ST1 Capstone Project

```
#Imports contents from google drive and libraries that will be used
from google.colab import drive
drive.mount('/content/drive')
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Step 1: Reading Dataset

```
carData = pd.read_csv('/content/drive/MyDrive/UC/ST1CapstoneProject/Data/train-data.csv')  #reads the file
carData = carData.drop(columns='Unnamed: 0')                                                #Removes the duplicate index number column that w
print('Shape with potential duplicates', carData.shape)
carData = carData.drop_duplicates()                                                         #Removes duplicate values if any
print('Shape with no duplicates', carData.shape)

# Removing the units of measurements on the values so they can be treated as integers/floats
# For Mileage, working under the assumption kmpl is going to mean the same as km/kg
carData['Mileage'] = carData['Mileage'].str.strip('kmpl/kg')                            #Removes these letters from all values in
carData['Mileage'] = carData['Mileage'].astype('float64')                               #Converts Mileage to float type
carData['Engine'] = carData['Engine'].str.strip('C')                                    #Same thing but for Engine
carData['Engine'] = carData['Engine'].astype('float64')
carData['Power'] = carData['Power'].str.strip('bhp ')                                   #Power uses the string 'null' instead of actual null
carData['Power'] = carData['Power'].replace('null', None)                               #Replaces string null with actual null
carData['Power'] = carData['Power'].astype('float64')

display(carData)                                                                            #Displays all data from dataset (shortens if too
```

```
Shape with potential duplicates (6019, 13)
Shape with no duplicates (6019, 13)
```

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type
0	Maruti Wagon R LXI CNG	Mumbai	2010	72000	CNG	Manual	First
1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000	Diesel	Manual	First
2	Honda Jazz V	Chennai	2011	46000	Petrol	Manual	First
3	Maruti Ertiga VDI	Chennai	2012	87000	Diesel	Manual	First
4	Audi A4 New 2.0 TDI Multitronic	Coimbatore	2013	40670	Diesel	Automatic	Second
...	...	...	...	...	...	...	...

Key Details

- There are 6019 car information in this dataset each specifying 13 attributes
- There are 66 entries using km/kg instead of kmpl due to gas-based fuel
- There are 2 entries using electric as fuel and have no mileage
- Mileage is in km/kg or kmpl depending on fuel type
  - km/kg = kilometer per kilogram (of gaseous fuel)
  - kmpl = kilometer per liter (of liquid fuel)
- Engine is in CC
  - CC = cubic centimeter

- Power is in bhp
  - bhp = brake horse power
- 1 Lakh = 100,000 Rupees (Indian Dollar)
- Price is in Lakh
- CNG, LPG are gas-based fuels

Step 2: Problem Statement Definition

- Create a prediction model to predict the prices of potential cars
- Target Variable: Price in Lakh
- Predictor/Features: Year, Kilometers Driven, Fuel Type, Transmission, Mileage, Engine, Power, Price

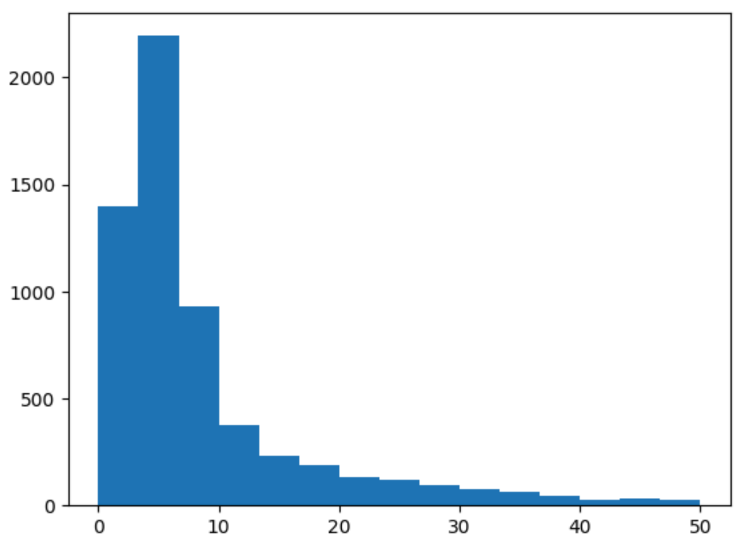
3: Choosing appropriate ML/AI algorithm for Data analysis

- ML because the problem is to create a prediction model which would need to be continuous

4: Visualising the distribution of Target variable

```
#Defines the target variable as a price for simplicity
carPrice = (carData['Price'])

#creates histogram with 20 different bars and ranges from 0 to 50 lakh
plt.hist(carPrice, bins=15, range=(0,50))
#There are values with higher lakh than the range but we can assume that they are outliers as the curve is flat
```

```
(array([1396., 2194.,  929.,  376.,  234.,  189.,  130.,  118.,   94.,
          77.,   62.,   45.,   27.,   34.,   24.]),
 array([ 0.        ,  3.33333333,  6.66666667, 10.        , 13.33333333,
        16.66666667, 20.        , 23.33333333, 26.66666667, 30.        ,
        33.33333333, 36.66666667, 40.        , 43.33333333, 46.66666667,
        50.        ]),
 <BarContainer object of 15 artists>)
```



Observation of Step 4

- The data distribution for target variable has a very large positive skew but is a bell curve
- There are sufficient rows for each type

5: Basic Exploratory Data Analysis

