1. Impoting Dependencies :

C-Number of row & columns:

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn import metrics
```

2. Data Collcetion and Analysis:

A- Loading dataset :

In [ ]:
```
data_car = pd.read_csv("C:/Machine_learning Python/projets/CarPrice/car data.csv
```

B- View the data (head)

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

Out[ ]:

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

C- type of the data (head)

In [ ]:
```
type(data_car)
```

Out[ ]:
```
pandas.core.frame.DataFrame
```

D-Number of row & columns:

In [ ]:
```
data_car.shape
```

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

E- Information about the data:

In [ ]:
```python
data_car.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
```

2. Statisctical measures :

A- General Statistic:

In [ ]:
```python
data_car.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

B- Number of missing value in each column;

In [ ]:
```python
data_car.isnull().sum()
#Any missing values
```

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
```

3. Label Encoding:

A- Distribution of categorical data:

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

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

B- Encoding the categorical Data:

In [ ]:
```
data_car.replace({"Fuel_Type": {'Petrol':0,'Diesel':1, 'CNG': 2 }}, inplace=True
data_car.replace({"Seller_Type": {'Dealer':0,'Individual':1}}, inplace=True)
data_car.replace({"Transmission": {'Manual':0,'Automatic':1}}, inplace=True)
data_car.head()
```

Out[ ]:

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

C- Review the type:

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

```
Fuel_Type
0    239
1     60
2      2
Name: count, dtype: int64
Seller_Type
0    195
1    106
Name: count, dtype: int64
Transmission
0    261
1     40
Name: count, dtype: int64
```

5. Train test split:

A- Separating a data & label

In [ ]:
```
X = data_car.drop(columns=["Car_Name","Selling_Price"], axis= 1)
Y = data_car["Selling_Price"]
print(X)
print(Y)
```

```
     Year  Present_Price  Kms_Driven  Fuel_Type  Seller_Type  Transmission  \
0    2014           5.59       27000          0            0             0
1    2013           9.54       43000          1            0             0
2    2017           9.85        6900          0            0             0
3    2011           4.15        5200          0            0             0
4    2014           6.87       42450          1            0             0
..    ...            ...         ...        ...          ...           ...
296  2016          11.60       33988          1            0             0
297  2015           5.90       60000          0            0             0
298  2009          11.00       87934          0            0             0
299  2017          12.50        9000          1            0             0
300  2016           5.90        5464          0            0             0

     Owner
0        0
1        0
2        0
3        0
4        0
..     ...
296      0
297      0
298      0
299      0
300      0

[301 rows x 7 columns]
0       3.35
1       4.75
2       7.25
3       2.85
4       4.60
       ...
296     9.50
297     4.00
298     3.35
299    11.50
300     5.30
Name: Selling_Price, Length: 301, dtype: float64
```

B- Test Split

In [ ]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1, randc
```

In [ ]:
```
print(X.shape,X_train.shape, X_test.shape)
```

```
(301, 7) (270, 7) (31, 7)
```

6. Training the model (Linear Regression):

A- Loading the model

In [ ]:
```
linear_model = LinearRegression()
```

B- Training the model:

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

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

7. Model Evaluation:

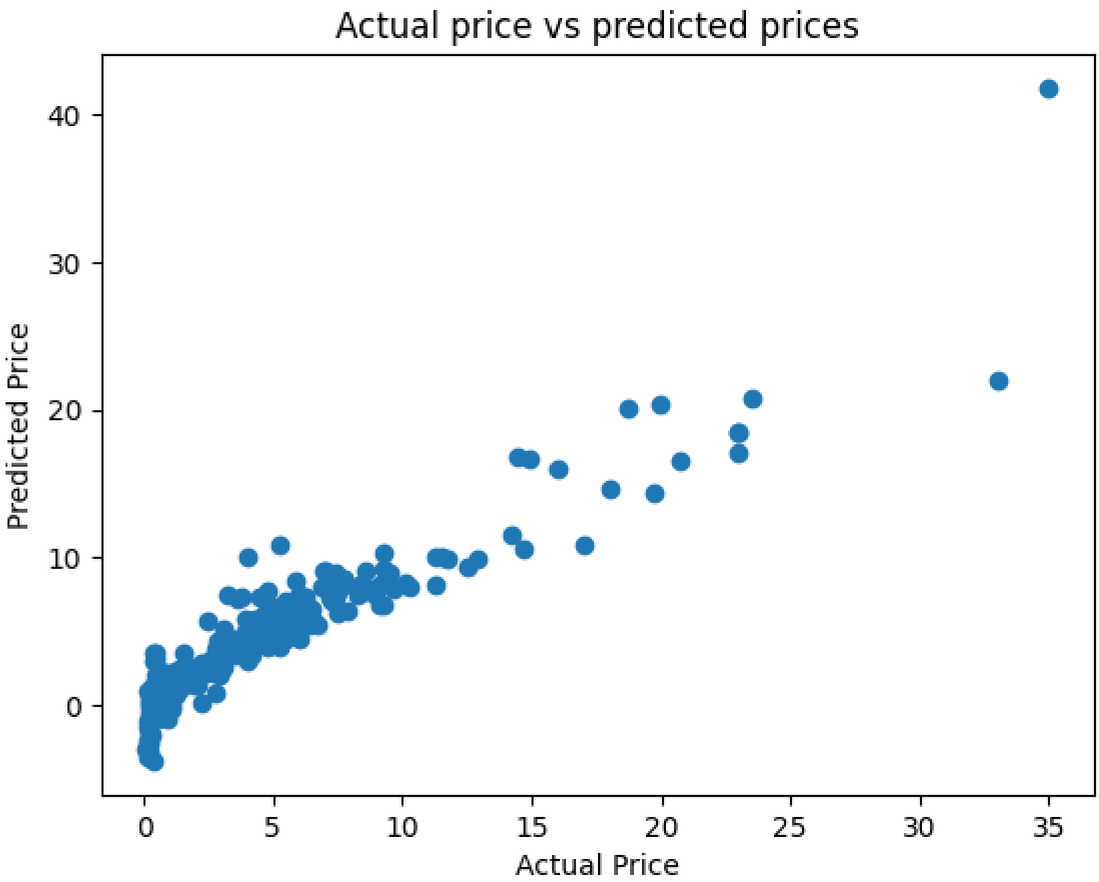
A- Error score of training data:

In [ ]:
```
X_train_prediction = linear_model.predict(X_train)
error_score = metrics.r2_score(Y_train, X_train_prediction)
print("R squared Error : ", error_score)
```

```
R squared Error :  0.8799451660493708
```

B- Visualisation of the actual & predicted prices:

In [ ]:
```
plt.scatter(Y_train, X_train_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual price vs predicted prices")
plt.show()
```



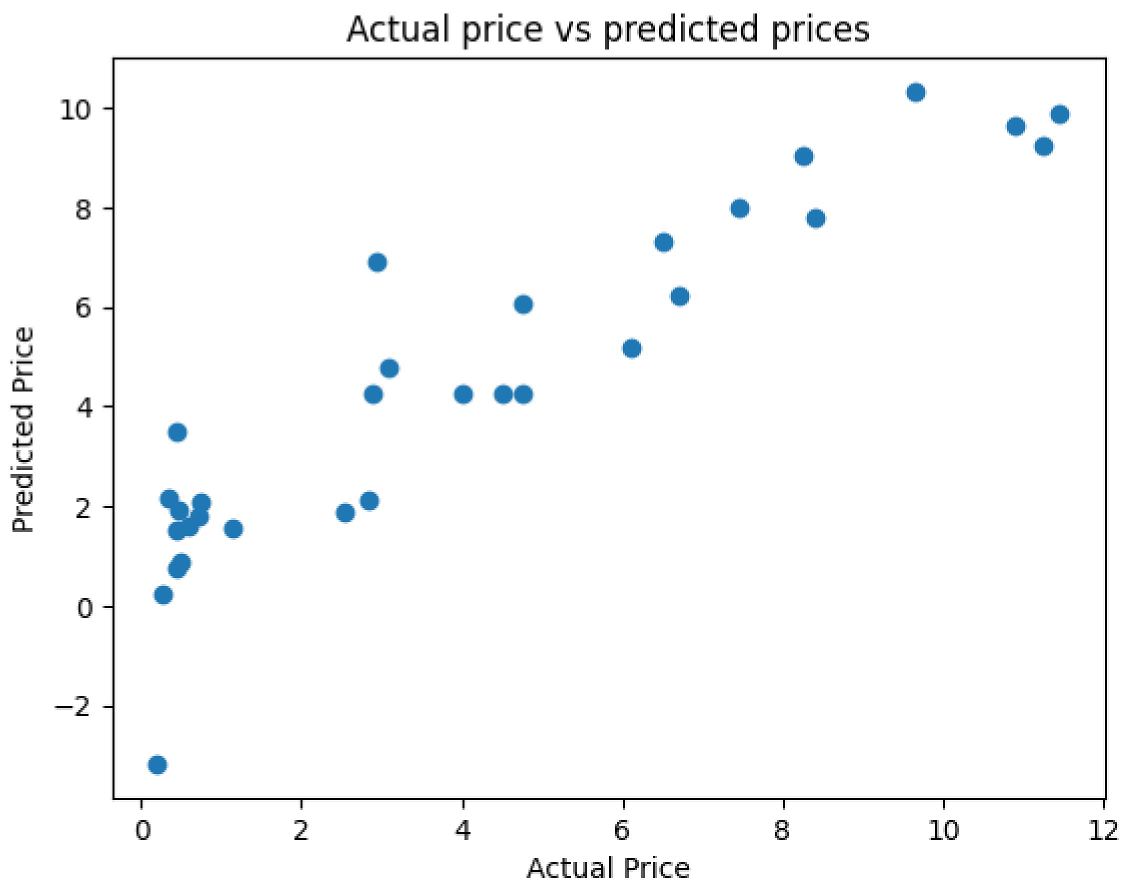
C- Error score of training data:

In [ ]:
```
X_train_predictionTest = linear_model.predict(X_test)
error_scoreTest = metrics.r2_score(Y_test, X_train_predictionTest)
print("R squared Error : ", error_scoreTest)
```

```
R squared Error :  0.8365766715026374
```

D- Visualisation of the actual & predicted prices:

In [ ]:
```
plt.scatter(Y_test, X_train_predictionTest)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual price vs predicted prices")
plt.show()
```



8. Training the model (Lasso Regression):

A- Loading the model:

In [ ]:
```
Lasso_Model = Lasso()
```

B- Training the model:

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

Out[ ]:
```
▾ Lasso
Lasso()
```

9. Model Evaluation:

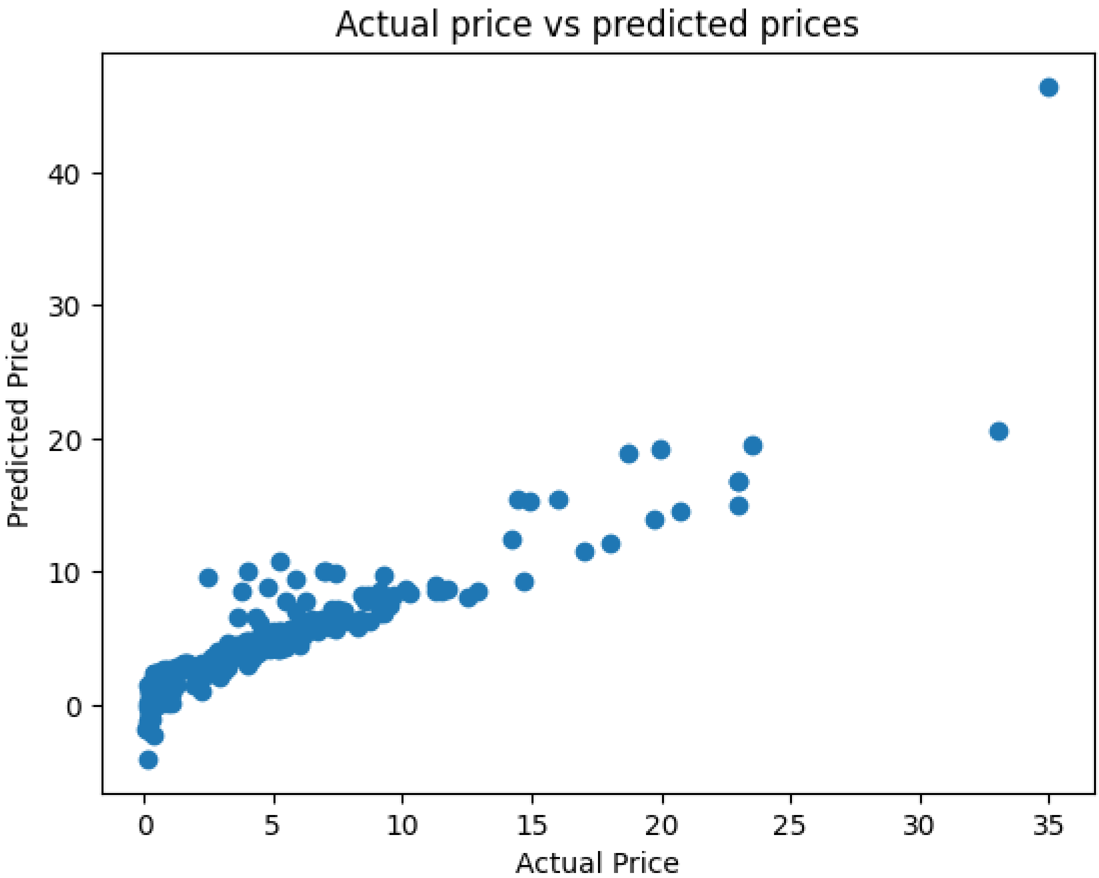
A- Error score of training data:

In [ ]:
```
X_train_prediction = Lasso_Model.predict(X_train)
error_score = metrics.r2_score(Y_train, X_train_prediction)
print("R squared Error : ", error_score)
```

```
R squared Error :  0.8427856123435794
```

B- Visualisation of the actual & predicted prices:

In [ ]:
```
plt.scatter(Y_train, X_train_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual price vs predicted prices")
plt.show()
```



C- Error score of training data:

In [ ]:
```
X_train_predictionTest = Lasso_Model.predict(X_test)
error_scoreTest = metrics.r2_score(Y_test, X_train_predictionTest)
print("R squared Error : ", error_scoreTest)
```

```
R squared Error :  0.8709167941173195
```

D- Visualisation of the actual & predicted prices:

In [ ]:
```
plt.scatter(Y_test, X_train_predictionTest)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual price vs predicted prices")
plt.show()
```


Actual price vs predicted prices
Predicted Price
Actual Price
10
8
6
4
2
0
0
2
4
6
8
10
12