Bike Price Prediction using Linear Regression

Importing libraries

```
import pandas as pd
```

```
import numpy as np
```

Import CSV as DataFrame

```
df=pd.read_csv('/content/sample_data/Bike Prices.csv')
```

Getting the first five rows of the DataFrame

```
df.head()
```

	Brand	Model	Selling_Price	Year	Seller_Type	Owner	KM_Driven	Ex_Showroom_Pric
0	TVS	TVS XL	30000	2017	Individual	1st	8000	30490.
1	Bajaj		18000	2017	Individual		35000	32000.

Getting information of DataFrame

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1061 entries, 0 to 1060
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Brand              1061 non-null   object 
 1   Model              1061 non-null   object 
 2   Selling_Price      1061 non-null   int64  
 3   Year               1061 non-null   int64  
 4   Seller_Type        1061 non-null   object 
 5   Owner              1061 non-null   object 
 6   KM_Driven          1061 non-null   int64  
 7   Ex_Showroom_Price  626 non-null    float64
dtypes: float64(1), int64(3), object(4)
memory usage: 66.4+ KB
```

Getting Missing Values Drop

```
df=df.dropna()
```

Getting summary statistics

```
df.describe()
```

	Selling_Price	Year	KM_Driven	Ex_Showroom_Price
count	626.000000	626.000000	626.000000	6.260000e+02
mean	59445.164537	2014.800319	32671.576677	8.795871e+04
std	59904.350888	3.018885	45479.661039	7.749659e+04
min	6000.000000	2001.000000	380.000000	3.049000e+04
25%	30000.000000	2013.000000	13031.250000	5.485200e+04
50%	45000.000000	2015.000000	25000.000000	7.275250e+04
max	760000.000000	2020.000000	585659.000000	1.278000e+06

Getting categories and counts of categorical variables

```
df[['Brand']].value_counts()
```

```
Brand
Honda       170
Bajaj       143
Hero        108
Yamaha       94
Royal        40
TVS          23
Suzuki       18
KTM           6
Mahindra      6
Kawasaki      4
UM            3
Activa        3
Harley        2
Vespa         2
BMW           1
Hyosung       1
Benelli       1
Yo            1
dtype: int64
```

```
df[['Model']].value_counts()
```

```
Model
Honda Activa [2000-2015]                    23
Honda CB Hornet 160R                        22
Bajaj Pulsar 180                            20
Yamaha FZ S V 2.0                           16
Bajaj Discover 125                          16
                                            ..
Royal Enfield Thunderbird 500                1
Royal Enfield Continental GT [2013 - 2018]   1
```

```
Royal Enfield Classic Stealth Black           1
Royal Enfield Classic Squadron Blue           1
Yo Style                                      1
Length: 183, dtype: int64
```

```
df[['Seller_Type']].value_counts()
```

```
Seller_Type
Individual     623
Dealer           3
dtype: int64
```

```
df[['Owner']].value_counts()
```

```
Owner
1st owner    556
2nd owner     66
3rd owner      3
4th owner      1
dtype: int64
```

Getting column names

```
df.columns
```

```
Index(['Brand', 'Model', 'Selling_Price', 'Year', 'Seller_Type', 'Owner',
       'KM_Driven', 'Ex_Showroom_Price'],
      dtype='object')
```

Getting Shape of DataFrame

```
df.shape
```

```
(626, 8)
```

Getting encoding of categorical features

```
df.replace({'Seller_Type':{'Individual':0,'Dealer':1}},inplace=True)
```

```
df.replace({'Owner':{'1st owner':0,'2nd owner':1, '3rd owner':2, '4th owner':3}},inplace=True
```

Defining y(dependent/label/target variable) and X(independent/features/attribute variable)

```
y=df['Selling_Price']
```

```
y.shape
```

```
(626,)
```

```
y
```

```
0       30000
1       18000
2       20000
3       25000
4       24999
        ...
621    330000
622    300000
623    425000
624    760000
625    750000
Name: Selling_Price, Length: 626, dtype: int64
```

```
X=df[['Year','Seller_Type','Owner','KM_Driven','Ex_Showroom_Price']]
```

```
X.shape
```

```
(626, 5)
```

```
X
```

	Year	Seller_Type	Owner	KM_Driven	Ex_Showroom_Price
0	2017	0	0	8000	30490.0
1	2017	0	0	35000	32000.0
2	2011	0	0	10000	37675.0
3	2010	0	0	43000	42859.0
4	2012	0	1	35000	42859.0
...	...	...	...	...	...
621	2014	0	3	6500	534000.0
622	2011	0	0	12000	589000.0
623	2017	0	1	13600	599000.0
624	2019	0	0	2800	752020.0

Getting Train Test Split

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =train_test_split(X, y, test_size=0.3, random_state=2529)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((438, 5), (188, 5), (438,), (188,))
```

Getting Model Train

```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()

lr.fit(X_train, y_train)
```

```
LinearRegression()
```

Getting model prediction

```
y_pred=lr.predict(X_test)
```

```
y_pred.shape
```

```
(188,)
```

```
y_pred
```

```
array([ 27210.52271465,  56340.08335163,  63471.94671996,  53627.63844785,
        55612.75744268,  53888.92259719,  33751.35275102,  60311.4950183 ,
       113713.05684467,  76639.49332954,  27826.7399381 ,  49919.83255841,
        65886.64311457,  26755.12664064,  48277.75426038, 127646.56079335,
        70047.10661635,  39350.67963653,  36081.03597878,  45360.79436339,
        48079.89470577,  44803.02464799,  55161.44026111,  71041.51821318,
        91689.22699159,  49301.53594645,  55988.19326252, 108171.54600296,
        32771.06897901,  25468.20072996,  17128.61806164, 179271.41130746,
        45698.99857622,  31371.09285079,  67886.52106737,  41492.49575815,
        56855.22238602,  47820.47003468,  74682.14053958,  24984.21822736,
        55374.00513699,  41412.36775222,  67991.60287764,  26553.59421844,
        89788.69870689,  45764.83633686, 133888.03770389, 106988.113825  ,
        71176.40667714,  25332.25485946,  79512.43778826,  63914.38088173,
        28632.12110986,  53656.13623937,  -5396.37132904,  70377.44571174,
        33313.03576476,  53994.92478411,  67509.85836352,  59735.05378847,
        22199.83644217,  15374.18984158,  44510.76819427,  30279.52476752,
       108243.77037514,  19291.8895874 ,  53614.312976  ,  59230.23269131,
        60174.2108109 ,  45924.63468736,  25770.81883496,  63471.36257814,
       242123.45729792,  61387.72544548,  56510.98127074,  48123.28087213,
        51668.27442011,  90279.76190495,  14827.76533556, 112437.70820504,
        35066.88027405,  30902.41069172,  31441.48921433, 125593.75847157,
        27705.38813164, -11590.29205553,  15582.17108685,  75113.64511232,
       504085.44522282, 123545.42050116,  74770.89327697,  50747.47663245,
        44174.3618212 ,  25426.7156106 ,  30298.3052462 ,  47625.67836414,
        27850.37544807,  28845.23330928,  31580.38624692,  32309.63375635,
        47979.16788554,  65955.46375944,  13432.28218017,  15368.80064986,
        31973.23052409, 110353.92870546,  68181.49509136,  23143.49139797,
        53194.65732076,  34603.36376989,  56002.50967868,  62432.66994305,
       391470.77533201,   3558.29480891,  36019.18494305,  70876.34866549,
        72890.00667025, 137596.01384364,  27620.36308877, 135789.30486854,
        39674.40366791,  58367.0924453 ,  42401.21202624,  61864.4379567 ,
        42688.89652842,  63710.34571021,  10604.39360071,  38458.82820943,
       112251.84744225, 115403.00577536,  13658.41734785,  36196.83359584,
        54146.22998932,  97297.85724851,  55029.68137265,  22923.26533437,
       104569.97029689,  41965.75852017,  38759.68546491,  28930.61369011,
        45231.66612551,  48475.43422775,  26739.7225731 ,  53598.65972203,
```

```
       32558.54954524,  32212.22834942,  68172.98738422,  71839.47716461,
       32003.46692215,  40652.69995971,  39935.92211843,  63444.41846202,
       44545.5818771 , 120873.38389616,  60926.58683174,  62641.82167496,
       60816.47379994,  27098.95433573,  26803.64749618,  48956.00468627,
       62032.88118713,  26471.97495723, 104937.23068766, 132903.3578847 ,
       37469.2040942 ,  57579.12080094,  40371.00915736,  -7039.40662503,
       26485.40030077,  90782.42554145,  52153.21149321,  56453.74542453,
       80440.59426003,  31890.46870273,  49505.97985573,  24288.36959514,
       25540.47481573, 117708.26333955,  23399.66596746,  63678.40865459,
       70144.29372668,  33434.89010059,  60885.29444481,  58389.55370878,
       35118.7040348 ,  58729.4540196 ,  34627.9532246 ,  38583.4623973 ])
```

Getting model evaluation

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
mean_squared_error(y_test,y_pred)
```

```
554715615.5043668
```

```
mean_absolute_error(y_test,y_pred)
```

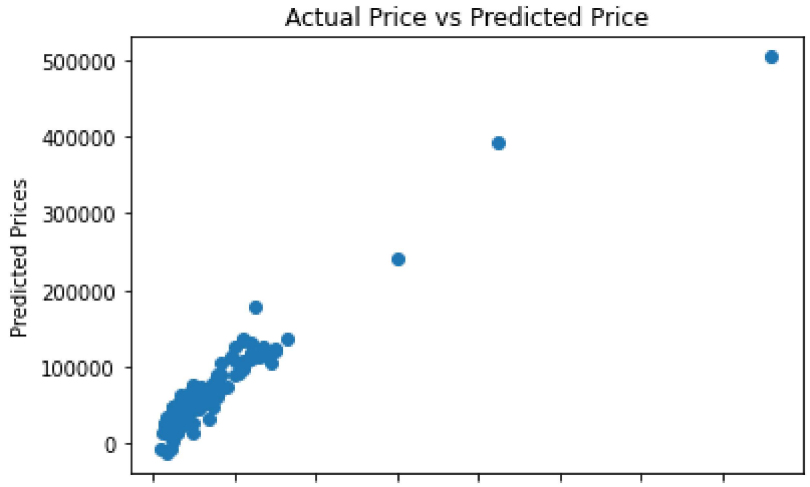
```
12225.7370104107
```

```
r2_score(y_test,y_pred)
```

```
0.8810414402984937
```

Getting visualization of actual vs predicted results

```
import matplotlib.pyplot as plt
plt.scatter(y_test,y_pred)
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual Price vs Predicted Price')
plt.show()
```



Getting future predictions

```
df_new=df.sample(1)
```

```
df_new
```

	Brand	Model	Selling_Price	Year	Seller_Type	Owner	KM_Driven	Ex_Showroom_Pri
225	Hero	Hero Passion XPro	25000	2013	0	0	25000	5964

```
df_new.shape
```

```
(1, 8)
```

```
X_new=df_new.drop(['Brand','Model','Selling_Price'], axis=1)
```

```
y_pred_new=lr.predict(X_new)
```

```
y_pred_new
```

```
array([33751.35275102])
```

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