

Importing the Dependencies

In []:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn import metrics
```

Data Collection and Processing

In []:

```
# loading the data from csv file to pandas dataframe
car_dataset = pd.read_csv('/content/car data.csv')
```

In []:

```
# inspecting the first 5 rows of the dataframe
car_dataset.head()
```

Out[]:

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

In []:

```
# checking the number of rows and columns
car_dataset.shape
```

Out[]:

(301, 9)

In []:

```
# getting some information about the dataset
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 []:

```
# checking the number of missing values
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 []:

```
# checking the distribution of categorical data
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 Categorical Data

In []:

```
# encoding "Fuel_Type" Column
car_dataset.replace({'Fuel_Type':{'Petrol':0, 'Diesel':1, 'CNG':2}}, inplace=True)

# encoding "Seller_Type" Column
car_dataset.replace({'Seller_Type':{'Dealer':0, 'Individual':1}}, inplace=True)

# encoding "Transmission" Column
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 | Owner |
|---|----------|------|---------------|---------------|------------|-----------|-------------|--------------|-------|
| 0 | ritz | 2014 | 3.35 | 5.59 | 27000 | 0 | 0 | 0 | 0 |
| 1 | sx4 | 2013 | 4.75 | 9.54 | 43000 | 1 | 0 | 0 | 0 |
| 2 | ciaz | 2017 | 7.25 | 9.85 | 6900 | 0 | 0 | 0 | 0 |
| 3 | wagon r | 2011 | 2.85 | 4.15 | 5200 | 0 | 0 | 0 | 0 |
| 4 | swift | 2014 | 4.60 | 6.87 | 42450 | 1 | 0 | 0 | 0 |

Splitting the data and Target

In []:

```
X = car_dataset.drop(['Car_Name', 'Selling_Price'], axis=1)
```

```
car_dataset.drop(['car_name', 'selling_price', 'kms_driven'], axis=1,  
Y = car_dataset['Selling_Price']
```

In []:

```
print(X)
```

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

[301 rows x 7 columns]

In []:

```
print(Y)
```

| | |
|---|------|
| 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

Splitting Training and Test data

In []:

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1, random_state=2)
```

Model Training

1. Linear Regression

In []:

```
# loading the linear regression model  
lin_reg_model = LinearRegression()
```

In []:

```
lin_reg_model.fit(X_train,Y_train)
```

Out[]:

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

Model Evaluation

In []:

```
# prediction on Training data  
training_data_prediction = lin_reg_model.predict(X_train)
```

In []:

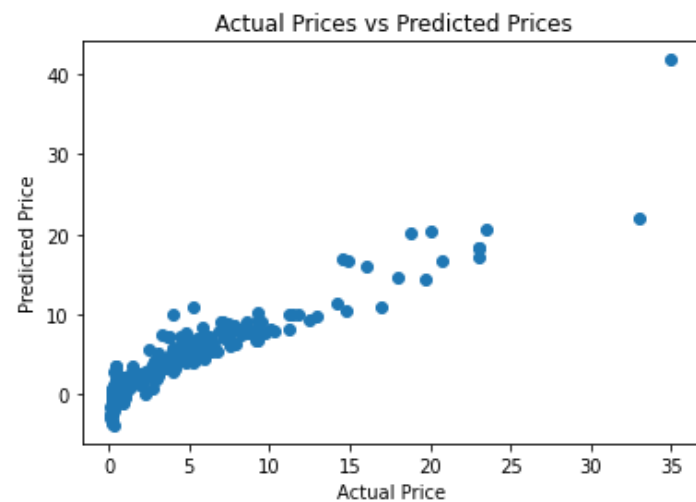
```
# R squared Error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error : ", error_score)
```

R squared Error : 0.8799451660493711

Visualize the actual prices and Predicted prices

In []:

```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```



In []:

```
# prediction on Training data
test_data_prediction = lin_reg_model.predict(X_test)
```

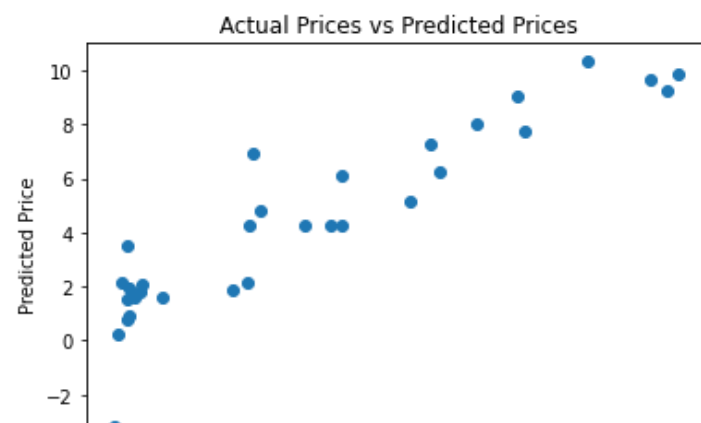
In []:

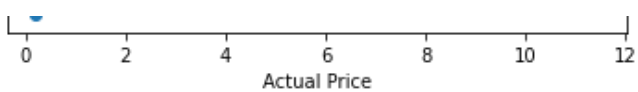
```
# R squared Error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared Error : ", error_score)
```

R squared Error : 0.8365766715027051

In []:

```
plt.scatter(Y_test, test_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```





1. Lasso Regression

In []:

```
# loading the linear regression model
lass_reg_model = Lasso()
```

In []:

```
lass_reg_model.fit(X_train,Y_train)
```

Out[]:

```
Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
```

Model Evaluation

In []:

```
# prediction on Training data
training_data_prediction = lass_reg_model.predict(X_train)
```

In []:

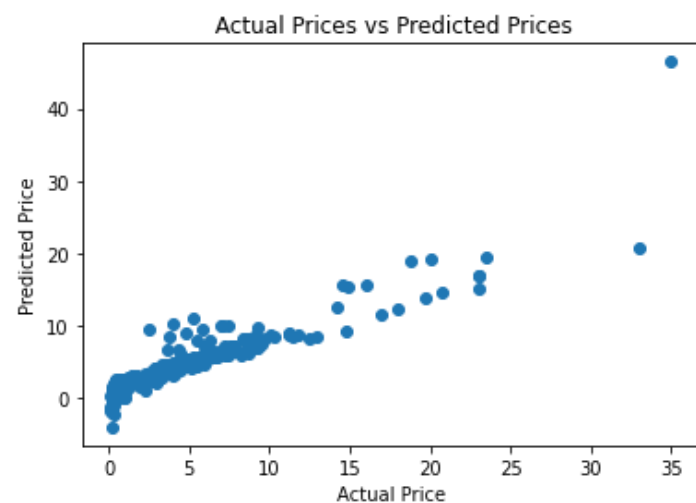
```
# R squared Error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error : ", error_score)
```

R squared Error : 0.8427856123435794

Visualize the actual prices and Predicted prices

In []:

```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```



In []:

```
# prediction on Training data
test_data_prediction = lass_reg_model.predict(X_test)
```

In []:

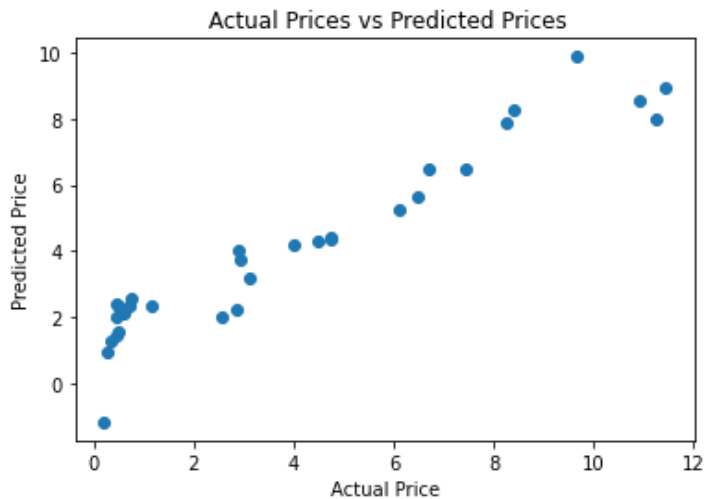
In []:

```
# R squared Error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared Error : ", error_score)
```

R squared Error : 0.8709167941173195

In []:

```
plt.scatter(Y_test, test_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```



In []: