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LAB : 4

House Price Prediction Using LR With Regularization

Step : 1

In [1]:
```
import pandas as pd
df=pd.read_csv('Ames_House_Sales_Cropped.csv')
```

In [2]:
```
df.head()
```

Out[2]:

	BldgType	CentralAir	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	...	OverallQual	PoolArea
0	1Fam	Y	856.0	854.0	0.0	3	706.0	0.0	1	0	...	7	0.0
1	1Fam	Y	1262.0	0.0	0.0	3	978.0	0.0	0	1	...	6	0.0
2	1Fam	Y	920.0	866.0	0.0	3	486.0	0.0	1	0	...	7	0.0
3	1Fam	Y	961.0	756.0	0.0	3	216.0	0.0	1	0	...	7	0.0
4	1Fam	Y	1145.0	1053.0	0.0	4	655.0	0.0	1	0	...	8	0.0

5 rows × 39 columns

In [3]:
```
df.shape
```

Out[3]:
```
(1379, 39)
```

In [4]:
```
df.size
```

Out[4]:
```
53781
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['BldgType', 'CentralAir', '1stFlrSF', '2ndFlrSF', '3SsnPorch',
       'BedroomAbvGr', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtFullBath',
       'BsmtHalfBath', 'BsmtUnfSF', 'EnclosedPorch', 'Fireplaces', 'FullBath',
       'GarageArea', 'GarageCars', 'GarageYrBlt', 'GrLivArea', 'HalfBath',
       'KitchenAbvGr', 'LotArea', 'LotFrontage', 'LowQualFinSF', 'MSSubClass',
       'MasVnrArea', 'MiscVal', 'MoSold', 'OpenPorchSF', 'OverallCond',
       'OverallQual', 'PoolArea', 'ScreenPorch', 'TotRmsAbvGrd', 'TotalBsmtSF',
       'WoodDeckSF', 'YearBuilt', 'YearRemodAdd', 'YrSold', 'SalePrice'],
      dtype='object')
```

In [7]:
```
type(df)
```

Out[7]:
```
pandas.core.frame.DataFrame
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1379 entries, 0 to 1378
Data columns (total 39 columns):
BldgType         1379 non-null object
CentralAir       1379 non-null object
1stFlrSF         1379 non-null float64
2ndFlrSF         1379 non-null float64
3SsnPorch        1379 non-null float64
BedroomAbvGr     1379 non-null int64
BsmtFinSF1       1379 non-null float64
BsmtFinSF2       1379 non-null float64
BsmtFullBath     1379 non-null int64
BsmtHalfBath     1379 non-null int64
BsmtUnfSF        1379 non-null float64
EnclosedPorch    1379 non-null float64
Fireplaces       1379 non-null int64
FullBath         1379 non-null int64
GarageArea       1379 non-null float64
GarageCars       1379 non-null int64
GarageYrBlt      1379 non-null float64
GrLivArea        1379 non-null float64
HalfBath         1379 non-null int64
KitchenAbvGr     1379 non-null int64
LotArea          1379 non-null float64
LotFrontage      1379 non-null float64
LowQualFinSF     1379 non-null float64
MSSubClass       1379 non-null int64
MasVnrArea       1379 non-null float64
MiscVal          1379 non-null float64
MoSold           1379 non-null int64
OpenPorchSF      1379 non-null float64
OverallCond      1379 non-null int64
OverallQual      1379 non-null int64
PoolArea         1379 non-null float64
ScreenPorch      1379 non-null float64
TotRmsAbvGrd     1379 non-null int64
TotalBsmtSF      1379 non-null float64
WoodDeckSF       1379 non-null float64
YearBuilt        1379 non-null int64
YearRemodAdd     1379 non-null int64
YrSold           1379 non-null int64
SalePrice        1379 non-null float64
dtypes: float64(21), int64(16), object(2)
memory usage: 420.2+ KB
```

In [11]:
```
df["SalePrice"].value_counts
print(df)
```

```
     BldgType CentralAir  1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  \
0       1Fam          Y     856.0     854.0        0.0             3
1       1Fam          Y    1262.0       0.0        0.0             3
2       1Fam          Y     920.0     866.0        0.0             3
3       1Fam          Y     961.0     756.0        0.0             3
4       1Fam          Y    1145.0    1053.0        0.0             4
5       1Fam          Y     796.0     566.0      320.0             1
6       1Fam          Y    1694.0       0.0        0.0             3
7       1Fam          Y    1107.0     983.0        0.0             3
8       1Fam          Y    1022.0     752.0        0.0             2
9     2fmCon          Y    1077.0       0.0        0.0             2
10      1Fam          Y    1040.0       0.0        0.0             3
11      1Fam          Y    1182.0    1142.0        0.0             4
12      1Fam          Y     912.0       0.0        0.0             2
13      1Fam          Y    1494.0       0.0        0.0             3
14      1Fam          Y    1253.0       0.0        0.0             2
15      1Fam          Y     854.0       0.0        0.0             2
16      1Fam          Y    1004.0       0.0        0.0             2
17    Duplex          Y    1296.0       0.0        0.0             2
```

