

Task-3:

Car Price Prediction With Machine Learning:

Predicting car prices using machine learning involves training a model on historical data with features like brand, model, mileage, age, etc., and then using this model to estimate the price of a car based on its attributes. This predictive model can assist buyers and sellers in making informed decisions about car pricing.

```
In [1]: 1 #Import required libraries
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 from sklearn.model_selection import train_test_split
6 from sklearn.linear_model import LinearRegression
7 from sklearn.linear_model import Lasso
8 from sklearn import metrics
```

Data Collection and Processing

```
In [2]: 1 data=pd.read_csv("car data.csv")
```

```
In [3]: 1 data.head()
```

```
Out[3]:
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Trans
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	

```
In [4]: 1 data.shape
```

```
Out[4]: (301, 9)
```

In [5]: 1 data.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   Driven_kms      301 non-null    int64
5   Fuel_Type       301 non-null    object
6   Selling_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 [6]: 1 *#Checking gthe numbeer of missing values*
2 data.isnull().sum()

```
Out[6]: Car_Name        0
Year            0
Selling_Price   0
Present_Price   0
Driven_kms      0
Fuel_Type       0
Selling_type    0
Transmission    0
Owner           0
dtype: int64
```

In [7]: 1 data.describe()

```
Out[7]:
```

	Year	Selling_Price	Present_Price	Driven_kms	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	8.642584	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

```
In [8]: 1 #Checking the distribution of categorical data
2
3 print(data.Fuel_Type.value_counts())
4 print(data.Selling_type.value_counts())
5 print(data.Transmission.value_counts())
```

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

Encoding the Categorical Data

```
In [9]: 1 #encoding "Fuel_Type" Column
2 data.replace({'Fuel_Type':{'Petrol':0,'Diesel':1,'CNG':2}},inplace=True)
3
4 #encoding the "Selling_type" Column
5 data.replace({'Selling_type':{'Dealer':0,'Individual':1}},inplace=True)
6
7 #ncoding the "Transmission" Column
8 data.replace({'Transmission':{'Manual':0,'Automatic':1}},inplace=True)
```

```
In [10]: 1 data.head()
```

```
Out[10]:
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Trans
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	

```
In [11]: 1 data.tail()
```

```
Out[11]:
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Tra
296	city	2016	9.50	11.6	33988	1	0	
297	brio	2015	4.00	5.9	60000	0	0	
298	city	2009	3.35	11.0	87934	0	0	
299	city	2017	11.50	12.5	9000	1	0	
300	brio	2016	5.30	5.9	5464	0	0	

Splitting the data and Target

In [13]:

1

#Splitting the data and Target

2

3

x=data.drop(["Car_Name", "Selling_Price"],axis=1)#here axis=1 because id

4

#Otherwise axis=0 when

In [14]:

1

y=data["Selling_Price"]

In [15]:

1

print(x)

	Year	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmissio
n \						
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]						

```
In [16]: 1 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 [17]: 1 X_train,X_test,Y_train,Y_test=train_test_split(x,y,test_size=0.2, random_state=42)
```

Model training

1.Linear Regression

```
In [18]: 1 #Loading the linear regression model
2
3 lin_reg_model=LinearRegression()
```

```
In [19]: 1 lin_reg_model.fit(X_train,Y_train)
```

```
Out[19]: LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Model evaluation

