7_Car_Price_Prediction_using_Linear_and_Lasso_Regression

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0.1 Predicting Car Prices: Leveraging Linear Regression and Lasso in Machine Learning - Vignesh Prabhu

In car prediction using machine learning with linear regression and Lasso, I developed models that use these techniques to analyze how different factors (like mileage, model year, etc.) affect car prices. Linear regression finds direct relationships, while Lasso helps by selecting the most important features, improving prediction accuracy by reducing overfitting. These models help forecast car prices based on data-driven insights, supporting better decision-making in the automotive market.

[35]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
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 PreProcessing

[36]:
```
car_data=pd.read_csv("/content/car data.csv")
```

[37]:
```
car_data.head()
```

[37]:
```
  Car_Name  Year  Selling_Price  Present_Price  Kms_Driven Fuel_Type  \
0     ritz  2014           3.35           5.59       27000    Petrol
1      sx4  2013           4.75           9.54       43000    Diesel
2     ciaz  2017           7.25           9.85        6900    Petrol
3  wagon r  2011           2.85           4.15        5200    Petrol
4    swift  2014           4.60           6.87       42450    Diesel

  Seller_Type Transmission  Owner
0      Dealer       Manual      0
1      Dealer       Manual      0
2      Dealer       Manual      0
3      Dealer       Manual      0
4      Dealer       Manual      0
```

[38]:
```
car_data.shape
```

[38]: (301, 9)

[39]:
```
car_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   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
```

[40]:
```
car_data.describe()
```

[40]:

	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

[41]:
```
#to Check null values in dataset
car_data.isnull().sum()
```

[41]:
```
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
```

[42]:
```python
# checking distribution of categorical Data
print(car_data.Fuel_Type.value_counts())
print(car_data.Seller_Type.value_counts())
print(car_data.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
```

Encoding The categorical Data

[43]:
```python
#Encoding "Fuel Type"
car_data.replace({'Fuel_Type':{'Petrol': 0, 'Diesel':1,'CNG'  :2}},inplace=True)
#Encoding "Seller Type"
car_data.replace({'Seller_Type':{'Dealer': 0, 'Individual':1}},inplace=True)
#Encoding "Transmission"
car_data.replace({'Transmission':{'Manual': 0, 'Automatic':1}},inplace=True)
```

[44]:
```python
car_data.head()
```

[44]:
```
  Car_Name  Year  Selling_Price  Present_Price  Kms_Driven  Fuel_Type  \
0     ritz  2014           3.35           5.59       27000          0
1      sx4  2013           4.75           9.54       43000          1
2     ciaz  2017           7.25           9.85        6900          0
3  wagon r  2011           2.85           4.15        5200          0
4    swift  2014           4.60           6.87       42450          1

   Seller_Type  Transmission  Owner
0            0             0      0
1            0             0      0
2            0             0      0
3            0             0      0
4            0             0      0
```

Spliting Data Into Label Data and Target data

[45]:
```python
X=car_data.drop(['Car_Name','Selling_Price'],axis=1)
Y=car_data['Selling_Price']
```

[46]:
```
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
```

Spliting Training and testing Data

[47]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.1,random_state=2)
```

[51]:
```
print(X.shape,X_train.shape,X_test.shape,)
```

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

Model Training

[57]:
```
lin_reg=LinearRegression()
```

[49]:
```
lin_reg.fit(X_train, Y_train)
```

[49]: LinearRegression()

Model Evalutaion

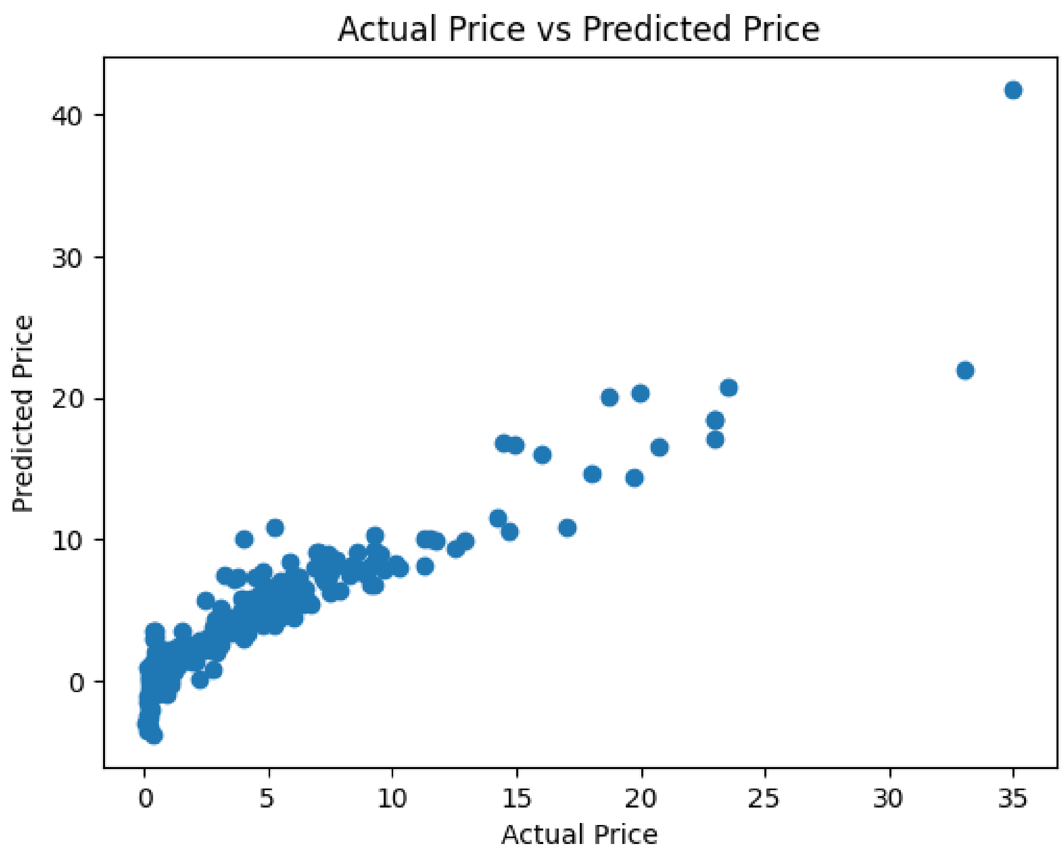
[50]:
```
#Prediction on Training Data
prediction_train=lin_reg.predict(X_train)
```

[52]:
```
#R squared Error
error_score=metrics.r2_score(Y_train,prediction_train)
print("R squared Error : ",error_score)
```

R squared Error : 0.8799451660493711

Visualise the Actual and Predicted Price

[53]:
```
plt.scatter(Y_train , prediction_train)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
plt.show()
```

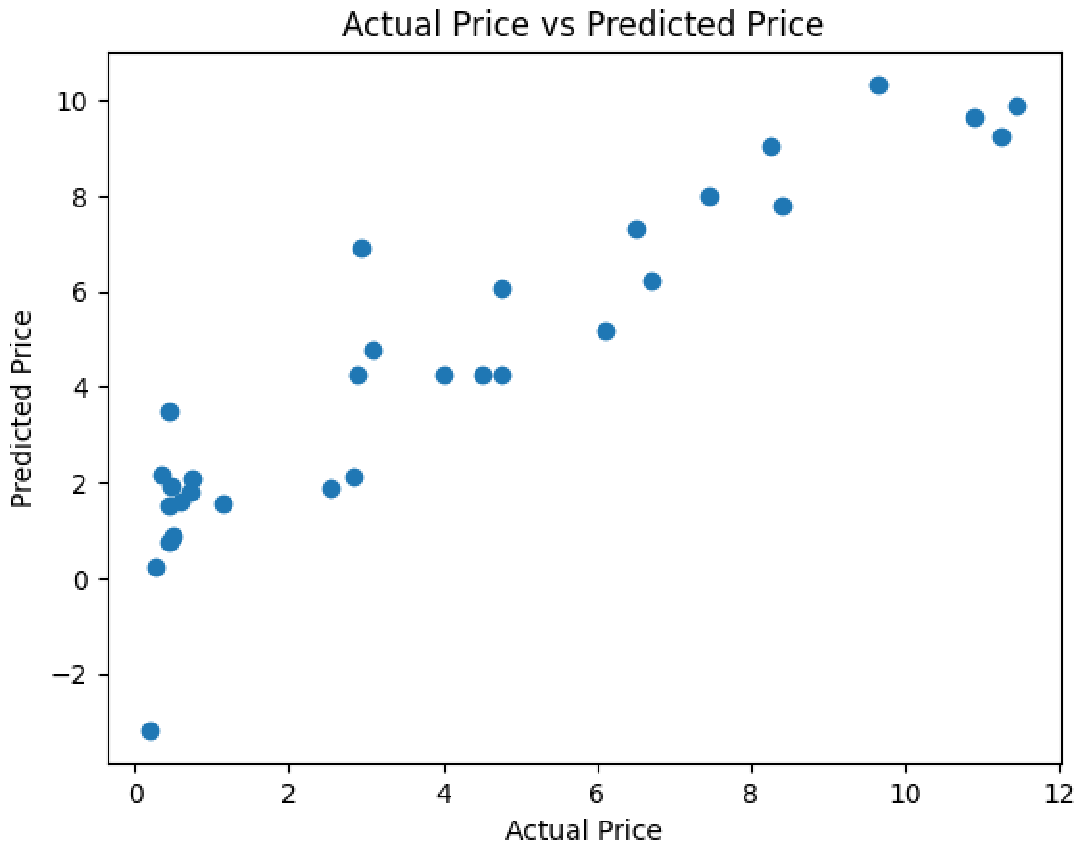


[54]:
```
#prediction on Test data
prediction_test=lin_reg.predict(X_test)
```

[55]:
```
error_score=metrics.r2_score(Y_test,prediction_test)
print("R squared Error : ",error_score)
```