Step : 2

In [14]:
```
d1=df.drop(["BldgType","CentralAir"],axis=1)
print(d1)
```

```
      1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  BsmtFinSF1  BsmtFinSF2  \
0        856.0     854.0        0.0             3       706.0         0.0
1       1262.0       0.0        0.0             3       978.0         0.0
2        920.0     866.0        0.0             3       486.0         0.0
3        961.0     756.0        0.0             3       216.0         0.0
4       1145.0    1053.0        0.0             4       655.0         0.0
5        796.0     566.0      320.0             1       732.0         0.0
6       1694.0       0.0        0.0             3      1369.0         0.0
7       1107.0     983.0        0.0             3       859.0        32.0
8       1022.0     752.0        0.0             2         0.0         0.0
9       1077.0       0.0        0.0             2       851.0         0.0
10      1040.0       0.0        0.0             3       906.0         0.0
11      1182.0    1142.0        0.0             4       998.0         0.0
12       912.0       0.0        0.0             2       737.0         0.0
13      1494.0       0.0        0.0             3         0.0         0.0
14      1253.0       0.0        0.0             2       733.0         0.0
15       854.0       0.0        0.0             2         0.0         0.0
16      1004.0       0.0        0.0             2       578.0         0.0
17      1296.0       0.0        0.0             2         0.0         0.0
```

In [17]:
```
#Prepare X matrix(36 feature columns) and y vector (salesPrice column)
X=dff.drop(["SalePrice"],axis=1)
print(X)
```

```
17      1296.0       0.0        0.0             2         0.0         0.0
18      1114.0       0.0        0.0             3       646.0         0.0
19      1339.0       0.0        0.0             3       504.0         0.0
20      1158.0    1218.0        0.0             4         0.0         0.0
21      1108.0       0.0        0.0             3         0.0         0.0
22      1795.0       0.0        0.0             3         0.0         0.0
23      1060.0       0.0        0.0             3       840.0         0.0
24      1060.0       0.0        0.0             3       188.0       668.0
25      1600.0       0.0        0.0             3         0.0         0.0
26       900.0       0.0        0.0             3       234.0       486.0
27      1704.0       0.0        0.0             3      1218.0         0.0
28      1600.0       0.0        0.0             2      1277.0         0.0
29       520.0       0.0        0.0             1         0.0         0.0
...        ...       ...        ...           ...         ...         ...
1349    1048.0     510.0        0.0             3       580.0         0.0
1350     804.0       0.0        0.0             2       510.0         0.0
1351    1440.0       0.0        0.0             3       678.0         0.0
1352     734.0    1104.0        0.0             4         0.0         0.0
1353     958.0       0.0        0.0             2       958.0         0.0
1354     968.0       0.0        0.0             4         0.0         0.0
```

In [19]:
```
y=dff["SalePrice"].values
y
```

Out[19]:
```
array([208500., 181500., 223500., ..., 266500., 142125., 147500.])
```

In [20]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.25,random_state=42)
```

In [21]:
```
from sklearn.linear_model import LinearRegression
reg=LinearRegression()
reg.fit(X_train,y_train)
```

Out[21]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [23]:
```
y_pred=reg.predict(X_test)
print(y_pred)
```

```
[257434.93050745 111083.7347476  100018.05832303 204028.53821314
 207319.25418312  38036.30928932 234153.38582868 205076.12689608
 187014.1265524  235636.78799031 100976.50943769 304119.53646983
 101769.64600713 288758.46001593 204767.89338328 145002.47279616
 248322.97436852 151533.68038634 209697.39458712 278312.23574148
  93329.85601474 153784.14868375 163237.87451138 241495.9121289
 372429.94726945 221672.07367609 119658.75685737 100039.78137073
 319435.0289208  172088.64665031 258772.64470117 199597.36129642
 156349.69283212 142311.22500101 204807.33161321 379608.17785443
 124176.23377551 141127.25006141 273832.43247645 212547.04205553
 169474.57176142 123305.65719311 200341.24016791 377957.32307114
 146941.7171239  283693.48760668 106694.19786718 221733.02172508
  87733.47014004 295005.66546305 125250.62019285  53569.11256022
 133831.0508612  170901.4292971  213273.17757301 110818.14723232
 103893.81849706 200665.21921033 137764.84464902 311840.64900748
  53035.52267594 184866.47797858 154675.79963879 298477.53600006
  78162.5407468  323728.93535803 169417.44138514 112718.07937635
 200547.87648954 205739.30910765 130292.88475647 271581.37221152
 119489.76459232 126635.29232505  77972.26780485 138563.37305272
  35555.51251487 163787.98080893 271929.13690186 115260.62742896
 319958.55004404 218515.16541529 291730.97232824 211176.53228423
  93761.81278837 263031.10150322 141886.3966699  118491.50416092
 143580.34191288 278395.85370477 265558.84177945 300839.51324225
 182673.3443797  168604.5492604  148322.24627425 213781.03244613
 247750.58741    221693.90686786 274474.96290575 242912.73279161
 111041.26737678 100160.66573767 193531.44933265 206050.88712632
 154584.47386041 217440.52365094 210904.23539265 125864.27688695
 171322.66919858 224459.70210717 155548.12334499 111942.7871775
 316624.83474109 298116.31992277 335573.77762719  86738.88506816
 146692.58771903 228471.5403292  123374.07354542 204867.33148103
 217343.21720916 120569.43114727 134354.1238425  223860.01643704
 138360.76267459 210765.75439351 145423.97229834 291155.26974376
 183089.17904138  98716.55524167 323896.46706846 170447.30657102
 123643.15346299 134345.24799853 309423.49789818 136836.97808937
 282083.02092584 132621.2237255   90821.15043377 164193.14328588
 147333.60026797 162030.92949963 177621.20328218 254054.45691355
 119092.92298357 140081.84030886 236509.39317212 318578.43961646
 105538.81578042 192023.58779383 174531.98294663 146314.75164225
  95146.46236358 250936.32825846 304056.57810773  55008.42319119
 281810.05395732  93402.68236907 138283.4460375  166415.3192293
 209758.26998556 205602.16976218 177026.58819395 248435.62725108
 145190.55457313 133283.94785764 171593.4339452  344925.23412401
 181194.80288331  98431.28117762 131287.46561773 110849.96802284
 131283.81966769 194221.20494195 156966.39268757 268340.58471943
 211804.83660278 151971.72881374 115946.37551381 243618.89320955
 136292.7606826  265335.41730193 302175.59064213  85054.45272476
 146007.43532809 150439.28821412 159145.83079286 232246.23120855
 231571.13532009 139178.99313677 355030.619324   127659.29864106
 235339.23724177 116707.21916901 103103.75191051 159574.23418457
 149485.12469048 408898.40096809 335368.65026123 290500.91914899
 281845.43486756 275341.8171841  321705.52591338 307549.31796899
 201661.19536934 142047.81494961 157876.45367574 258695.10810332
 207592.92972056 146121.60182471 107032.8224214  151245.32235213
 100804.2036383  296980.23153195 341413.30991677 255158.86136987
 147006.3495448  199721.99255174 127291.41093944 264030.58756771
 121760.19396639 134138.79148625 307661.79229119 170331.68886912
 173593.89056669 567240.20119424 182277.72265598 144159.48526101
 199515.17896325 107691.20503754 181383.00130498 328401.72331
 139225.20214766 197660.10401731 116340.37479629  54949.57465389
 199375.67314461 272915.38777822 119902.62390774 197573.81604289
 231881.98496935 119555.98822715 128709.5470232  289158.80585494
 200733.61408622 364228.39366113 119308.94568436 124086.7225403
 225161.62739518 171005.22659817  93631.91767228 178506.48207587
 215661.64584809 226225.30038962 132391.85608602  73443.41948308
 242913.00968351 141042.39030912 114633.38186071  89093.07024776
 208503.15479642 172828.98634139 270797.22136173 253693.44924276
 103518.85057198 220521.27460707 185034.32129269 169518.90296985
 154846.17459061 224605.38839967  85972.23828462 151323.12661355
 180628.92554331 200106.98029834 179499.8172794  223755.69902625
  73639.52734133  86011.8149164  110000.03909838 231518.89807261
 153369.35976787 320899.35432162 194412.83170324  57741.65743007
 203877.63015232 109803.05085704 194633.36256922  99160.35922065
 230240.81594374 211484.77477044 198342.97693781 109749.28794511
  95564.23930705 235396.44527254 184775.90385427 188806.96222903
 265328.01705249 245862.13668724 107422.00402518 164786.63106786
 268303.4442141  116075.01592356 222914.33666726 102600.4329218
 226400.49839176 156093.55758651 112003.82907499 218089.37220887
  81085.92660263  85015.51341434  98208.34263398 304262.27895919
 143757.79043406 195367.3512202  241835.21911123  60944.84144938
 143731.15831778 110459.58351734 438412.24654518 123265.07239636
 116119.87930811 277961.71617821 201687.81739715 237947.02580917
 206117.84987333  99453.60459331 115124.57035037 209795.31353811
 167537.15563245 162970.26517749 151279.43057796 189724.86274087
  96455.47006118 168652.82586918  83051.31596953 171340.42959854
 176868.33711878 175644.68961803 131414.67048231 204543.74960377
```

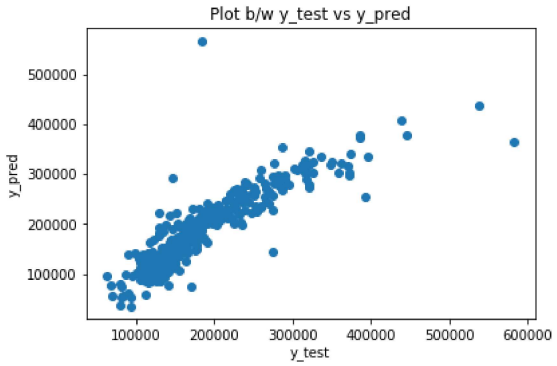
```
233147.40044683 125478.90203711 175060.50167495 258877.30470763
229115.65129666]
```

In [24]:
```
import sklearn.metrics as metrics
mse=metrics.mean_squared_error(y_test,y_pred)
print("MSE without Categorical: ",mse)
```

