Car-Price-Prediction

#Project Statement : Car Price Prediction Analysis

###Objective : Data science helps businesses to get insights and trends from collected data and using those insights and analysis, customers can easily get an idea about the ongoing market price and trends. We choose this project because there are few car dealers or brokers who manipulate the market for their own profit and scam the buyers. So our team thought about making a car price prediction analysis to give a clear picture , what are the driving features that can affect the car price and how are those features affecting the price.

[ ]:
```
#importing libaries needed for the project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
import csv
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_absolute_error
from sklearn import linear_model
from scipy import stats
%matplotlib inline
```

[ ]:
```
# Installing pip
!pip install -U -q PyDrive

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
# Commenting out auth.authenticate_user() to avoid potential conflicts
# auth.authenticate_user()
gauth = GoogleAuth()
# Using local webserver flow for authentication
```

```
drive = GoogleDrive(gauth)
```

[ ]:
```
# Linking the dataset with google collab
df = pd.read_csv('/content/drive/MyDrive/ML and DL DataSets/Machine Learning/
↪CarPriceDataset_Final.csv')
print(df)
```

```
      ID      Company     Model       Type    Fuel Transmission  Engine  \
0      1       Maruti      Alto  Hatchback  Petrol       Manual     796
1      2       Maruti   Wagon R  Hatchback  Petrol       Manual     998
2      3       Maruti   Wagon R  Hatchback  Petrol       Manual     998
3      4       Maruti    Ertiga        MUV  Petrol    Automatic    1462
4      5       Maruti    Ertiga        MUV  Petrol    Automatic    1462
..   …          …       …        …      …          …       …
145  146  Rolls Royce   Phantom      Sedan  Petrol    Automatic    6749
146  147  Rolls Royce     Ghost      Sedan  Petrol    Automatic    6592
147  148  Rolls Royce  Cullinan      Sedan  Petrol    Automatic    6749
148  149  Rolls Royce  Cullinan      Sedan  Petrol    Automatic    6749
149  150  Rolls Royce      Dawn      Sedan  Petrol    Automatic    6598

     Mileage  Kms_driven  Buyers  Horsepower (kw)  Year  Price (Lakhs)
0      19.70       45000       2               32  2010            1.2
1      20.50       40005       2               46  2011            3.0
2      20.50       40005       2               46  2018            4.0
3      18.50       28000       2               73  2012            5.1
4      18.50       40000       2               73  2012            4.0
..       …          …     …              …    …            …
145     6.71       35000       4              417  2016          189.0
146     8.40       38000       3              430  2019          370.0
147     9.50       18000       5              430  2016          495.0
148     9.50       40000       5              430  2015          280.0
149     9.80       13500       3              420  2017          292.0

[150 rows x 13 columns]
```

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

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

[ ]:
```
# inspecting the first 5 rows of the dataframe
df.head()
```

[ ]:
```
   ID Company    Model       Type    Fuel Transmission  Engine  Mileage  \
0   1  Maruti     Alto  Hatchback  Petrol       Manual     796     19.7
1   2  Maruti  Wagon R  Hatchback  Petrol       Manual     998     20.5
```

```
2   3  Maruti  Wagon R  Hatchback  Petrol       Manual     998       20.5
3   4  Maruti   Ertiga        MUV  Petrol    Automatic    1462       18.5
4   5  Maruti   Ertiga        MUV  Petrol    Automatic    1462       18.5

   Kms_driven  Buyers  Horsepower (kw)  Year  Price (Lakhs)
0       45000       2               32  2010            1.2
1       40005       2               46  2011            3.0
2       40005       2               46  2018            4.0
3       28000       2               73  2012            5.1
4       40000       2               73  2012            4.0
```

[ ]:
```
# getting some information about the dataset
df.describe()
```

[ ]:
```
               ID       Engine     Mileage     Kms_driven      Buyers  \
count  150.000000   150.000000  147.000000     150.000000  150.000000
mean    75.500000  2573.346667   15.870748   36673.753333    2.320000
std     43.445368  1687.191300    6.884811   19426.665542    0.698224
min      1.000000     0.000000    3.800000    3600.000000    2.000000
25%     38.250000  1462.000000   10.430000   23721.500000    2.000000
50%     75.500000  1997.000000   15.000000   36000.000000    2.000000
75%    112.750000  2998.000000   20.170000   45647.250000    2.000000
max    150.000000  6749.000000   47.450000  130000.000000    5.000000

       Horsepower (kw)         Year  Price (Lakhs)
count       150.000000   150.000000     150.000000
mean        222.046667  2015.553333      62.030733
std         209.008312     3.398651      98.571347
min          27.000000  2005.000000       0.800000
25%          74.000000  2014.000000       4.765000
50%         131.000000  2016.000000      19.980000
75%         314.000000  2018.000000      80.000000
max         985.000000  2021.000000     605.000000
```

[ ]:
```
# checking the number of missing values
df.isnull().sum()
```

[ ]:
```
ID                 0
Company            0
Model              0
Type               0
Fuel               0
Transmission       0
Engine             0
Mileage            3
Kms_driven         0
Buyers             0
```

```
Horsepower (kw)    0
Year               0
Price (Lakhs)      0
dtype: int64
```

[ ]:
```
# checking the distribution of categorical data
print(df.Fuel.value_counts())
print(df.Transmission.value_counts())
print(df.Type.value_counts())
```

```
Fuel
Petrol      95
Diesel      46
Hybride      3
Eletric      3
Gas          2
Gasoline     1
Name: count, dtype: int64
Transmission
Automatic    129
Manual        19
Semi-Auto      2
Name: count, dtype: int64
Type
SUV            58
Sedan          36
Hatchback      24
Coupe          24
MUV             6
Convertible     2
Name: count, dtype: int64
```

1 Pearson Correlation

The Pearson Correlation measures the linear dependence between two variables X and Y. The resulting coefficient is a value between -1 and 1 inclusive, where:

1: total positive linear correlation,

0: no linear correlation,the two variables most likely do not affect each other

-1: total negative linear correlation.

P-value: What is this P-value? The P-value is the probability value that the correlation between these two variables is statistically significant. Normally, we choose a significance level of 0.05, which means that we are 95% confident that the correlation between the variables is significant.

By convention, when the p-value is $<$ 0.001 we say there is strong evidence that the correlation is significant, p-value is < 0.05, there is moderate evidence that the correlation is significant,

p-value is < 0.1, there is weak evidence that the correlation is significant,and

p-value is > 0.1, there is no evidence that the correlation is significant.

[ ]:
```
# Select only numeric columns for correlation
# numeric_df = df.select_dtypes(include=['number']) # Also, we can use this

# Calculate Pearson correlation on numeric columns
pearsoncorr = df.iloc[:, 6:].corr(method='pearson')

pearsoncorr
```

[ ]:
```
                   Engine   Mileage  Kms_driven    Buyers  Horsepower (kw)  \
Engine           1.000000 -0.688670   -0.064021  0.543387         0.838818
Mileage         -0.688670  1.000000    0.167036 -0.324920        -0.546172
Kms_driven      -0.064021  0.167036    1.000000 -0.008538         0.022244
Buyers           0.543387 -0.324920   -0.008538  1.000000         0.372087
Horsepower (kw)  0.838818 -0.546172    0.022244  0.372087         1.000000
Year             0.287434 -0.233363   -0.072064  0.185078         0.287582
Price (Lakhs)    0.774528 -0.426583    0.010209  0.513689         0.745483

                     Year  Price (Lakhs)
Engine           0.287434       0.774528
Mileage         -0.233363      -0.426583
Kms_driven      -0.072064       0.010209
Buyers           0.185078       0.513689
Horsepower (kw)  0.287582       0.745483
Year             1.000000       0.249994
Price (Lakhs)    0.249994       1.000000
```

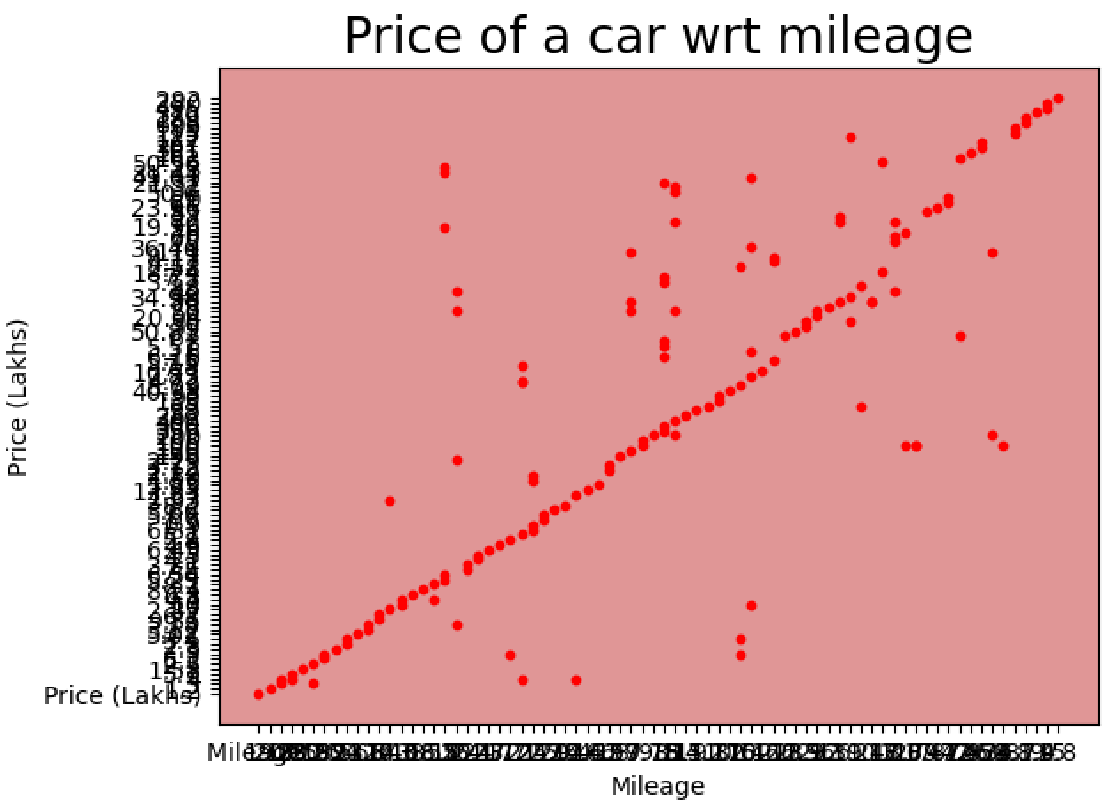
1.1 Data Visualization

Data visualization is the graphical representation of information and data. By using visual elements like charts and graphs, data visualization tools provide an accessible way to see and understand trends and patterns in data.

Bivariate analysis of quantitative values

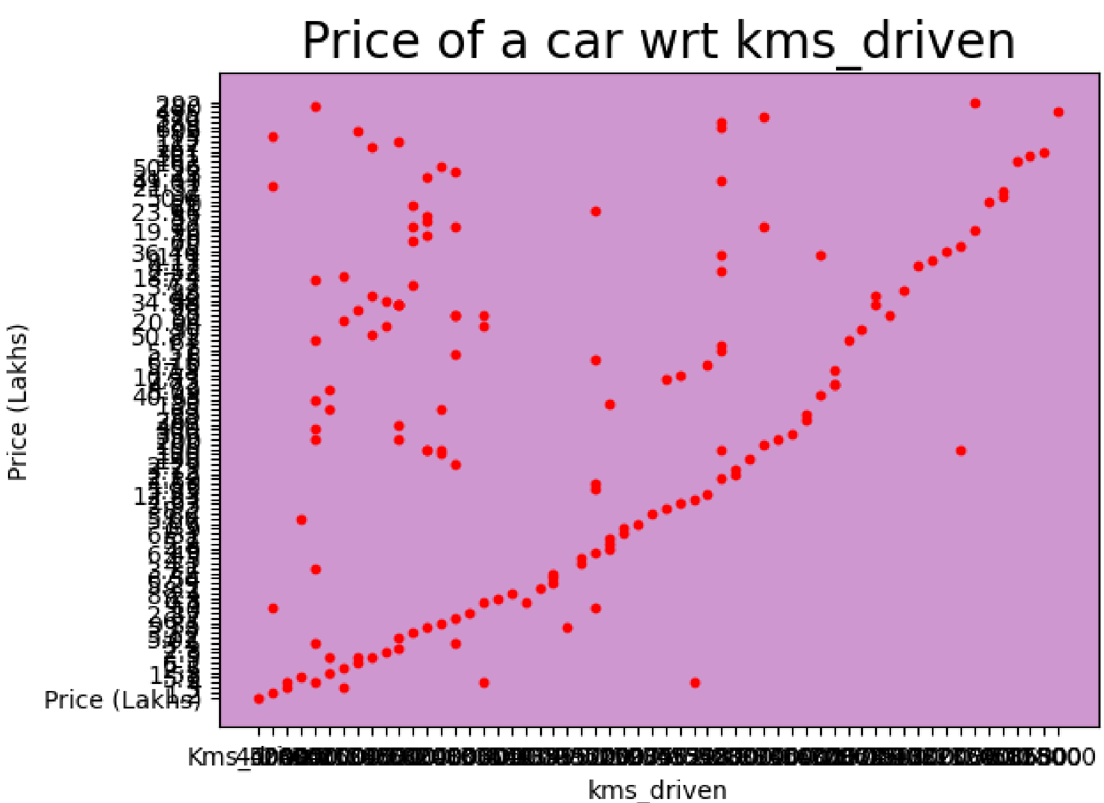
[ ]:
```
import csv
import matplotlib.pyplot as plt

#Plotting a graph establishing the relation of price wrt mileage
x = []
y= []

# Update the path to the file if it's in a different location.
```

```
file_path = '/content/drive/MyDrive/ML and DL DataSets/Machine Learning/
 ↪CarPriceDataset_Final.csv'

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[7])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#e09696")

plt.scatter(x, y, color = 'r',s = 10)
plt.xlabel('Mileage')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt mileage', fontsize = 20)

plt.show()
```



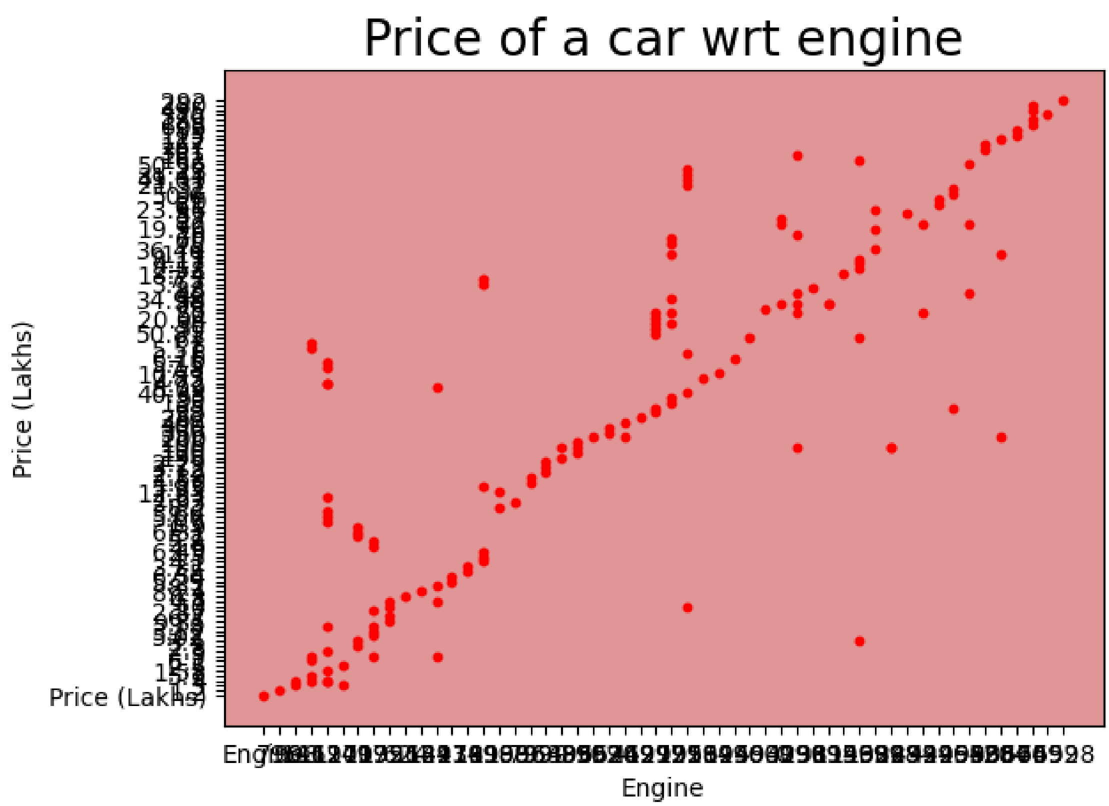
[ ]:
```
#Plotting a graph establishing the relation of price wrt kms driven
x = []
```

```python
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[8])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color = 'r',s = 10)
plt.xlabel('kms_driven')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt kms_driven', fontsize = 20)

plt.show()
```



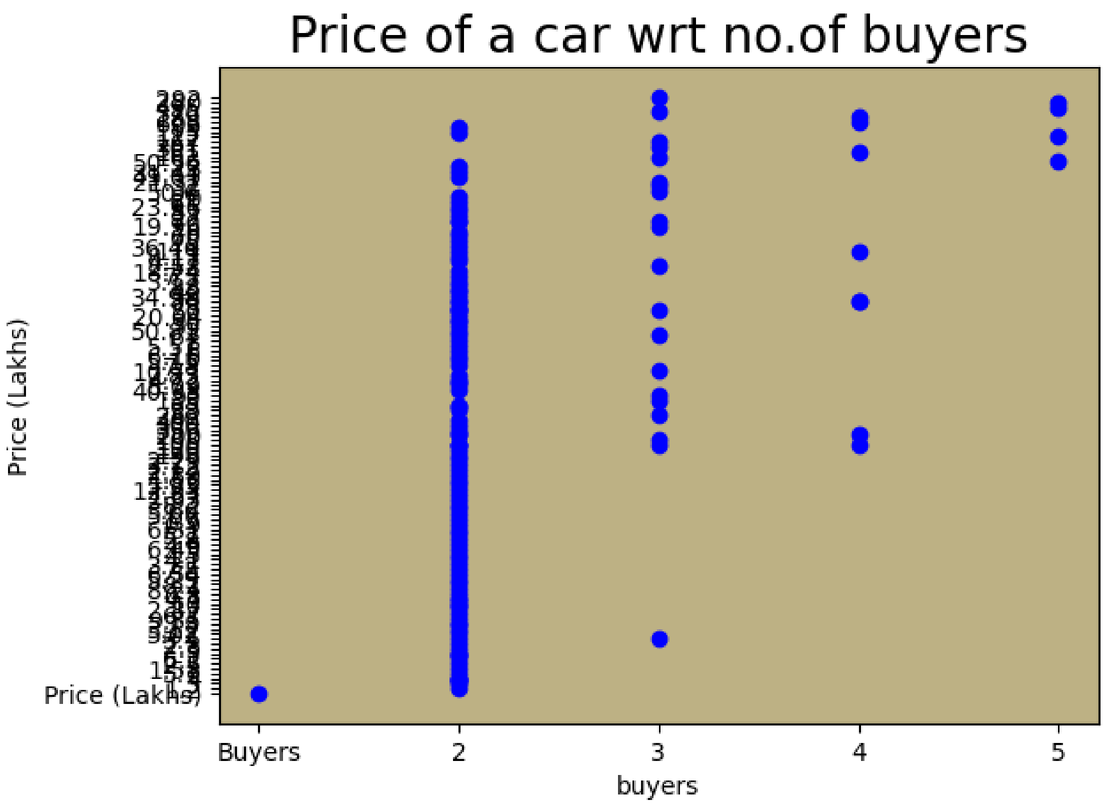
[ ]:
```python
#Plotting a graph establishing the relation of price wrt engine
x = []
y= []
```

```
with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[6])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#e09696")

plt.scatter(x, y, color = 'r',s = 10)
plt.xlabel('Engine')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt engine', fontsize = 20)

plt.show()
```



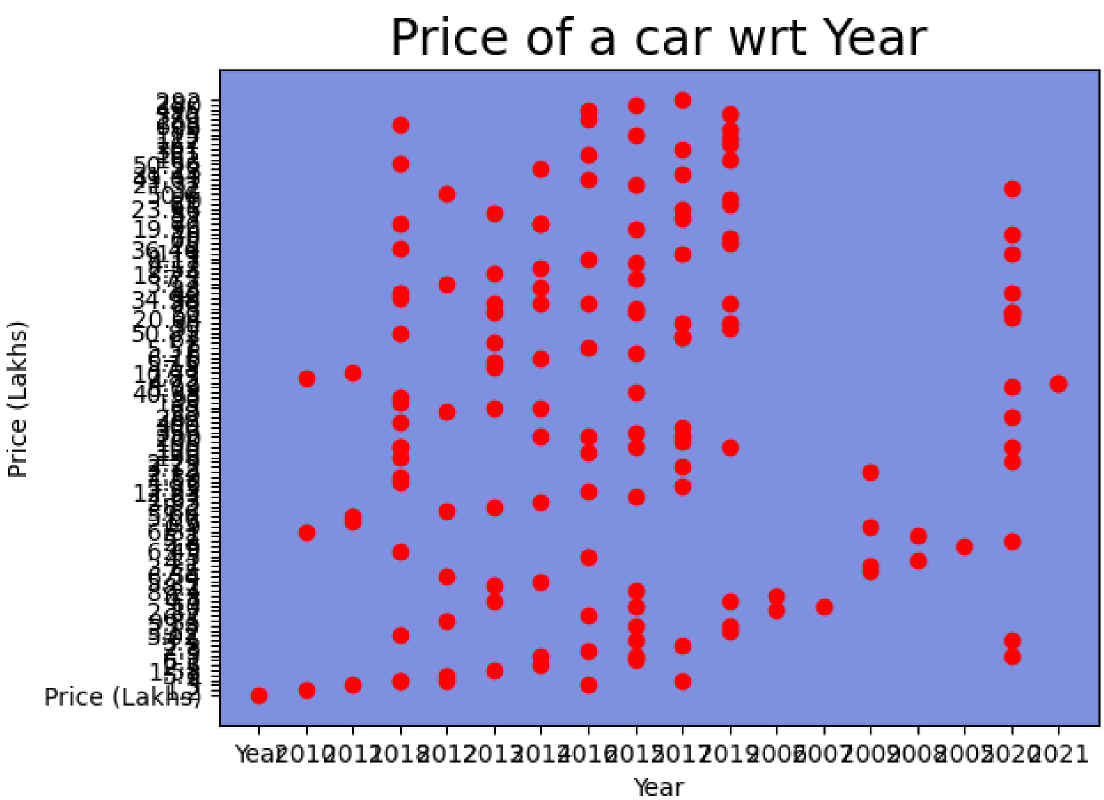
[ ]:
```
#Plotting a graph establishing the relation of price wrt no of buyers
x = []
y= []
```

```
with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[9])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#bdb184")

plt.scatter(x, y, color = 'b')
plt.xlabel('buyers')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt no.of buyers', fontsize = 20)

plt.show()
```



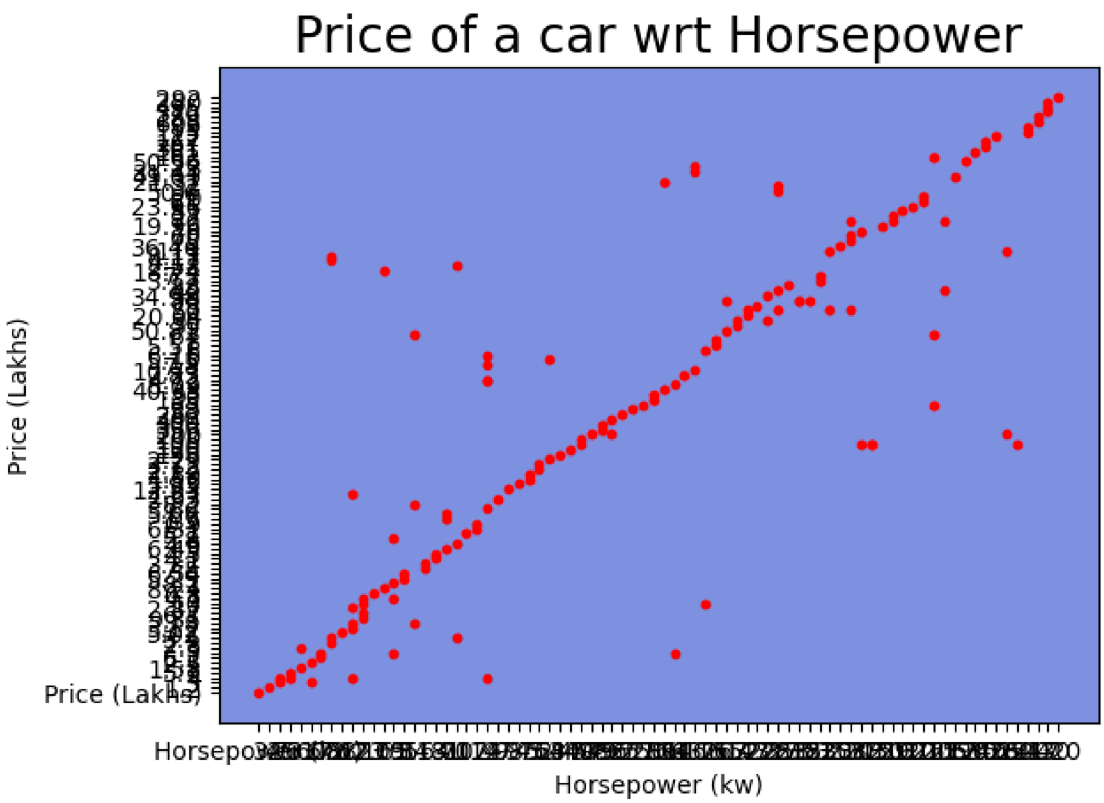
[ ]:
```
#Plotting a graph establishing the relation of price wrt year
x = []
y= []

with open(file_path,'r') as csvfile:
```

```
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[11])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#7e91e0")

plt.scatter(x, y, color = 'r')
plt.xlabel('Year')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Year', fontsize = 20)

plt.show()
```



[ ]:
```
#Plotting a graph establishing the relation of price wrt Horsepower
x = []
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
```

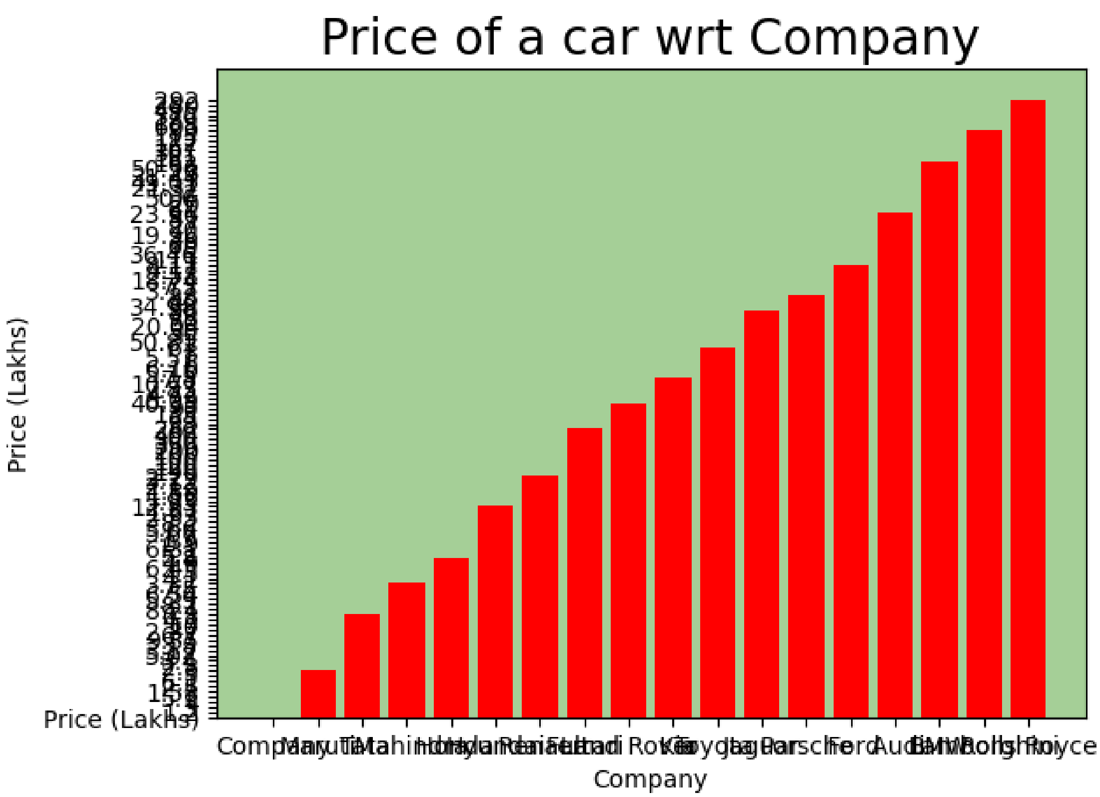
```python
    for row in lines:
        x.append(row[10])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#7e91e0")

plt.scatter(x, y, color = 'r' ,s = 10)
plt.xlabel('Horsepower (kw)')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Horsepower', fontsize = 20)

plt.show()
```



Bivariate analysis of qualitative analysis

[ ]:
```python
#Plotting a graph establishing the relation of price wrt company
x = []
y= []

with open(file_path,'r') as csvfile:
```

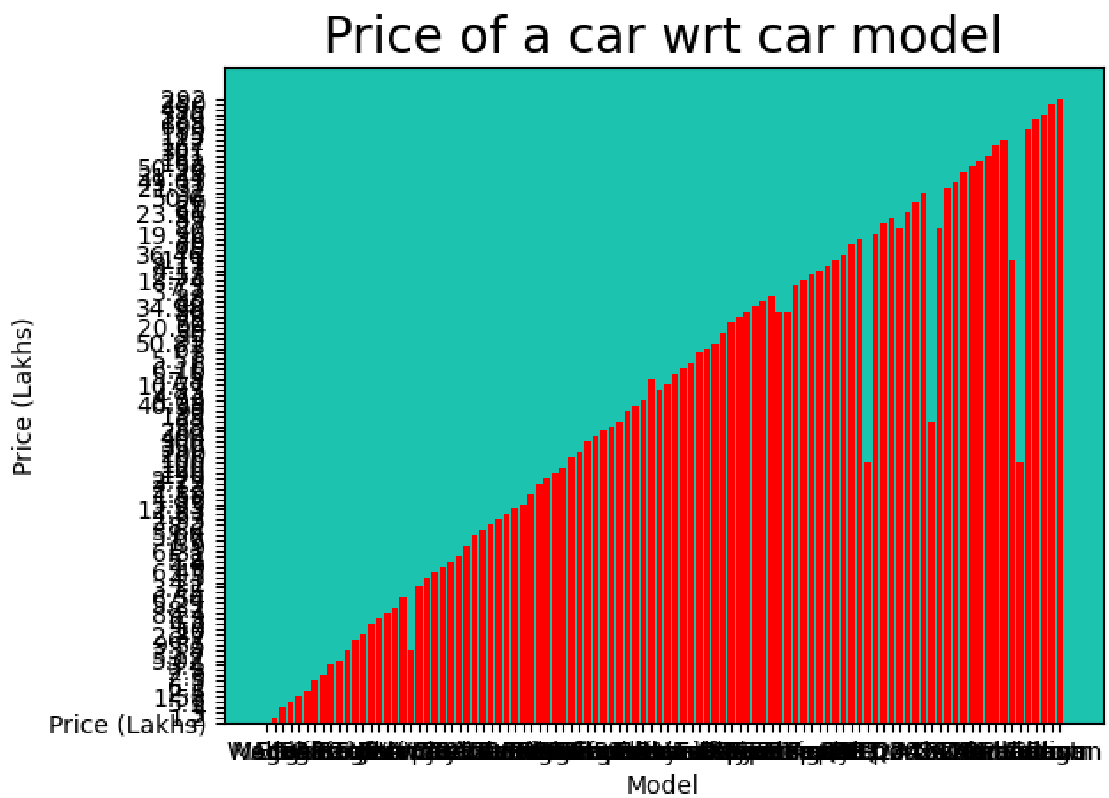
```
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[1])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#a5cf97")

plt.bar(x, y, color = 'r')
plt.xlabel('Company')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Company', fontsize = 20)

plt.show()
```



[ ]:

```
#Plotting a graph establishing the relation of price wrt car model
x = []
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
```

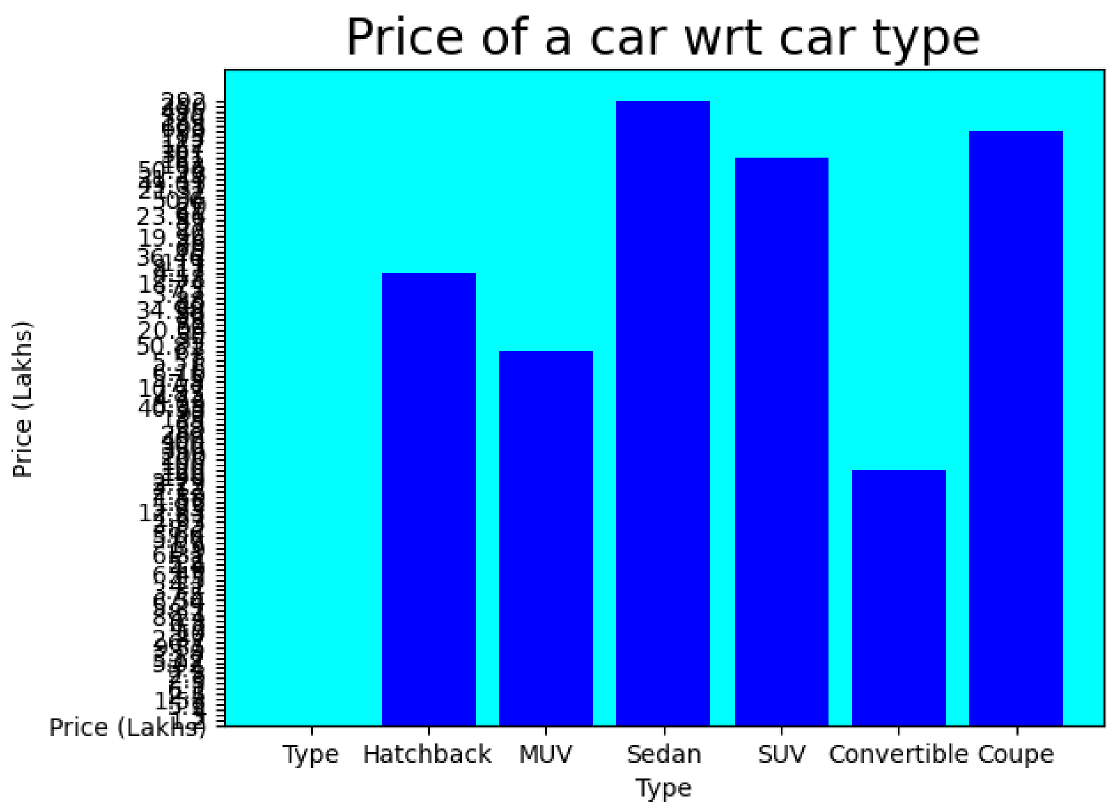
```
    for row in lines:
        x.append(row[2])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("#1CC4AF")

plt.bar(x, y, color = 'r')
plt.xlabel('Model')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt car model', fontsize = 20)

plt.show()
```



[ ]:

```
#Plotting a graph establishing the relation of price wrt car type
x = []
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
```

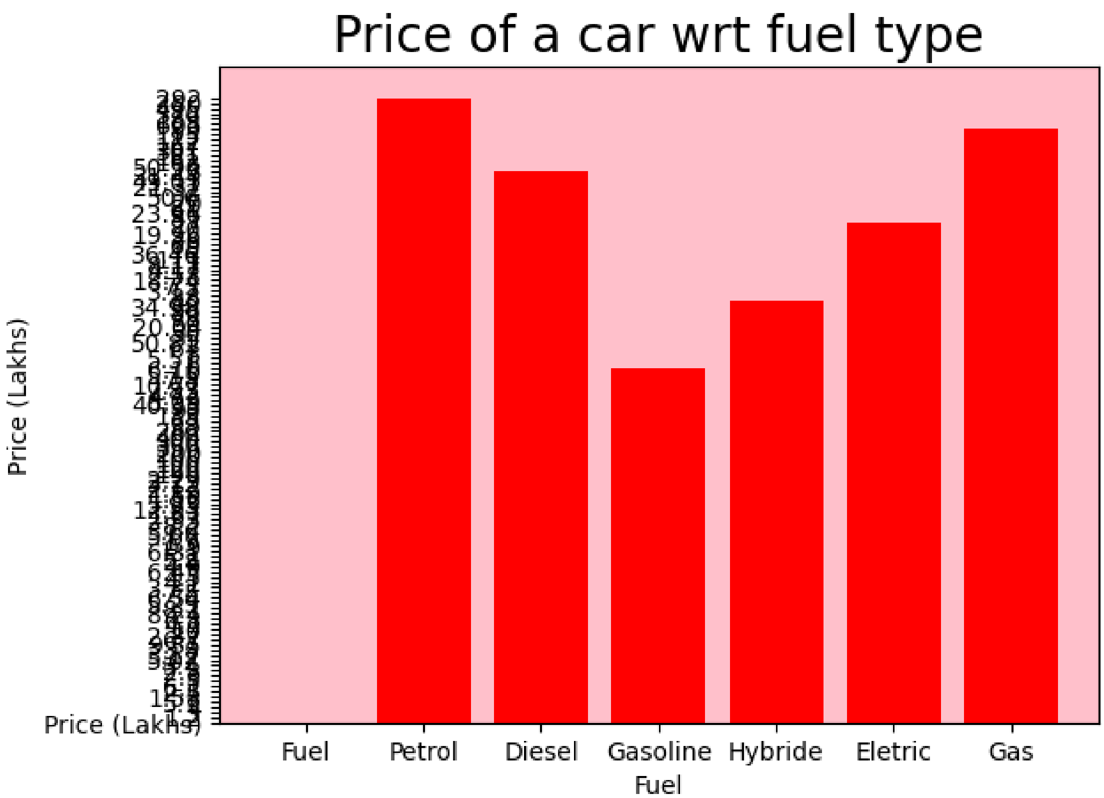
```
        x.append(row[3])
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("cyan")

plt.bar(x, y, color = 'b')
plt.xlabel('Type')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt car type', fontsize = 20)

plt.show()
```



[ ]:

```
#Plotting a graph establishing the relation of price wrt Fuel type
x = []
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[4])
```

