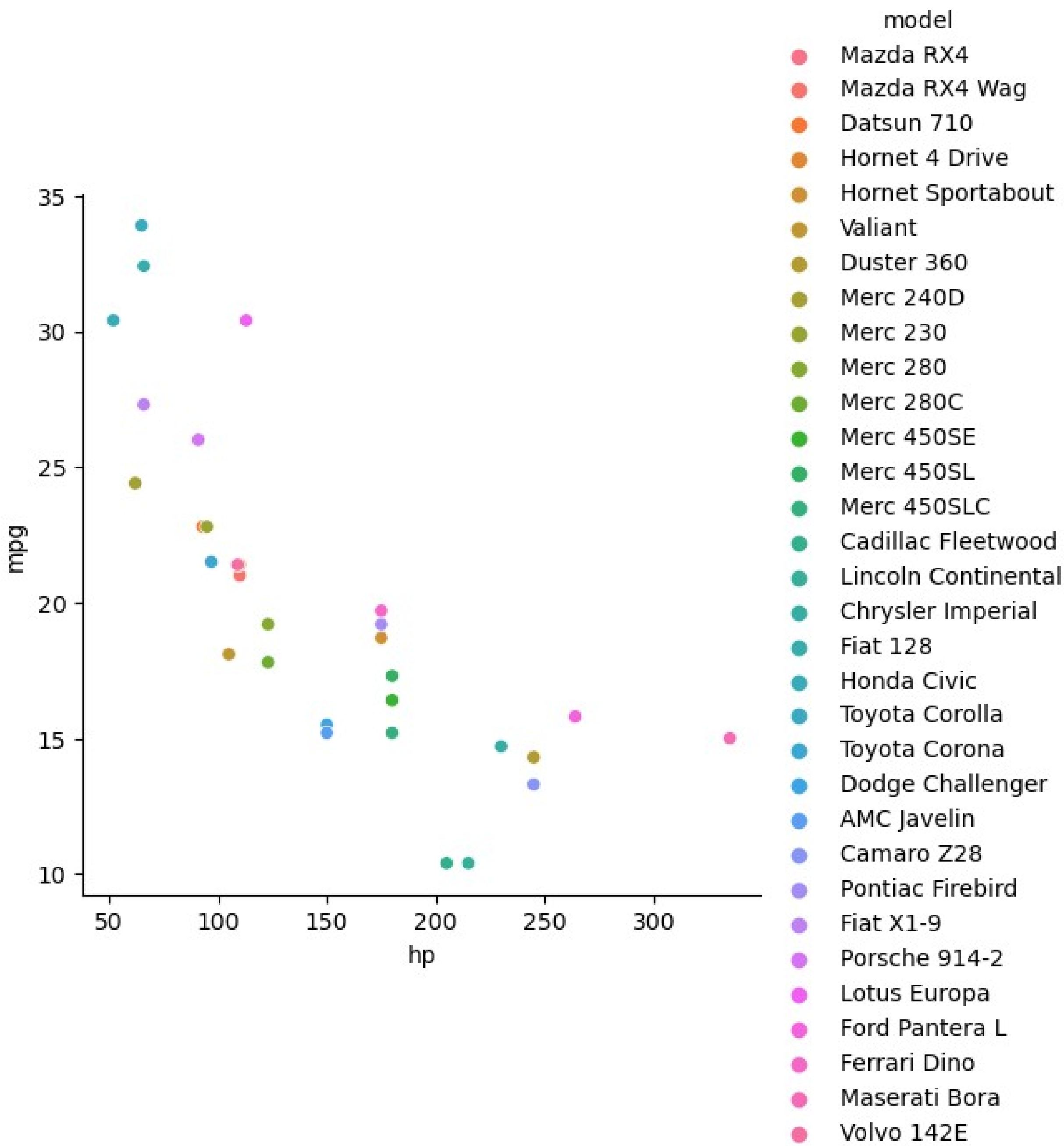
This pairplot represents all the data correlation points. A few of them look interesting so I decided to replot them individually below this massive pairplot for further observation.

```
sns.pairplot(mtcars_dataset, hue="model")
```

```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.PairGrid at 0x1ba05f85190>
```



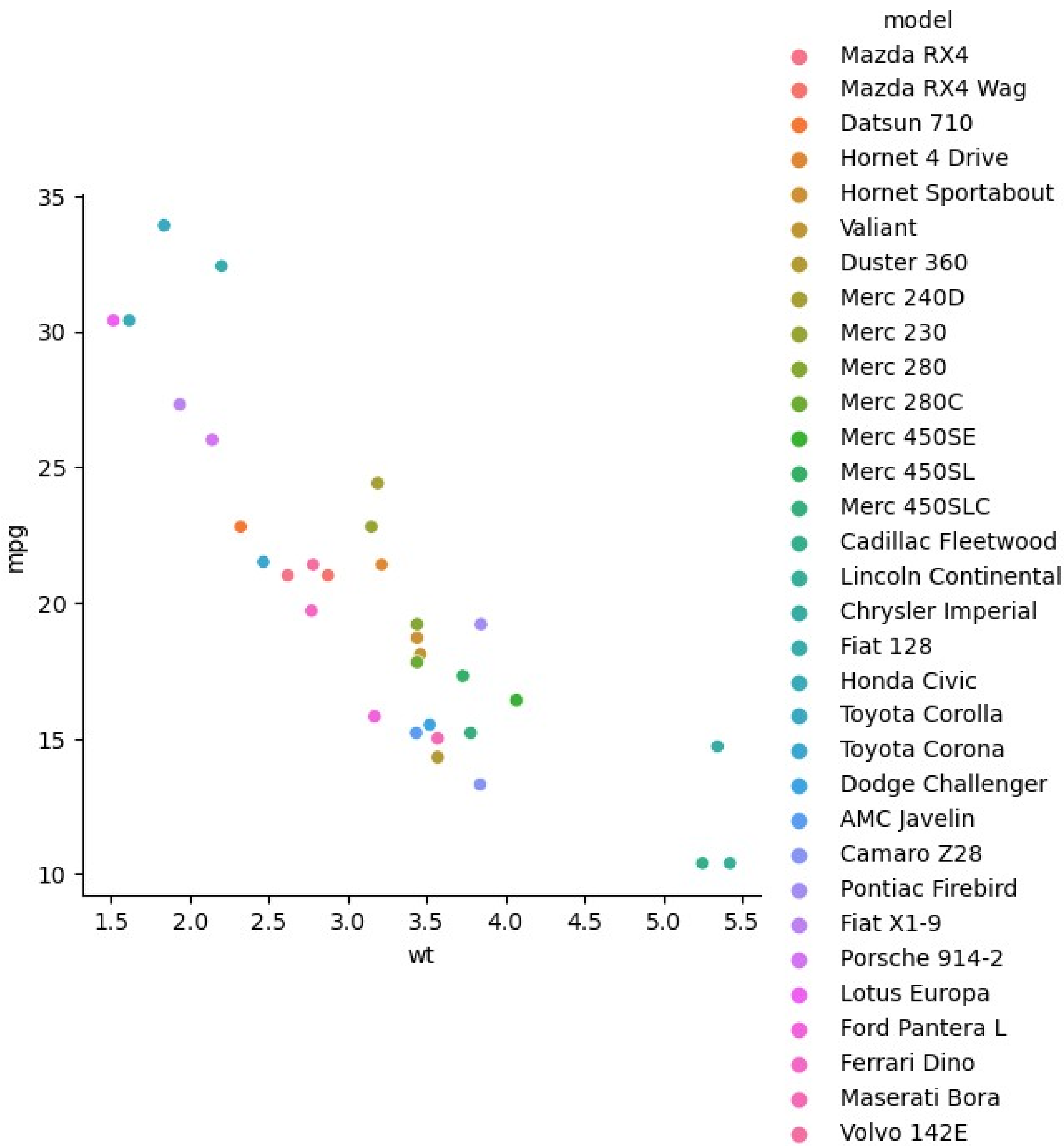

```
sns.relplot(x = "hp", y = "mpg", hue = "model", data= mtcars_dataset)
plt.figure(figsize=(20,10))
plt.show()

c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