```
MSE without Categorical:  1474827325.5975406
```

Step : 3

In [25]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.scatter(y_test,y_pred)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.title("Plot b/w y_test vs y_pred")
plt.show()
```



Step : 4

In [27]:
```
encoding=pd.get_dummies(df)
print(encoding)
```

```
      1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  BsmtFinSF1  BsmtFinSF2  \
0        856.0     854.0        0.0             3       706.0         0.0
1       1262.0       0.0        0.0             3       978.0         0.0
2        920.0     866.0        0.0             3       486.0         0.0
3        961.0     756.0        0.0             3       216.0         0.0
4       1145.0    1053.0        0.0             4       655.0         0.0
5        796.0     566.0      320.0             1       732.0         0.0
6       1694.0       0.0        0.0             3      1369.0         0.0
7       1107.0     983.0        0.0             3       859.0        32.0
8       1022.0     752.0        0.0             2         0.0         0.0
9       1077.0       0.0        0.0             2       851.0         0.0
10      1040.0       0.0        0.0             3       906.0         0.0
11      1182.0    1142.0        0.0             4       998.0         0.0
12       912.0       0.0        0.0             2       737.0         0.0
13      1494.0       0.0        0.0             3         0.0         0.0
14      1253.0       0.0        0.0             2       733.0         0.0
15       854.0       0.0        0.0             2         0.0         0.0
16      1004.0       0.0        0.0             2       578.0         0.0
17      1296.0       0.0        0.0             2         0.0         0.0
```

Step : 5

In [29]:
```
X=encoding.drop(["SalePrice"],axis=1)
print(X)
```

```
      1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  BsmtFinSF1  BsmtFinSF2  \
0        856.0     854.0        0.0             3       706.0         0.0
1       1262.0       0.0        0.0             3       978.0         0.0
2        920.0     866.0        0.0             3       486.0         0.0
3        961.0     756.0        0.0             3       216.0         0.0
4       1145.0    1053.0        0.0             4       655.0         0.0
5        796.0     566.0      320.0             1       732.0         0.0
6       1694.0       0.0        0.0             3      1369.0         0.0
7       1107.0     983.0        0.0             3       859.0        32.0
8       1022.0     752.0        0.0             2         0.0         0.0
9       1077.0       0.0        0.0             2       851.0         0.0
10      1040.0       0.0        0.0             3       906.0         0.0
11      1182.0    1142.0        0.0             4       998.0         0.0
12       912.0       0.0        0.0             2       737.0         0.0
13      1494.0       0.0        0.0             3         0.0         0.0
14      1253.0       0.0        0.0             2       733.0         0.0
15       854.0       0.0        0.0             2         0.0         0.0
16      1004.0       0.0        0.0             2       578.0         0.0
17      1296.0       0.0        0.0             2         0.0         0.0
```

In [30]:
```
y=encoding["SalePrice"].values
y
```

Out[30]:
```
array([208500., 181500., 223500., ..., 266500., 142125., 147500.])
```

In [31]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.25,random_state=42)
```

In [32]:
```
from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics
reg=LinearRegression()
reg.fit(X_train,y_train)
y_pred=reg.predict(X_test)
print(y)
mse_cd=metrics.mean_squared_error(y_test,y_pred)
print("MSE with Categorical data: ",mse_cd)
```

```
[208500. 181500. 223500. ... 266500. 142125. 147500.]
MSE with Categorical data:  1461036570.1436336
```

Step : 6

In [33]:
```
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
ss_X_train=ss.fit_transform(X_train)
ss_X_train
```

Out[33]:
```
array([[ 0.39851037, -0.79290427, -0.11340519, ...,  3.45325933,
        -0.22777619,  0.22777619],
       [ 1.57467708, -0.79290427, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       [ 0.37564751,  0.70143387, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       ...,
       [ 1.22157303, -0.79290427, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       [-1.11297817,  0.90510323, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       [ 0.11145456, -0.79290427, -0.11340519, ...,  3.45325933,
        -0.22777619,  0.22777619]])
```

In [34]:
```
ss_X_test=ss.transform(X_test)
ss_X_test
```

Out[34]:
```
array([[ 0.85830772, -0.79290427, -0.11340519, ...,  3.45325933,
        -0.22777619,  0.22777619],
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       [-0.21624632,  0.76093278, -0.11340519, ..., -0.2895815 ,
         4.39027446, -4.39027446],
       ...,
       [-0.04350477,  0.37647826, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       [-0.64301955,  1.46805451, -0.11340519, ..., -0.2895815 ,
        -0.22777619,  0.22777619],
       [-0.29499614,  0.81585486, -0.11340519, ...,  3.45325933,
        -0.22777619,  0.22777619]])
```

In [36]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(ss_X_train,y_train)
ss_y_pred=lr.predict(ss_X_test)
print(ss_y_pred)
```

```
[257746.67634751 113257.14215097  83086.83449793 204109.44696503
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```

```
236536.65155886 125744.91988448 173333.02038791 259092.37349783
227361.55928746]
```

In [37]:
```
ss_mse=metrics.mean_squared_error(y_test,ss_y_pred)
print("SS_MSE: ",ss_mse)
```

```
SS_MSE:  1461036570.1437433
```

Step : 7

In [38]:
```
from sklearn.preprocessing import MinMaxScaler
mm=MinMaxScaler()
mm_X_train=mm.fit_transform(X_train)
mm_X_test=mm.transform(X_test)
mm_lr=LinearRegression()
mm_lr.fit(mm_X_train,y_train)
mm_y_pred=mm_lr.predict(mm_X_test)
print("Predictions of scaled data using MinMaxScaler:",mm_y_pred)
```

```
Predictions of scaled data using MinMaxScaler: [257746.67634751 113257.14215097  83086.83449793 204109.44696503
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 195389.49394275 110000.52031067 181425.05998225 326697.98513269
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 200892.30994253 274120.15715879 110287.72265007 195830.60427729
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 218235.04083371 225391.98842006 133701.6669314   67245.43233413
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 103491.65134387 221152.52727064 184240.39768591 170413.54111433
 156767.28870157 225874.2187855   85067.50220226 152614.17988863
 180110.39735029 200365.40564938 181240.47868432 225088.28569024
  74809.64993437  81056.03121343 138531.42801458 231176.80557566
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 201332.72073446  98680.14396138 142896.01985585 211430.3435048
 167955.3826565  161745.94065555 150329.86791651 191659.61015824
  98638.48036051 167674.58655871  81251.41418888 169289.1270314
 175822.84359349 165634.36808713 132604.67079394 205548.45244987
```

```
236536.65155886 125744.91988448 173333.02038791 259092.37349783
227361.55928746]
```

In [39]:
```
mm_mse=metrics.mean_squared_error(y_test,mm_y_pred)
print("MM_MSE: ",mm_mse)
```

```
MM_MSE:  1461036570.1437414
```

Step : 8

In [40]:
```
from sklearn.linear_model import SGDRegressor
sgd=SGDRegressor()
sgd.fit(ss_X_train, y_train)
sgd_y_pred=sgd.predict(ss_X_test)
print("Predictions of scaled data using SGDRegressor:", sgd_y_pred)
```

```
Predictions of scaled data using SGDRegressor: [261575.86203383 104401.47535968  93589.62507687 205277.79618898
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 223265.12756186 213995.50279251 207392.2215238  110061.1131844
  94021.28565641 243671.13221527 191639.73874488 193253.96096818
 266860.02838347 242082.64565414 104367.44198253 145833.2590129
 273431.63923945 107308.90703125 219351.4132555  105348.61648331
 231815.8422397  155144.52997003 100676.47732982 221929.95987589
  74438.94391235  71739.79524838  84884.44987396 314658.67415408
 218090.01765794 175193.9562324  253182.4675157   51316.46787752
 142754.11125192 111070.27765498 458835.78253092 114022.07548388
 112666.14931759 284457.66771205 197619.08435852 235813.81198064
 219447.61128581  93277.95843783 135705.10943976 209342.49185457
 163165.81146112 146655.38212161 152964.94791716 189395.24436883
  89616.9604968  173372.29322911  68841.59992556 169197.23361504
 178125.41755917 154288.48748212 130961.84494807 202200.34642997
```

```
 234315.03091738 123317.60530338 176266.11349468 266608.86527095
 220689.47945904]
```

```
C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\linear_model\stochastic_gradien
t.py:128: FutureWarning: max_iter and tol parameters have been added in <class 'sklearn.linear_model.stochastic_gradient.SGD
Regressor'> in 0.19. If both are left unset, they default to max_iter=5 and tol=None. If tol is not None, max_iter defaults
to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

In [41]:

```
sgd_mse=metrics.mean_squared_error(y_test, sgd_y_pred)
print("SGD_MSE:",sgd_mse)
```

```
SGD_MSE: 1505789243.6148124
```

In [42]:
```
from sklearn.linear_model import Ridge
ridge=Ridge()
ridge.fit(ss_X_train, y_train)
ridge_y_pred=ridge.predict(ss_X_test)
print("Predictions of scaled data using RIDGERegression:", ridge_y_pred)
```

```
Predictions of scaled data using RIDGERegression: [257716.40699318 113188.83783395  83441.68622524 204093.86685461
 209046.77119427  68968.95970424 235166.85073532 205709.18701907
 187608.88092307 234127.91986613 101442.61753652 303996.83085985
 102207.81104997 289201.83025972 204530.52882459 142227.09469735
 249528.85892308 147950.18211509 210586.82424173 277366.73836724
  91543.67482183 153978.54592712 160695.6139235  243057.53405206
 372495.11731184 219840.91884082 116956.95574687 100878.46795325
 318603.53970706 168136.34840742 258058.73912129 201180.97018482
 154470.04859036 142707.68415143 205133.17128488 382062.98759242
 124795.49109482 141435.74207829 273560.58911851 214075.03676925
 170494.5832031  124523.92339387 197429.91336254 375822.0370805
 148108.22483297 288075.31154386 108608.62662542 218573.47618249
  88587.3998216  295171.57452763 125737.07110059  54833.67931716
 133481.71022526 173594.36273487 214840.0746121  110380.72176421
 101840.39812262 198576.07688518 139894.58865439 312964.61939685
  71367.79689775 185112.92538069 154029.67686384 299492.62825149
  76893.88517706 324365.26359029 165376.0785674  112254.3704445
 200819.07169113 206550.44800728 130800.86405237 271523.0063293
 119196.14940404 144867.37804993  75254.15912227 136728.43245701
  35597.59046173 164058.34969126 273927.80986891 115902.45464437
 319919.85988921 219089.91634213 293822.16290467 211832.71038627
  91537.74860448 265620.40558168 142587.28712764 118497.81994793
 143635.30184965 279152.61891253 269311.1413232  301659.46840395
 184286.35253708 165184.74414324 149891.99972881 213980.4719389
 249049.04209643 224051.13974668 274369.96952527 245841.61643708
 111585.23921014  99285.36721984 195203.7216061  207989.92499748
 155028.88974981 218022.83766913 212660.79772296 122538.52182907
 162728.69874836 221971.18357146 146945.09391568 110067.72428323
 319814.93647477 298246.38587609 336941.24594611  87997.01636518
 146981.74764146 227505.54712528 122965.2544359  205344.88888641
 217541.64749768 107771.77680053 133765.67836363 220260.06460657
 134647.30943604 212445.40571604 145599.53125656 291949.61121746
 184043.36581726  97697.33647965 325733.33460483 168143.84275303
 122906.74152174 134080.67606878 309437.41884789 134751.59695772
 281790.27252733 130974.90646071  92697.37462197 161091.5892275
 148171.12579169 158819.52635399 178223.97509849 257107.00153039
 115122.62646454 138141.80491198 238057.41121163 318549.26633768
 104371.57134771 193635.25761937 172077.14595925 144885.03564327
  95554.92759806 250953.38099348 304541.02238179  53219.0448574
 284176.85264899  93400.71982017 137995.60254859 164465.60061817
 209777.47549039 203563.29570254 176679.65980431 250553.4609179
 142724.97393041 134288.63707225 171785.11537111 344054.87023123
 182442.95972596  99605.68463271 131552.70068821 102458.6004887
 123461.42545918 193291.78508491 156540.42729331 269762.81773183
 214029.99936865 151955.03692603 116513.08932336 244970.39361538
 134699.2149871  264939.1730608  302655.25814127 112765.72171924
 146343.51688839 141400.89021689 159152.01443607 231882.27246478
 233340.47229044 140170.23115364 355837.95593261 125123.6071953
 236563.7287866  118584.91492874 103674.34219114 158279.89652213
 146239.3763445  414236.75239941 337687.01869556 292095.33884883
 281975.96957962 275157.5265404  322473.52623347 307559.16658245
 202413.61321578 141543.52304339 156938.45535856 264430.93571626
 208855.42690191 148534.23761202 104695.9156791  149705.7343585
 101509.83486213 298235.68040125 342471.41568024 255288.59034683
 144073.37987936 195222.06016888 128842.95043884 264722.55264243
 122814.74476713 133278.4795676  307911.95867229 167263.61643095
 173717.5283684  566453.75411051 182844.43105375 143056.66623968
 195459.9517828  110031.5315688  181380.27781101 326642.05493544
 138687.73082    197539.06193031 116397.95911794  57864.29190174
 200870.72982498 274103.15023701 110331.98749734 195890.18985712
 234230.62113975 121111.45520781 137725.6391029  288996.92043677
 200176.68183782 364232.50615443 116188.37153176 125646.49499415
 225859.82479563 172176.23953285  93470.49188531 178488.39571047
 218214.18556022 225439.50186818 133730.67670966  67582.3120787
 243455.16368461 138315.47306896 113560.16506458  85012.3660346
 207779.94088431 171952.5210419  270402.27760786 254250.36145244
 103501.7808304  221091.33159311 184406.69839004 170462.34462181
 156799.2718875  225871.67203851  85108.65590281 152543.1330664
 180044.96550306 200375.75191088 181254.45434812 224810.46414272
  75144.10407593  81393.67998095 138318.56519304 231082.14246835
 152831.73330562 322773.27244389 196234.30285594  56775.45518337
 206549.14444971 109613.97109879 196192.45958022 100157.9526367
 222746.15990955 211519.5786086  199144.99012675 111277.72707786
  98150.90782231 236864.33886554 184958.66514372 189263.28121445
 265567.5169301  247763.83830809 108255.75070666 161646.28974509
 267710.34135243 116069.83636697 220248.79455542  99220.40041001
 227742.28703343 157984.25550973 107798.91813747 219704.63978513
  81507.24588044  76481.69523773  97652.61391762 303713.02140765
 146284.60208933 186530.14642609 241387.0772794   61365.50896352
 144289.97596438 108982.77136529 440530.78372543 120246.58324455
 115308.70156278 275911.79875926 201932.31328927 234498.94963676
 201583.06918458  98700.9196783  142687.06236746 211412.15970588
 167807.49540674 161636.28609433 150436.44626318 191662.32787741
  98527.88338021 167785.99502907  81294.88719425 169177.67605055
 175874.39752831 165547.40376838 132551.96525579 205527.52636725
```

```
 236395.29650392 125794.65643289 173406.69375672 259033.27747268
 227234.37218332]
```

In [43]:

```
ridge_mse=metrics.mean_squared_error(y_test, ridge_y_pred)
ridge_r2=metrics.r2_score(y_test, sgd_y_pred)
print("RIDGE_MSE:",ridge_mse)
```

```
RIDGE_MSE: 1458946958.0904446
```

In [44]:

```
from sklearn.linear_model import Lasso
lasso=Lasso()
lasso.fit(ss_X_train, y_train)
lasso_y_pred=lasso.predict(ss_X_test)
print("Predictions of scaled data using LASSORegression:", lasso_y_pred)
```

```
Predictions of scaled data using LASSORegression: [257729.69686228 113247.68204486  83142.29454527 204106.43998851
 209066.49021888  69054.81228022 235176.11930442 205711.84838767
 187608.59515698 234284.06084395 101449.25460271 304193.6360213
 102109.0711376  289198.43257911 204491.12189758 142122.85239194
 249633.03850946 147889.3873303  210566.82234788 277458.74148889
  91422.16023407 153936.54170005 160629.24135716 243131.57205681
 372542.62040315 219872.31056047 116863.87010022 100885.24049767
 318608.68254302 168098.13679091 258090.97848895 201288.31490053
 154603.02948577 142756.31460187 205137.22911272 382237.47687556
 124919.66167664 141572.72803651 273666.16449995 214125.2076817
 170460.20631671 124565.97224865 197629.92077736 376132.94977617
 148005.53413165 288031.84338491 108663.12260663 218568.08286906
  88451.65003835 295193.48660115 125792.5796616   54906.97302469
 133434.7793381  173716.93120033 214868.54616558 110315.71602181
 101776.23316753 198433.20185705 139852.85532953 313008.51176235
  71372.35173051 185193.16837526 153957.25028227 299596.82600383
  76797.56928684 324385.12193927 165298.44677344 112130.60821731
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  35552.84939405 163985.23467214 273973.46020853 116015.84441149
 319949.02350894 219061.27031023 293870.99785338 211806.30759287
  91284.37825021 265712.38394797 142676.37351153 118565.93663895
 143674.04796073 279150.78978229 269350.79958902 301749.09017645
 184238.16223454 165127.83870291 149749.971759   213932.73020163
 249099.03142859 224103.21830794 274398.78074231 245917.53728663
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 154996.99469861 218133.62585452 212678.72001038 122425.46620394
 162745.4701208  221876.0238869  146954.89801987 109955.96291884
 319902.41000277 298399.98697946 337080.93758278  88041.26768065
 146956.67018354 227528.07763404 122783.32119227 205361.95445653
 217572.36672847 107445.89506261 133733.93273959 220237.13185881
 134562.85513962 212441.22565528 145664.6490619  291990.19815932
 183992.81011514  97710.74841533 325888.23318497 168160.98330115
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 281846.16771076 130925.21004783  92692.33683927 160945.68481687
 148205.17349014 158737.18245717 178212.15350491 257197.05522751
 114904.770572   138119.73032986 238108.69937308 318640.59412828
 104227.02007034 193572.95306041 172128.45114871 144831.00706529
  95568.83603287 250976.29637637 304506.20094194  53074.03126872
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 209750.74474024 203507.35157691 176605.11071809 250433.47941814
 142442.56296303 134372.47735183 171734.75893015 344242.61402369
 182535.72149748  99606.43760465 131556.77246267 102404.11838037
 123442.09968805 193351.73679664 156603.51624856 269864.8398754
 214055.85227124 151934.36274075 116604.28215523 244959.99451503
 134838.25785952 264898.68559226 302725.58777033 112731.7446967
 146413.91028759 141404.48991242 159092.12693511 231871.85339525
 233356.97471515 140184.4923673  356182.13216459 125098.80530538
 236563.67234591 118595.96441677 103720.0363061  158211.47689343
 146208.52042129 414448.62868843 337706.51862255 292089.54342658
 282067.39287353 275220.38527458 322598.62605758 307607.66942813
 202374.38645492 141564.96112    156913.87655793 264220.52332684
 208842.25175567 148495.28954641 104610.26939919 149704.15186406
 101505.94260441 298200.94930269 342555.63710936 255293.96192183
 143941.00968853 195070.94331289 128759.7558806  264731.27944764
 122738.81214254 133202.40385339 307879.92219547 167198.36515005
 173655.27272885 566791.4626781  182859.08759158 142978.96172471
 195411.89902191 109989.97237563 181424.62759165 326700.99083302
 138742.78214564 197520.5489765  116241.60249896  57889.11718413
 200889.63670003 274133.72241038 110284.19196382 195834.57014334
 234280.54148409 121025.73789444 137750.5533365  289102.2483371
 200107.11126573 364167.65133585 116093.7426804  125692.84631828
 225912.27728164 172268.27034232  93550.38096287 178436.21724116
 218228.05492206 225394.75569643 133705.24490148  67286.84252492
 243435.3352886  138212.91208172 113575.12067421  84763.0571555
 207893.46649157 172014.92872346 270368.22866089 254308.20269938
 103489.48936776 221152.56639884 184242.04200553 170421.97540171
 156761.53497604 225877.48743629  85073.90472036 152603.94331392
 180102.85191822 200371.14356128 181240.6625634  225061.98394381
  74826.71147585  81085.1939571  138486.98130548 231190.09881719
 152862.5234824  322870.83873105 196244.21793811  56726.64940312
 206524.79485726 109539.23259487 196178.63293578 100010.70807563
 222777.79438513 211539.35671092 199094.64072609 111278.51445755
  98154.13024319 236845.81680032 184872.18562098 189199.77805113
 265551.01867187 247875.47829531 108230.38633121 161861.58888709
 267828.77750227 116126.80380291 220329.46846636  99009.18854187
 227723.3048807  158054.99967295 107672.10313119 219802.67568716
  81445.94291229  76355.17286645  97708.71173269 303750.99022453
 146164.36964155 186675.79492752 241397.08830316  61402.63825225
 144276.21302137 108876.91545721 440705.04938866 120132.90211529
 115315.14265229 275893.22780201 201923.10589601 234448.28372038
 201360.63783727  98674.76411393 142858.79213935 211418.19972226
 167946.77034753 161744.898088   150329.68930056 191652.17462118
  98628.76165898 167691.68791082  81271.31765368 169263.90002432
 175828.08068586 165632.53323128 132599.66558174 205533.56435214
```

```
 236522.60127319 125734.98875162 173340.82150737 259083.66035875
 227358.42738081]

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\linear_model\coordinate_descent.py:491: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations. Fitting data with very small alpha may cause precision problems.
  ConvergenceWarning)
```

In [45]:
```
lasso_mse=metrics.mean_squared_error(y_test, lasso_y_pred)
print("LASSO_MSE:",lasso_mse)
```

```
LASSO_MSE: 1460906418.115903
```

Step : 9

In [48]:
```
import numpy as np
print("RMSE without CD: ",np.sqrt(mse))
print("RMSE with CD: ",np.sqrt(mse_cd))
print("RMSE with CD and SS: ",np.sqrt(ss_mse))
print("RMSE with CD and MnMaxScaling: ",np.sqrt(mm_mse))
print("RMSE of SGDRegressor with CD and StandardScaler: ",np.sqrt(sgd_mse))
print("RMSE of Ridgecv with CD and Standard Scaler: ",np.sqrt(ridge_mse))
print("RMSE of LassoCV with CD and StandardScaler",np.sqrt(lasso_mse))
```

```
RMSE without CD:  38403.48064430541
RMSE with CD:  38223.50808263985
RMSE with CD and SS:  38223.50808264128
RMSE with CD and MnMaxScaling:  38223.50808264125
RMSE of SGDRegressor with CD and StandardScaler:  38804.500301058026
RMSE of Ridgecv with CD and Standard Scaler:  38196.164180326334
RMSE of LassoCV with CD and StandardScaler 38221.805531867576
```

In [ ]:
```

```