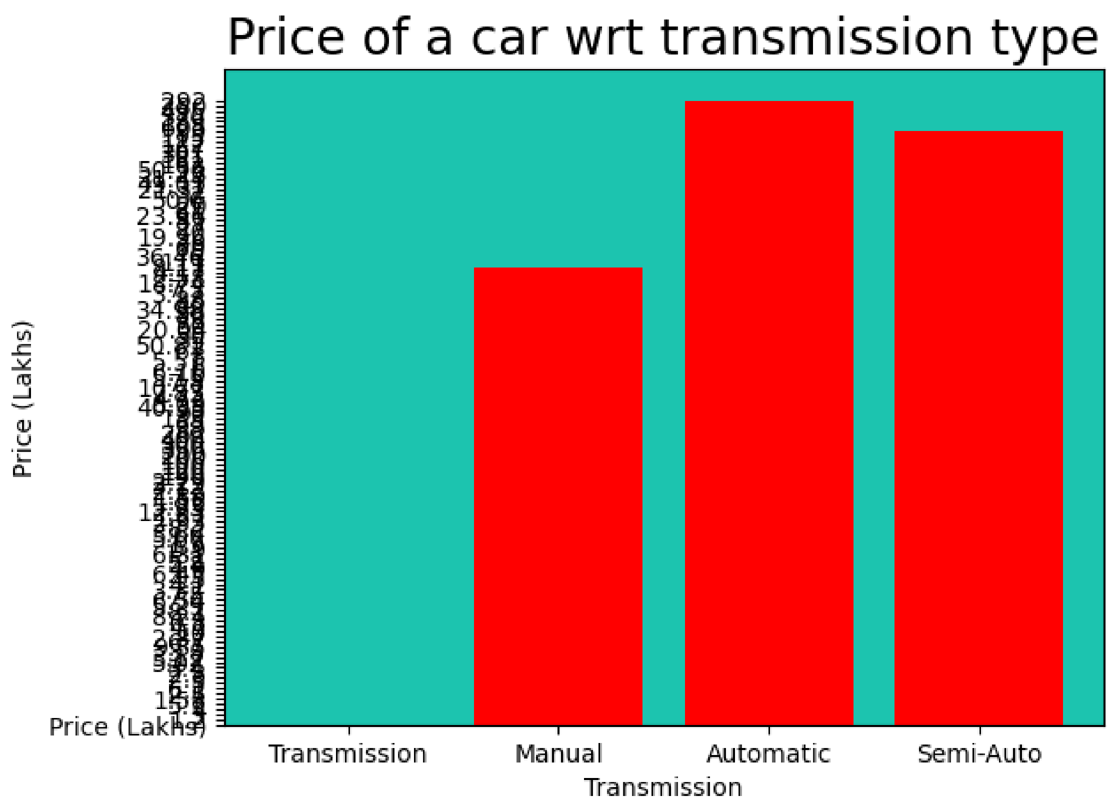
```
        y.append((row[12]))

ax = plt.axes()
ax.set_facecolor("pink")

plt.bar(x, y, color = 'r')
plt.xlabel('Fuel')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt fuel type', fontsize = 20)

plt.show()
```



[ ]:

```
#Plotting a graph establishing the relation of price wrt transmission type
x = []
y= []

with open(file_path,'r') as csvfile:
    lines = csv.reader(csvfile, delimiter=',')
    for row in lines:
        x.append(row[5])
        y.append((row[12]))
```

```
ax = plt.axes()
ax.set_facecolor("#1CC4AF")

plt.bar(x, y, color = 'r')
plt.xlabel('Transmission')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt transmission type', fontsize = 20)

plt.show()
```



1.2 Data Preparation

Missing values can be handled by deleting the rows and columns having null values. In those scenarios we use drop function and then check the number of rows and columns using shape function.

[ ]:
```
df.shape
```

[ ]:
```
(150, 13)
```

[ ]:
```
# Deleting unwanted datapoints
df.dropna(inplace=True)
```

[ ]:
```
# Checking the no.of rows and columns
df.shape
```

[ ]: (147, 13)

[ ]:
```
# Again deleting unwanted datapoints
df = df.drop(df.index[[79,84,94,95,144,145]])
```

[ ]:
```
# Final no.of rows and columns after eliminating unwanted data
df.shape
```

[ ]: (141, 13)

[ ]:
```
# Eliminating unwanted columns
df.drop([ 'ID'] , axis =1 , inplace = True)
```

[ ]:
```
# No.of rows and columns after deleting three columns
df.shape
```

[ ]: (141, 12)

2 Univariate Linear Regression

Linear regression focuses on determining relationship between one independent variable and one dependent variable. Regression is mainly used when we need to predict any value when there is a positive linear trend.

Calculating the relation between price of a car and its mileage

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Mileage ']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.22707955237183142

Case 2 [20% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.13542634731078562

Case 3 [30% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.1388848826666671

Case 4 [40% data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.17765988780799136

Calculating the relation between price of a car and no.of buyers

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Buyers']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -1.389846057894935
```

Case 2 [20% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -0.45308837193176843
```

Case 3 [30% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -0.3462998327450231
```

Case 4 [40% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.4502680131961483

Calculating the relation between price of a car and year of production

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Year']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -1.3402199334521652

Case 2 [20% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.04752011613010909

Case 3 [30% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.15462609945282146

Case 4 [40% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -0.2196045302951113
```

Calculating the relation between price of a car and kilometers driven

```
[ ]: #Assigning the predictor variable and target variable
x = df[['Kms_driven']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -1.2543401714330011
```

Case 2 [20% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: -0.05729198164479077
```

Case 3 [30% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
 ↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.16361913604973233

Case 4 [40% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: -0.22073857236656935

Calculating the relation between price of a car and Engine

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Engine']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.5423153231352085

Case 2 [20% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
```

```
clf.score(x_test , y_test)
```

[ ]: 0.2337001305417128

Case 3 [30% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
 ↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.18132752277297937

Case 4 [40% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
 ↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.08827776994052916

Calculating the relation between price of a car and Horsepower

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Horsepower (kw)']]
y = df[['Price (Lakhs)']]
```

Case 1 [10% test data]

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
 ↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]: 0.4078795826496524

Case 2 [20% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: 0.6000689635529655
```

Case 3 [30% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: 0.6277982239521187
```

Case 4 [40% test data]

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4,␣
 ↪random_state=2)
```

```
[ ]: #Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

```
[ ]: 0.46367637131670103
```

####After implementing linear regression using all the four scenarios , we came to a conclusion that taking 30-70 test_train data is the most ideal one for prediction.

##Underfitting and Overfitting model

A statistical model or a machine learning algorithm is said to have underfitting when it cannot capture the underlying trend of the data. Its occurrence simply means that our model or the algorithm does not fit the data well enough. It usually happens when we have fewer data to build an accurate model.

A statistical model is said to be overfitted when we train it with a lot of data. When a model gets trained with so much data, it starts learning from the noise and inaccurate data entries in our data set.

#Decision tree

Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.

Case 1 : Engine

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Engine']]
y = df[['Price (Lakhs)']]
```

[ ]:
```
#Split the Dataset into Training and Test Dataset
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=0)
```

[ ]:
```
#Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
 ↪y_train
DtReg.fit(x_train, y_train)
```

[ ]:
```
DecisionTreeRegressor(random_state=0)
```

[ ]:
```
#Showing x_train and y_train data
print(x_train, y_train)
```

```
     Engine
78     1998
139    5204
68     1493
98     1498
87     1997
..      …
9      1462
108    2995
67     1998
124    2998
47     1498
```

```
[98 rows x 1 columns]      Price (Lakhs)
78            10.00
139          111.00
68             8.09
98             3.17
87            50.00
..              …
9              5.00
108           75.00
67            40.33
124           32.00
47             5.93

[98 rows x 1 columns]
```

[ ]:

```
#Showing x_test and y_test data
print (x_test, y_test)
```

```
     Engine
45     1197
60     6262
7      1200
51      999
66     2995
27     1197
71     1197
54     3855
130    1998
8      1462
76     1197
16     1956
132    2993
129    1998
131    1998
103    1499
110    3996
85     1997
33     1199
56     3855
94     2981
22     2184
144    6749
24     1493
2       998
118    2994
26     2179
128    1998
18     1199
```

```
10     1197
101    1499
43     1086
105    2995
113    3998
50      999
86     1997
61     6262
112    3998
93     3996
59     3990
44     1197
30     1498
119    2994      Price (Lakhs)
45             4.00
60           400.00
7              3.00
51             3.72
66            90.00
27             3.80
71             4.00
54           120.00
130           31.44
8              6.10
76             5.15
16             9.35
132           50.56
129           49.01
131           23.00
103            4.17
110          100.00
85            30.00
33             4.90
56           106.00
94            88.00
22             8.24
144          605.00
24             8.10
2              4.00
118           50.00
26             6.54
128           21.32
18             2.87
10             2.30
101            2.58
43             2.33
105          111.00
113          100.00
```

```
50             2.12
86            20.04
61           200.00
112          100.00
93            50.00
59           300.00
44             1.67
30             4.10
119           70.00
```

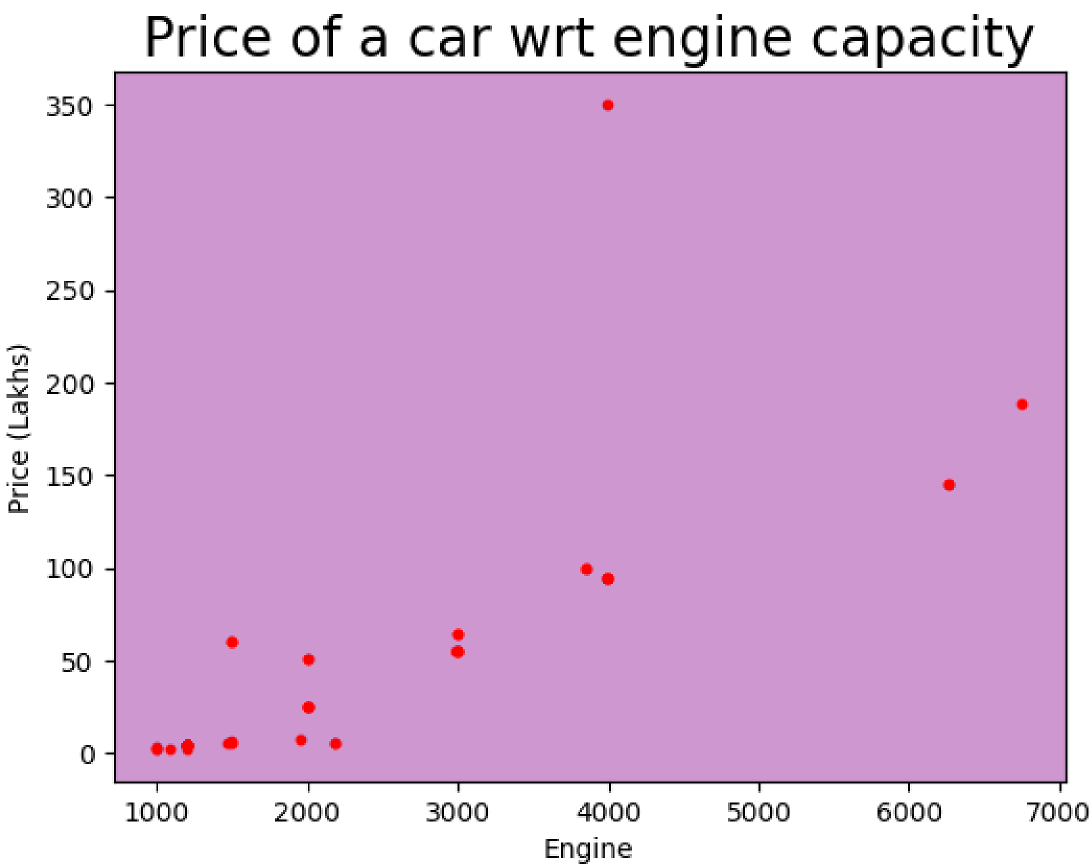
[ ]:

```
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[  4.29285714 145.           2.5          2.29        63.83
   4.29285714   4.29285714 100.          25.165        5.522
   4.29285714   7.13333333  55.          25.165       25.165
  60.1425      94.25        50.9525       4.548      100.
  55.           5.29       189.           5.93         3.
  55.           5.29        25.165        4.548        4.29285714
  60.1425       2.29        63.83        94.25         2.29
  50.9525     145.          94.25        94.25       350.
   4.29285714   5.47        55.        ]
R-Square Error associated with Decision Tree Regression is: 0.5498105746040209
```

[ ]:

```
#Plotting a graph establishing the relation of price wrt engine capacity
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color = 'r', s = 10)
plt.xlabel('Engine')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt engine capacity', fontsize = 20)

plt.show()
```



Case 2 : Horsepower

```
[ ]: #Assigning the predictor variable and target variable
x = df[['Horsepower (kw)']]
y = df[['Price (Lakhs)']]
```

```
[ ]: #Split the Dataset into Training and Test Dataset
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=0)
```

```
[ ]: #Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
 ↪y_train
DtReg.fit(x_train, y_train)
```

[ ]: DecisionTreeRegressor(random_state=0)

[ ]:
```
#Showing x_train and y_train data
print(x_train, y_train)
```

```
     Horsepower (kw)
78               115
139              522
68                94
98                82
87               147
..               …
9                 67
108              220
67               166
124              327
47                97

[98 rows x 1 columns]       Price (Lakhs)
78           10.00
139         111.00
68            8.09
98            3.17
87           50.00
..             …
9             5.00
108          75.00
67           40.33
124          32.00
47            5.93

[98 rows x 1 columns]
```

[ ]:
```
print (x_test)
```

```
     Horsepower (kw)
45                62
60               795
7                 60
51                52
66               286
27                84
71                74
54               440
130              132
8                 67
76                63
16               123
```

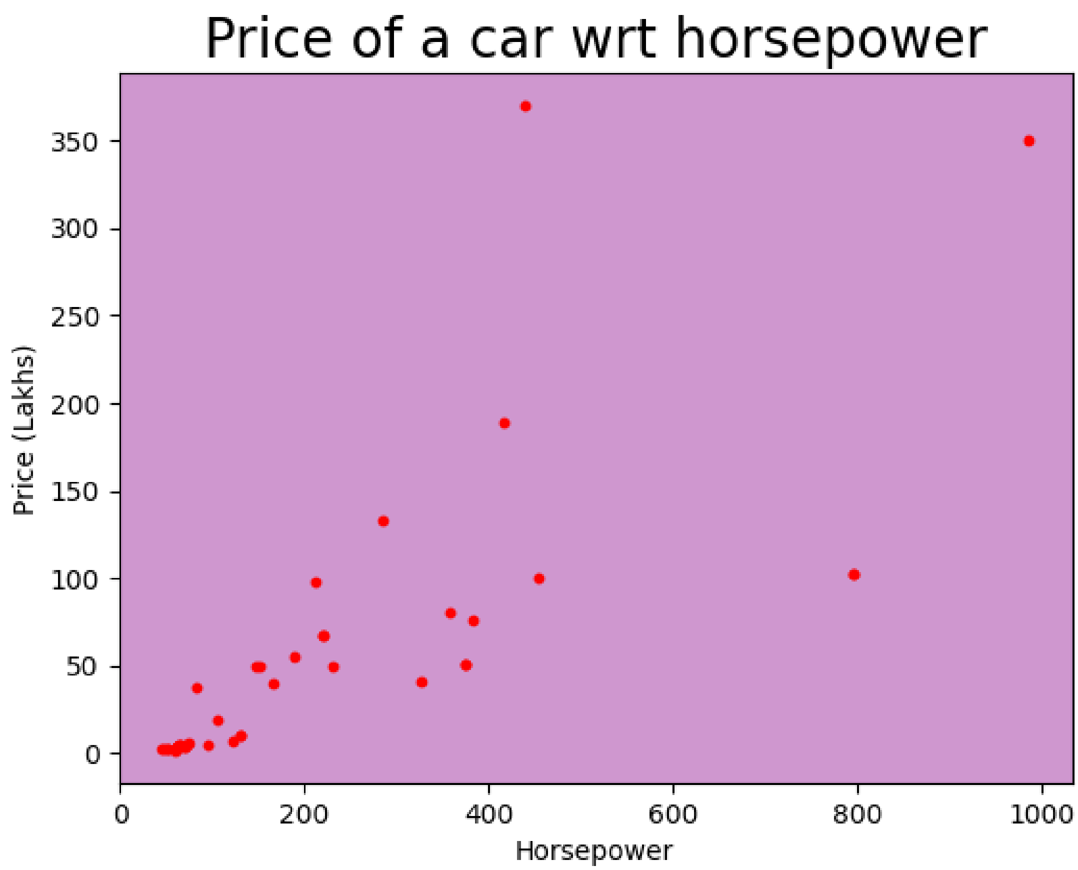
```
132     190
129     212
131     132
103      72
110     383
85      152
33       70
56      454
94      358
22      105
144     417
24       65
2        46
118     220
26       95
128     166
18       62
10       61
101      70
43       47
105     230
113     375
50       52
86      147
61      795
112     375
93      327
59      985
44       62
30       64
119     220
```

[ ]:
```python
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[  3.46       102.           2.5          3.         133.
  37.6          5.412      370.          10.77         5.
   2.29         7.13333333  55.          98.          10.77
   4.79        76.          50.           3.4        100.
```

```
 80.          18.74       189.          5.16666667   3.
 67.5          5.29        40.33        3.46         1.58
  3.4          3.          50.         50.5          3.
 50.         102.          50.5        40.86666667 350.
  3.46         4.5         67.5       ]
R-Square Error associated with Decision Tree Regression is: 0.38447343918725185
```

[ ]:
```python
#Plotting a graph establishing the relation of price wrt horsepower
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color = 'r', s = 10)
plt.xlabel('Horsepower')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt horsepower', fontsize = 20)

plt.show()
```



Case 3 : Buyers

```
[ ]: #Assigning the predictor variable and target variable
x = df[['Buyers']]
y = df[['Price (Lakhs)']]
```

```
[ ]: #Split the Dataset into Training and Test Dataset
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=0)
```

```
[ ]: #Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
 ↪y_train
DtReg.fit(x_train, y_train)
```

```
[ ]: DecisionTreeRegressor(random_state=0)
```

```
[ ]: print (x_train , y_train)
```

```
     Buyers
78        2
139       4
68        2
98        2
87        2
..      …
9         2
108       2
67        2
124       3
47        2

[98 rows x 1 columns]      Price (Lakhs)
78             10.00
139           111.00
68              8.09
98              3.17
87             50.00
..               …
9               5.00
108            75.00
67             40.33
```

```
124          32.00
47            5.93

[98 rows x 1 columns]
```

[ ]:
```
print (x_test , y_test)
```

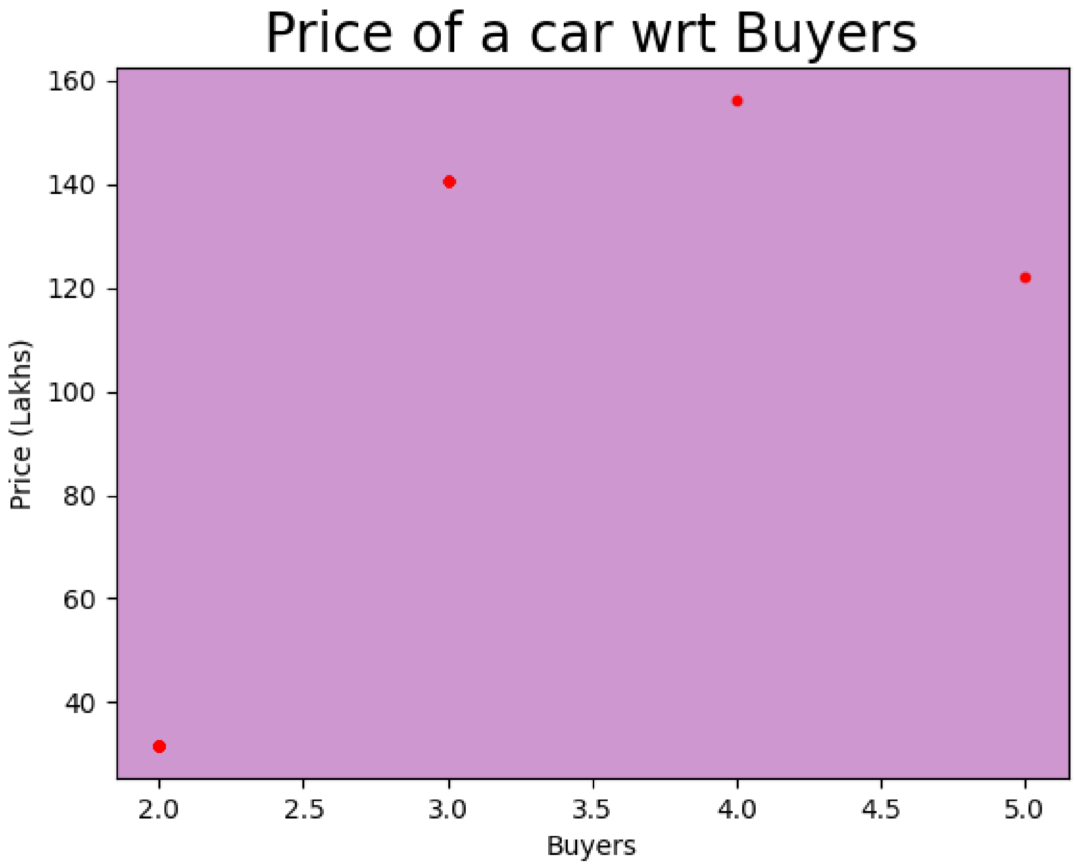
```
     Buyers
45        2
60        2
7         2
51        2
66        3
27        2
71        2
54        2
130       2
8         2
76        2
16        2
132       5
129       2
131       2
103       2
110       2
85        2
33        2
56        3
94        2
22        2
144       4
24        2
2         2
118       3
26        2
128       3
18        2
10        2
101       3
43        2
105       2
113       2
50        2
86        2
61        2
112       2
93        2
59        2
```

```
44         2
30         2
119        3      Price (Lakhs)
45             4.00
60           400.00
7              3.00
51             3.72
66            90.00
27             3.80
71             4.00
54           120.00
130           31.44
8              6.10
76             5.15
16             9.35
132           50.56
129           49.01
131           23.00
103            4.17
110          100.00
85            30.00
33             4.90
56           106.00
94            88.00
22             8.24
144          605.00
24             8.10
2              4.00
118           50.00
26             6.54
128           21.32
18             2.87
10             2.30
101            2.58
43             2.33
105          111.00
113          100.00
50             2.12
86            20.04
61           200.00
112          100.00
93            50.00
59           300.00
44             1.67
30             4.10
119           70.00
```

[ ]:
```
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[ 31.65987179  31.65987179  31.65987179  31.65987179 140.76642857
  31.65987179  31.65987179  31.65987179  31.65987179  31.65987179
  31.65987179  31.65987179 122.          31.65987179  31.65987179
  31.65987179  31.65987179  31.65987179  31.65987179 140.76642857
  31.65987179  31.65987179 156.2         31.65987179  31.65987179
 140.76642857  31.65987179 140.76642857  31.65987179  31.65987179
 140.76642857  31.65987179  31.65987179  31.65987179  31.65987179
  31.65987179  31.65987179  31.65987179  31.65987179  31.65987179
  31.65987179  31.65987179 140.76642857]
R-Square Error associated with Decision Tree Regression is: 0.06112448692031136
```

[ ]:
```
#Plotting a graph establishing the relation of price wrt Buyers
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color ='r', s = 10)
plt.xlabel('Buyers')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Buyers', fontsize = 20)

plt.show()
```



Case 4 : Kilometers Driven

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Kms_driven']]
y = df[['Price (Lakhs)']]
```

[ ]:
```
#Split the Dataset into Training and Test Dataset
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=0)
```

[ ]:
```
#Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
  ↪y_train
DtReg.fit(x_train, y_train)
```

[ ]: DecisionTreeRegressor(random_state=0)

```
[ ]: print (x_train , y_train)
```

```
     Kms_driven
78        39000
139       35000
68        36000
98        30000
87        20000
..          …
9         15000
108       22000
67        16000
124        3600
47        39000

[98 rows x 1 columns]      Price (Lakhs)
78            10.00
139          111.00
68             8.09
98             3.17
87            50.00
..              …
9              5.00
108           75.00
67            40.33
124           32.00
47             5.93

[98 rows x 1 columns]
```

```
[ ]: print (x_test , y_test)
```

```
     Kms_driven
45        48508
60        60000
7         41000
51        82000
66        40000
27        35550
71        10000
54        32000
130       50000
8         25000
76        15487
16        32000
132       32000
```

```
129      35000
131      20000
103      54000
110      22000
85       10000
33       55000
56       38000
94       19000
22        4000
144      35000
24        5000
2        40005
118      20000
26       43000
128      45000
18       48660
10       24530
101      35000
43       35522
105      16000
113      50000
50       82000
86       41000
61       60000
112      50000
93        7000
59       40000
44       48508
30       39522
119      20000      Price (Lakhs)
45             4.00
60           400.00
7              3.00
51             3.72
66            90.00
27             3.80
71             4.00
54           120.00
130           31.44
8              6.10
76             5.15
16             9.35
132           50.56
129           49.01
131           23.00
103            4.17
110          100.00
85            30.00
```

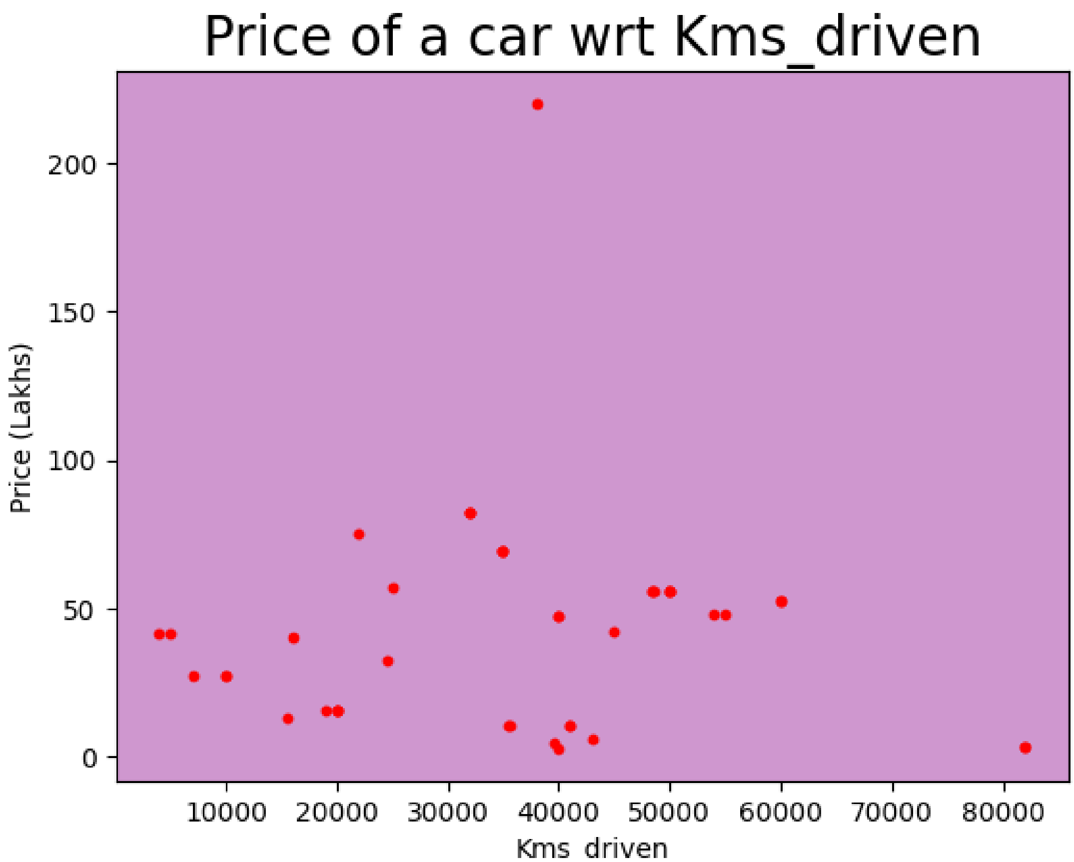
```
33           4.90
56         106.00
94          88.00
22           8.24
144        605.00
24           8.10
2            4.00
118         50.00
26           6.54
128         21.32
18           2.87
10           2.30
101          2.58
43           2.33
105        111.00
113        100.00
50           2.12
86          20.04
61         200.00
112        100.00
93          50.00
59         300.00
44           1.67
30           4.10
119         70.00
```

[ ]:

```python
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[ 55.6         52.455       10.62         3.605       47.50333333
  10.77        27.35        82.5         55.6         57.33333333
  12.93        82.5         82.5         69.23333333  15.5975
  48.          75.          27.35        48.         220.
  15.5975      41.3         69.23333333  41.3          3.
  15.5975       6.395       42.06666667  55.6         32.49
  69.23333333  10.77        40.33        55.6          3.605
  10.62        52.455       55.6         27.35        47.50333333
  55.6          4.5         15.5975    ]
R-Square Error associated with Decision Tree Regression is: 0.026045402038831766
```

[ ]:
```
#Plotting a graph establishing the relation of price wrt Kms_driven
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color ='r', s = 10)
plt.xlabel('Kms_driven')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Kms_driven', fontsize = 20)

plt.show()
```



Case 5: Year of Production

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Year']]
y = df[['Price (Lakhs)']]
```

[ ]:
```python
#Split the Dataset into Training and Test Dataset
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=0)
```

[ ]:
```python
#Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
↪y_train
DtReg.fit(x_train, y_train)
```

[ ]: DecisionTreeRegressor(random_state=0)

[ ]:
```python
print (x_train , y_train)
```

```
     Year
78   2015
139  2020
68   2020
98   2012
87   2020
..    …
9    2015
108  2019
67   2015
124  2020
47   2017

[98 rows x 1 columns]      Price (Lakhs)
78             10.00
139           111.00
68              8.09
98              3.17
87             50.00
..               …
9               5.00
108            75.00
67             40.33
124            32.00
47              5.93

[98 rows x 1 columns]
```

[ ]:
```
print (x_test , y_test)
```

```
     Year
45   2018
60   2018
7    2016
51   2017
66   2018
27   2015
71   2017
54   2016
130  2017
8    2015
76   2013
16   2012
132  2018
129  2016
131  2014
103  2015
110  2020
85   2019
33   2005
56   2017
94   2014
22   2015
144  2018
24   2013
2    2018
118  2015
26   2012
128  2015
18   2006
10   2016
101  2014
43   2014
105  2017
113  2015
50   2009
86   2020
61   2016
112  2018
93   2020
59   2017
44   2015
30   2008
119  2018       Price (Lakhs)
45             4.00
```

```
60     400.00
7        3.00
51       3.72
66      90.00
27       3.80
71       4.00
54     120.00
130     31.44
8        6.10
76       5.15
16       9.35
132     50.56
129     49.01
131     23.00
103      4.17
110    100.00
85      30.00
33       4.90
56     106.00
94      88.00
22       8.24
144    605.00
24       8.10
2        4.00
118     50.00
26       6.54
128     21.32
18       2.87
10       2.30
101      2.58
43       2.33
105    111.00
113    100.00
50       2.12
86      20.04
61     200.00
112    100.00
93      50.00
59     300.00
44       1.67
30       4.10
119     70.00
```

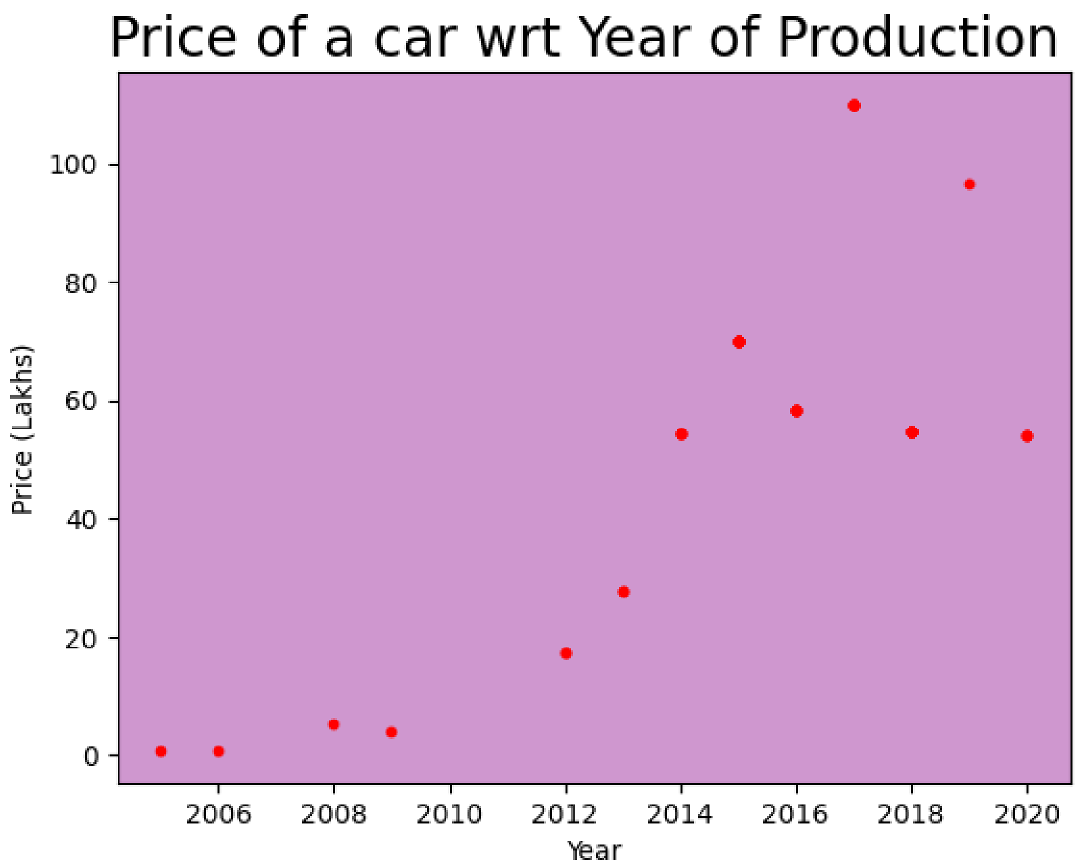
[ ]:
```
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))
```

```python
print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[ 54.56090909  54.56090909  58.25857143 109.96555556  54.56090909
  69.88777778 109.96555556  58.25857143 109.96555556  69.88777778
  27.89111111  17.42166667  54.56090909  58.25857143  54.24375
  69.88777778  54.14363636  96.74         0.8        109.96555556
  54.24375     69.88777778  54.56090909  27.89111111  54.56090909
  69.88777778  17.42166667  69.88777778   0.8         58.25857143
  54.24375     54.24375    109.96555556  69.88777778   3.90666667
  54.14363636  58.25857143  54.56090909  54.14363636 109.96555556
  69.88777778   5.2         54.56090909]
R-Square Error associated with Decision Tree Regression is: 0.013648697045410718
```

[ ]:

```python
#Plotting a graph establishing the relation of price wrt year of production
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color ='r', s = 10)
plt.xlabel('Year')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Year of Production ', fontsize = 20)

plt.show()
```



Case 6 : Mileage

```
[ ]: #Assigning the predictor variable and target variable
     x = df[['Mileage ']]
     y = df[['Price (Lakhs)']]
```

```
[ ]: #Split the Dataset into Training and Test Dataset
     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=0)
```

```
[ ]: #Import the Decision Tree Regressor
     from sklearn.tree import DecisionTreeRegressor

     #Create a decision tree regressor object  from DecisionTreeRegressor class
     DtReg = DecisionTreeRegressor(random_state = 0)

     #Fit the decision tree regressor with training data represented by x_train and␣
      ↪y_train
     DtReg.fit(x_train, y_train)
```

[ ]: DecisionTreeRegressor(random_state=0)

[ ]:
```
print (x_train , y_train)
```

```
     Mileage
78     14.00
139     6.40
68     16.00
98     18.00
87     12.66
..       …
9      20.04
108    12.00
67     10.60
124    11.00
47     16.50

[98 rows x 1 columns]      Price (Lakhs)
78             10.00
139           111.00
68              8.09
98              3.17
87             50.00
..               …
9               5.00
108            75.00
67             40.33
124            32.00
47              5.93

[98 rows x 1 columns]
```

[ ]:
```
print (x_test , y_test)
```

```
     Mileage
45     25.40
60     11.00
7      20.89
51     19.00
66      9.32
27     20.00
71     21.00
54      9.00
130    15.00
8      20.04
76     22.00
16     17.00
132    13.00
```

129	14.00
131	15.00
103	22.00
110	8.70
85	13.12
33	23.70
56	8.93
94	10.00
22	16.55
144	6.71
24	16.70
2	20.50
118	11.00
26	15.00
128	18.00
18	20.30
10	19.56
101	16.00
43	20.30
105	9.00
113	8.00
50	19.00
86	12.66
61	11.00
112	8.00
93	20.00
59	18.00
44	25.40
30	24.70
119	11.00

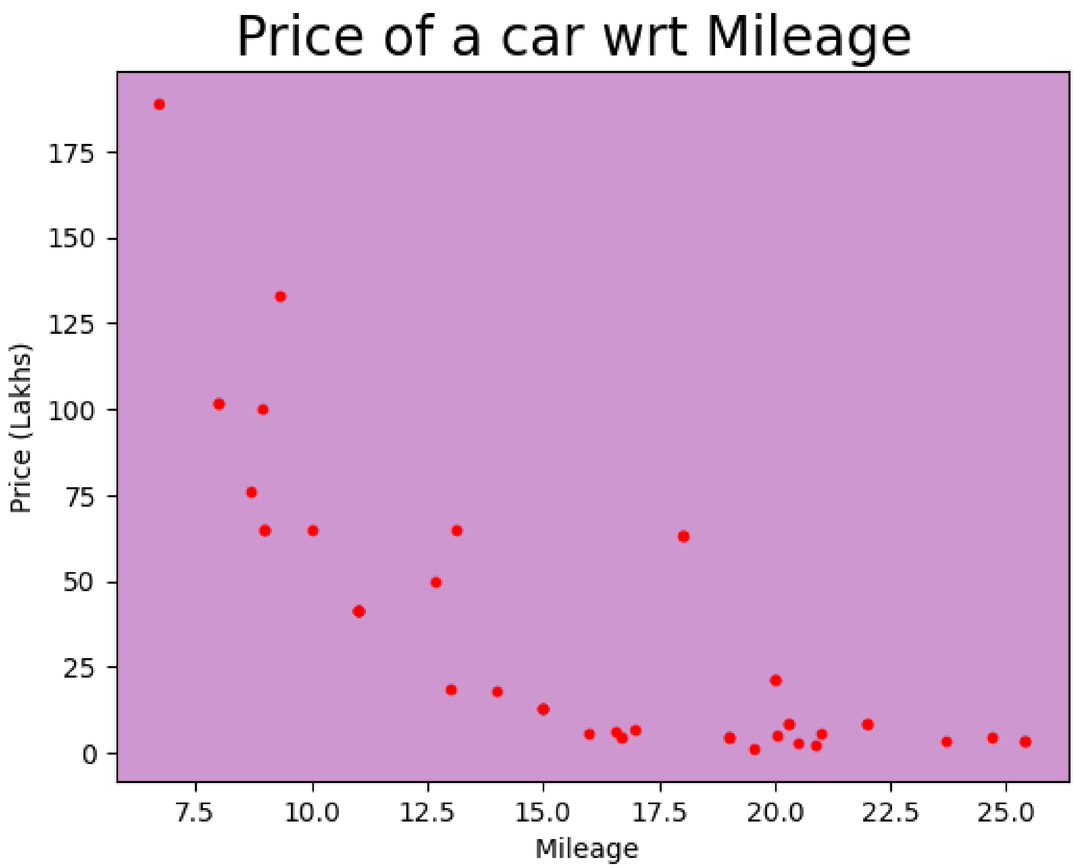
	Price (Lakhs)
45	4.00
60	400.00
7	3.00
51	3.72
66	90.00
27	3.80
71	4.00
54	120.00
130	31.44
8	6.10
76	5.15
16	9.35
132	50.56
129	49.01
131	23.00
103	4.17
110	100.00
85	30.00

```
33        4.90
56      106.00
94       88.00
22        8.24
144     605.00
24        8.10
2         4.00
118      50.00
26        6.54
128      21.32
18        2.87
10        2.30
101       2.58
43        2.33
105     111.00
113     100.00
50        2.12
86       20.04
61      200.00
112     100.00
93       50.00
59      300.00
44        1.67
30        4.10
119      70.00
```

[ ]:
```python
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[  3.66        41.3          2.5          4.55       133.
  21.145        5.61        65.         12.625        5.
   8.17         6.7         18.74        18.09666667  12.625
   8.17        76.          65.           3.46       100.
  65.           5.93       189.           4.7          3.
  41.3         12.625       63.35666667   8.2          1.2
   5.49666667   8.2         65.         102.           4.55
  50.          41.3        102.          21.145       63.35666667
   3.66         4.5         41.3       ]
R-Square Error associated with Decision Tree Regression is: 0.3051337479872578
```

[ ]:
```python
#Plotting a graph establishing the relation of price wrt Mileage
x = x_test
y= y_predict_dtr

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.scatter(x, y, color ='r', s = 10)
plt.xlabel('Mileage ')
plt.ylabel('Price (Lakhs)')
plt.title('Price of a car wrt Mileage  ', fontsize = 20)

plt.show()
```

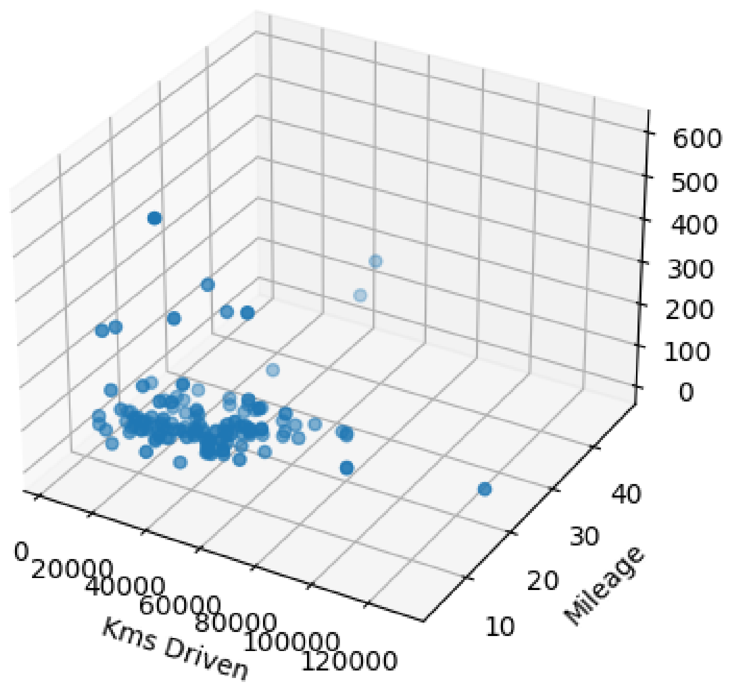


#3D Plotting

###3d plotting with reference to orginal dataset

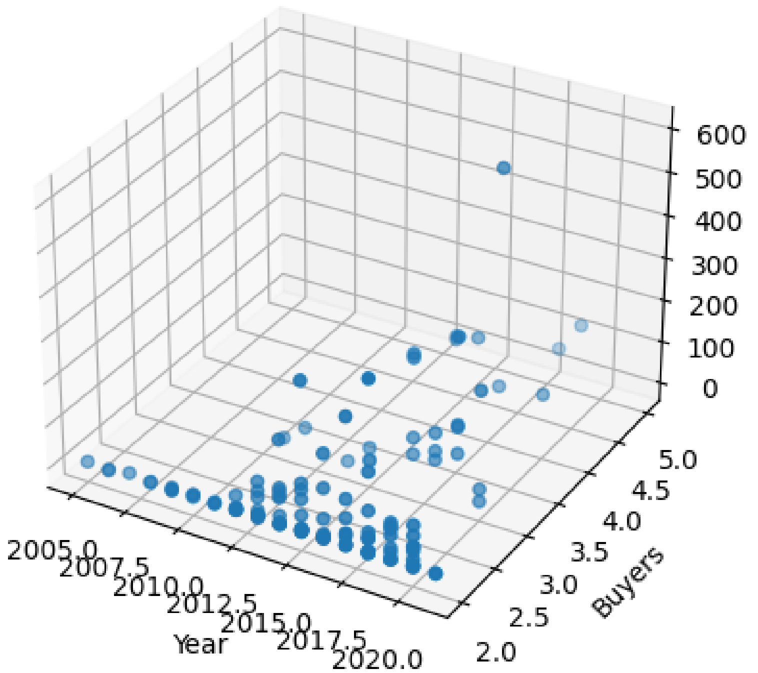
[ ]:
```python
#3d plotting of Kms Driven and Mileage wrt Price
fig = plt.figure()
```

```
ax1 = fig.add_subplot(111 , projection = '3d')

x = df[['Kms_driven']]
y = df[['Mileage ']]
z = df[['Price (Lakhs)']]

ax1.scatter (x,y,z)

ax1.set_xlabel ('Kms Driven')
ax1.set_ylabel ('Mileage')
ax1.set_zlabel ('Price')

plt.show()
```

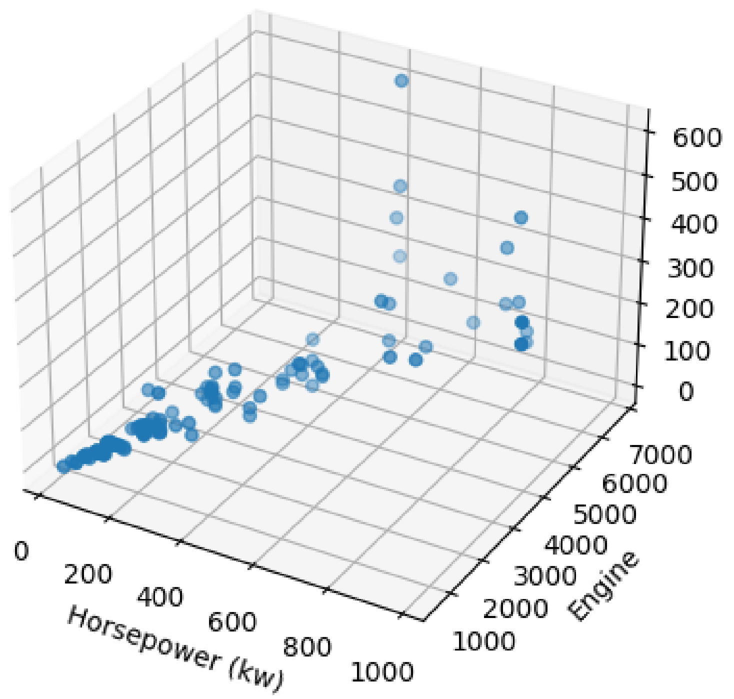


[ ]:
```
#3d plotting of Year and Buyers wrt Price
fig = plt.figure()
ax1 = fig.add_subplot(111 , projection = '3d')

x = df[['Year']]
y = df[['Buyers']]
z = df[['Price (Lakhs)']]

ax1.scatter (x,y,z)
```

```
ax1.set_xlabel ('Year')
ax1.set_ylabel ('Buyers')
ax1.set_zlabel ('Price')

plt.show()
```



[ ]:
```
#3d plotting of Horsepower and Engine wrt Price
fig = plt.figure()
ax1 = fig.add_subplot(111 , projection = '3d')

x = df[['Horsepower (kw)']]
y = df[['Engine']]
z = df[['Price (Lakhs)']]

ax1.scatter (x,y,z)

ax1.set_xlabel ('Horsepower (kw)')
ax1.set_ylabel ('Engine')
ax1.set_zlabel ('Price')

plt.show()
```



###3d Plotting using test data

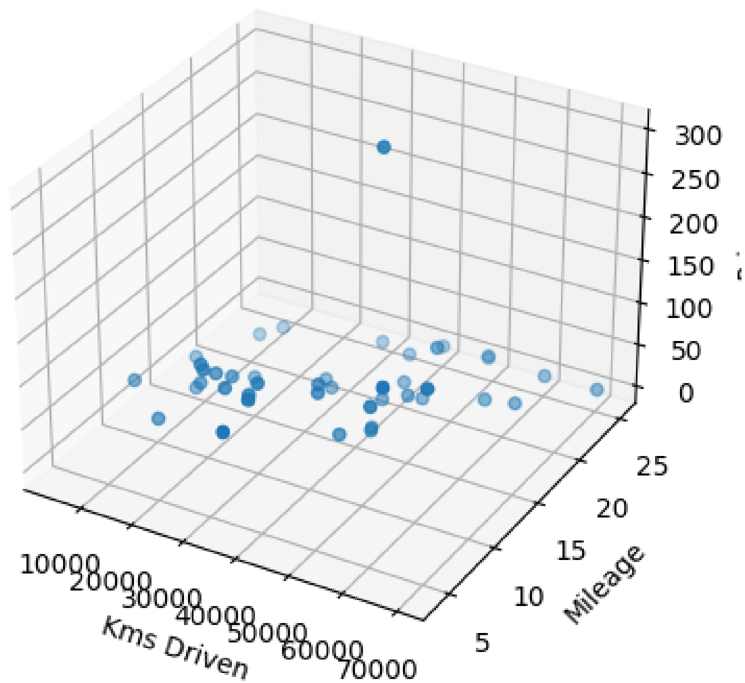
Case 1 : Kms Driven and Mileage

```
[ ]: #Assigning the predictor variable and target variable
x = df[['Kms_driven']]
y = df[['Mileage ']]
z = df[['Price (Lakhs)']]
```

```
[ ]: #splitting the dataset into test and train set
x_train, x_test, z_train, z_test = train_test_split(x, z, test_size = 0.3,␣
↪random_state=2)
y_train, y_test, z_train, z_test = train_test_split(y, z, test_size = 0.3,␣
↪random_state=2)
```

```
[ ]: #3d plotting of Kms Driven and Mileage wrt Price
fig = plt.figure()
ax1 = fig.add_subplot(111 , projection = '3d')

x = x_test
y = y_test
z = z_test
```

```
ax1.scatter (x,y,z)

ax1.set_xlabel ('Kms Driven')
ax1.set_ylabel ('Mileage')
ax1.set_zlabel ('Price')

plt.show()
```



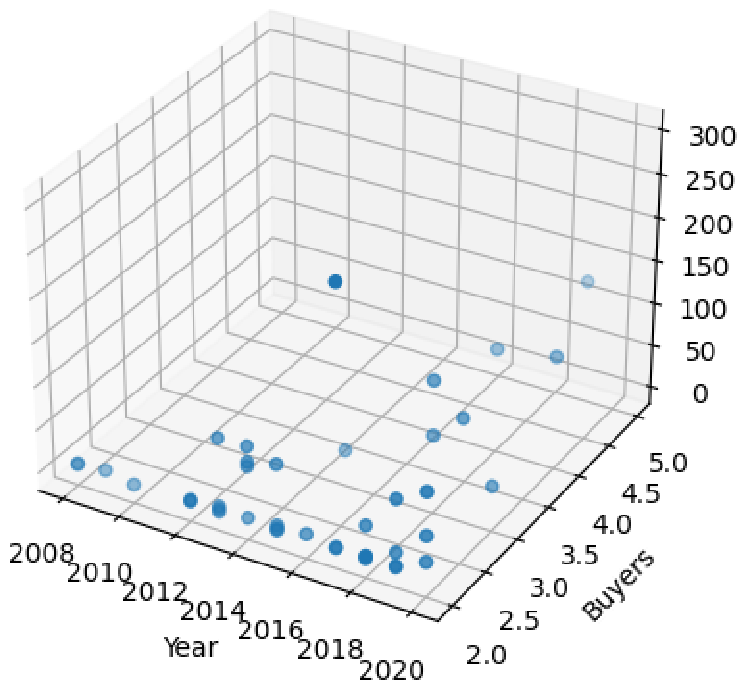
Case 2 : Year and Buyers

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Year']]
y = df[['Buyers']]
z = df[['Price (Lakhs)']]
```

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, z_train, z_test = train_test_split(x, z, test_size = 0.3,␣
 ↪random_state=2)
y_train, y_test, z_train, z_test = train_test_split(y, z, test_size = 0.3,␣
 ↪random_state=2)
```

[ ]:
```
#3d plotting of Year and Buyers wrt Price
fig = plt.figure()
```

```
ax1 = fig.add_subplot(111 , projection = '3d')

x = x_test
y = y_test
z = z_test

ax1.scatter (x,y,z)

ax1.set_xlabel ('Year')
ax1.set_ylabel ('Buyers')
ax1.set_zlabel ('Price')

plt.show()
```



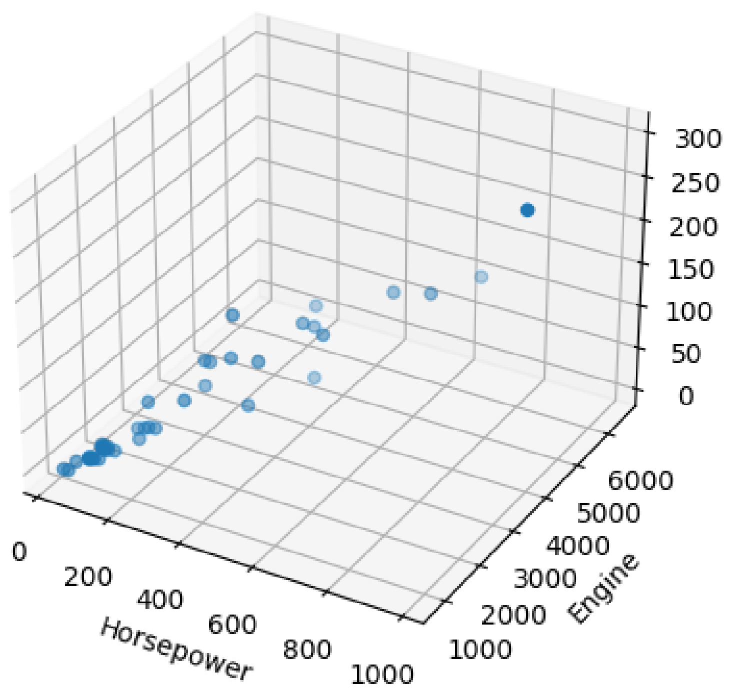
Case 3 : Horsepower and Engine

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Horsepower (kw)']]
y = df[['Engine']]
z = df[['Price (Lakhs)']]
```

[ ]:
```
#splitting the dataset into test and train set
```

```
x_train, x_test, z_train, z_test = train_test_split(x, z, test_size = 0.3,␣
 ↪random_state=2)
y_train, y_test, z_train, z_test = train_test_split(y, z, test_size = 0.3,␣
 ↪random_state=2)
```

```
[ ]: #3d plotting of Horsepower and Engine wrt Price
fig = plt.figure()
ax1 = fig.add_subplot(111 , projection = '3d')

x = x_test
y = y_test
z = z_test

ax1.scatter (x,y,z)

ax1.set_xlabel ('Horsepower')
ax1.set_ylabel ('Engine')
ax1.set_zlabel ('Price')

plt.show()
```



##As we can see that the case3 plotting shows linear trend , we will now perform multivariate linear regression and decision tree and then compare the two results.

Case 1 : Multivariate Linear Regression

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Horsepower (kw)' , 'Engine']]
y = df[['Price (Lakhs)']]
```

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
↪random_state=2)
```

[ ]:
```
#Using the linear regression function the predict the value
clf = LinearRegression()
clf.fit(x_train , y_train)
clf.score(x_test , y_test)
```

[ ]:
```
0.35592119049116866
```

[ ]:
```
regr = linear_model.LinearRegression()
regr.fit(x_test, y_test)
```

[ ]:
```
LinearRegression()
```

[ ]:
```
print (x_test , y_test)
```

```
     Horsepower (kw)  Engine
138              626    5204
104               72    1499
98                82    1498
41                74    1197
3                 73    1462
24                65    1493
48                45     799
127              205    2993
2                 46     998
5                 61    1197
71                74    1197
124              327    2998
86               147    1997
23                65    1493
94               358    2981
55               454    3855
45                62    1197
12                72    1497
59               985    3990
87               147    1997
122              376    4395
139              522    5204
110              383    3996
```

```
126              205    2993
117              290    2894
128              166    1998
25                95    2179
44                62    1197
141              651    6496
88               322    5000
65               286    2995
14                62    1199
11                72    1497
28               113    2189
0                 32     796
119              220    2994
36               102    1497
64               250    1997
20               123    1956
99                82    1498
121              376    4395
13                88    1199
30                64    1498      Price (Lakhs)
138           122.00
104             8.17
98              3.17
41              3.66
3               5.10
24              8.10
48              1.56
127            40.00
2               4.00
5               1.58
71              4.00
124            32.00
86             20.04
23              4.70
94             88.00
55            100.00
45              4.00
12              3.40
59            300.00
87             50.00
122            20.00
139           111.00
110           100.00
126            70.00
117            87.00
128            21.32
25              5.29
44              1.67
```

```
141     100.00
88       78.00
65      133.00
14        3.12
11        2.80
28        7.50
0         1.20
119      70.00
36        5.20
64       65.00
20        4.70
99        7.30
121      81.00
13        5.02
30        4.10
```

[ ]:
```
#Predicted Price from test dataset w.r.t Linear Regression
y_predict_lr = regr.predict((x_test))


print (y_predict_lr)


#Model Evaluation using R-Square for Linear Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_lr)
print('R-Square Error associated with Linear Regression is:', r_square)
```

```
[[146.31977924]
 [  7.11264966]
 [ 10.51493323]
 [ 11.74814226]
 [  7.93644603]
 [  4.81885349]
 [  7.13524385]
 [ 32.61011992]
 [  4.86630175]
 [  7.34220989]
 [ 11.74814226]
 [ 73.8925765 ]
 [ 26.0052879 ]
 [  4.81885349]
 [ 84.62181262]
 [105.7043124 ]
 [  7.68112777]
 [  7.13885931]
 [283.90055256]
 [ 26.0052879 ]
```

```
 [ 72.19211322]
 [111.07232029]
 [ 79.79336312]
 [ 32.61011992]
 [ 62.71551684]
 [ 32.4316227 ]
 [  5.99648046]
 [  7.68112777]
 [137.86129349]
 [ 45.96212947]
 [ 60.03625811]
 [  7.65491812]
 [  7.13885931]
 [ 11.96595396]
 [  2.76862596]
 [ 37.68078321]
 [ 17.30639555]
 [ 60.91382898]
 [ 18.4085567 ]
 [ 10.51493323]
 [ 72.19211322]
 [ 16.46678286]
 [  4.41441149]]
R-Square Error associated with Linear Regression is: 0.8684308205411453
```

Case 2 : Multivariate Decision Tree

[ ]:
```
#Assigning the predictor variable and target variable
x = df[['Horsepower (kw)' , 'Engine']]
y = df[['Price (Lakhs)']]
```

[ ]:
```
#splitting the dataset into test and train set
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
↪random_state=2)
```

[ ]:
```
#Import the Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

#Create a decision tree regressor object  from DecisionTreeRegressor class
DtReg = DecisionTreeRegressor(random_state = 0)

#Fit the decision tree regressor with training data represented by x_train and␣
↪y_train
DtReg.fit(x_train, y_train)
```

[ ]:
```
DecisionTreeRegressor(random_state=0)
```

[ ]:
```
print ( x_train , y_train)
```

```
     Horsepower (kw)  Engine
103               72    1499
118              220    2994
142              800    6500
74                74    1197
6                 60    1200
..               …     …
75                74    1197
43                47    1086
22               105    2184
72               146    2199
15                62    1199

[98 rows x 2 columns]      Price (Lakhs)
103           4.17
118          50.00
142         115.00
74            4.72
6             2.50
..             …
75            7.80
43            2.33
22            8.24
72            7.83
15            3.80

[98 rows x 1 columns]
```

[ ]:
```python
print ( x_test , y_test)
```

```
     Horsepower (kw)  Engine
138              626    5204
104               72    1499
98                82    1498
41                74    1197
3                 73    1462
24                65    1493
48                45     799
127              205    2993
2                 46     998
5                 61    1197
71                74    1197
124              327    2998
86               147    1997
23                65    1493
94               358    2981
55               454    3855
45                62    1197
```

12	72	1497
59	985	3990
87	147	1997
122	376	4395
139	522	5204
110	383	3996
126	205	2993
117	290	2894
128	166	1998
25	95	2179
44	62	1197
141	651	6496
88	322	5000
65	286	2995
14	62	1199
11	72	1497
28	113	2189
0	32	796
119	220	2994
36	102	1497
64	250	1997
20	123	1956
99	82	1498
121	376	4395
13	88	1199
30	64	1498

	Price (Lakhs)
138	122.00
104	8.17
98	3.17
41	3.66
3	5.10
24	8.10
48	1.56
127	40.00
2	4.00
5	1.58
71	4.00
124	32.00
86	20.04
23	4.70
94	88.00
55	100.00
45	4.00
12	3.40
59	300.00
87	50.00
122	20.00
139	111.00

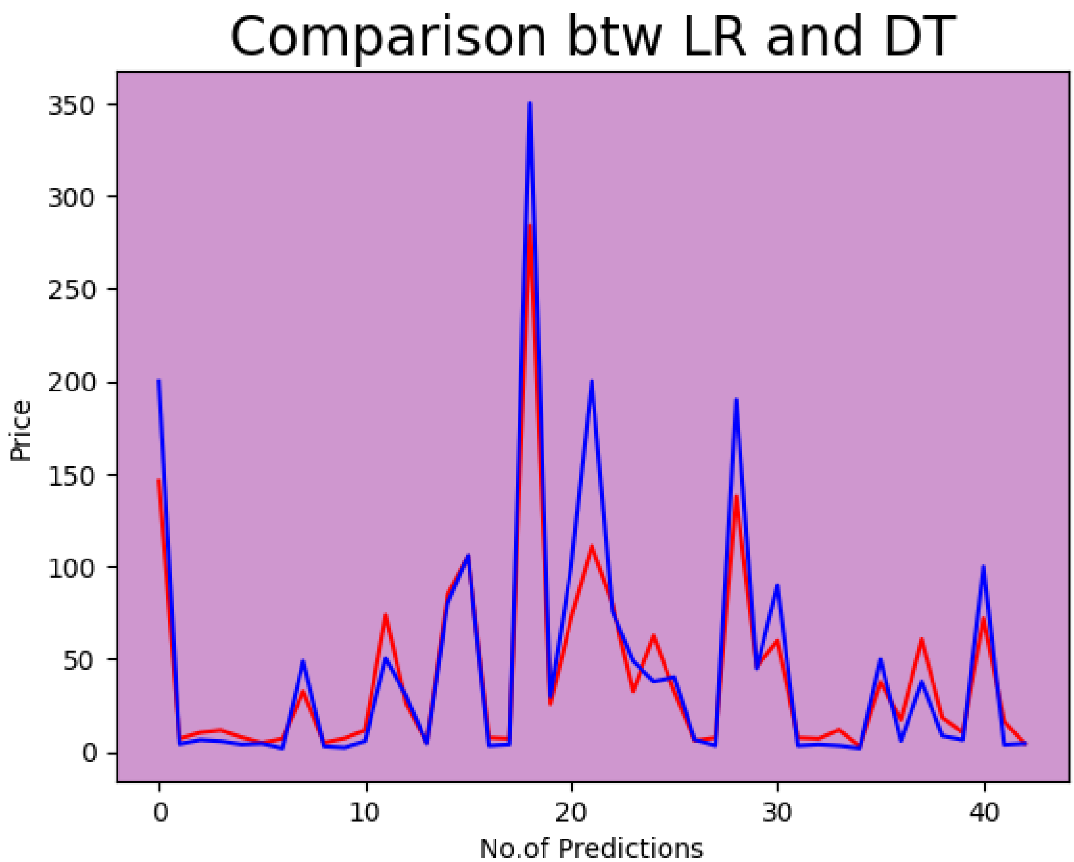
```
110        100.00
126         70.00
117         87.00
128         21.32
25           5.29
44           1.67
141        100.00
88          78.00
65         133.00
14           3.12
11           2.80
28           7.50
0            1.20
119         70.00
36           5.20
64          65.00
20           4.70
99           7.30
121         81.00
13           5.02
30           4.10
```

[ ]:
```python
#Predicted Price from test dataset w.r.t Decision Tree Regression
y_predict_dtr = DtReg.predict((x_test))


print (y_predict_dtr)


#Model Evaluation using R-Square for Decision Tree Regression
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict_dtr)
print('R-Square Error associated with Decision Tree Regression is:', r_square)
```

```
[200.          4.17        6.45        5.74666667   4.
   4.5          1.89       49.01        3.           2.3
   5.74666667  50.6        30.          4.5         80.
 106.           3.335       4.        350.          30.
 100.         200.         76.         49.01        38.
  40.33         6.54        3.335     190.          45.
  90.           3.335       4.          3.32         1.89
  50.           5.93       38.          8.68333333   6.45
 100.           3.8         4.5      ]
R-Square Error associated with Decision Tree Regression is: 0.7107876888797969
```

##Comparing the predicted price of Linear Regression and Decision Tree

[ ]:
```python
#Plotting a graph to compare the predicted prices

ax = plt.axes()
ax.set_facecolor("#cf97cf")

plt.plot (y_predict_lr, color = 'r')
plt.plot (y_predict_dtr, color = 'b')

plt.xlabel('No.of Predictions')
plt.ylabel('Price')
plt.title('Comparison btw LR and DT', fontsize = 20)

plt.show()
```



###Conclusion : After the analysis we can conclude that the features " engine" and "horsepower" are the most important variables that play a key role in affecting the car price. The predicted price using LR and DT are somewhat similar. Our model using these variables are 70-80% accurate and can be used in real life for business analytics.

[ ]:
```python

```