Module 2 Peer Review

==

Import Libraries

In [1]:
```
import numpy as np
from numpy import count_nonzero, median, mean
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
#import squarify


import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
# Import variance_inflation_factor from statsmodels
from statsmodels.stats.outliers_influence import variance_inflation_factor
# Import Tukey's HSD function
from statsmodels.stats.multicomp import pairwise_tukeyhsd

import datetime
from datetime import datetime, timedelta, date

import scipy
from scipy import stats
from scipy.stats.mstats import normaltest # D'Agostino K^2 Test
from scipy.stats import boxcox
from collections import Counter

import sklearn
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder, OneHo

from sklearn.model_selection import cross_val_score, train_test_split, cross_valida
from sklearn.model_selection import KFold, cross_val_predict, RandomizedSearchCV, S

from sklearn.metrics import accuracy_score, auc, classification_report, confusion_m
from sklearn.metrics import plot_confusion_matrix, plot_roc_curve, precision_score,
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

from sklearn.feature_selection import f_regression, f_classif, chi2, RFE, RFECV
from sklearn.feature_selection import mutual_info_regression, mutual_info_classif
from sklearn.feature_selection import VarianceThreshold, GenericUnivariateSelect
from sklearn.feature_selection import SelectFromModel, SelectKBest, SelectPercentil

from sklearn.inspection import permutation_importance

from sklearn.linear_model import ElasticNet, Lasso, LinearRegression, LogisticRegre
```

```python
import feature_engine

from feature_engine.selection import (DropConstantFeatures, DropDuplicateFeatures,
                                      DropCorrelatedFeatures, SmartCorrelatedSelect
from feature_engine.selection import SelectBySingleFeaturePerformance, SelectByShuf
from feature_engine.selection import RecursiveFeatureAddition

%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)

import warnings
warnings.filterwarnings('ignore')

# This module lets us save our models once we fit them.
# import pickle

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows', None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

==

Quick Data Glance

In [2]:
```python
df = pd.read_csv("mtcars.csv")
```

In [3]:
```python
df.head()
```

Out[3]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.00	6	160.00	110	3.90	2.62	16.46	0	1	4	4
1	Mazda RX4 Wag	21.00	6	160.00	110	3.90	2.88	17.02	0	1	4	4
2	Datsun 710	22.80	4	108.00	93	3.85	2.32	18.61	1	1	4	1
3	Hornet 4 Drive	21.40	6	258.00	110	3.08	3.21	19.44	1	0	3	1
4	Hornet Sportabout	18.70	8	360.00	175	3.15	3.44	17.02	0	0	3	2

In [4]:
```
df.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
```

In [5]:
```
df.dtypes.value_counts()
```

Out[5]:
```
int64      6
float64    5
object     1
dtype: int64
```

In [6]:
```
# Descriptive Statistical Analysis
df.describe(include="all")
```

Out[6]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
count	32	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00
unique	32	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	Mazda RX4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	20.09	6.19	230.72	146.69	3.60	3.22	17.85	0.44	0.41	3.69	2.81
std	NaN	6.03	1.79	123.94	68.56	0.53	0.98	1.79	0.50	0.50	0.74	1.62
min	NaN	10.40	4.00	71.10	52.00	2.76	1.51	14.50	0.00	0.00	3.00	1.00
25%	NaN	15.43	4.00	120.83	96.50	3.08	2.58	16.89	0.00	0.00	3.00	2.00
50%	NaN	19.20	6.00	196.30	123.00	3.70	3.33	17.71	0.00	0.00	4.00	2.00
75%	NaN	22.80	8.00	326.00	180.00	3.92	3.61	18.90	1.00	1.00	4.00	4.00
max	NaN	33.90	8.00	472.00	335.00	4.93	5.42	22.90	1.00	1.00	5.00	8.00

In [7]:
```
# Descriptive Statistical Analysis
```

```
df.describe(include=["int", "float"])
```

Out[7]:

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
count	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00
mean	20.09	6.19	230.72	146.69	3.60	3.22	17.85	0.44	0.41	3.69	2.81
std	6.03	1.79	123.94	68.56	0.53	0.98	1.79	0.50	0.50	0.74	1.62
min	10.40	4.00	71.10	52.00	2.76	1.51	14.50	0.00	0.00	3.00	1.00
25%	15.43	4.00	120.83	96.50	3.08	2.58	16.89	0.00	0.00	3.00	2.00
50%	19.20	6.00	196.30	123.00	3.70	3.33	17.71	0.00	0.00	4.00	2.00
75%	22.80	8.00	326.00	180.00	3.92	3.61	18.90	1.00	1.00	4.00	4.00
max	33.90	8.00	472.00	335.00	4.93	5.42	22.90	1.00	1.00	5.00	8.00

In [8]:

```
# Descriptive Statistical Analysis
df.describe(include="object")
```

Out[8]:

	model
count	32
unique	32
top	Mazda RX4
freq	1

In [9]:

```
df.shape
```

Out[9]:

```
(32, 12)
```

In [10]:

```
df.columns
```

Out[10]:

```
Index(['model', 'mpg', 'cyl', 'disp', 'hp', 'drat', 'wt', 'qsec', 'vs', 'am', 'gea
r', 'carb'], dtype='object')
```

```
=======================================================================
```

Linear Regression

Let's first understand what exactly `Regression` means it is a statistical method used in finance, investing, and other disciplines that attempts to determine the `strength` and `character` of the relationship between one `dependent variable` (usually denoted by `Y`) and a series of other variables known as `independent variables`.
`Linear Regression` is a statistical technique where based on a set of `independent variable(s)` a dependent variable is `predicted`.

$$y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

y = dependent variable

β_0 = population of intercept

β_i = population of co-efficient

x = independent variable

ε_i = Random error

Simple Linear Regression (StatsModel)

First Model - Weight – Miles_per_Gallon(mpg)

In [11]:
```
df.head()
```

Out[11]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.00	6	160.00	110	3.90	2.62	16.46	0	1	4	4
1	Mazda RX4 Wag	21.00	6	160.00	110	3.90	2.88	17.02	0	1	4	4
2	Datsun 710	22.80	4	108.00	93	3.85	2.32	18.61	1	1	4	1
3	Hornet 4 Drive	21.40	6	258.00	110	3.08	3.21	19.44	1	0	3	1
4	Hornet Sportabout	18.70	8	360.00	175	3.15	3.44	17.02	0	0	3	2

In [12]:
```
df.columns
```

Out[12]:
```
Index(['model', 'mpg', 'cyl', 'disp', 'hp', 'drat', 'wt', 'qsec', 'vs', 'am', 'gea
r', 'carb'], dtype='object')
```

In [13]:
```
## X is the input variables (or independent variables)
X = df['wt']
## y is the target/dependent variable
y = df['mpg']
```

In [14]:
```
## add an intercept (beta_0) to our model
X = sm.add_constant(X)
```

In [15]:
```
lrmodel1 = sm.OLS(y,X).fit()
```

In [16]:
```
lrprediction1 = lrmodel1.predict(X)
```

In [17]:
```
lrprediction1[0:5]
```

Out[17]:
```
0    23.28
1    21.92
2    24.89
3    20.10
4    18.90
dtype: float64
```

In [18]:
```
# Print out the statistics
lrmodel1.summary()
```

Out[18]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.753
Model:	OLS	**Adj. R-squared:**	0.745
Method:	Least Squares	**F-statistic:**	91.38
Date:	Sun, 09 Jul 2023	**Prob (F-statistic):**	1.29e-10
Time:	19:33:49	**Log-Likelihood:**	-80.015
No. Observations:	32	**AIC:**	164.0
Df Residuals:	30	**BIC:**	167.0
Df Model:	1		
Covariance Type:	nonrobust		

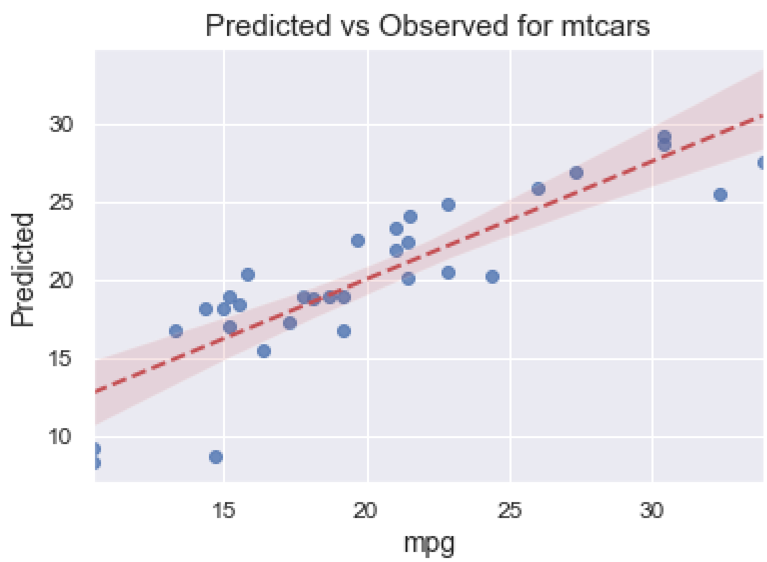
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	37.2851	1.878	19.858	0.000	33.450	41.120
wt	-5.3445	0.559	-9.559	0.000	-6.486	-4.203

Omnibus:	2.988	**Durbin-Watson:**	1.252
Prob(Omnibus):	0.225	**Jarque-Bera (JB):**	2.399
Skew:	0.668	**Prob(JB):**	0.301
Kurtosis:	2.877	**Cond. No.**	12.7

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Interpretation: The Weight – Miles_per_Gallon(mpg) model estimates a decrease in mileage of 5.34 miles per gallon with 1 unit increase in weight, and about 75 % of the variation in percentage of Miles_per_Gallon is associated with variation in weight.

In [19]:
```
sns.regplot(x=y, y=lrprediction1, data=df, line_kws={"lw": 2, 'linestyle':'--','col
plt.title("Predicted vs Observed for mtcars", size=15)
plt.ylabel("Predicted")
plt.show()
```



Interpretation: Pseudo R squared is 0.7528 . The “predicted vs observed” line is the line when our predictions are perfect. As we see the “linear fit to points” has almost similar slope, we would conclude we have a very good fit.

Horse_Power – Miles_per_Gallon (mpg):

In [20]:
```
## X is the input variables (or independent variables)
X = df['hp']
## y is the target/dependent variable
y = df['mpg']
```

In [21]:
```
## add an intercept (beta_0) to our model
X = sm.add_constant(X)
```

In [22]:
```
lrmodel2 = sm.OLS(y,X).fit()
```

In [23]:
```
lrprediction2 = lrmodel2.predict(X)
```

In [24]:
```
lrprediction2[0:5]
```

Out[24]:
```
0    22.59
1    22.59
2    23.75
3    22.59
4    18.16
dtype: float64
```

In [25]:
```
# prediction = pd.DataFrame(data=lrprediction, columns=['predicted'])
# prediction
```

In [26]:
```
# Print out the statistics
lrmodel2.summary()
```

Out[26]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.602
Model:	OLS	**Adj. R-squared:**	0.589
Method:	Least Squares	**F-statistic:**	45.46
Date:	Sun, 09 Jul 2023	**Prob (F-statistic):**	1.79e-07
Time:	19:33:49	**Log-Likelihood:**	-87.619
No. Observations:	32	**AIC:**	179.2
Df Residuals:	30	**BIC:**	182.2
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	30.0989	1.634	18.421	0.000	26.762	33.436
hp	-0.0682	0.010	-6.742	0.000	-0.089	-0.048

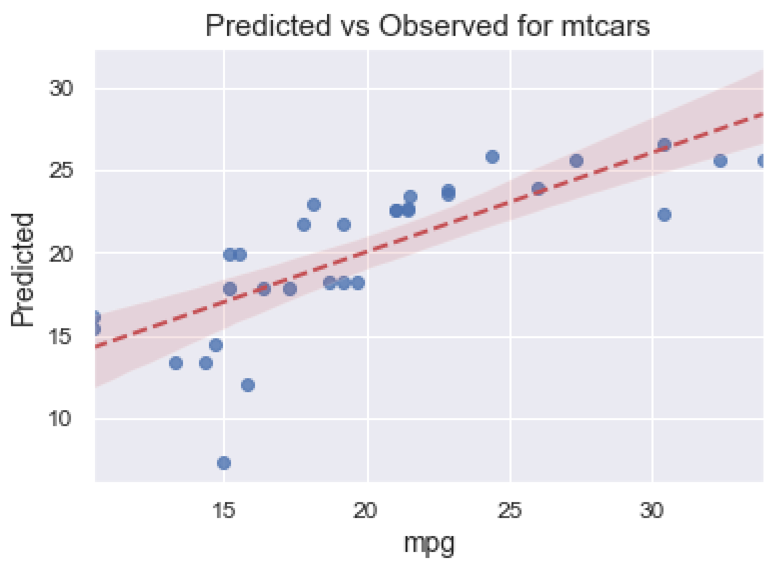
Omnibus:	3.692	**Durbin-Watson:**	1.134
Prob(Omnibus):	0.158	**Jarque-Bera (JB):**	2.984
Skew:	0.747	**Prob(JB):**	0.225
Kurtosis:	2.935	**Cond. No.**	386.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Interpretation: The Horse_Power – Miles_per_Gallon (mpg) model estimates a decrease in mileage of 0.06 miles per gallon with 1 unit increase in horse power, and about 60% of the variation in percentage of Miles_per_Gallon is associated with variation in horse power.

In [27]:

```
sns.regplot(x=y, y=lrprediction2, data=df, line_kws={"lw": 2, 'linestyle':'--','col
plt.title("Predicted vs Observed for mtcars", size=15)
plt.ylabel("Predicted")
plt.show()
```



Interpretation: Pseudo R squared is 0.6616. The “predicted vs observed” line is the line when our predictions are perfect. As we see the “linear fit to points” has slope somewhat similar, we would conclude we have a good fit.

Make mpg as target and both wt & hp should be taken as input variables

In [28]:
```
## X is the input variables (or independent variables)
X = df[['wt','hp']]
## y is the target/dependent variable
y = df[['mpg']]
```

In [29]:
```
## add an intercept (beta_0) to our model
X = sm.add_constant(X)
```

In [30]:
```
lrmodel3 = sm.OLS(y,X).fit()
```

In [31]:
```
lrprediction3 = lrmodel3.predict(X)
```

In [32]:
```
lrprediction3[0:5]
```

Out[32]:
```
0    23.57
1    22.58
2    25.28
3    21.27
4    18.33
dtype: float64
```

In [33]:
```
# Print out the statistics
lrmodel3.summary()
```

Out[33]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.827
Model:	OLS	**Adj. R-squared:**	0.815
Method:	Least Squares	**F-statistic:**	69.21
Date:	Sun, 09 Jul 2023	**Prob (F-statistic):**	9.11e-12
Time:	19:33:50	**Log-Likelihood:**	-74.326
No. Observations:	32	**AIC:**	154.7
Df Residuals:	29	**BIC:**	159.0
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	37.2273	1.599	23.285	0.000	33.957	40.497
wt	-3.8778	0.633	-6.129	0.000	-5.172	-2.584
hp	-0.0318	0.009	-3.519	0.001	-0.050	-0.013

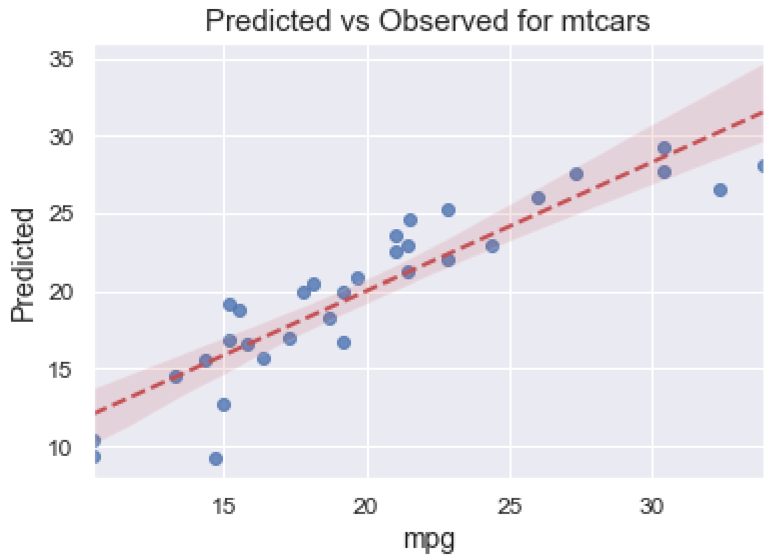
Omnibus:	5.303	**Durbin-Watson:**	1.362
Prob(Omnibus):	0.071	**Jarque-Bera (JB):**	4.046
Skew:	0.855	**Prob(JB):**	0.132
Kurtosis:	3.332	**Cond. No.**	588.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Interpretation: About 82% of the variation in percentage of Miles_per_Gallon is associated with variation in horse power and weight.

In [34]:

```
sns.regplot(x=y, y=lrprediction3, data=df, line_kws={"lw": 2, 'linestyle':'--','col
plt.title("Predicted vs Observed for mtcars", size=15)
plt.ylabel("Predicted")
plt.show()
```



Interpretation: Pseudo R squared has increased to 0.82. The “predicted vs observed” line is the line when our predictions are perfect. As we see the “linear fit to points” has a slope very close to the slope of “predicted vs observed” line , we conclude we have excellent fit. This means that adding two predictors improves fit a lot.

==

```
In [ ]:
```