```
<Figure size 2000x1000 with 0 Axes>
```

```
sns.relplot(x = "wt", y = "mpg", hue = "model", data= mtcars_dataset)
plt.figure(figsize=(20,10))
plt.show()
```

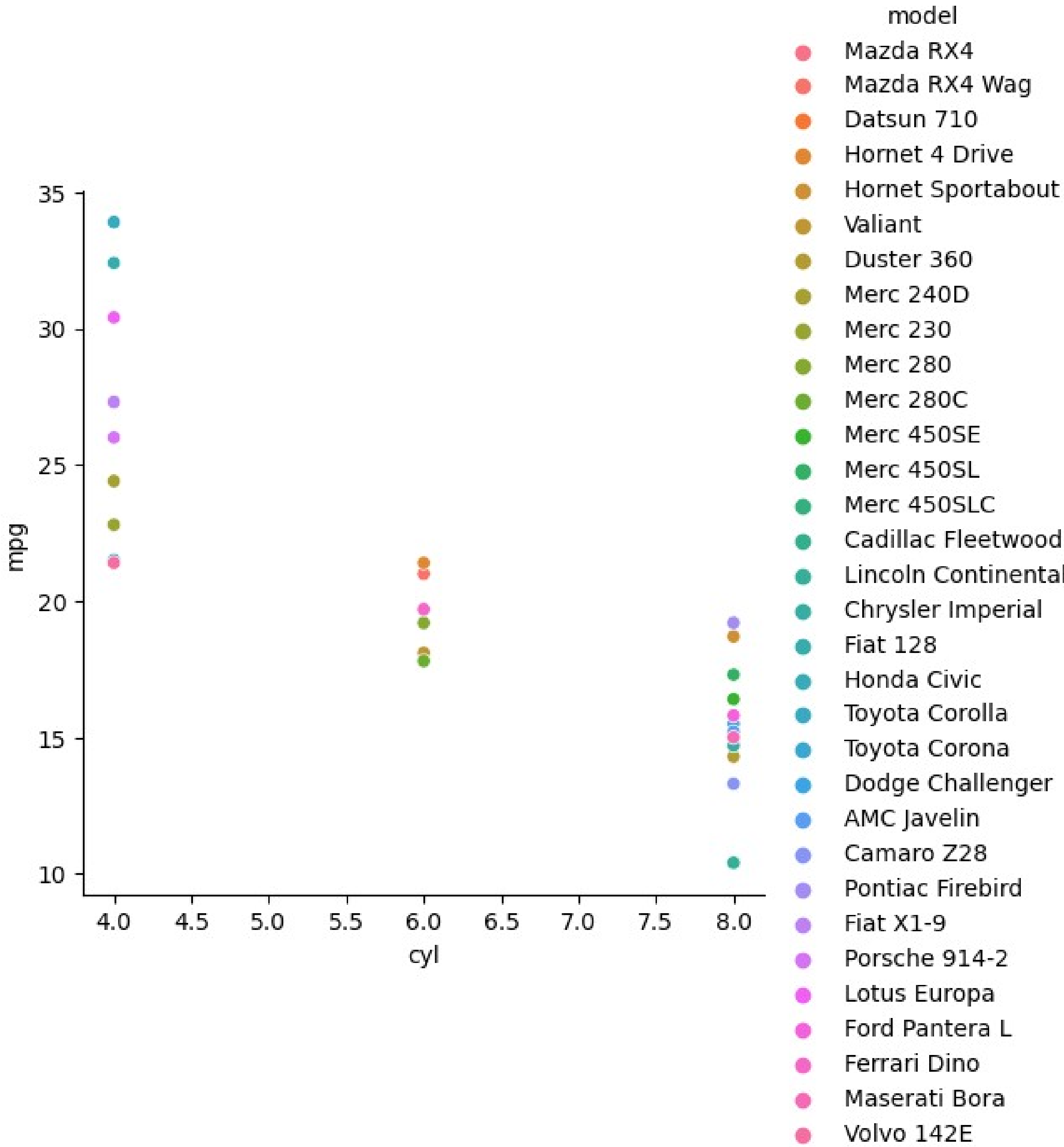
```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




```
<Figure size 2000x1000 with 0 Axes>
```

```
sns.relplot(x = "cyl", y = "mpg", hue = "model", data= mtcars_dataset)
plt.figure(figsize=(20,10))
plt.show()
```

```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




```
<Figure size 2000x1000 with 0 Axes>

print(mtcars_dataset.query('mpg > 33'))

                model   mpg  cyl  disp  hp  drat     wt  qsec  vs  am
gear  carb
19  Toyota Corolla  33.9    4  71.1  65  4.22  1.835  19.9   1   1
4     1

print(mtcars_dataset.query('mpg < 11'))
```

```
                  model   mpg  cyl   disp   hp  drat     wt   qsec  vs  
am  \
14   Cadillac Fleetwood  10.4    8  472.0  205  2.93  5.250  17.98   0   
0   
15  Lincoln Continental  10.4    8  460.0  215  3.00  5.424  17.82   0   
0   

    gear  carb  
14     3     4  
15     3     4  
```

Toyota Corrolla seems to be the highest model for miles for gallon. As we can observe from the scatter plots as the weight decreases the miles for gallon increase. The Cadillac and the Lincoln both have low miles per gallon but higher weight compared to the Toyota. This may mean that weight could have a strong association with miles per gallon.

Taking out the model column so i can show a correlation matrix for all the numeric varaibles in the mt cars dataset in order to see a visual representation of the independent and dependant variables. I print out the first few rows just to see if it worked. Note it worked for the full set, I just wanted to decrease the space used up.

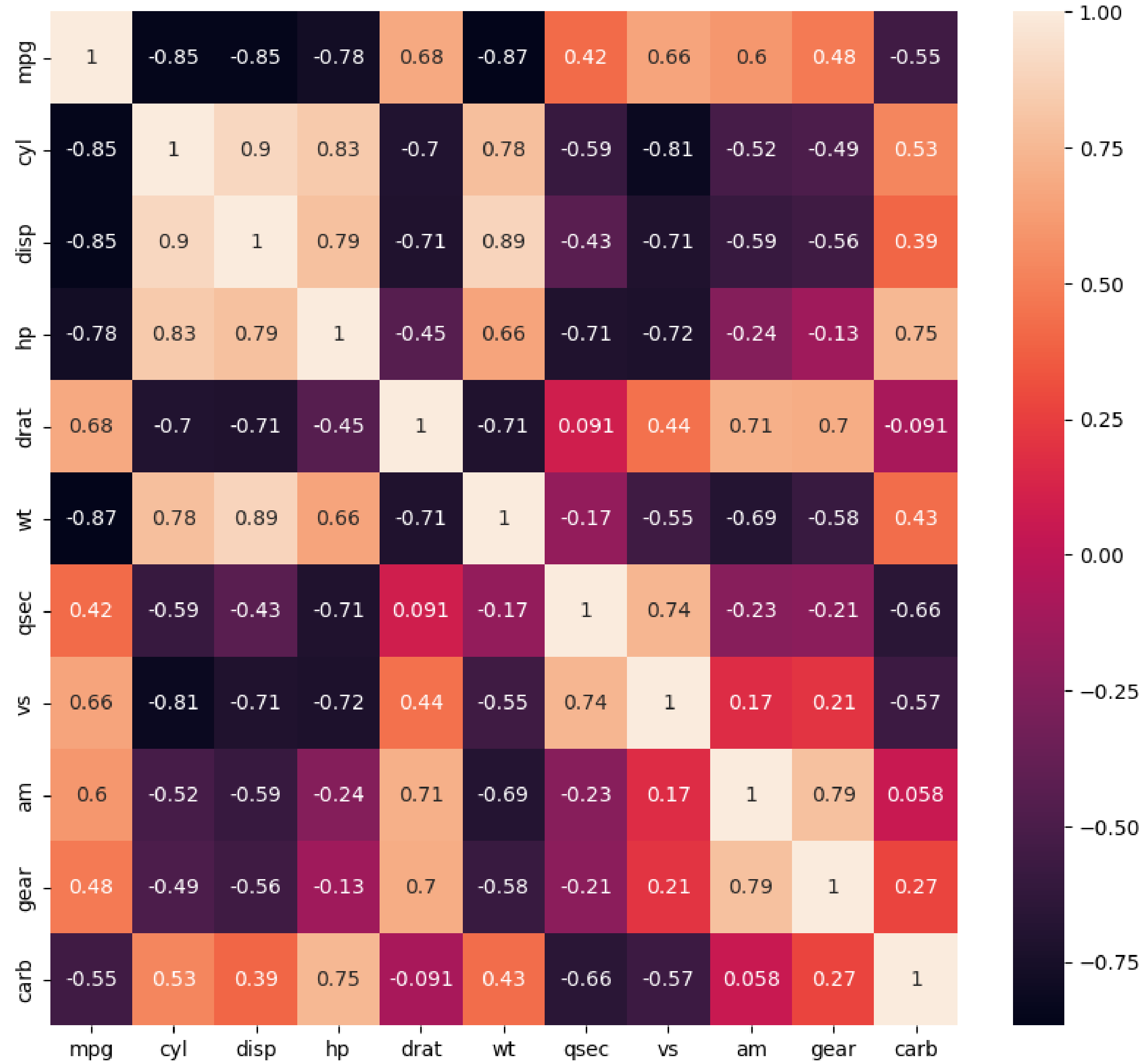
```
#iris_dataframe.corr
mtcars_subset = mtcars_dataset.drop(columns="model")
mtcars_subset.head()
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