```
#Looking at sample rows in the data
carData.head()
```

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	M:
0	Maruti Wagon R LXI CNG	Mumbai	2010	72000	CNG	Manual	First	
1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000	Diesel	Manual	First	

```
#Looking at sample rows in the data
carData.tail()
```

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type
6014	Maruti Swift VDI	Delhi	2014	27365	Diesel	Manual	First
6015	Hyundai Xcent 1.1 CRDi S	Jaipur	2015	100000	Diesel	Manual	First
6016	Mahindra Xylo D4	Jaipur	2012	55000	Diesel	Manual	Second

```
# Observing the summarized data information
# Remove variables which have too many missing values (Missing Values > 30%)
# New_Price will be removed
carData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6019 entries, 0 to 6018
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Name               6019 non-null   object
 1   Location           6019 non-null   object
 2   Year               6019 non-null   int64
 3   Kilometers_Driven  6019 non-null   int64
 4   Fuel_Type          6019 non-null   object
 5   Transmission       6019 non-null   object
 6   Owner_Type         6019 non-null   object
 7   Mileage            6017 non-null   float64
 8   Engine             5983 non-null   float64
 9   Power              5876 non-null   float64
 10  Seats              5977 non-null   float64
 11  New_Price          824 non-null    object
 12  Price              6019 non-null   float64
dtypes: float64(5), int64(2), object(6)
memory usage: 611.4+ KB
```

```
# Looking at the descriptive statistics of the data
# Removing value units becomes relevant here
carData.describe(include='all')
```

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owne
count	6019	6019	6019.000000	6.019000e+03	6019	6019	
unique	1876	11	NaN	NaN	5	2	
top	Mahindra XUV500 W8 2WD	Mumbai	NaN	NaN	Diesel	Manual	
freq	49	790	NaN	NaN	3205	4299	
mean	NaN	NaN	2013.358199	5.873838e+04	NaN	NaN	
std	NaN	NaN	3.269742	9.126884e+04	NaN	NaN	
min	NaN	NaN	1998.000000	1.710000e+02	NaN	NaN	
25%	NaN	NaN	2011.000000	3.400000e+04	NaN	NaN	
50%	NaN	NaN	2014.000000	5.300000e+04	NaN	NaN	
75%	NaN	NaN	2016.000000	7.300000e+04	NaN	NaN	

```
# Finding unique values for each column
# If unique values < 20 then the variable is likely a category

carData.nunique()
```

```
Name                 1876
Location               11
Year                   22
Kilometers_Driven    3093
Fuel_Type               5
Transmission            2
Owner_Type              4
Mileage               430
Engine                146
Power                 369
Seats                   9
New_Price             540
Price                1373
dtype: int64
```

Step 5 Observations

- Name - Categorical (There is no reason to quantify names)
- Year - Continuous
- Kilometers_Driven - Continuous
- Fuel_Type - Categorical
- Transmission - Categorical
- Owner_Type - Categorical
- Mileage - Continuous
- Engine - Continuous
- Power - Continuous
- Seats - Categorical
- New_Price - Continuous
- Price - Continuous

Step 6: Removing Unwanted columns

Qualitative data includes:

- Name
- Location
- Fuel_Type - Keep
- Transmission - Keep
- Owner_Type

Additionally Seats and New_Price will be remove due to redundancy

```
#Removes the previously listed colums
carData = carData.drop(columns=['Name', 'Location', 'Owner_Type', 'Seats', 'New_Price'])
display(carData)
```

	Year	Kilometers_Driven	Fuel_Type	Transmission	Mileage	Engine	Power	Price
0	2010	72000	CNG	Manual	26.60	998.0	58.16	1.75
1	2015	41000	Diesel	Manual	19.67	1582.0	126.20	12.50
2	2011	46000	Petrol	Manual	18.20	1199.0	88.70	4.50
3	2012	87000	Diesel	Manual	20.77	1248.0	88.76	6.00
4	2013	40670	Diesel	Automatic	15.20	1968.0	140.80	17.74
...	...	...	...	...	...	...	...	...
6014	2014	27365	Diesel	Manual	28.40	1248.0	74.00	4.75
6015	2015	100000	Diesel	Manual	24.40	1120.0	71.00	4.00
6016	2012	55000	Diesel	Manual	14.00	2498.0	112.00	2.90
6017	2013	46000	Petrol	Manual	18.90	998.0	67.10	2.65
6018	2011	47000	Diesel	Manual	25.44	936.0	57.60	2.50

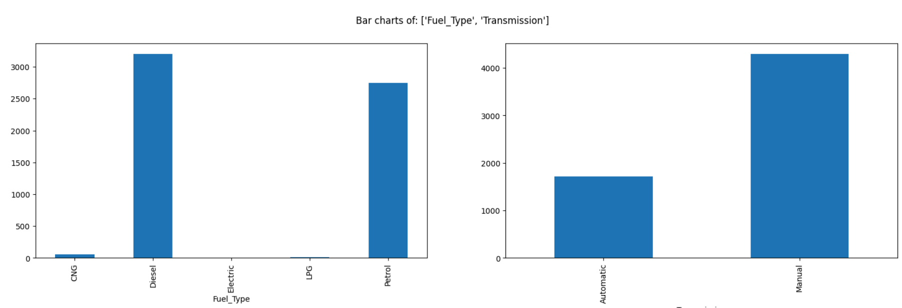
6019 rows × 8 columns

Step 7: Visual Exploratory Data Analysis

Categorical Predictors:

- Fuel_Type
- Transmission

```
# Plotting multiple bar charts at once for categorical variables

def PlotBarCharts(inpData, colsToPlot):
  fig, subPlot = plt.subplots(nrows=1, ncols=len(colsToPlot), figsize=(20,5))
  fig.suptitle('Bar charts of: ' + str(colsToPlot))

  for colName, plotNumber in zip(colsToPlot, range(len(colsToPlot))):
    inpData.groupby(colName).size().plot(kind='bar', ax=subPlot[plotNumber])

PlotBarCharts(inpData=carData, colsToPlot=['Fuel_Type', 'Transmission'])
```



Observations from Step 7

- There are primarily Petrol and Diesel Cars
    - CNG, LPG and Electric are too few to be considered viable categories and will be removed later
- There are more Manual cars than Automatic but enough not to be skewed

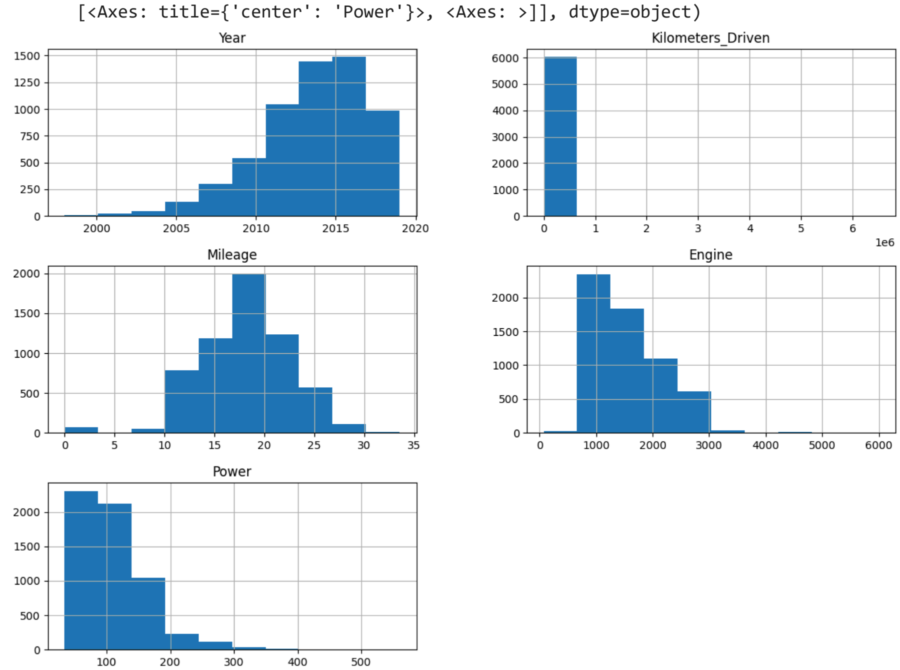
Step 8: Visualize distribution of all Coninuous Predictors

Continuous Columns include

- Year
- Kilometers_Driven
- Mileage
- Engine
- Power

```
#Plot histogram for all continuous columns
carData.hist(['Year', 'Kilometers_Driven', 'Mileage', 'Engine', 'Power'], figsize=(14,10))
```

```
array([[<Axes: title={'center': 'Year'}>,
        <Axes: title={'center': 'Kilometers_Driven'}>],
       [<Axes: title={'center': 'Mileage'}>,
        <Axes: title={'center': 'Engine'}>],
       [<Axes: title={'center': 'Power'}>, <Axes: >]], dtype=object)
```



Observations from Step 8

- For Year around 1500 are between 2015 to 2017
- For Mileage around 2000 are between 16 to 20 kmpl
- For Engine around 2400 are between 800 to 1200 CC
- For Power around 3400 are around 50 to 110 bhp
- For kilometers_driven, there are outliers beyond 600000
- All distribution looks good, except kilometers_driven

Step 9: Outlier Analysis

```
#Observing the outliers for
outliers = carData[carData['Kilometers_Driven']<600000].sort_values(by=['Kilometers_Driven'], ascending=False)
outliers['Kilometers_Driven']
```

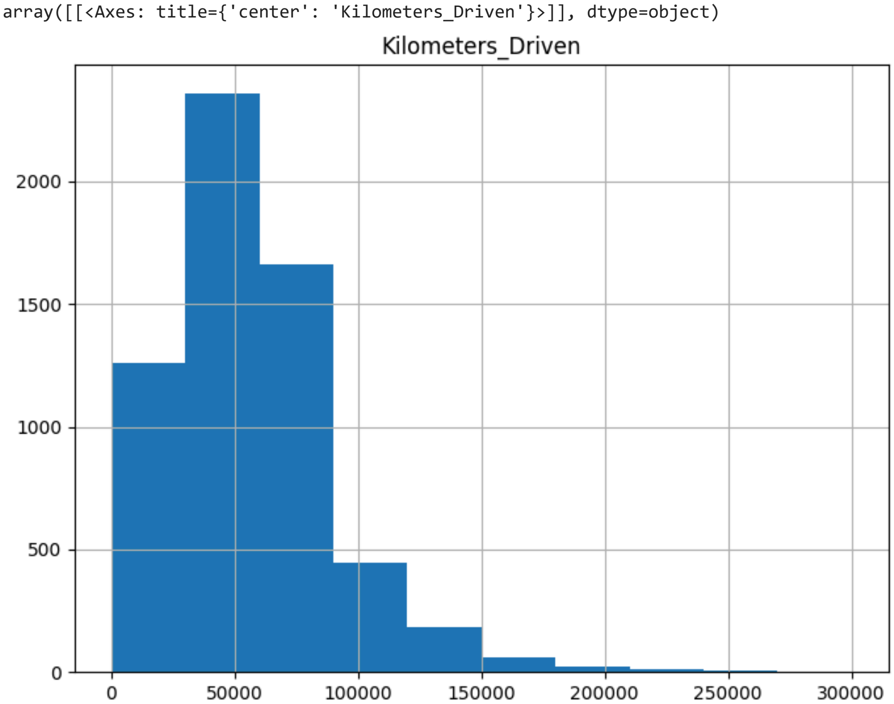
```
2823    480000
3092    480000
4491    445000
3649    300000
1528    299322
         ...
1198      1000
1242      1000
5941      1000
5606       600
1361       171
Name: Kilometers_Driven, Length: 6015, dtype: int64
```