```
R squared Error :  0.8365766715027051
```

[56]:
```
plt.scatter(Y_test , prediction_test)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
plt.show()
```



Lasso Regression

[61]:
```
lasso_reg=Lasso()
```

[62]:
```
lasso_reg.fit(X_train, Y_train)
```

[62]:
```
Lasso()
```

Model Evalutaion

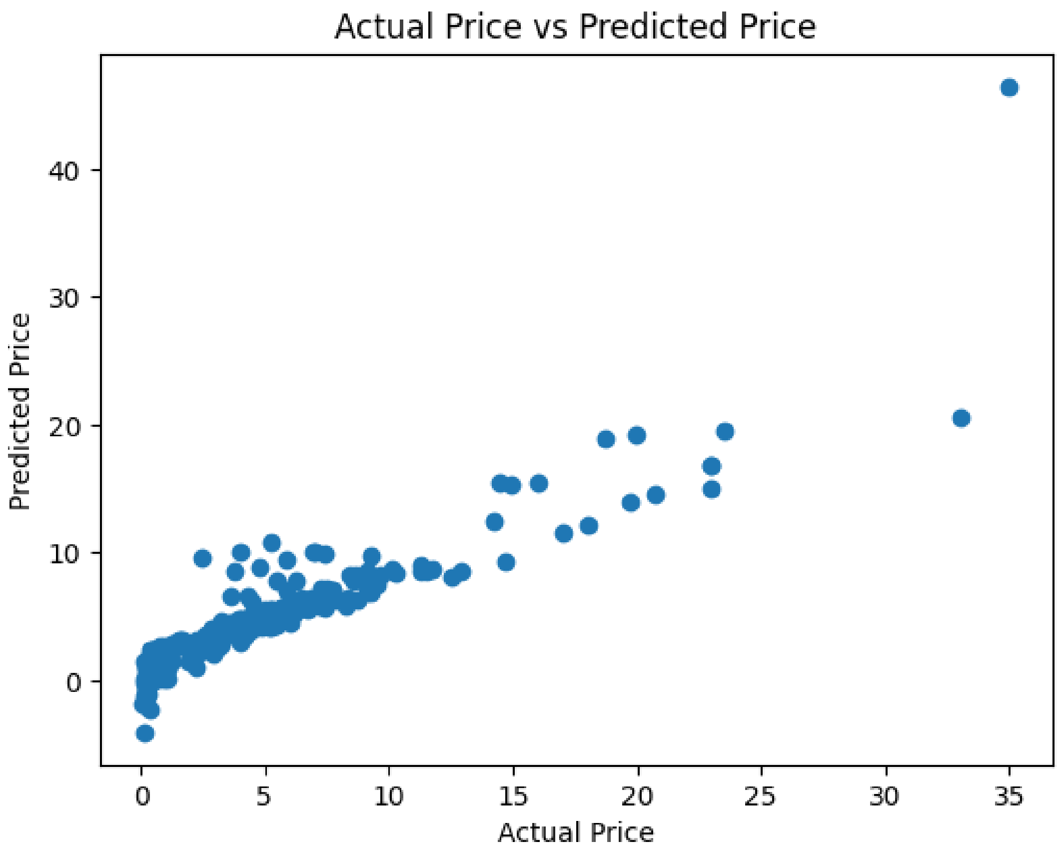
[65]:
```
#Prediction on Training Data
prediction_train=lasso_reg.predict(X_train)
```

[66]:
```
#R squared Error
error_score=metrics.r2_score(Y_train,prediction_train)
print("R squared Error : ",error_score)
```