Correlation Matrix

```
#iris_dataframe.corr

fig, ax = plt.subplots(figsize =(10,9))
sns.heatmap(mtcars_subset.corr(), annot=True, ax=ax)
```

```
<Axes: >
```



I found the correlation metric online to help me gauge the correlation of the mtcars dataset.

Perfectly Positive Correlation: When correlation value is exactly 1.

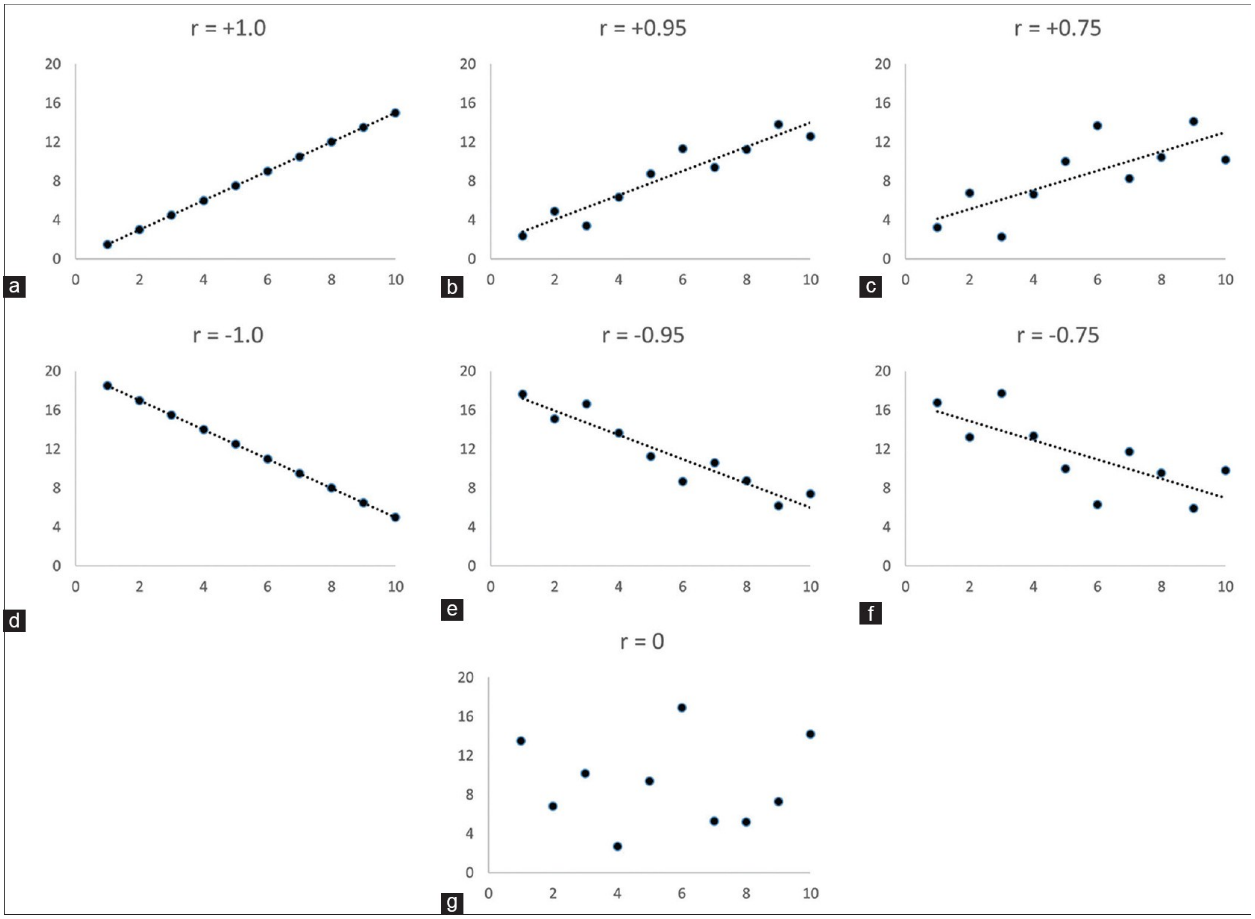
Positive Correlation: When correlation value falls between 0 to 1.

No Correlation: When correlation value is 0.

Negative Correlation: When correlation value falls between -1 to 0.

Perfectly Negative Correlation: When correlation value is exactly -1.

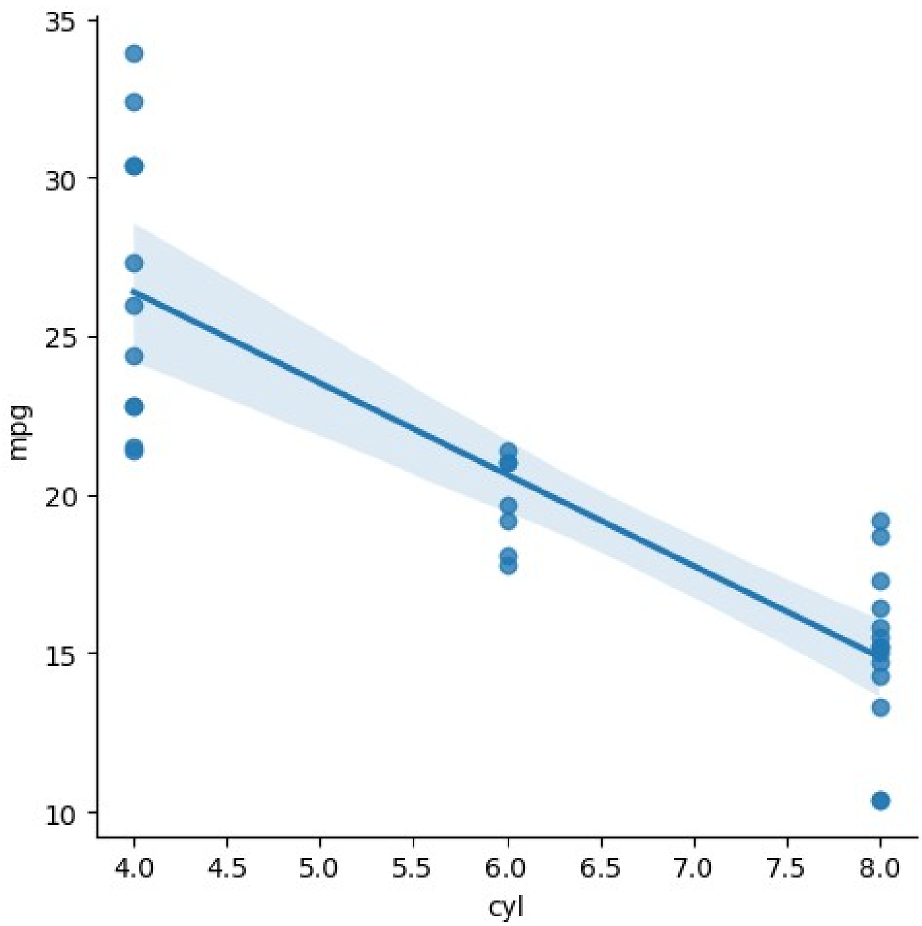
```
from IPython import display
display.Image("correlation metric.jpg")
```



I decided to plot out a few of the ones that had a strong correlation with mpg such as cyl, disp, wt, hp and drat.

```
sns.lmplot(x="cyl", y="mpg", data=mtcars_dataset)
```

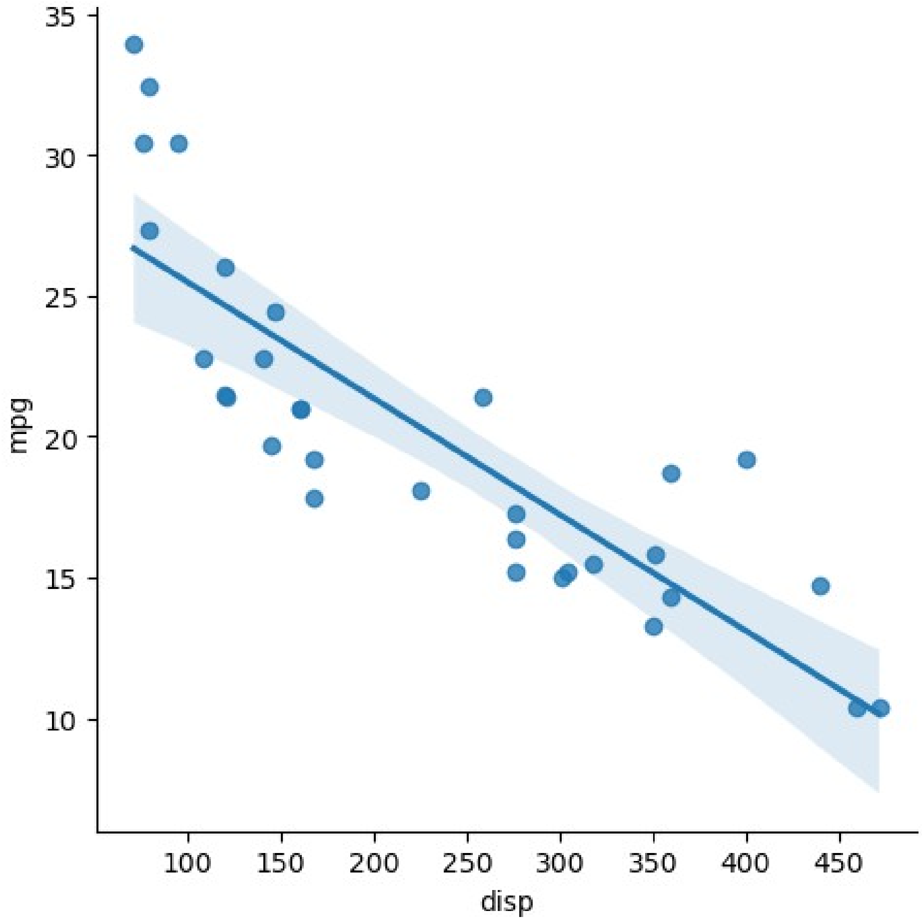
```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x1ba0e6c3250>
```




```
sns.lmplot(x="disp", y="mpg", data=mtcars_dataset)
```

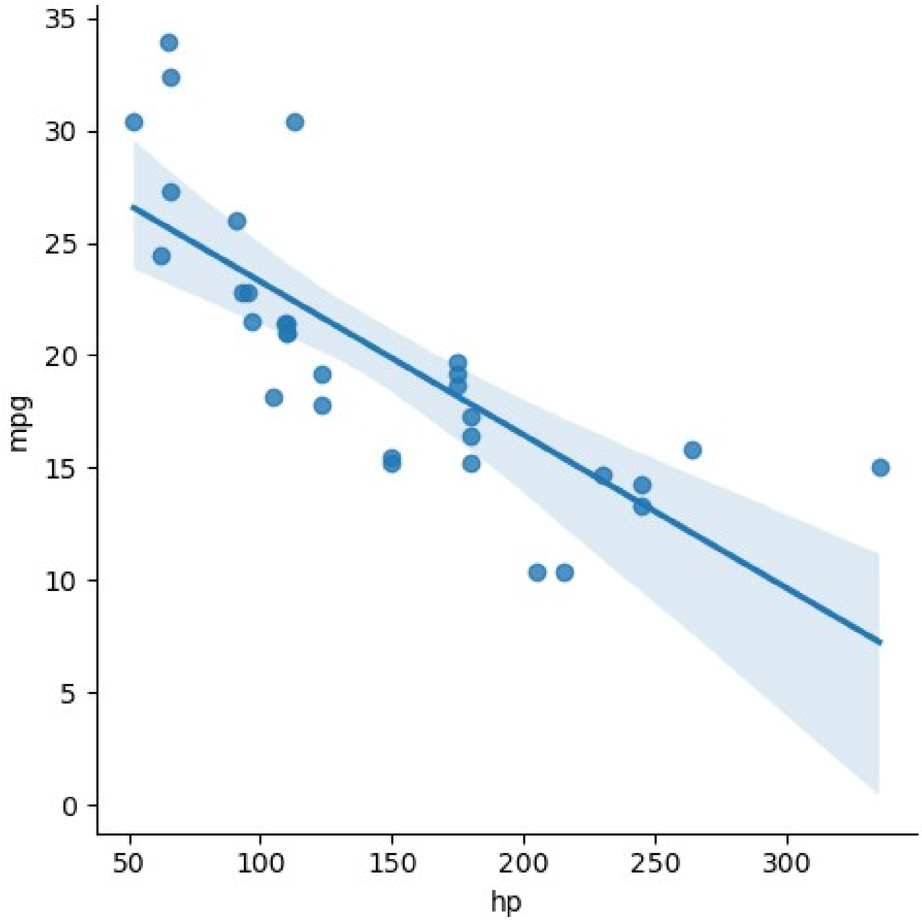
```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<seaborn.axisgrid.FacetGrid at 0x1ba0ee33090>
```




```
sns.lmplot(x="hp", y="mpg", data=mtcars_dataset)
```

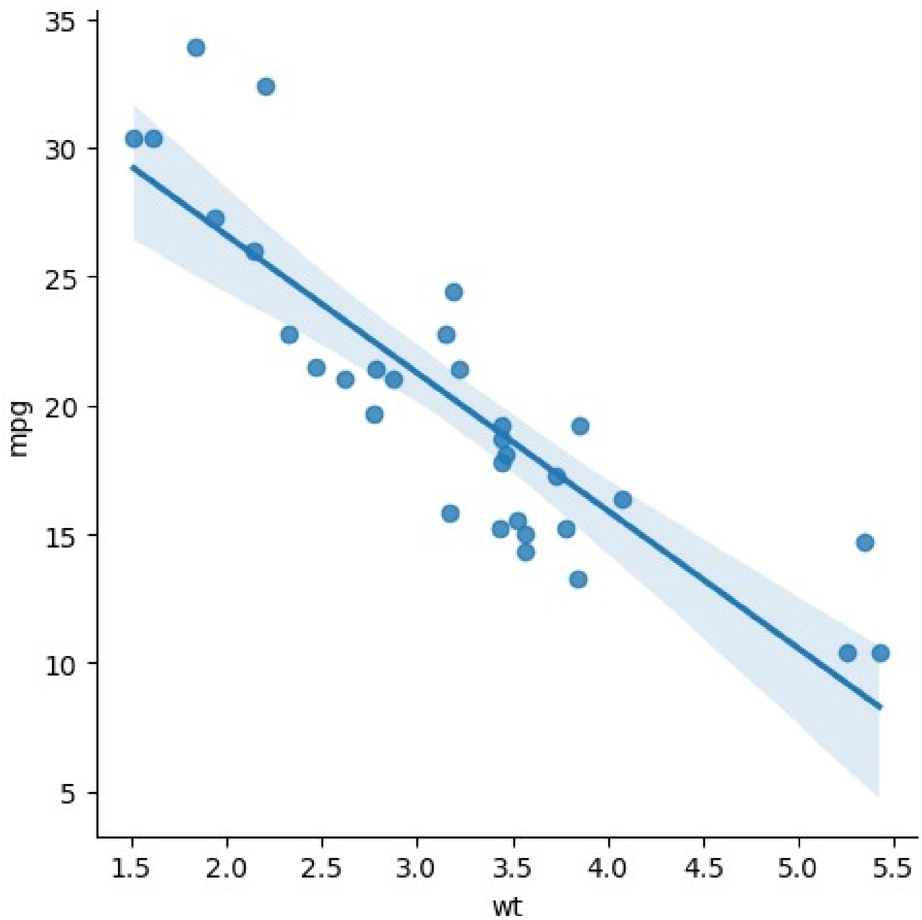
```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x1ba0f85f050>
```



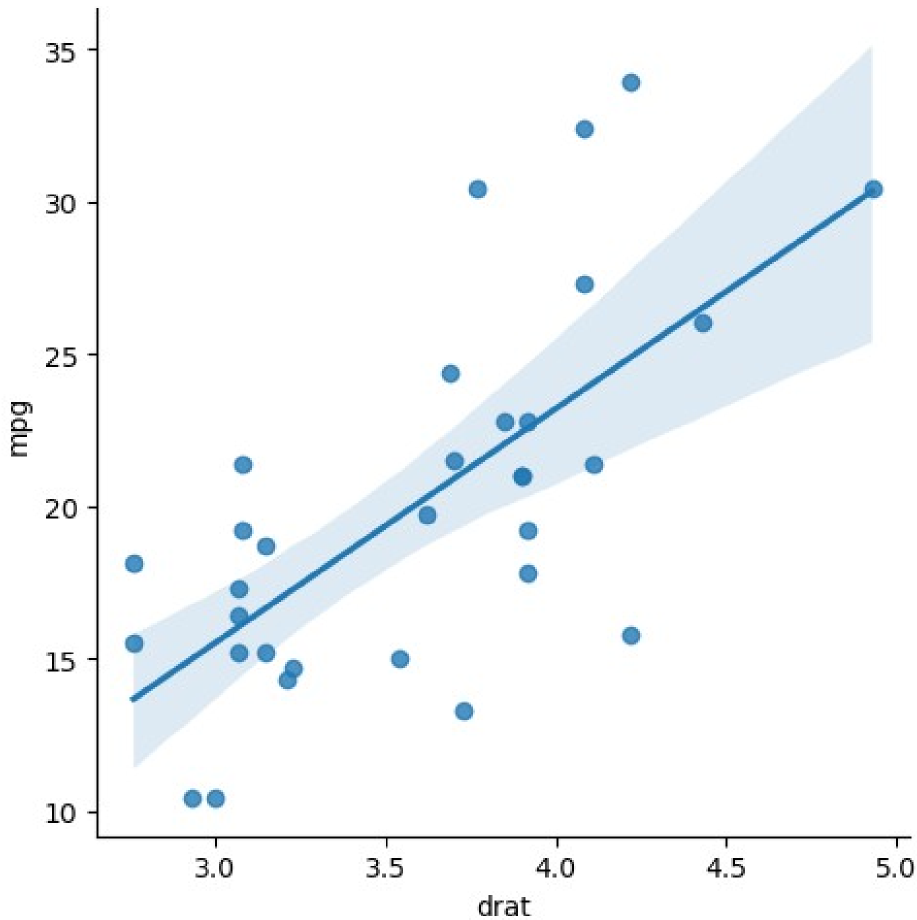

```
sns.lmplot(x="wt", y="mpg", data=mtcars_dataset)
```

```
c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<seaborn.axisgrid.FacetGrid at 0x1ba0f7b4a90>
```




```
sns.lmplot(x="drat", y="mpg", data=mtcars_dataset)

c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x1ba0f398310>
```



According to the Correlation matrix and metrics I have provided the variables hp,wt, cyl and disp all have a strong negative linear relationship with the target variable mpg. The variable drat has a medium strength linear relationship with the target variable mpg. We shall choose one of these for values and implement it into a simple linear regression model to train it to predict the target variable outcomes.

Simple Linear Regression (30 points):

2.1 Select one independent variable from the "mtcars" dataset that you believe may have a strong linear relationship with the target variable (mpg).

I shall select weight as it has a strong negative relationship with mpg as I have shown above.

```
from sklearn.model_selection import train_test_split
```

2.2 Implement a simple linear regression model to predict mpg using the selected independent variable.

Weight will be my x value and Y will be my target value. I split the train test set into 80% training and 20% testing. Im not sure if we are supposed to go lower since it is a smaller dataset but I may change up the numbers and record the difference. For now, the model seems to be able to explain 75% of the data according to the r2 score metrics which I am recording now in case I change the variance later.

```
x = mtcars_dataset.wt
Y = mtcars_dataset.mpg


x_train, x_test, Y_train, Y_test = train_test_split(x, Y, test_size=
0.2, random_state= 42)
```

According to tutorials I was following online, we need to reshape the data so there is 1 column but as many n rows as possible to make it into a 1 dimensional array to feed into the linear regression model.

```
x_train = np.array(x_train).reshape(-1, 1)
x_test = np.array(x_test).reshape(-1, 1)
```

I import the linear regression model and fit the data into it to train the model.

```
from sklearn.linear_model import LinearRegression
linearReg_model = LinearRegression()
linearReg_model.fit(x_train, Y_train)
```

```
LinearRegression()
```

2.3 Calculate the model's coefficients (slope and intercept) and evaluate its performance using appropriate regression evaluation metrics (on testing dataset).

Checking the training data

```
#intercept in maths
c = linearReg_model.intercept_
c
```

```
36.93731031351841
```

```
#slope in maths
m = linearReg_model.coef_
m
```

```
array([-5.3369414])
```

Predicted Values for the training set

```
# y = mx + c -> slope formula

Y_pred = (m*x_train) + c
Y_pred
```

```
array([[26.6103287 ],
       [17.03051889],
       [22.95452384],
       [18.5782319 ],
       [ 8.41135853],
       [18.47149307],
       [16.76367182],
       [15.21595881],
       [16.44345534],
       [21.59360379],
       [24.55560626],
       [25.51625572],
       [19.77904371],
       [18.15127658],
       [28.86251797],
       [18.6049166 ],
       [28.31814995],
       [22.10061322],
       [23.78174976],
       [19.91246725],
       [18.5782319 ],
       [ 8.91836796],
       [20.01920607],
       [27.14402284],
       [17.88442951]])
```

```
y_pred1 = linearReg_model.predict(x_train)
y_pred1
```

```
array([26.6103287 , 17.03051889, 22.95452384, 18.5782319 ,
8.41135853,
       18.47149307, 16.76367182, 15.21595881, 16.44345534,
21.59360379,
       24.55560626, 25.51625572, 19.77904371, 18.15127658,
28.86251797,
       18.6049166 , 28.31814995, 22.10061322, 23.78174976,
19.91246725,
       18.5782319 ,  8.91836796, 20.01920607, 27.14402284,
17.88442951])
```

the predicted values from the model for the training data and the manually calculated values seem to match which means the model is doing well on its predictions.

```
from IPython import display
display.Image("r_squared formula.png")
```

$$\text{R2 Squared} = 1 - \frac{SSr}{SSm}$$

SSr = Squared sum error of regression line

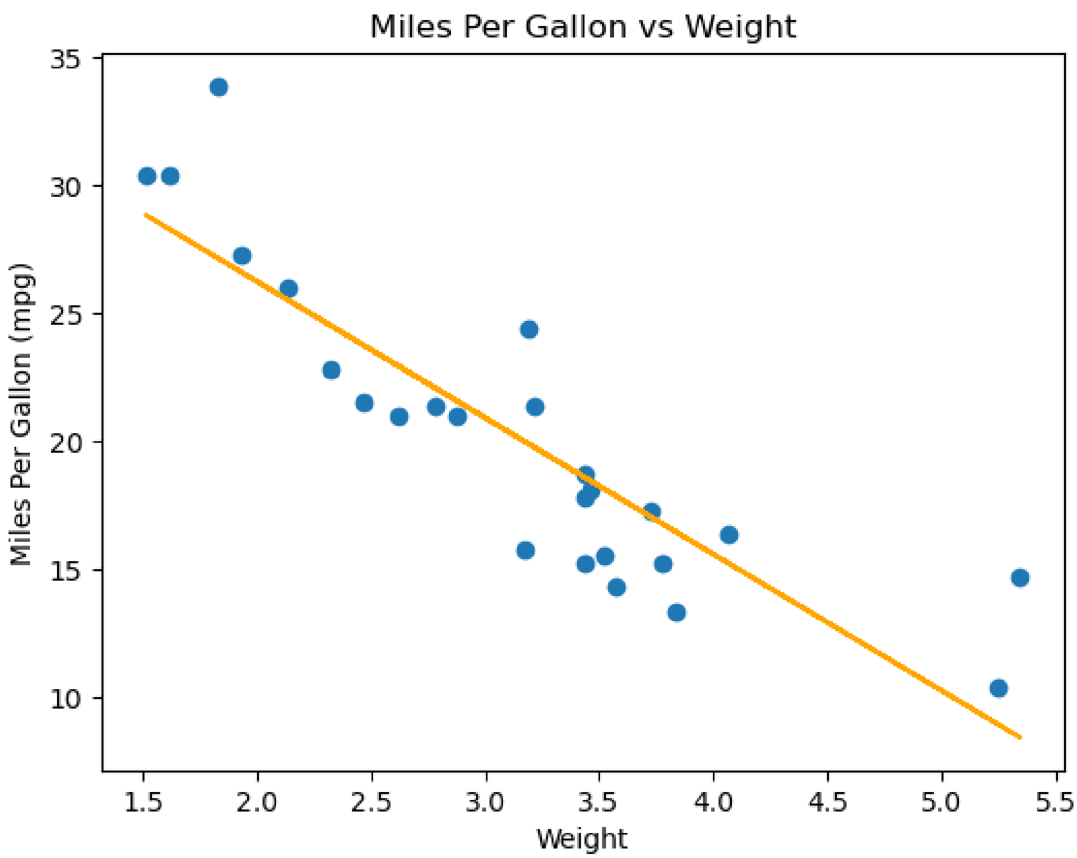
SSm = Squared sum error of mean line

```
r_sq = linearReg_model.score(x_train, Y_train)
r_sq
```

```
0.7701379909791617
```

Showing the linear correlation between weight and miles per gallon.

```
plt.scatter(x_train,Y_train)
plt.plot(x_train, y_pred1, color = "orange")
plt.xlabel("Weight")
plt.ylabel("Miles Per Gallon (mpg)")
plt.title("Miles Per Gallon vs Weight")
plt.show()
```

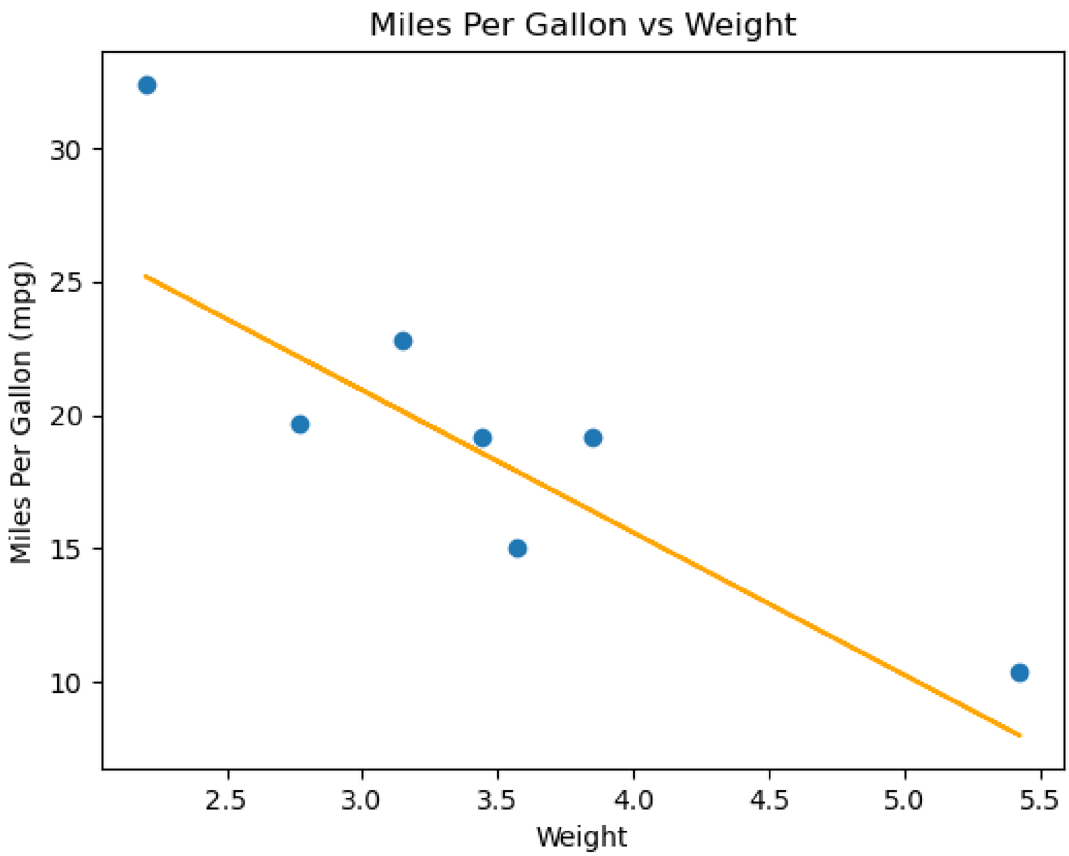


Noting down observation, it seems if i dont reshape the target variable data the model is trained better. I find this interesting. Perhaps its cuz of the random state.

Checking the testing data and looking at the predicted values for the testing set.

```
y_pred2 = linearReg_model.predict(x_test)
y_pred2

array([22.15398263,  7.98974016, 16.41677063, 25.19603923,
20.1259449 ,
       18.5782319 , 17.88442951])

# y = mx + c

y_pred3 = (m* x_test) + c
y_pred3

array([[22.15398263],
       [ 7.98974016],
       [16.41677063],
       [25.19603923],
       [20.1259449 ],
       [18.5782319 ],
       [17.88442951]])
```

```
plt.scatter(x_test,Y_test)
plt.plot(x_test, y_pred2, color = "orange")
plt.xlabel("Weight")
plt.ylabel("Miles Per Gallon (mpg)")
plt.title("Miles Per Gallon vs Weight")
plt.show()
```



With about 20% of the testing data it doesnt look as pretty, perhaps because of the data size. However, it does seem a lot easier to spot the outlier in this case.

