CAR PRICE PREDICTION MODEL

Importing Dependencies

In [ ]:
```
import pandas as pd #for python libraries
import matplotlib.pyplot as plt #visualisation library
import seaborn as sns #for data visualisation
```

In [ ]:
```
from sklearn.model_selection import train_test_split #for splitting data into two p
from sklearn.linear_model import LinearRegression #for importing linear regression
from sklearn.linear_model import Lasso #for importing lasso model
from sklearn import metrics #for finding the accuracy of the data
```

Data Collection and Processing

In [ ]:
```
car_dataset = pd.read_csv('/content/car data.csv')
```

In [ ]:
```
car_dataset.head()
```

Out[ ]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manua
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manua
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manua
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manua
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manua

In [ ]:
```
car_dataset.shape
```

Out[ ]:
```
(301, 9)
```

In [ ]:
```
car_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Seller_Type    301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

In [ ]:
```
car_dataset.describe()
```

Out[ ]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.644115	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

Checking The Missing Values

In [ ]:
```
car_dataset.isnull().sum()
```

Out[ ]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

In [ ]:
```
print(car_dataset.Fuel_Type.value_counts())
print(car_dataset.Seller_Type.value_counts())
print(car_dataset.Transmission.value_counts())
```

```
Petrol    239
Diesel     60
CNG         2
Name: Fuel_Type, dtype: int64
Dealer        195
Individual    106
Name: Seller_Type, dtype: int64
Manual       261
Automatic     40
Name: Transmission, dtype: int64
```

Encoding the data set

In [ ]:
```
car_dataset.replace({'Fuel_Type' : {"Petrol": 0 , "Diesel": 1 , "CNG" : 2}},inplace
#We change values of petrol,diesel and cng to 0,1,2 respectively

#We change the values for seller type as well just as we did for fuel type
car_dataset.replace({'Seller_Type' : {"Dealer": 0 , "Individual": 1}},inplace=True)

#We change the values for Transmission into 0,1,2 values as well
car_dataset.replace({'Transmission' : {"Manual": 0 , "Automatic": 1}},inplace=True)
```

In [ ]:
```
car_dataset.head()
```

Out[ ]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
0	ritz	2014	3.35	5.59	27000	0	0	0
1	sx4	2013	4.75	9.54	43000	1	0	0
2	ciaz	2017	7.25	9.85	6900	0	0	0
3	wagon r	2011	2.85	4.15	5200	0	0	0
4	swift	2014	4.60	6.87	42450	1	0	0

Splitting Data and Target

In [ ]:
```
#For performing splitting of data we take two vectors 'X' and 'Y'
X = car_dataset.drop(['Car_Name','Selling_Price'],axis=1)
Y = car_dataset['Selling_Price'] #Y contains our target values
```

In [ ]:
```
X.head()
```

Out[ ]:

	Year	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	2014	5.59	27000	0	0	0	0
1	2013	9.54	43000	1	0	0	0
2	2017	9.85	6900	0	0	0	0
3	2011	4.15	5200	0	0	0	0
4	2014	6.87	42450	1	0	0	0

In [ ]:
```
Y.head()
```

Out[ ]:
```
0    3.35
1    4.75
2    7.25
3    2.85
4    4.60
Name: Selling_Price, dtype: float64
```

Splitting Training and Test Data

In [ ]:
```
#We take 4 variables;
#Xtrain-contains all independent variables that are used to train the model
#Ytrain-it is the dependent variable,that the model predicts using independent vari
#Xtest- the portion of independent variables which are used for testing(accuracy te
#Ytest- will be used to test the accuracy of actual values and the predicted values
# 0.1- denotes 10% testing data and remaining 90% data is training data

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1,random_st
```

Model Training

1. Linear Regression model

In [ ]:
```
#storing the LinearRegression() into a smaller variable called lin_reg_model
lin_reg_model = LinearRegression()
```

In [ ]:
```
lin_reg_model.fit(X_train,Y_train)
```

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

Model Evaluation using Training Data

In [ ]:
```
#prediction using Training Data
training_data_prediction = lin_reg_model.predict(X_train)
```

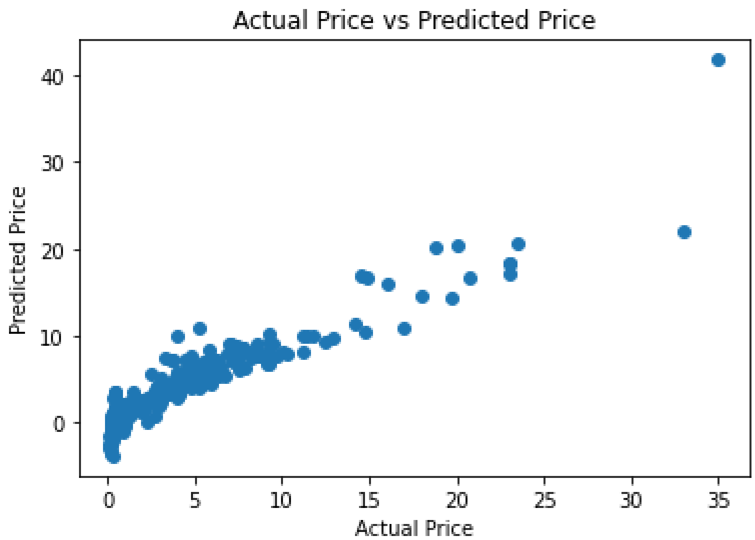
In [ ]:
```
#comparing the predicted values with the original values using R2 error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error: ",error_score)
```

```
R squared Error:  0.8799451660493711
```

Visualizing the above Data

In [ ]:
```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
```

Out[ ]:
```
Text(0.5, 1.0, 'Actual Price vs Predicted Price')
```



Accuracy Evaluation Using Test Data

In [ ]:
```
#test data prediction
test_data_prediction = lin_reg_model.predict(X_test)
```

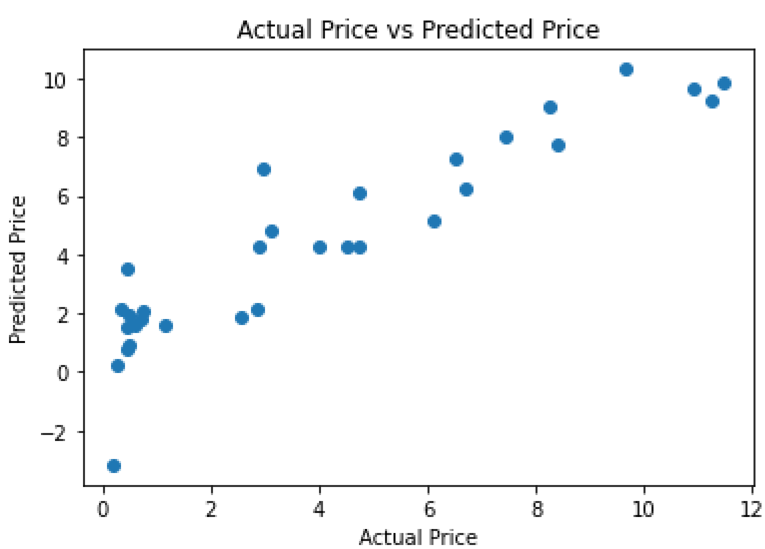
In [ ]:
```
#comparing the predicted values with the original values using R2 error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared Error: ",error_score)
```

```
R squared Error:  0.8365766715027051
```

Visualising the above data

In [ ]:
```
plt.scatter(Y_test, test_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
```

Out[ ]:
```
Text(0.5, 1.0, 'Actual Price vs Predicted Price')
```



2. Lasso Regression

In [ ]:
```
#storing the LassoRegression() into a smaller variable called lin_reg_model
lass_reg_model = Lasso()
```

In [ ]:
```
#fit function is used to train our model
lass_reg_model.fit(X_train,Y_train)
```

Out[ ]:
```
Lasso()
```

Model Evaluation using Training Data

In [ ]:
```
#prediction using Training Data and storing it in training data prediction variable
training_data_prediction = lass_reg_model.predict(X_train)
```

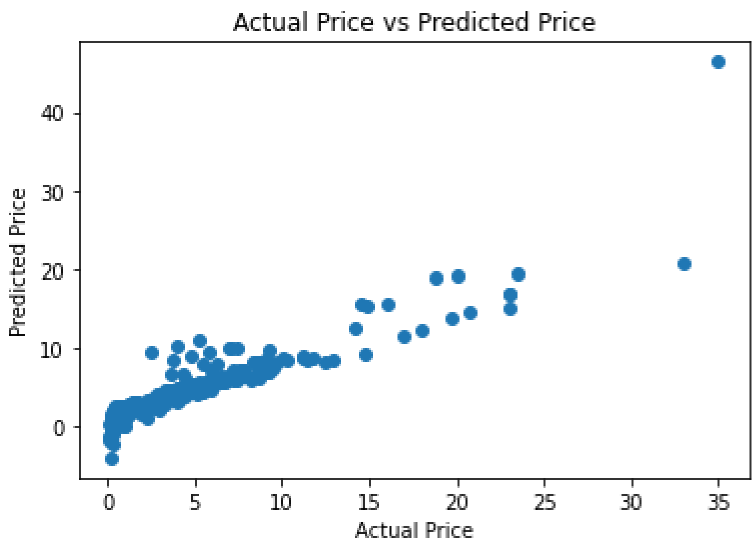
In [ ]:
```
#comparing the predicted values with the original values using R2 error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error: ",error_score)
```

```
R squared Error:  0.8427856123435794
```

Visualizing the above Data

In [ ]:
```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
```

Out[ ]:
```
Text(0.5, 1.0, 'Actual Price vs Predicted Price')
```



Accuracy Evaluation Using Test Data

In [ ]:
```
#test data prediction
test_data_prediction = lass_reg_model.predict(X_test)
```

In [ ]:
```
#comparing the predicted values with the original values using R2 error
error_score = metrics.r2_score(Y_test, test_data_prediction)
```

```
print("R squared Error: ",error_score)
```

```
R squared Error:  0.8709167941173195
```

Visualising the above data

```
In [ ]: plt.scatter(Y_test, test_data_prediction)
        plt.xlabel("Actual Price")
        plt.ylabel("Predicted Price")
        plt.title("Actual Price vs Predicted Price")
```

```
Out[ ]: Text(0.5, 1.0, 'Actual Price vs Predicted Price')
```