```
R squared Error :  0.8427856123435794
```

Visualise the Actual and Predicted Price

[67]:
```
plt.scatter(Y_train , prediction_train)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
plt.show()
```

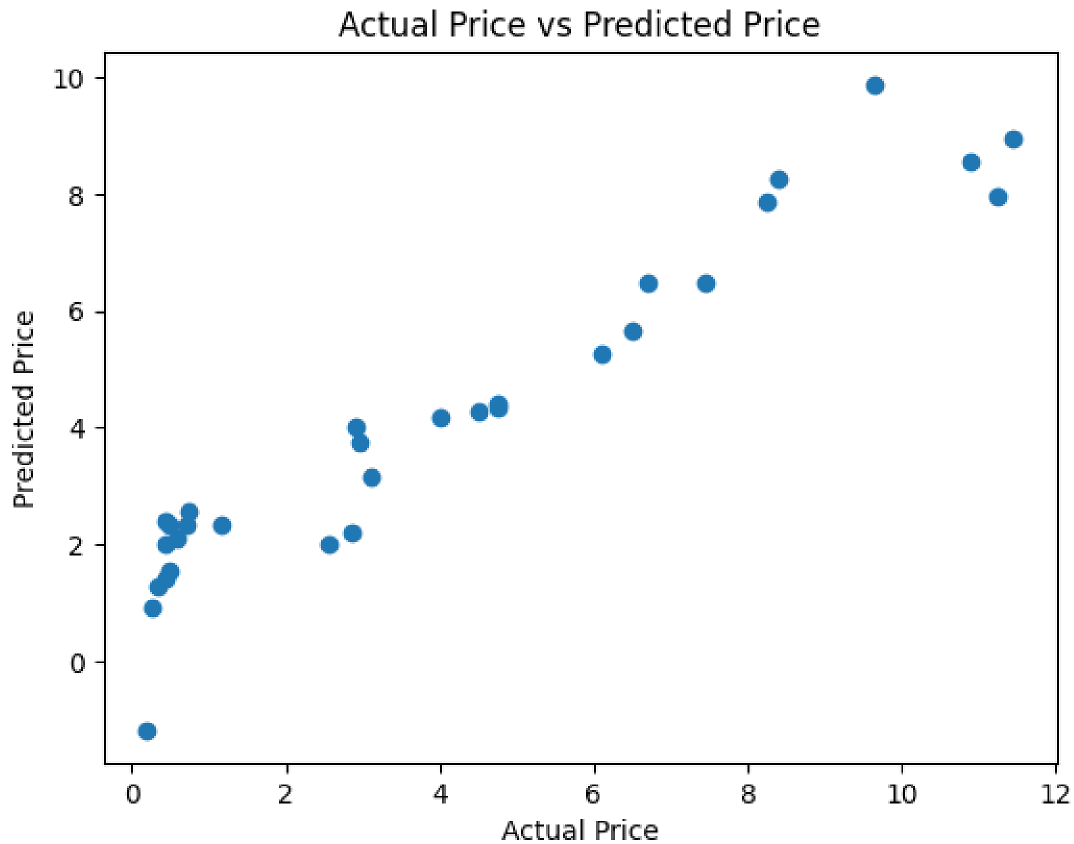


[68]:
```
#prediction on Test data
prediction_test=lasso_reg.predict(X_test)
```

[ ]:
```
error_score=metrics.r2_score(Y_test,prediction_test)
print("R squared Error : ",error_score)
```

```
R squared Error :  0.8365766715027051
```

[70]:
```
plt.scatter(Y_test , prediction_test)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
plt.show()
```


Actual Price vs Predicted Price
Predicted Price
Actual Price
10
8
6
4
2
0
0
2
4
6
8
10
12

0.2 Thank You !