Multiple Linear Regression (40 points):

3.1 Implement a multiple linear regression model using a combination of independent variables from the "mtcars" dataset

```
#split dataset in features and target variable
feature_cols = ['cyl', 'disp', 'hp', 'drat', 'wt']
X = mtcars_dataset[feature_cols] # Features
y = mtcars_dataset.mpg # Target variable
# Split dataset into training set and test set
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state= 42) # 80% training and 20% test
```

```
multiLinearReg_model = LinearRegression()
```

```
multiLinearReg_model.fit(X_train, y_train)
```

```
LinearRegression()
```

```
c = multiLinearReg_model.intercept_
c
```

```
33.6943590758315
```

```
m = multiLinearReg_model.coef_
m
```

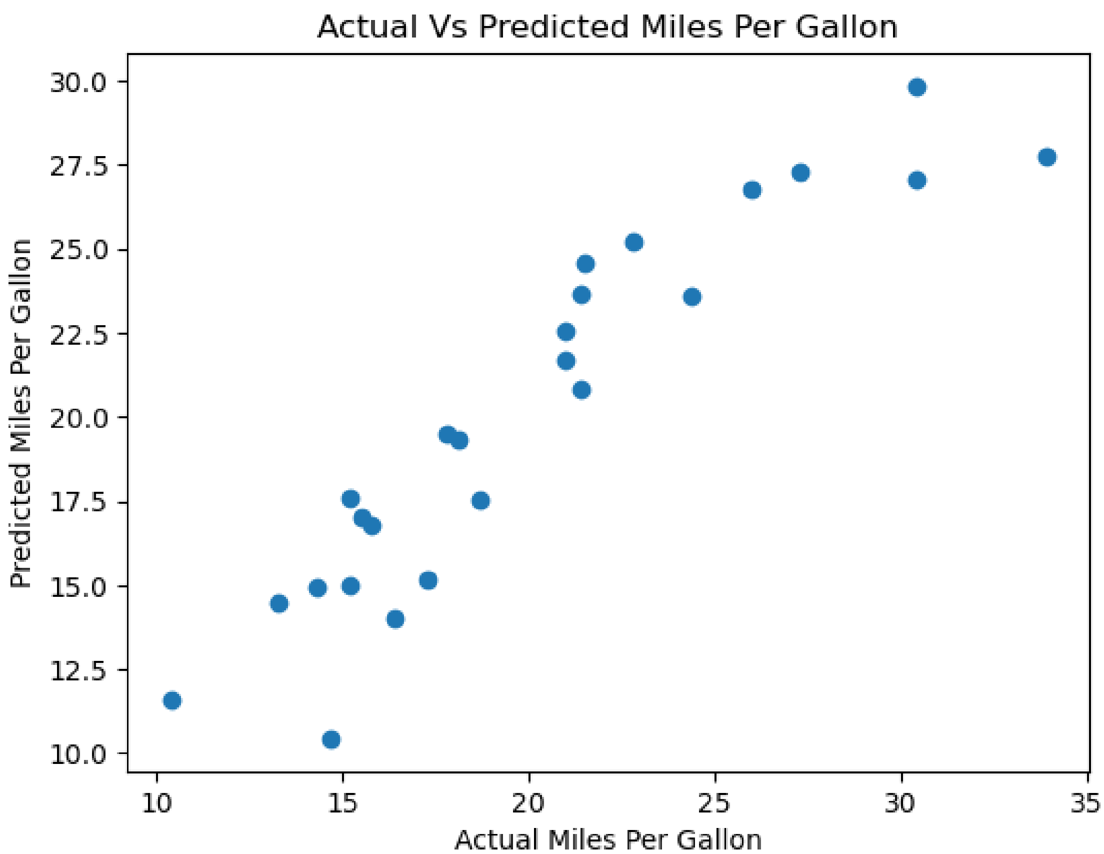
```
array([-0.93251579,  0.01298582, -0.03194703,  1.22293942, -
3.38988582])
```

3.2 Train the model to predict mpg using multiple features

```
y_pred4 = multiLinearReg_model.predict(X_train)
y_pred4
```

```
array([27.31183506, 15.17540508, 22.55078433, 17.50944809,
10.43132932,
       19.31294258, 15.00591079, 14.0228439 , 14.49664815,
21.68636345,
       25.23947176, 26.78257569, 20.80360203, 17.01458236,
27.07081676,
       17.59786759, 29.8405023 , 23.65575163, 24.59383766,
23.58750994,
       19.47891753, 11.60070862, 16.77310415, 27.75139424,
14.90584699])
```

```
plt.scatter(y_train, y_pred4)
plt.xlabel("Actual Miles Per Gallon")
plt.ylabel("Predicted Miles Per Gallon")
plt.title("Actual Vs Predicted Miles Per Gallon")
plt.show()
```



To the human eyes this appears to be slightly curved and not very linear. It could be because of the multiple variables I chose to try and predict the target value mpg.

```
from sklearn.metrics import r2_score

score = r2_score(y_train, y_pred4)
score
```

```
0.8572631834562161
```

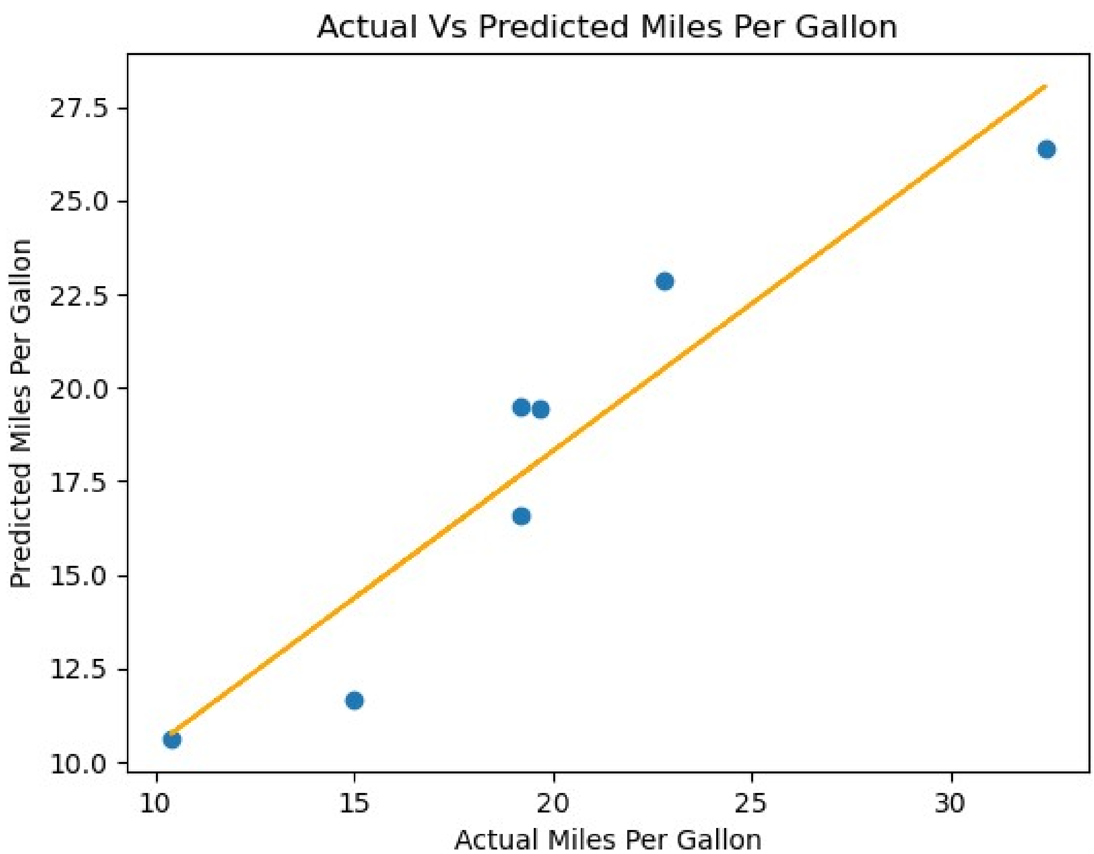
Even tho the line is curved it seems that the model is doing better than the simple linear regression model at predicting the training data, with a score of 85%.

```
y_pred5 = multiLinearReg_model.predict(X_test)
y_pred5
```

```
array([19.42853401, 10.62117411, 16.57037127, 26.40961957,
22.87351303,
       19.47891753, 11.66802081])
```

```
a, b = np.polyfit(y_test, y_pred5, 1)
plt.scatter(y_test, y_pred5)
plt.plot(y_test, a*y_test+b, color = "orange")
#plt.plot(y_test, y_pred5,color = "orange")
```

```
plt.xlabel("Actual Miles Per Gallon")
plt.ylabel("Predicted Miles Per Gallon")
plt.title("Actual Vs Predicted Miles Per Gallon")
plt.show()
```

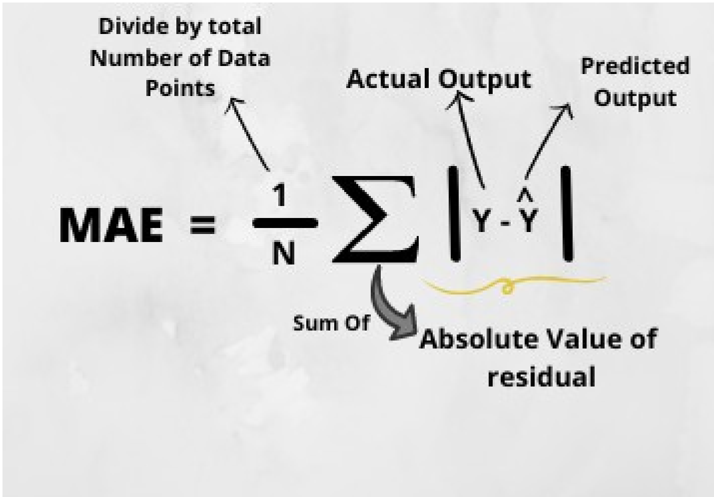


Even the testing data looks closer to a line and there seems to be 1 perfect value that is situated on the line.

3.3 Evaluate the model's performance using appropriate regression evaluation metrics (on testing dataset).

I implemented a couple of metrics as none were neccessarily specified. The reason also was because I was reading an article that explained for multi linear regression a few evaluation metrics were needed in order to properly gauge the performance of the model.

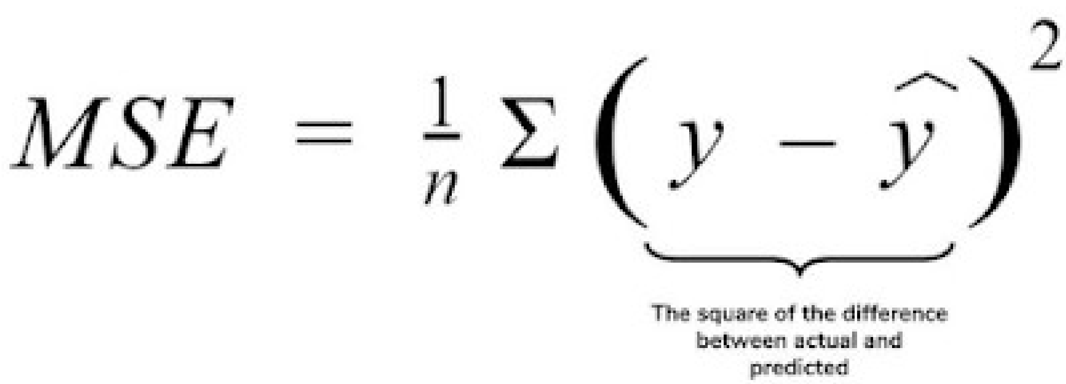
```
from IPython import display
display.Image("mean_absolute_error formula.png")
```




```
from sklearn.metrics import mean_absolute_error
print("MAE",mean_absolute_error(y_test,y_pred5))

MAE 1.828151287251054
```

The MAE or Mean Absolute Error value represents the error gauge within the data. It is not the best metric but there are some advantages to using it, which were noted in the article (in References section). The smaller the error value the better for the model.

```
from IPython import display
display.Image("mean_squared_error formula.png")
```

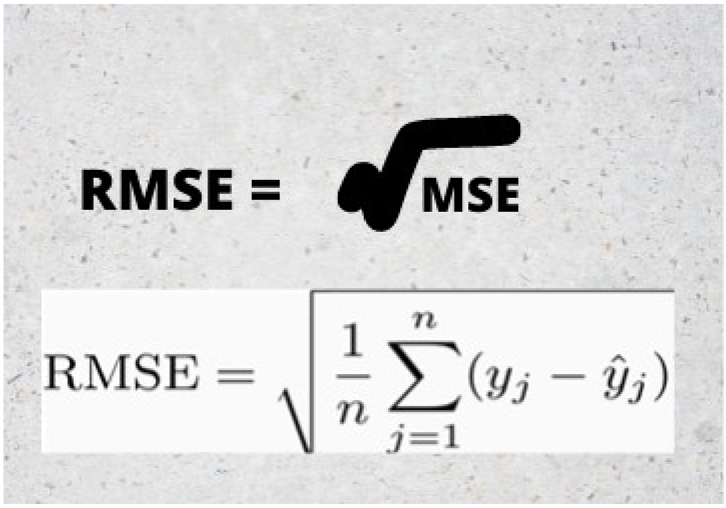


Mean Squared Error was next and though the value is larger, it is because it has cast aside the outliers in the data and now represents the mean squared error of the distance between the actual and predicted values of the data.

```
from sklearn.metrics import mean_squared_error
print("MSE",mean_squared_error(y_test,y_pred5))
```

```
MSE 7.729643024715775
```

```python
from IPython import display
display.Image("root_mean_squared_error formula.png")
```

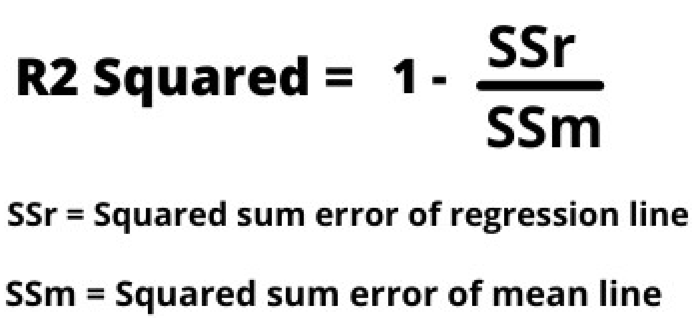


According to the article the output value for Root Mean Squared Error is the in the same unit as the output value for the data. This means that the value represents the target value weight. And it seems that there is a sort of large gap in error when it comes to the weight. As we have seen from the 13 model cars, the weight range is from 1 up to 5.5 approximately.

```python
print("RMSE",np.sqrt(mean_squared_error(y_test,y_pred5)))
```

```
RMSE 2.7802235566075932
```

```python
from IPython import display
display.Image("r_squared formula.png")
```



The r2 squared formula says how much of the data can be explained by the variables. So far 80% of the data can be explained by the variables I have chosen.

```
score1 = r2_score(y_test, y_pred5)
score1
```

```
0.8066819917053353
```

Discussion and Conclusion (20 points):

4.1 Compare the performance and interpretability of the simple linear regression model with the multiple linear regression model. Discuss the trade-offs between simplicity and complexity

There is a small difference between the performance and interpretability of the simple linear regression model and the multiple linear regression model. Starting off the simiple regression model had 1 input variable and 1 output target variable to focus on. There was still a high accuracy range from the model and it seemed if we trained it further the score would improve significantly. Then we have the multiple linear regression model, in which it did better than the simple linear regression model which was to be expected. But the performance gauge is smaller than I would have thought just from a quick observation. There were multiple variables chosen which seemed to have a strong correlation with mpg. I do believe with further training and more data it could also definitely improve. As for the trade offs uh the simplicity gave me a clear understanding of the model while the complexity was pretty foggy as I was unsure which variables were contributing to the prediction of the target variable.

4.2 Reflect on the insights gained from the assignment and the implications for predicting fuel efficiency in car models.

Insights I have gained were that linear regression metrics are very similar to what I have done in secondary school when it comes to the intercept formula especially. So it was handy to have my memory refreshed. There were no null values in the data. However, I did note that there may have been outliers instead. I did not deal with them as I wanted tos ee how the model would do with the outliers. It seems that I am on the right track when it comes to the variables I have chosen to predict mpg. I believe with more time, quality data and resources the model could get closer to perfection

References

where I downloaded the dataset from:

https://gist.github.com/seankross/a412dfbd88b3db70b74b

Dictionary for the meanings

https://www.rdocumentation.org/packages/datasets/versions/3.6.2/topics/mtcars

Correlation metrics

https://www.analyticsvidhya.com/blog/2021/09/different-type-of-correlation-metrics-used-by-data-scientist/

Tutorials

https://youtu.be/feDJkDaNuOk?si=54Xi_Rn8ezbocjpN

https://scikit-learn.org/stable/modules/linear_model.html

https://realpython.com/linear-regression-in-python/

https://machinelearningmastery.com/regression-metrics-for-machine-learning/

Evaluation Metrics

https://www.analyticsvidhya.com/blog/2021/05/know-the-best-evaluation-metrics-for-your-regression-model/