```
#Observation shows only 4 of the 6019 data points would be lost if they were to be removed
# Additionally the outliers that are above 300,000 can be removed as there are 3 of them
# The loss of 7 rows is negligible
#Removing outliers
carData = carData.drop(carData[carData['Kilometers_Driven']>300000].index)
```

Step 10: Visualising Data after outlier removal

```
carData.hist(['Kilometers_Driven'], figsize=(8,6))
```

```
array([[<Axes: title={'center': 'Kilometers_Driven'}>]], dtype=object)
```



Observation from Step 10

- The distribution has improved and is no longer just a single pole
- There is a small but noticeable tail around 250,000 but since it is noticeable it is enough to be kept

Step 11: Missing Values Analysis

```
#Finding how many missing values are in each column
carData.isnull().sum()
```

```
Year                   0
Kilometers_Driven      0
Fuel_Type              0
Transmission           0
Mileage                2
Engine                36
Power                143
Price                  0
dtype: int64
```

Observations from Step 11

- There are a few missing values, but is not over 30% as such can be treated

```
# Treating the data by inputting the median values for Mileage, Engine and Power

# Medians of the columns with missing values
mileage_med = carData['Mileage'].median()
engine_med = carData['Engine'].median()
power_med = carData['Power'].median()

# Replacing the missing values with the median
carData['Mileage'] = carData['Mileage'].fillna(value=mileage_med)
carData['Engine'] = carData['Engine'].fillna(value=engine_med)
carData['Power'] = carData['Power'].fillna(value=power_med)
```

Step 12: Feature Selection

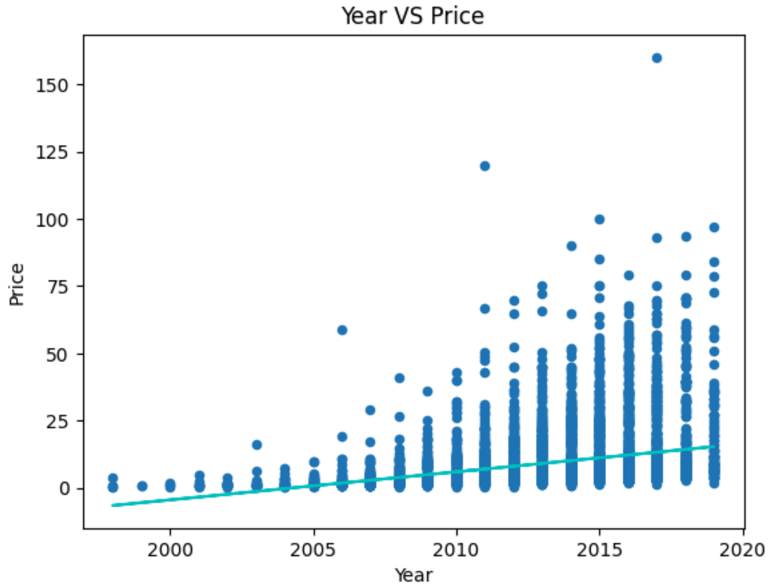
- The target variable for this dataset is continuous as such the following two scenarios will need attention
- Continuous Target Variable Vs Continuous Predictor
- Continuous Target Variable Vs Categorical Predictor

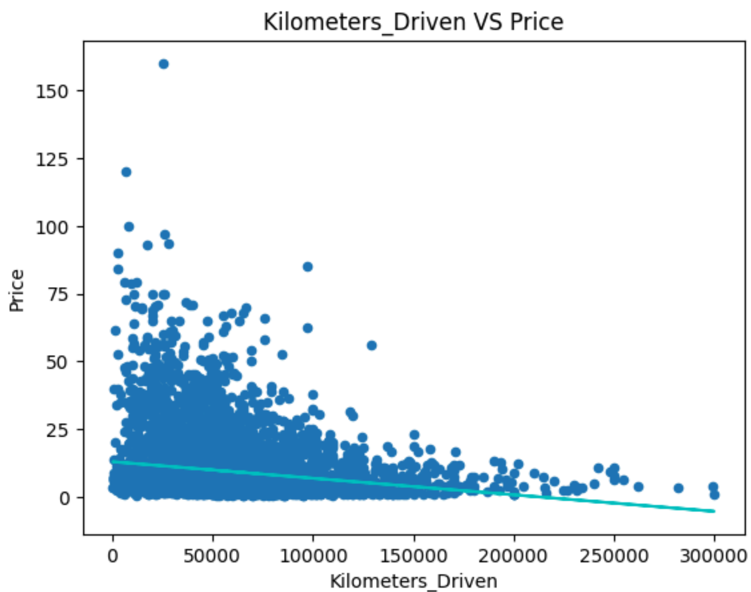
Relationship Exploration: Continuous vs Continuous

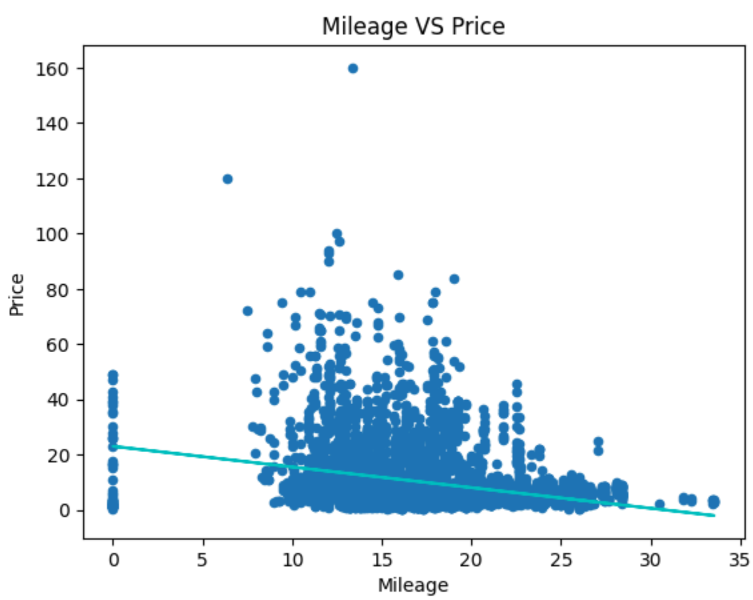
- For Continuous vs Continuous relationships, it can be visualised using scatter plot
- The strength of the relationship can be measured using Pearson's correlation value

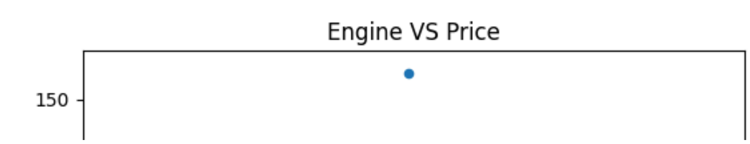
```
ContinuousVals = ['Year', 'Kilometers_Driven', 'Mileage', 'Engine', 'Power']
#Using numpy here to produce lines of best fit (LoBF)
#Plots scatter chart for the above values compared to target variable
for val in ContinuousVals:
  #converts the columns into numpy arrays so it can read them
  x = np.array(carData[val])
  y = np.array(carData['Price'])

  #Plots the data
  carData.plot.scatter(x=val, y = 'Price', title = val+' VS Price')

  #determines the least squares polynomial fit of the current val and price
  a, b = np.polyfit(x, y, 1)

  #Plots the LoBF in cyan
```

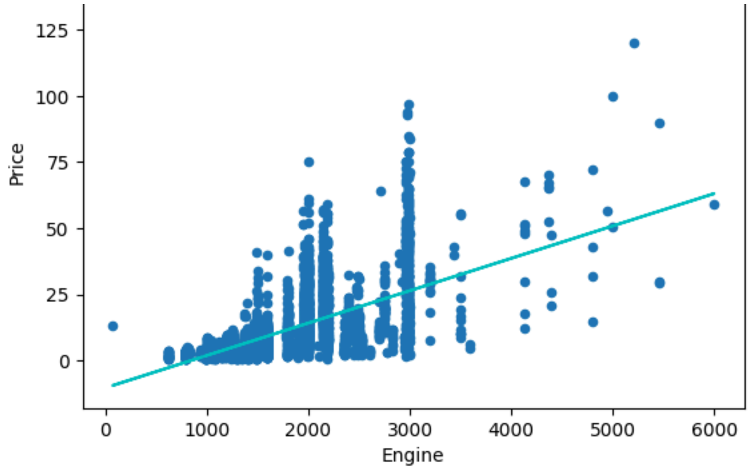
```
# ax+b is a the formula for a linear equation
plt.plot(x, a*x+b, 'c')
```

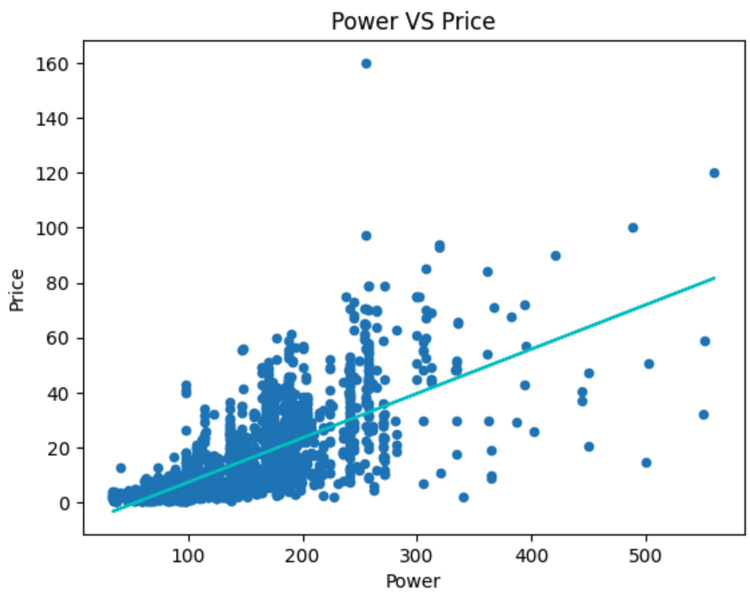

Year VS Price
Price
Year
0
25
50
75
100
125
150
2000
2005
2010
2015
2020


Kilometers_Driven VS Price
Price
Kilometers_Driven
0
25
50
75
100
125
150
0
50000
100000
150000
200000
250000
300000


Mileage VS Price
Price
Mileage
0
20
40
60
80
100
120
140
160
0
5
10
15
20
25
30
35


Engine VS Price
150





Observations of Continuous vs Continuous correlation

- Year vs Price: Increasing trend
- Kilometers_Driven vs Price: Decreasing Trend
- Mileage vs Price: Decreasing trend (according to LoBF)
- Engine vs Price: Increasing trend (good angle from LoBF)
- Power vs Price: Increasing trend (good angle from LoBF)

Step 13: Statistical Feature Selection (Cont. vs Cont.) using Correlation value

- Correlation coefficient between (0,1] means there is a positive linear relation
- Correlation coefficient between [-1,0) means there is a negative linear relation
- Correlation coefficient near 0 means there is very low or no relation.
- If |r|>0.5 then it is a good relationshipt

```
#Calculating the correlation matrix
# Now ContinuousVals include price
ContinuousVals = ['Year', 'Kilometers_Driven', 'Mileage', 'Engine', 'Power', 'Price']

# Creates the matrix
correlationData = carData[ContinuousVals].corr()
correlationData['Price']
```

```
Year                 0.305004
Kilometers_Driven   -0.184500
```

```
Mileage            -0.306781
Engine              0.657084
Power               0.769537
Price               1.000000
Name: Price, dtype: float64
```

```
# filters columns where the absulute correlations is >0.5 with price
priceCorrelation = correlationData[abs(correlationData['Price']> 0.5)]
priceCorrelation['Price']
```

```
Engine    0.657084
Power     0.769537
Price     1.000000
Name: Price, dtype: float64
```

Observations from Step 13

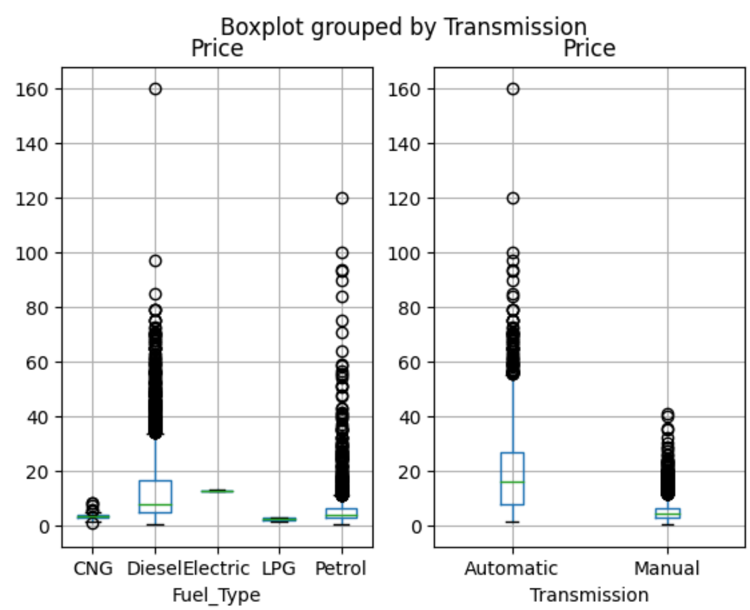
The final selected continuous columns are:

- Engine
- Power

Step 14: Relationship exploration: Categorical vs Continuous

- For Categorical vs Continuous, box plots will be used
- Also the relation strength will be measured using Anova test

```
# The categorical columns
categoricalVals = ['Fuel_Type', 'Transmission']

fig, plotCanvas=plt.subplots(nrows=1, ncols=len(categoricalVals))

for val, i in zip(categoricalVals, range(len(categoricalVals))):
  carData.boxplot(column='Price', by=val, figsize=(10,8), vert=True, ax=plotCanvas[i])
```



Observation from Step 14

Both predictors have varying positions as such appear to be correlated to the value

- Overall, Diesel seems to be more expensive than all other fuel types
- Automatics are generally more expensive than manual

Step 15: Statistical Feature Selection using ANOVA test

Assumptions:

- Null hypothesis (H0): There is no relation between the collected data
- The values follow a normal distribution (standard bell curve)
- We are looking for the p value being < 0.05

```
# imports the one-way ANOVA function
from scipy.stats import f_oneway
categoricalVals = ['Fuel_Type', 'Transmission']
for val in categoricalVals:
  #Groups columns in the categoricalVals into several list sorted by price
  categoricalList = carData.groupby(val)['Price'].apply(list)

  #Puts that group of lists into a one-way ANOVA test
  results = f_oneway(*categoricalList)
  print(f"For {val}: {results}")
```

```
For Fuel_Type: F_onewayResult(statistic=173.09286050018878, pvalue=1.5784654962268312e-140)
For Transmission: F_onewayResult(statistic=3146.229956617416, pvalue=0.0)
```

Observations from step 15

- Fuel type: F value is 173.09 and P value is 1.5e-140 (Pretty much 0)
- Transmission: F value is 3146.22 and p value is 0
- Both values are less than 0.05 as such it is very likely they have significant effects on the Price

Final Predictors

Through several extensive tests these are the final predictors:

- Engine
- Power
- Fuel_Type
- Transmission

```
# Final selection
selectedData = ['Engine','Power','Fuel_Type','Transmission']

MLdata = carData[selectedData]
display(MLdata)
```

	Engine	Power	Fuel_Type	Transmission
0	998.0	58.16	CNG	Manual
1	1582.0	126.20	Diesel	Manual
2	1199.0	88.70	Petrol	Manual
3	1248.0	88.76	Diesel	Manual
4	1968.0	140.80	Diesel	Automatic
...	...	...	...	...
6014	1248.0	74.00	Diesel	Manual
6015	1120.0	71.00	Diesel	Manual
6016	2498.0	112.00	Diesel	Manual
6017	998.0	67.10	Petrol	Manual
6018	936.0	57.60	Diesel	Manual

6012 rows × 4 columns

Step 16: Data Pre-processing for Model Development

- Data transformation will be necessary because Prices are skewed
- The categorical data needs to be converted into numeric
- There are no:
  - Ordinal Categorical variables

Target variable transformation

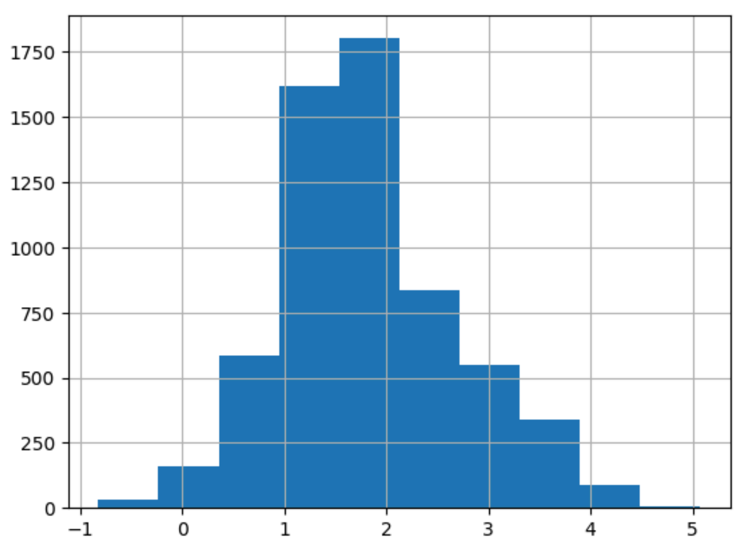
- since the target variable has a large positive skew, it needs correcting
- this will be done using log transformation

```
# log transformation

priceLog = np.log(carData['Price'])
```

Price after Log normalisation

```
priceLog.hist()
```

```
<Axes: >
```



Converting nominal categorical variables to numeric

- For this step we are using pandas.get_dummies to change categorical data into a form which could be ordered

```
# Applying the variables with get_dummy() and represent in integer form so it is numeric
MLdata_Numeric=pd.get_dummies(MLdata, dtype=int)

# Adding the normalised target variable to the dataset
MLdata_Numeric['Price']=priceLog

#Saving this version of dataset for the future
MLdata_Numeric.to_pickle('MLdata_Numeric.pkl')

display(MLdata_Numeric)
```

	Engine	Power	Fuel_Type_CNG	Fuel_Type_Diesel	Fuel_Type_Electric	Fuel_Type_LPG
0	998.0	58.16	1	0	0	0
1	1582.0	126.20	0	1	0	0
2	1199.0	88.70	0	0	0	0
3	1248.0	88.76	0	1	0	0
4	1968.0	140.80	0	1	0	0
...	...	...	...	...	...	...
6014	1248.0	74.00	0	1	0	0
6015	1120.0	71.00	0	1	0	0
6016	2498.0	112.00	0	1	0	0
6017	998.0	67.10	0	0	0	0
6018	936.0	57.60	0	1	0	0

6012 rows × 10 columns

Step 17: Machine Learning Model Development

- There is a separate test dataset provided but due to it lacking the target variable, it not be used for the time being
- Because the accuracy test later requires the recorded target variable, the given test dataset will not be used

```
# Separate Target variable from predictors
targetVar = 'Price'
predictors = ['Engine', 'Power', 'Fuel_Type_CNG', 'Fuel_Type_Diesel', 'Fuel_Type_Electric', 'Fuel_Type_LPG', 'Fuel_Type_Petrol', 'Transmissi

x = MLdata_Numeric[predictors].values
y = MLdata_Numeric[targetVar].values

# Split data into train and test
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.3, random_state=600)
```

Step 18: Multiple Linear Regression Algorithm

```
#Import the necessary library
from sklearn import linear_model

#Applies linear regression model on the training data
regr = linear_model.LinearRegression()

linearModel = regr.fit(x_train, y_train)
```

Step 19: Model validation and accuracy calculation

- For accuracy calculations it will be gauged with r^2 test, Mean Absolute Percentage Error (MAPE) test and cross validation
    - since the algorithm is predicting a value, MAPE should be used as it tests the accuracy of the prediction
- Since the target variable was normalised, the process must be reversed for this part expecially since it would result in dividing by 0.
- This test will be applied on other models

```
# Generalised variables for validation and accuracy tests
currentModel = linearModel
currentPrediction = currentModel.predict(x_test)

################################################################################
#r2 test
from sklearn.metrics import r2_score

r2_score = r2_score(y_train, currentModel.predict(x_train))

print(f'r2 score: {r2_score}')


################################################################################
# MAPE test
realVal = np.exp(y_test.tolist())
predictVal = np.exp(currentModel.predict(x_test))
errorList = []

#Loop for all value index of the list
for index in range(len(realVal)):

# finds the percentage error of the predicted and real value as a decimal
  percError = (realVal[index] - predictVal[index]) / realVal[index]
  percError = abs(percError)
# Appends the error value to list
  errorList.append(percError)

MAPE = sum(errorList)/len(errorList)

print(f'MAPE inacurracy percentage: {round ((MAPE)*100, 2)}%')

################################################################################
# Cross Validation
#Importing k-fold and cross validation
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import KFold, cross_val_score

# using 10-fold since it is the common ammount
k_folds = KFold(n_splits = 10)

scores = cross_val_score(currentModel, x, y, cv = k_folds)
average_score = scores.mean()

print(f'10-fold cross validation accuracy results: {scores}')
print(f'cross validation accuracy: {round(average_score*100, 2)}%')

################################################################################
# Displays a sample of the real and predicted data

dataSample = pd.DataFrame(data=x_test, columns=predictors)
dataSample['TargetVariable'] = np.exp(y_test)
# Reverts the log normalisation done before with exponent
dataSample[('Predicted '+targetVar)] = np.round(np.exp(currentPrediction), 2)

print(dataSample.head())
```

```
r2 score: 0.6622965424118143
MAPE inacurracy percentage: 46.92%
10-fold cross validation accuracy results: [0.65693237 0.66390576 0.63821191 0.68462009 0.6869403  0.63755092
 0.63352483 0.6477737  0.65859848 0.64995519]
cross validation accuracy: 65.58%
   Engine   Power  Fuel_Type_CNG  Fuel_Type_Diesel  Fuel_Type_Electric  \
0   814.0   55.20            0.0               0.0                 0.0
1  1248.0   73.90            0.0               1.0                 0.0
2  2148.0  170.00            0.0               1.0                 0.0
3  1198.0   73.75            0.0               0.0                 0.0
```

```
 4  1248.0   74.00            0.0              1.0                 0.0

    Fuel_Type_LPG  Fuel_Type_Petrol  Transmission_Automatic  \
 0            0.0               1.0                     0.0
 1            0.0               0.0                     0.0
 2            0.0               0.0                     0.0
 3            0.0               1.0                     0.0
 4            0.0               0.0                     0.0

    Transmission_Manual  TargetVariable  Predicted Price
 0                  1.0            2.55             2.59
 1                  1.0            5.40             4.71
 2                  1.0           15.50            10.82
 3                  1.0            5.40             3.06
 4                  1.0            5.69             4.72
```

KNN algorithm

- Second algorithm will be K-nearest neighbour algorithm

```
from sklearn.neighbors import KNeighborsRegressor

# using 3 neighbors for better effect
knn = KNeighborsRegressor(n_neighbors=3)
#fitting the data into the algorithm
knnModel = knn.fit(x_train, y_train)
```

```
#KNN test

# Generalised variables for validation and accuracy tests
currentModel = knnModel
currentPrediction = currentModel.predict(x_test)

################################################################################
#r2 test
from sklearn.metrics import r2_score

r2_score = r2_score(y_train, currentModel.predict(x_train))

print(f'r2 score: {r2_score}')


################################################################################
# MAPE test
realVal = np.exp(y_test.tolist())
predictVal = np.exp(currentModel.predict(x_test))
errorList = []

#Loop for all value index of the list
for index in range(len(realVal)):

# finds the percentage error of the predicted and real value as a decimal
  percError = (realVal[index] - predictVal[index]) / realVal[index]
  percError = abs(percError)
# Appends the error value to list
  errorList.append(percError)

MAPE = sum(errorList)/len(errorList)

print(f'MAPE inacurracy percentage: {round ((MAPE)*100, 2)}%')

################################################################################
# Cross Validation
```

XGBoost algorithm

- third model is the XGboost algorithm

```
from xgboost import XGBRegressor
# XG model setup, using squarederror instead of linear due to deprecation of linear
xg = XGBRegressor(max_depth=2, learning_rate=0.1,n_estimators=1000, objective='reg:squarederror', booster='gbtree')
# Fitting data into the model
xgModel = xg.fit(x_train,y_train)
```

```
#XGboost test

# Generalised variables for validation and accuracy tests
currentModel = xgModel
currentPrediction = currentModel.predict(x_test)

################################################################################
#r2 test
from sklearn.metrics import r2_score

r2_score = r2_score(y_train, currentModel.predict(x_train))
```