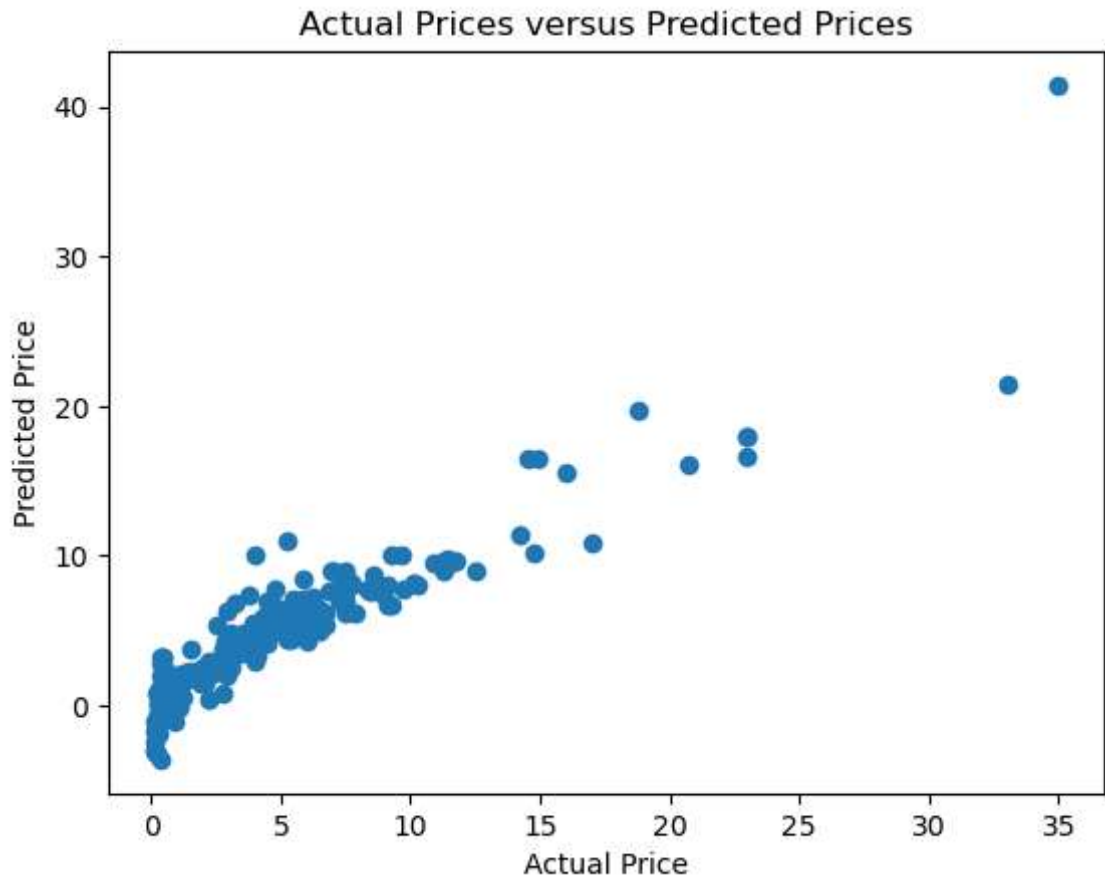
```
In [20]: 1 #prediction on training data
2
3 training_data_prediction=lin_reg_model.predict(X_train)
```

```
In [21]: 1 # R-squared error
2 error_score=metrics.r2_score(Y_train,training_data_prediction)
3 print("R squared Error:",error_score)
```

```
R squared Error: 0.8680830940612677
```

Visualize the actual prices and Predicted prices:

```
In [22]: 1 #Visualize the prices and predicted prices
2 plt.scatter(Y_train,training_data_prediction)
3 plt.xlabel("Actual Price")
4 plt.ylabel("Predicted Price")
5 plt.title("Actual Prices versus Predicted Prices")
6 plt.show()
```

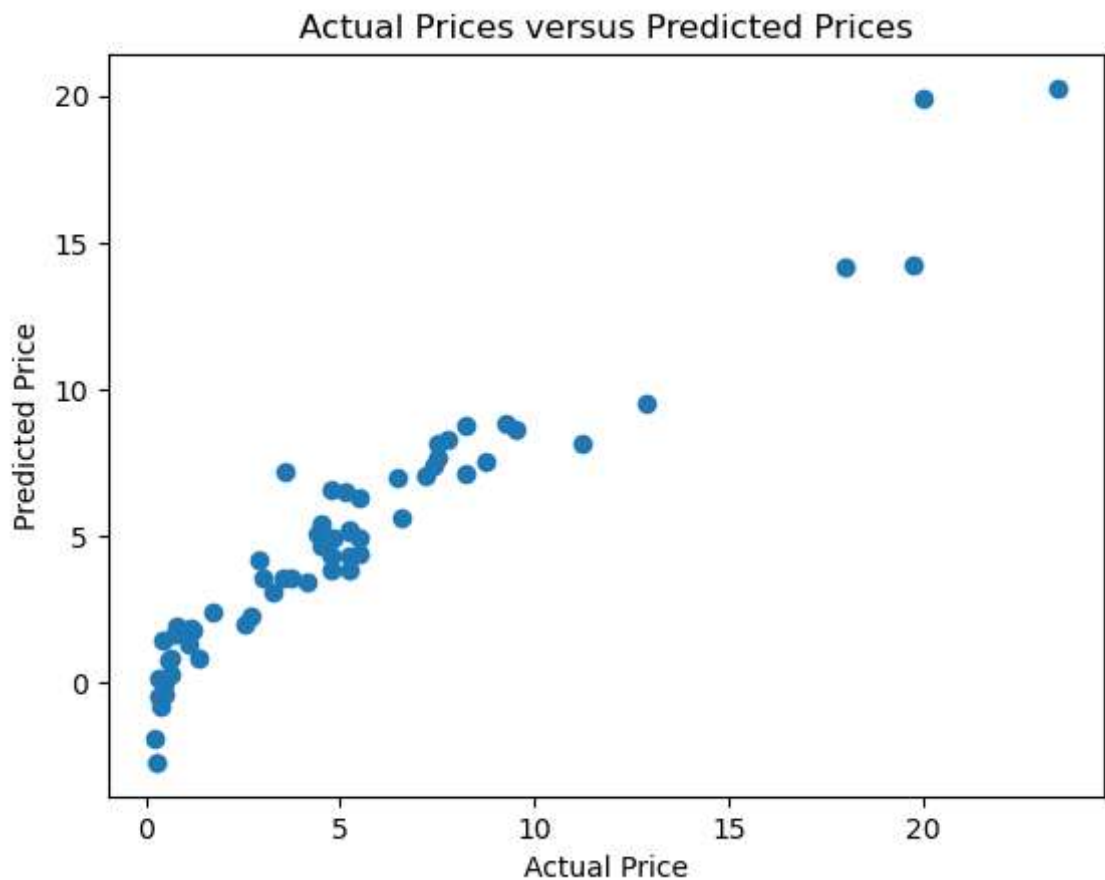


```
In [23]: 1 #prediction on test data
2
3 test_data_prediction=lin_reg_model.predict(X_test)
```

```
In [24]: 1 # R-squared error
2 error_score=metrics.r2_score(Y_test,test_data_prediction)
3 print("R squared Eroor:",error_score)
```

R squared Eroor: 0.9133788577646775

```
In [25]: 1 #Visualize the prices and predicted prices
2 plt.scatter(Y_test,test_data_prediction)
3 plt.xlabel("Actual Price")
4 plt.ylabel("Predicted Price")
5 plt.title("Actual Prices versus Predicted Prices")
6 plt.show()
```



2.Lasso Regression model:

```
In [26]: 1 #Loading the Lasso Regression model
2
3 lass_reg_model=Lasso()
```

```
In [27]: 1 lass_reg_model.fit(X_train,Y_train)
```

Out[27]: Lasso()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

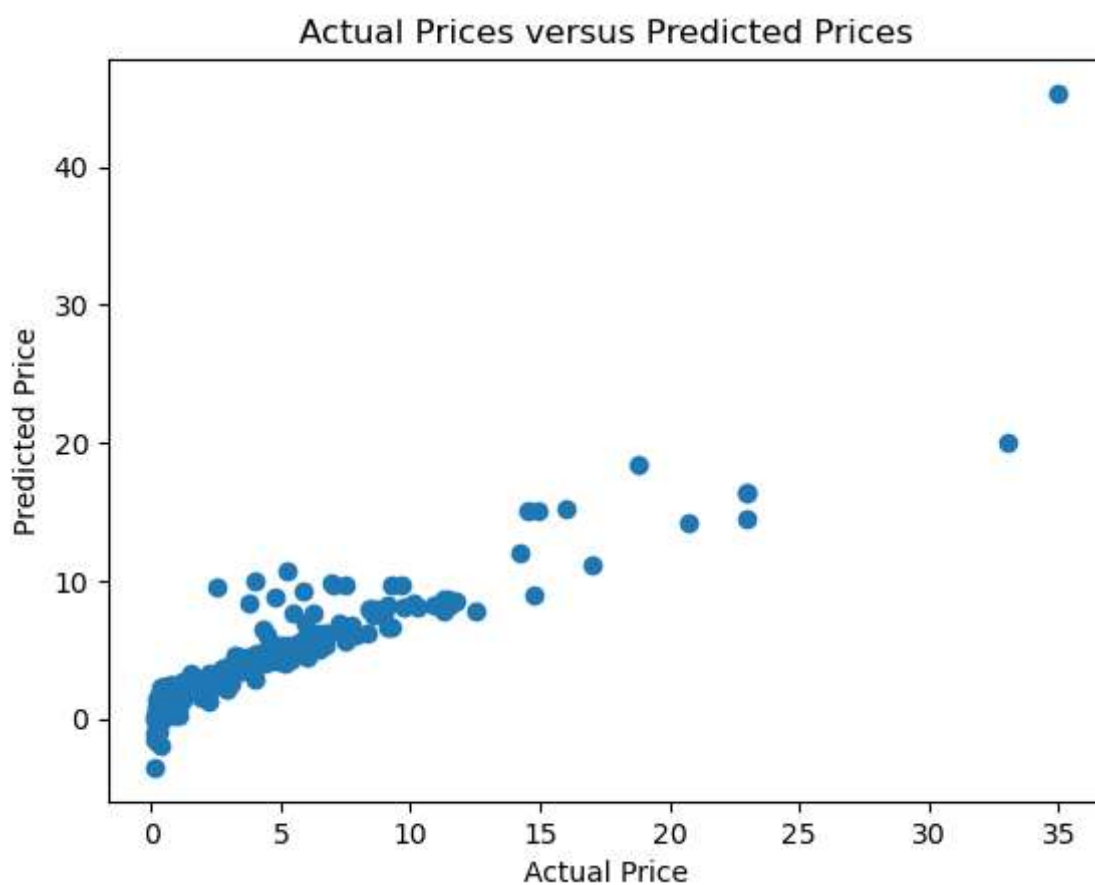
```
In [28]: 1 #prediction on traning data
2
3 training_data_prediction=lass_reg_model.predict(X_train)
```

```
In [29]: 1 # R-squared error
2 error_score=metrics.r2_score(Y_train,training_data_prediction)
3 print("R squared Eroor:",error_score)
```

R squared Eroor: 0.8315232865153553

Visualize the actual prices and Predicted prices:

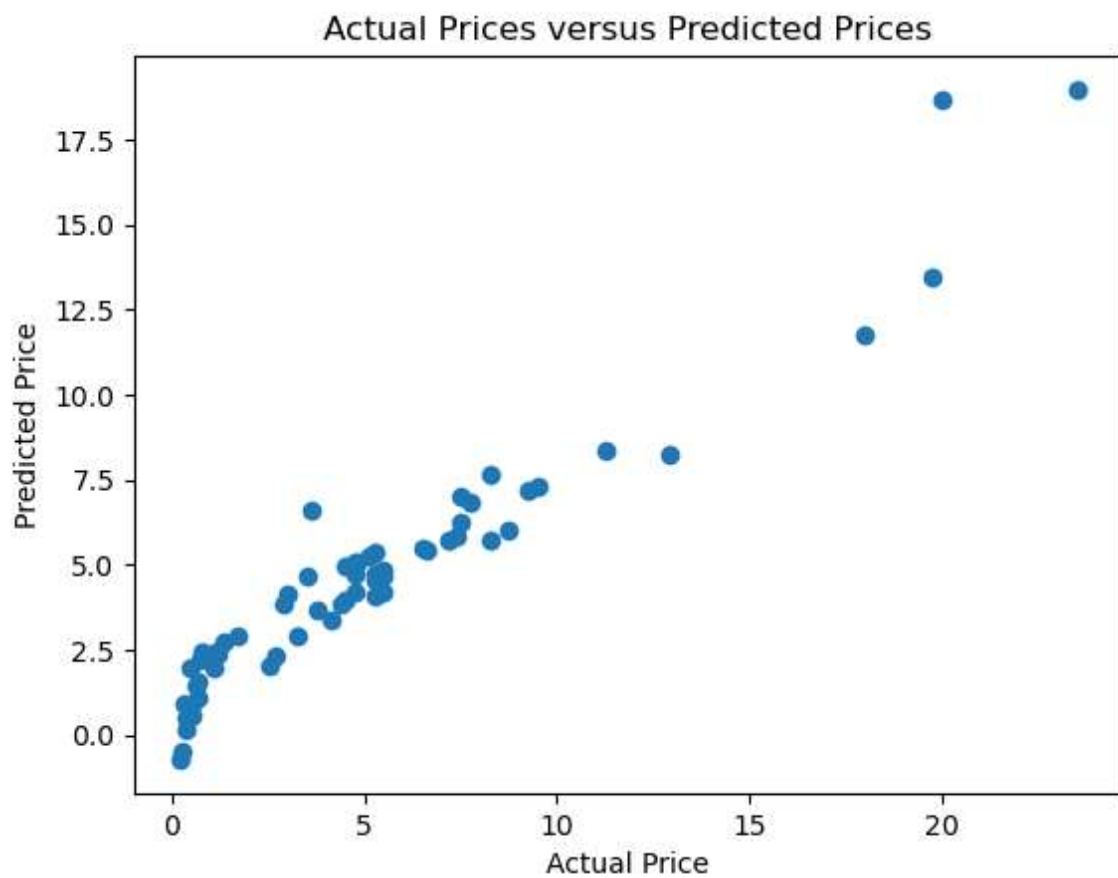
```
In [30]: 1 #Visualize the prices and predicted prices
2 plt.scatter(Y_train,training_data_prediction)
3 plt.xlabel("Actual Price")
4 plt.ylabel("Predicted Price")
5 plt.title("Actual Prices versus Predicted Prices")
6 plt.show()
```



```
In [31]: 1 #prediction on test data
2
3 test_data_prediction=lass_reg_model.predict(X_test)
```



```
In [32]: 1 #Visualize the prices and predicted prices
2 plt.scatter(Y_test,test_data_prediction)
3 plt.xlabel("Actual Price")
4 plt.ylabel("Predicted Price")
5 plt.title("Actual Prices versus Predicted Prices")
6 plt.show()
```



```
In [ ]: 1
```