

Roll no : 225229110

## Lab4.House Price Prediction using LR with Regularization

### Step1.Import dataset

```
In [180]: import pandas as pd
```

```
In [181]: data=pd.read_csv("Ames_House_Sales_Cropped.csv")
data
```

	Id	Metro	T	1107.0	965.0	0.0	3	659.0	32.0	1	0 ...	7	0.0
8	1Fam	Y	1022.0	752.0	0.0	2	0.0	0.0	0	0	0 ...	7	0.0
9	2fmCon	Y	1077.0	0.0	0.0	2	851.0	0.0	1	0	0 ...	5	0.0
10	1Fam	Y	1040.0	0.0	0.0	3	906.0	0.0	1	0	0 ...	5	0.0
11	1Fam	Y	1182.0	1142.0	0.0	4	998.0	0.0	1	0	0 ...	9	0.0
12	1Fam	Y	912.0	0.0	0.0	2	737.0	0.0	1	0	0 ...	5	0.0
13	1Fam	Y	1494.0	0.0	0.0	3	0.0	0.0	0	0	0 ...	7	0.0
14	1Fam	Y	1253.0	0.0	0.0	2	733.0	0.0	1	0	0 ...	6	0.0
15	1Fam	Y	854.0	0.0	0.0	2	0.0	0.0	0	0	0 ...	7	0.0
16	1Fam	Y	1004.0	0.0	0.0	2	578.0	0.0	1	0	0 ...	6	0.0
17	Duplex	Y	1296.0	0.0	0.0	2	0.0	0.0	0	0	0 ...	4	0.0
18	1Fam	Y	1114.0	0.0	0.0	3	646.0	0.0	1	0	0 ...	5	0.0
19	1Fam	Y	1339.0	0.0	0.0	3	504.0	0.0	0	0	0 ...	5	0.0

```
In [182]: #head
data.head()
```

Out[182]:

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

5 rows × 39 columns

```
In [183]: #shape
data.shape
```

Out[183]: (1379, 39)

```
In [184]: #columns
data.shape[1]
```

Out[184]: 39

```
In [185]: #dtype  
data.dtypes
```

```
Out[185]: BldgType          object  
CentralAir         object  
1stFlrSF          float64  
2ndFlrSF          float64  
3SsnPorch         float64  
BedroomAbvGr      int64  
BsmtFinSF1        float64  
BsmtFinSF2        float64  
BsmtFullBath      int64  
BsmtHalfBath      int64  
BsmtUnfSF         float64  
EnclosedPorch     float64  
Fireplaces         int64  
FullBath          int64  
GarageArea         float64  
GarageCars         int64  
GarageYrBlt        float64  
GrLivArea          float64  
HalfBath           int64  
KitchenAbvGr       int64  
LotArea            float64  
LotFrontage        float64  
LowQualFinSF      float64  
MSSubClass         int64  
MasVnrArea         float64  
MiscVal            float64  
MoSold             int64  
OpenPorchSF        float64  
OverallCond        int64  
OverallQual        int64  
PoolArea           float64  
ScreenPorch        float64  
TotRmsAbvGrd      int64  
TotalBsmtSF        float64  
WoodDeckSF         float64  
YearBuilt          int64  
YearRemodAdd       int64  
YrSold             int64  
SalePrice           float64  
dtype: object
```

In [186]: `#info  
data.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 [187]: `#value_counts  
data.CentralAir.value_counts()`

Out[187]: Y 1310  
N 69  
Name: CentralAir, dtype: int64

### Step2.Predict Sale Price without Categorical features

In [188]: `df=data.drop("BldgType",axis=1)  
print(df)`

1367	Y	913.0	0.0	0.0	3	187.0
1368	Y	1188.0	0.0	0.0	3	593.0
1369	Y	1220.0	870.0	0.0	3	1079.0
1370	N	796.0	550.0	0.0	2	0.0
1371	Y	1578.0	0.0	0.0	3	0.0
1372	Y	1072.0	0.0	0.0	2	547.0
1373	Y	1221.0	0.0	0.0	2	410.0
1374	Y	953.0	694.0	0.0	3	0.0
1375	Y	2073.0	0.0	0.0	3	790.0
1376	Y	1188.0	1152.0	0.0	4	275.0
1377	Y	1078.0	0.0	0.0	2	49.0
1378	Y	1256.0	0.0	0.0	3	830.0
		BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	...
0		0.0	1	0	150.0	...
1		0.0	0	1	284.0	...
2		0.0	1	0	434.0	...
3		0.0	1	0	540.0	...
4		0.0	1	0	490.0	...
5		0.0	1	0	64.0	...

```
In [189]: df.drop("CentralAir",axis=1)
```

Out[189]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Poo
0	856.0	854.0	0.0	3	706.0	0.0	1	0	150.0	0.0	...	7	
1	1262.0	0.0	0.0	3	978.0	0.0	0	1	284.0	0.0	...	6	
2	920.0	866.0	0.0	3	486.0	0.0	1	0	434.0	0.0	...	7	
3	961.0	756.0	0.0	3	216.0	0.0	1	0	540.0	272.0	...	7	
4	1145.0	1053.0	0.0	4	655.0	0.0	1	0	490.0	0.0	...	8	
5	796.0	566.0	320.0	1	732.0	0.0	1	0	64.0	0.0	...	5	
6	1694.0	0.0	0.0	3	1369.0	0.0	1	0	317.0	0.0	...	8	
7	1107.0	983.0	0.0	3	859.0	32.0	1	0	216.0	228.0	...	7	
8	1022.0	752.0	0.0	2	0.0	0.0	0	0	952.0	205.0	...	7	
9	1077.0	0.0	0.0	2	851.0	0.0	1	0	140.0	0.0	...	5	
10	1040.0	0.0	0.0	3	906.0	0.0	1	0	134.0	0.0	...	5	
11	1182.0	1142.0	0.0	4	998.0	0.0	1	0	177.0	0.0	...	9	
12	912.0	0.0	0.0	2	737.0	0.0	1	0	175.0	0.0	...	5	
13	1494.0	0.0	0.0	3	0.0	0.0	0	0	1494.0	0.0	...	7	
14	1253.0	0.0	0.0	2	733.0	0.0	1	0	520.0	176.0	...	6	
15	854.0	0.0	0.0	2	0.0	0.0	0	0	832.0	0.0	...	7	
16	1004.0	0.0	0.0	2	578.0	0.0	1	0	426.0	0.0	...	6	
17	1296.0	0.0	0.0	2	0.0	0.0	0	0	0.0	0.0	...	4	
18	1114.0	0.0	0.0	3	646.0	0.0	1	0	468.0	0.0	...	5	
19	1339.0	0.0	0.0	3	504.0	0.0	0	0	525.0	0.0	...	5	
20	1158.0	1218.0	0.0	4	0.0	0.0	0	0	1158.0	0.0	...	8	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
22	1795.0	0.0	0.0	3	0.0	0.0	0	0	1777.0	0.0	...	8	
23	1060.0	0.0	0.0	3	840.0	0.0	1	0	200.0	0.0	...	5	
24	1060.0	0.0	0.0	3	188.0	668.0	1	0	204.0	0.0	...	5	
25	1600.0	0.0	0.0	3	0.0	0.0	0	0	1566.0	0.0	...	8	
26	900.0	0.0	0.0	3	234.0	486.0	0	1	180.0	0.0	...	5	
27	1704.0	0.0	0.0	3	1218.0	0.0	1	0	486.0	0.0	...	8	
28	1600.0	0.0	0.0	2	1277.0	0.0	1	0	207.0	0.0	...	5	
29	520.0	0.0	0.0	1	0.0	0.0	0	0	520.0	87.0	...	4	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1349	1048.0	510.0	0.0	3	580.0	0.0	1	0	333.0	0.0	...	5	
1350	804.0	0.0	0.0	2	510.0	0.0	1	0	278.0	154.0	...	5	
1351	1440.0	0.0	0.0	3	678.0	0.0	0	0	762.0	99.0	...	6	
1352	734.0	1104.0	0.0	4	0.0	0.0	0	0	732.0	0.0	...	5	
1353	958.0	0.0	0.0	2	958.0	0.0	0	0	0.0	0.0	...	6	
1354	968.0	0.0	0.0	4	0.0	0.0	0	0	656.0	0.0	...	4	
1355	962.0	830.0	0.0	3	0.0	0.0	1	0	936.0	0.0	...	6	
1356	1126.0	0.0	0.0	3	936.0	0.0	1	0	190.0	0.0	...	5	
1357	1537.0	0.0	0.0	3	0.0	0.0	1	0	1319.0	0.0	...	6	
1358	864.0	0.0	0.0	3	616.0	0.0	0	0	248.0	0.0	...	4	
1359	1932.0	0.0	304.0	2	1336.0	0.0	1	0	596.0	0.0	...	8	
1360	1236.0	0.0	0.0	2	600.0	0.0	1	0	312.0	158.0	...	6	
1361	1040.0	685.0	0.0	3	315.0	110.0	0	0	114.0	216.0	...	7	
1362	1423.0	748.0	0.0	3	0.0	0.0	0	0	588.0	0.0	...	6	
1363	848.0	0.0	0.0	1	697.0	0.0	1	0	151.0	0.0	...	6	
1364	1026.0	981.0	0.0	3	765.0	0.0	1	0	252.0	0.0	...	10	
1365	952.0	0.0	0.0	2	0.0	0.0	0	0	952.0	0.0	...	6	
1366	1422.0	0.0	0.0	3	0.0	0.0	0	0	1422.0	0.0	...	7	
1367	913.0	0.0	0.0	3	187.0	627.0	1	0	0.0	252.0	...	6	
1368	1188.0	0.0	0.0	3	593.0	0.0	0	0	595.0	0.0	...	5	
1369	1220.0	870.0	0.0	3	1079.0	0.0	1	0	141.0	0.0	...	8	
1370	796.0	550.0	0.0	2	0.0	0.0	0	0	560.0	0.0	...	4	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	8	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Po
1372	1072.0	0.0	0.0	2	547.0	0.0	1	0	0.0	0.0	...	5	
1373	1221.0	0.0	0.0	2	410.0	0.0	1	0	811.0	0.0	...	7	
1374	953.0	694.0	0.0	3	0.0	0.0	0	0	953.0	0.0	...	6	
1375	2073.0	0.0	0.0	3	790.0	163.0	1	0	589.0	0.0	...	6	
1376	1188.0	1152.0	0.0	4	275.0	0.0	0	0	877.0	0.0	...	7	
1377	1078.0	0.0	0.0	2	49.0	1029.0	1	0	0.0	112.0	...	5	
1378	1256.0	0.0	0.0	3	830.0	290.0	1	0	136.0	0.0	...	5	

1379 rows × 37 columns

```
In [190]: df3=data.pop("BldgType")
print(df3)
```

```
0      1Fam
1      1Fam
2      1Fam
3      1Fam
4      1Fam
5      1Fam
6      1Fam
7      1Fam
8      1Fam
9      2fmCon
10     1Fam
11     1Fam
12     1Fam
13     1Fam
14     1Fam
15     1Fam
16     1Fam
17     Duplex
18     1Fam
19     1Fam
20     1Fam
21     1Fam
22     1Fam
23     TwnhsE
24     1Fam
25     1Fam
26     1Fam
27     1Fam
28     1Fam
29     1Fam
...
1349    1Fam
1350    1Fam
1351    1Fam
1352    1Fam
1353    TwnhsE
1354    1Fam
1355    1Fam
1356    1Fam
1357    1Fam
1358    1Fam
1359    1Fam
1360    1Fam
1361    1Fam
1362    1Fam
1363    TwnhsE
1364    1Fam
1365    1Fam
1366    1Fam
1367    1Fam
1368    1Fam
1369    1Fam
1370    1Fam
1371    1Fam
1372    TwnhsE
1373    1Fam
1374    1Fam
1375    1Fam
1376    1Fam
1377    1Fam
1378    1Fam
```

Name: BldgType, Length: 1379, dtype: object

```
In [191]: df=data.pop("CentralAir")
df
```

```
Out[191]: 0      Y
1      Y
2      Y
3      Y
4      Y
5      Y
6      Y
7      Y
8      Y
9      Y
10     Y
11     Y
12     Y
13     Y
14     Y
15     Y
16     Y
17     Y
18     Y
19     Y
20     Y
21     Y
22     Y
23     Y
24     Y
25     Y
26     Y
27     Y
28     Y
29     N
..
1349    Y
1350    Y
1351    Y
1352    Y
1353    Y
1354    Y
1355    Y
1356    Y
1357    Y
1358    Y
1359    Y
1360    Y
1361    Y
1362    Y
1363    Y
1364    Y
1365    N
1366    Y
1367    Y
1368    Y
1369    Y
1370    N
1371    Y
1372    Y
1373    Y
1374    Y
1375    Y
1376    Y
1377    Y
1378    Y
```

Name: CentralAir, Length: 1379, dtype: object

In [192]: data

Out[192]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Poo
0	856.0	854.0	0.0	3	706.0	0.0	1	0	150.0	0.0	...	7	
1	1262.0	0.0	0.0	3	978.0	0.0	0	1	284.0	0.0	...	6	
2	920.0	866.0	0.0	3	486.0	0.0	1	0	434.0	0.0	...	7	
3	961.0	756.0	0.0	3	216.0	0.0	1	0	540.0	272.0	...	7	
4	1145.0	1053.0	0.0	4	655.0	0.0	1	0	490.0	0.0	...	8	
5	796.0	566.0	320.0	1	732.0	0.0	1	0	64.0	0.0	...	5	
6	1694.0	0.0	0.0	3	1369.0	0.0	1	0	317.0	0.0	...	8	
7	1107.0	983.0	0.0	3	859.0	32.0	1	0	216.0	228.0	...	7	
8	1022.0	752.0	0.0	2	0.0	0.0	0	0	952.0	205.0	...	7	
9	1077.0	0.0	0.0	2	851.0	0.0	1	0	140.0	0.0	...	5	
10	1040.0	0.0	0.0	3	906.0	0.0	1	0	134.0	0.0	...	5	
11	1182.0	1142.0	0.0	4	998.0	0.0	1	0	177.0	0.0	...	9	
12	912.0	0.0	0.0	2	737.0	0.0	1	0	175.0	0.0	...	5	
13	1494.0	0.0	0.0	3	0.0	0.0	0	0	1494.0	0.0	...	7	
14	1253.0	0.0	0.0	2	733.0	0.0	1	0	520.0	176.0	...	6	
15	854.0	0.0	0.0	2	0.0	0.0	0	0	832.0	0.0	...	7	
16	1004.0	0.0	0.0	2	578.0	0.0	1	0	426.0	0.0	...	6	
17	1296.0	0.0	0.0	2	0.0	0.0	0	0	0.0	0.0	...	4	
18	1114.0	0.0	0.0	3	646.0	0.0	1	0	468.0	0.0	...	5	
19	1339.0	0.0	0.0	3	504.0	0.0	0	0	525.0	0.0	...	5	
20	1158.0	1218.0	0.0	4	0.0	0.0	0	0	1158.0	0.0	...	8	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
22	1795.0	0.0	0.0	3	0.0	0.0	0	0	1777.0	0.0	...	8	
23	1060.0	0.0	0.0	3	840.0	0.0	1	0	200.0	0.0	...	5	
24	1060.0	0.0	0.0	3	188.0	668.0	1	0	204.0	0.0	...	5	
25	1600.0	0.0	0.0	3	0.0	0.0	0	0	1566.0	0.0	...	8	
26	900.0	0.0	0.0	3	234.0	486.0	0	1	180.0	0.0	...	5	
27	1704.0	0.0	0.0	3	1218.0	0.0	1	0	486.0	0.0	...	8	
28	1600.0	0.0	0.0	2	1277.0	0.0	1	0	207.0	0.0	...	5	
29	520.0	0.0	0.0	1	0.0	0.0	0	0	520.0	87.0	...	4	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1349	1048.0	510.0	0.0	3	580.0	0.0	1	0	333.0	0.0	...	5	
1350	804.0	0.0	0.0	2	510.0	0.0	1	0	278.0	154.0	...	5	
1351	1440.0	0.0	0.0	3	678.0	0.0	0	0	762.0	99.0	...	6	
1352	734.0	1104.0	0.0	4	0.0	0.0	0	0	732.0	0.0	...	5	
1353	958.0	0.0	0.0	2	958.0	0.0	0	0	0.0	0.0	...	6	
1354	968.0	0.0	0.0	4	0.0	0.0	0	0	656.0	0.0	...	4	
1355	962.0	830.0	0.0	3	0.0	0.0	1	0	936.0	0.0	...	6	
1356	1126.0	0.0	0.0	3	936.0	0.0	1	0	190.0	0.0	...	5	
1357	1537.0	0.0	0.0	3	0.0	0.0	1	0	1319.0	0.0	...	6	
1358	864.0	0.0	0.0	3	616.0	0.0	0	0	248.0	0.0	...	4	
1359	1932.0	0.0	304.0	2	1336.0	0.0	1	0	596.0	0.0	...	8	
1360	1236.0	0.0	0.0	2	600.0	0.0	1	0	312.0	158.0	...	6	
1361	1040.0	685.0	0.0	3	315.0	110.0	0	0	114.0	216.0	...	7	
1362	1423.0	748.0	0.0	3	0.0	0.0	0	0	588.0	0.0	...	6	
1363	848.0	0.0	0.0	1	697.0	0.0	1	0	151.0	0.0	...	6	
1364	1026.0	981.0	0.0	3	765.0	0.0	1	0	252.0	0.0	...	10	
1365	952.0	0.0	0.0	2	0.0	0.0	0	0	952.0	0.0	...	6	
1366	1422.0	0.0	0.0	3	0.0	0.0	0	0	1422.0	0.0	...	7	
1367	913.0	0.0	0.0	3	187.0	627.0	1	0	0.0	252.0	...	6	
1368	1188.0	0.0	0.0	3	593.0	0.0	0	0	595.0	0.0	...	5	
1369	1220.0	870.0	0.0	3	1079.0	0.0	1	0	141.0	0.0	...	8	
1370	796.0	550.0	0.0	2	0.0	0.0	0	0	560.0	0.0	...	4	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	8	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Po
1372	1072.0	0.0	0.0	2	547.0	0.0	1	0	0.0	0.0	...	5	
1373	1221.0	0.0	0.0	2	410.0	0.0	1	0	811.0	0.0	...	7	
1374	953.0	694.0	0.0	3	0.0	0.0	0	0	953.0	0.0	...	6	
1375	2073.0	0.0	0.0	3	790.0	163.0	1	0	589.0	0.0	...	6	
1376	1188.0	1152.0	0.0	4	275.0	0.0	0	0	877.0	0.0	...	7	
1377	1078.0	0.0	0.0	2	49.0	1029.0	1	0	0.0	112.0	...	5	
1378	1256.0	0.0	0.0	3	830.0	290.0	1	0	136.0	0.0	...	5	

1379 rows × 37 columns

```
In [193]: X=df1.drop("SalePrice",axis=1)
print(X)
```

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	\
0	1	0	150.0	0.0	...	
1	0	1	284.0	0.0	...	
2	1	0	434.0	0.0	...	
3	1	0	540.0	272.0	...	
4	1	0	490.0	0.0	...	
5	1	0	64.0	0.0	...	
6	1	0	317.0	0.0	...	
7	1	0	216.0	228.0	...	
8	0	0	952.0	205.0	...	
9	1	0	140.0	0.0	...	
10	1	0	134.0	0.0	...	
11	1	0	177.0	0.0	...	
12	1	0	175.0	0.0	...	
13	0	0	1494.0	0.0	...	
14	1	0	520.0	176.0	...	
15	0	0	832.0	0.0	...	
16	1	0	426.0	0.0	...	
17	0	0	0.0	0.0	...	

```
In [194]: y=data[["SalePrice"]]
y
```

20	325300.0
21	139400.0
22	230000.0
23	129900.0
24	154000.0
25	256300.0
26	134800.0
27	306000.0
28	207500.0
29	68500.0
...	...
1349	140000.0
1350	110000.0

```
In [195]: from sklearn.model_selection import train_test_split
```

```
In [196]: X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=42)
```

In [197]: X\_train

Out[197]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
1193	1337.0	0.0	0.0	2	266.0	0.0	1	0	1139.0	0.0	...	5	
910	1800.0	0.0	0.0	2	0.0	0.0	0	0	1800.0	0.0	...	5	
1068	1328.0	653.0	0.0	4	622.0	0.0	1	0	500.0	0.0	...	3	
1196	2018.0	0.0	0.0	3	0.0	0.0	0	0	2002.0	0.0	...	5	
1102	959.0	712.0	0.0	3	786.0	0.0	1	0	173.0	0.0	...	5	
447	970.0	0.0	0.0	2	630.0	0.0	1	0	340.0	0.0	...	6	
796	1701.0	0.0	0.0	3	1390.0	0.0	1	0	0.0	0.0	...	5	
543	1320.0	0.0	0.0	3	328.0	551.0	1	0	285.0	240.0	...	6	
901	768.0	0.0	0.0	2	660.0	0.0	0	1	108.0	0.0	...	8	
968	1264.0	0.0	0.0	3	697.0	0.0	1	0	571.0	0.0	...	5	
411	904.0	0.0	0.0	2	0.0	0.0	0	0	884.0	105.0	...	7	
96	1535.0	0.0	0.0	4	0.0	0.0	0	0	0.0	0.0	...	5	
429	624.0	720.0	0.0	4	0.0	0.0	0	0	624.0	96.0	...	5	
361	784.0	0.0	0.0	2	0.0	0.0	0	0	784.0	91.0	...	3	
933	778.0	798.0	0.0	3	0.0	0.0	0	0	770.0	0.0	...	5	
588	1422.0	0.0	0.0	3	0.0	0.0	0	0	978.0	36.0	...	5	
156	854.0	0.0	0.0	2	360.0	0.0	0	0	360.0	0.0	...	6	
528	1389.0	0.0	0.0	2	1071.0	123.0	1	0	195.0	0.0	...	5	
654	616.0	0.0	0.0	2	616.0	0.0	0	0	0.0	129.0	...	7	
857	1636.0	0.0	0.0	3	63.0	0.0	1	0	1560.0	0.0	...	5	
1237	1294.0	0.0	0.0	3	1200.0	0.0	1	0	78.0	0.0	...	5	
534	1496.0	636.0	0.0	1	1441.0	0.0	1	0	55.0	0.0	...	8	
1078	1466.0	1362.0	0.0	4	1150.0	0.0	1	0	316.0	0.0	...	5	
1190	1050.0	0.0	0.0	2	504.0	0.0	0	0	546.0	0.0	...	6	
1312	869.0	349.0	0.0	3	375.0	0.0	0	1	360.0	0.0	...	6	
371	1144.0	0.0	0.0	3	739.0	0.0	1	0	405.0	0.0	...	6	
677	848.0	0.0	0.0	1	662.0	0.0	1	0	186.0	0.0	...	5	
308	596.0	596.0	0.0	3	0.0	0.0	0	0	596.0	137.0	...	5	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	5	
710	866.0	902.0	0.0	3	20.0	0.0	0	0	846.0	0.0	...	5	
...	...	...	...	...	...	...	...	...	...	...	...	...	
474	1801.0	0.0	0.0	1	1247.0	0.0	1	0	254.0	0.0	...	8	
856	1063.0	0.0	0.0	3	354.0	290.0	1	0	412.0	164.0	...	5	
747	1086.0	809.0	0.0	3	0.0	0.0	0	0	712.0	0.0	...	5	
252	1095.0	844.0	0.0	3	0.0	0.0	0	0	1095.0	0.0	...	5	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
1337	1569.0	0.0	0.0	1	988.0	0.0	0	1	398.0	0.0	...	5	
459	1484.0	0.0	0.0	3	998.0	0.0	0	0	486.0	0.0	...	6	
1184	760.0	896.0	0.0	3	0.0	0.0	0	0	746.0	0.0	...	5	
276	910.0	648.0	0.0	4	420.0	0.0	0	0	490.0	0.0	...	5	
955	1022.0	0.0	0.0	2	247.0	465.0	1	0	310.0	226.0	...	4	
1215	1582.0	0.0	0.0	4	812.0	0.0	0	1	812.0	0.0	...	5	
385	1050.0	1028.0	0.0	3	789.0	0.0	1	0	245.0	0.0	...	5	
805	1779.0	0.0	0.0	3	306.0	1085.0	1	0	372.0	0.0	...	4	
343	790.0	784.0	0.0	3	712.0	0.0	1	0	84.0	0.0	...	5	
769	1008.0	0.0	0.0	2	486.0	0.0	0	0	522.0	120.0	...	6	
1332	944.0	896.0	0.0	3	666.0	0.0	1	0	278.0	0.0	...	5	
130	928.0	836.0	0.0	3	821.0	0.0	1	0	107.0	0.0	...	5	
871	936.0	785.0	0.0	3	814.0	0.0	0	1	114.0	0.0	...	5	
1123	1622.0	0.0	0.0	3	1159.0	0.0	1	0	90.0	0.0	...	4	
87	964.0	0.0	0.0	2	713.0	0.0	1	0	163.0	44.0	...	7	
330	1453.0	0.0	0.0	2	1082.0	0.0	1	0	371.0	0.0	...	5	
1238	1902.0	0.0	0.0	3	1406.0	0.0	1	0	496.0	162.0	...	8	
466	886.0	0.0	0.0	2	0.0	0.0	0	0	190.0	80.0	...	8	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
121	1216.0	941.0	0.0	4	445.0	0.0	0	0	479.0	0.0	...	6	
1044	1500.0	1122.0	0.0	3	1032.0	0.0	1	0	431.0	0.0	...	5	
1095	855.0	601.0	0.0	3	311.0	0.0	0	0	544.0	0.0	...	5	
1130	815.0	875.0	0.0	3	0.0	0.0	0	0	815.0	330.0	...	6	
1294	1661.0	0.0	0.0	3	831.0	0.0	1	0	161.0	0.0	...	6	
860	742.0	742.0	0.0	3	0.0	0.0	0	0	742.0	0.0	...	5	
1126	1224.0	0.0	0.0	2	883.0	0.0	1	0	341.0	0.0	...	5	

1034 rows × 36 columns



In [198]: X\_test

Out[198]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
599	1518.0	0.0	0.0	1	1218.0	0.0	0	0	300.0	0.0	...	5	
881	925.0	0.0	0.0	2	338.0	466.0	0	1	121.0	0.0	...	6	
634	1095.0	679.0	0.0	4	0.0	0.0	1	0	1095.0	90.0	...	2	
425	888.0	868.0	0.0	3	742.0	0.0	1	0	130.0	0.0	...	5	
906	1337.0	0.0	0.0	3	699.0	0.0	1	0	638.0	0.0	...	5	
1079	672.0	252.0	0.0	2	348.0	0.0	1	0	324.0	0.0	...	4	
65	1479.0	0.0	0.0	3	1013.0	0.0	1	0	440.0	0.0	...	5	
1351	1440.0	0.0	0.0	3	678.0	0.0	0	0	762.0	99.0	...	7	
479	689.0	689.0	0.0	3	141.0	0.0	0	0	548.0	116.0	...	9	
67	1304.0	983.0	0.0	3	603.0	0.0	0	0	701.0	114.0	...	4	
939	774.0	456.0	0.0	3	384.0	0.0	1	0	363.0	0.0	...	7	
573	1940.0	1254.0	0.0	4	428.0	0.0	0	0	537.0	0.0	...	6	
917	918.0	0.0	0.0	2	0.0	0.0	0	0	918.0	0.0	...	5	
1054	1734.0	0.0	0.0	3	1004.0	0.0	1	0	730.0	0.0	...	5	
941	1442.0	0.0	0.0	2	0.0	0.0	0	0	1442.0	0.0	...	6	
1116	1130.0	0.0	0.0	2	821.0	0.0	1	0	299.0	0.0	...	6	
237	1005.0	1286.0	0.0	4	0.0	0.0	0	0	975.0	0.0	...	5	
578	1054.0	0.0	0.0	3	763.0	0.0	1	0	173.0	0.0	...	7	
772	1358.0	0.0	0.0	2	733.0	0.0	1	0	625.0	0.0	...	5	
303	1898.0	1080.0	0.0	5	0.0	0.0	0	0	710.0	0.0	...	7	
953	720.0	551.0	0.0	4	0.0	0.0	0	0	720.0	108.0	...	5	
783	520.0	600.0	0.0	2	0.0	0.0	0	0	600.0	0.0	...	5	
339	912.0	0.0	0.0	2	773.0	0.0	1	0	115.0	0.0	...	6	
718	1494.0	0.0	0.0	2	437.0	1057.0	1	0	0.0	0.0	...	5	
208	2392.0	0.0	0.0	3	56.0	0.0	0	0	2336.0	0.0	...	5	
624	1465.0	915.0	0.0	3	187.0	723.0	0	0	111.0	0.0	...	5	
1075	1167.0	0.0	0.0	3	645.0	0.0	0	0	270.0	216.0	...	5	
1040	950.0	0.0	0.0	3	412.0	287.0	0	0	251.0	0.0	...	5	
575	1476.0	677.0	0.0	3	904.0	0.0	1	0	536.0	0.0	...	5	
244	1212.0	0.0	0.0	3	506.0	0.0	1	0	0.0	0.0	...	7	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1334	1040.0	0.0	0.0	2	0.0	0.0	0	0	0.0	0.0	...	5	
199	1236.0	0.0	0.0	2	360.0	0.0	0	1	710.0	0.0	...	6	
367	961.0	406.0	0.0	4	241.0	391.0	1	0	229.0	112.0	...	8	
723	1690.0	1589.0	0.0	4	1416.0	0.0	1	0	234.0	0.0	...	5	
354	914.0	0.0	0.0	2	298.0	0.0	0	0	572.0	0.0	...	5	
10	1040.0	0.0	0.0	3	906.0	0.0	1	0	134.0	0.0	...	5	
147	1392.0	1070.0	168.0	4	57.0	0.0	1	0	1335.0	0.0	...	5	
538	846.0	846.0	0.0	3	0.0	0.0	0	0	846.0	0.0	...	5	
282	1541.0	0.0	0.0	3	0.0	0.0	0	0	1541.0	0.0	...	5	
298	1472.0	0.0	0.0	3	1036.0	0.0	1	0	336.0	0.0	...	5	
522	1048.0	0.0	0.0	2	0.0	0.0	0	0	993.0	116.0	...	6	
291	793.0	325.0	0.0	3	507.0	0.0	1	0	286.0	0.0	...	7	
503	880.0	844.0	0.0	3	0.0	0.0	0	0	880.0	0.0	...	5	
903	979.0	979.0	0.0	4	484.0	0.0	0	0	495.0	0.0	...	6	
930	1001.0	634.0	0.0	2	0.0	0.0	0	0	485.0	0.0	...	8	
439	888.0	756.0	0.0	3	386.0	0.0	0	0	342.0	0.0	...	7	
1033	1200.0	0.0	0.0	1	661.0	0.0	1	0	203.0	0.0	...	8	
331	616.0	495.0	0.0	3	236.0	380.0	0	1	0.0	0.0	...	6	
527	1392.0	0.0	0.0	3	1302.0	0.0	1	0	90.0	0.0	...	6	
462	616.0	688.0	0.0	3	0.0	0.0	0	0	264.0	0.0	...	6	
861	1105.0	1169.0	0.0	5	443.0	0.0	0	0	662.0	0.0	...	5	
630	1208.0	0.0	0.0	3	767.0	0.0	1	0	441.0	0.0	...	6	
135	970.0	739.0	0.0	3	0.0	0.0	0	0	970.0	0.0	...	5	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
358	1026.0	665.0	0.0	3	218.0	0.0	0	0	808.0	242.0	...	6	
363	1269.0	0.0	0.0	2	24.0	0.0	0	0	1232.0	0.0	...	5	
618	1142.0	793.0	0.0	3	0.0	0.0	0	0	793.0	252.0	...	7	
561	684.0	684.0	0.0	3	0.0	0.0	0	0	684.0	0.0	...	7	
529	1163.0	511.0	0.0	4	0.0	0.0	0	0	1163.0	0.0	...	7	
567	927.0	988.0	0.0	3	789.0	0.0	1	0	119.0	0.0	...	5	
158	1064.0	703.0	0.0	2	495.0	215.0	1	0	354.0	0.0	...	7	

345 rows × 36 columns

```
In [199]: from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(X_train,y_train)
```

```
Out[199]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

```
In [200]: y_pred=lr.predict(X_test)
y_pred
```

```
[ 9329.85601474,
[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],
```

```
In [201]: from sklearn.metrics import mean_squared_error
```

```
In [202]: mse_In=mean_squared_error(y_test,y_pred)
mse_In
```

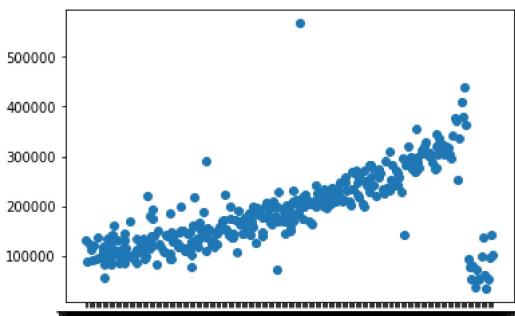
```
Out[202]: 1474827325.5975406
```

### Step3.Create Scatter Plot

```
In [203]: import matplotlib.pyplot as plt
```

```
In [204]: plt.scatter(y_test,y_pred)
```

```
Out[204]: <matplotlib.collections.PathCollection at 0x2a83441b5c0>
```



### Step4.Encode Categorical columns

```
In [205]: gd=pd.get_dummies(data)
gd
```

Out[205]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Poo
0	856.0	854.0	0.0	3	706.0	0.0	1	0	150.0	0.0	...	7	
1	1262.0	0.0	0.0	3	978.0	0.0	0	1	284.0	0.0	...	6	
2	920.0	866.0	0.0	3	486.0	0.0	1	0	434.0	0.0	...	7	
3	961.0	756.0	0.0	3	216.0	0.0	1	0	540.0	272.0	...	7	
4	1145.0	1053.0	0.0	4	655.0	0.0	1	0	490.0	0.0	...	8	
5	796.0	566.0	320.0	1	732.0	0.0	1	0	64.0	0.0	...	5	
6	1694.0	0.0	0.0	3	1369.0	0.0	1	0	317.0	0.0	...	8	
7	1107.0	983.0	0.0	3	859.0	32.0	1	0	216.0	228.0	...	7	
8	1022.0	752.0	0.0	2	0.0	0.0	0	0	952.0	205.0	...	7	
9	1077.0	0.0	0.0	2	851.0	0.0	1	0	140.0	0.0	...	5	
10	1040.0	0.0	0.0	3	906.0	0.0	1	0	134.0	0.0	...	5	
11	1182.0	1142.0	0.0	4	998.0	0.0	1	0	177.0	0.0	...	9	
12	912.0	0.0	0.0	2	737.0	0.0	1	0	175.0	0.0	...	5	
13	1494.0	0.0	0.0	3	0.0	0.0	0	0	1494.0	0.0	...	7	
14	1253.0	0.0	0.0	2	733.0	0.0	1	0	520.0	176.0	...	6	
15	854.0	0.0	0.0	2	0.0	0.0	0	0	832.0	0.0	...	7	
16	1004.0	0.0	0.0	2	578.0	0.0	1	0	426.0	0.0	...	6	
17	1296.0	0.0	0.0	2	0.0	0.0	0	0	0.0	0.0	...	4	
18	1114.0	0.0	0.0	3	646.0	0.0	1	0	468.0	0.0	...	5	
19	1339.0	0.0	0.0	3	504.0	0.0	0	0	525.0	0.0	...	5	
20	1158.0	1218.0	0.0	4	0.0	0.0	0	0	1158.0	0.0	...	8	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
22	1795.0	0.0	0.0	3	0.0	0.0	0	0	1777.0	0.0	...	8	
23	1060.0	0.0	0.0	3	840.0	0.0	1	0	200.0	0.0	...	5	
24	1060.0	0.0	0.0	3	188.0	668.0	1	0	204.0	0.0	...	5	
25	1600.0	0.0	0.0	3	0.0	0.0	0	0	1566.0	0.0	...	8	
26	900.0	0.0	0.0	3	234.0	486.0	0	1	180.0	0.0	...	5	
27	1704.0	0.0	0.0	3	1218.0	0.0	1	0	486.0	0.0	...	8	
28	1600.0	0.0	0.0	2	1277.0	0.0	1	0	207.0	0.0	...	5	
29	520.0	0.0	0.0	1	0.0	0.0	0	0	520.0	87.0	...	4	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1349	1048.0	510.0	0.0	3	580.0	0.0	1	0	333.0	0.0	...	5	
1350	804.0	0.0	0.0	2	510.0	0.0	1	0	278.0	154.0	...	5	
1351	1440.0	0.0	0.0	3	678.0	0.0	0	0	762.0	99.0	...	6	
1352	734.0	1104.0	0.0	4	0.0	0.0	0	0	732.0	0.0	...	5	
1353	958.0	0.0	0.0	2	958.0	0.0	0	0	0.0	0.0	...	6	
1354	968.0	0.0	0.0	4	0.0	0.0	0	0	656.0	0.0	...	4	
1355	962.0	830.0	0.0	3	0.0	0.0	1	0	936.0	0.0	...	6	
1356	1126.0	0.0	0.0	3	936.0	0.0	1	0	190.0	0.0	...	5	
1357	1537.0	0.0	0.0	3	0.0	0.0	1	0	1319.0	0.0	...	6	
1358	864.0	0.0	0.0	3	616.0	0.0	0	0	248.0	0.0	...	4	
1359	1932.0	0.0	304.0	2	1336.0	0.0	1	0	596.0	0.0	...	8	
1360	1236.0	0.0	0.0	2	600.0	0.0	1	0	312.0	158.0	...	6	
1361	1040.0	685.0	0.0	3	315.0	110.0	0	0	114.0	216.0	...	7	
1362	1423.0	748.0	0.0	3	0.0	0.0	0	0	588.0	0.0	...	6	
1363	848.0	0.0	0.0	1	697.0	0.0	1	0	151.0	0.0	...	6	
1364	1026.0	981.0	0.0	3	765.0	0.0	1	0	252.0	0.0	...	10	
1365	952.0	0.0	0.0	2	0.0	0.0	0	0	952.0	0.0	...	6	
1366	1422.0	0.0	0.0	3	0.0	0.0	0	0	1422.0	0.0	...	7	
1367	913.0	0.0	0.0	3	187.0	627.0	1	0	0.0	252.0	...	6	
1368	1188.0	0.0	0.0	3	593.0	0.0	0	0	595.0	0.0	...	5	
1369	1220.0	870.0	0.0	3	1079.0	0.0	1	0	141.0	0.0	...	8	
1370	796.0	550.0	0.0	2	0.0	0.0	0	0	560.0	0.0	...	4	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	8	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallQual	Po
1372	1072.0	0.0	0.0	2	547.0	0.0	1	0	0.0	0.0	...	5	
1373	1221.0	0.0	0.0	2	410.0	0.0	1	0	811.0	0.0	...	7	
1374	953.0	694.0	0.0	3	0.0	0.0	0	0	953.0	0.0	...	6	
1375	2073.0	0.0	0.0	3	790.0	163.0	1	0	589.0	0.0	...	6	
1376	1188.0	1152.0	0.0	4	275.0	0.0	0	0	877.0	0.0	...	7	
1377	1078.0	0.0	0.0	2	49.0	1029.0	1	0	0.0	112.0	...	5	
1378	1256.0	0.0	0.0	3	830.0	290.0	1	0	136.0	0.0	...	5	

1379 rows × 37 columns



### Step5.Predict Sale Price with Categorical features

```
In [206]: x=gd.drop("SalePrice",axis=1)  
x
```

Out[206]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
0	856.0	854.0	0.0	3	706.0	0.0	1	0	150.0	0.0	...	5	
1	1262.0	0.0	0.0	3	978.0	0.0	0	1	284.0	0.0	...	8	
2	920.0	866.0	0.0	3	486.0	0.0	1	0	434.0	0.0	...	5	
3	961.0	756.0	0.0	3	216.0	0.0	1	0	540.0	272.0	...	5	
4	1145.0	1053.0	0.0	4	655.0	0.0	1	0	490.0	0.0	...	5	
5	796.0	566.0	320.0	1	732.0	0.0	1	0	64.0	0.0	...	5	
6	1694.0	0.0	0.0	3	1369.0	0.0	1	0	317.0	0.0	...	5	
7	1107.0	983.0	0.0	3	859.0	32.0	1	0	216.0	228.0	...	6	
8	1022.0	752.0	0.0	2	0.0	0.0	0	0	952.0	205.0	...	5	
9	1077.0	0.0	0.0	2	851.0	0.0	1	0	140.0	0.0	...	6	
10	1040.0	0.0	0.0	3	906.0	0.0	1	0	134.0	0.0	...	5	
11	1182.0	1142.0	0.0	4	998.0	0.0	1	0	177.0	0.0	...	5	
12	912.0	0.0	0.0	2	737.0	0.0	1	0	175.0	0.0	...	6	
13	1494.0	0.0	0.0	3	0.0	0.0	0	0	1494.0	0.0	...	5	
14	1253.0	0.0	0.0	2	733.0	0.0	1	0	520.0	176.0	...	5	
15	854.0	0.0	0.0	2	0.0	0.0	0	0	832.0	0.0	...	8	
16	1004.0	0.0	0.0	2	578.0	0.0	1	0	426.0	0.0	...	7	
17	1296.0	0.0	0.0	2	0.0	0.0	0	0	0.0	0.0	...	5	
18	1114.0	0.0	0.0	3	646.0	0.0	1	0	468.0	0.0	...	5	
19	1339.0	0.0	0.0	3	504.0	0.0	0	0	525.0	0.0	...	6	
20	1158.0	1218.0	0.0	4	0.0	0.0	0	0	1158.0	0.0	...	5	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
22	1795.0	0.0	0.0	3	0.0	0.0	0	0	1777.0	0.0	...	5	
23	1060.0	0.0	0.0	3	840.0	0.0	1	0	200.0	0.0	...	7	
24	1060.0	0.0	0.0	3	188.0	668.0	1	0	204.0	0.0	...	8	
25	1600.0	0.0	0.0	3	0.0	0.0	0	0	1566.0	0.0	...	5	
26	900.0	0.0	0.0	3	234.0	486.0	0	1	180.0	0.0	...	7	
27	1704.0	0.0	0.0	3	1218.0	0.0	1	0	486.0	0.0	...	5	
28	1600.0	0.0	0.0	2	1277.0	0.0	1	0	207.0	0.0	...	6	
29	520.0	0.0	0.0	1	0.0	0.0	0	0	520.0	87.0	...	6	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1349	1048.0	510.0	0.0	3	580.0	0.0	1	0	333.0	0.0	...	6	
1350	804.0	0.0	0.0	2	510.0	0.0	1	0	278.0	154.0	...	7	
1351	1440.0	0.0	0.0	3	678.0	0.0	0	0	762.0	99.0	...	7	
1352	734.0	1104.0	0.0	4	0.0	0.0	0	0	732.0	0.0	...	5	
1353	958.0	0.0	0.0	2	958.0	0.0	0	0	0.0	0.0	...	6	
1354	968.0	0.0	0.0	4	0.0	0.0	0	0	656.0	0.0	...	6	
1355	962.0	830.0	0.0	3	0.0	0.0	1	0	936.0	0.0	...	5	
1356	1126.0	0.0	0.0	3	936.0	0.0	1	0	190.0	0.0	...	5	
1357	1537.0	0.0	0.0	3	0.0	0.0	1	0	1319.0	0.0	...	9	
1358	864.0	0.0	0.0	3	616.0	0.0	0	0	248.0	0.0	...	6	
1359	1932.0	0.0	304.0	2	1336.0	0.0	1	0	596.0	0.0	...	5	
1360	1236.0	0.0	0.0	2	600.0	0.0	1	0	312.0	158.0	...	7	
1361	1040.0	685.0	0.0	3	315.0	110.0	0	0	114.0	216.0	...	6	
1362	1423.0	748.0	0.0	3	0.0	0.0	0	0	588.0	0.0	...	7	
1363	848.0	0.0	0.0	1	697.0	0.0	1	0	151.0	0.0	...	5	
1364	1026.0	981.0	0.0	3	765.0	0.0	1	0	252.0	0.0	...	5	
1365	952.0	0.0	0.0	2	0.0	0.0	0	0	952.0	0.0	...	6	
1366	1422.0	0.0	0.0	3	0.0	0.0	0	0	1422.0	0.0	...	5	
1367	913.0	0.0	0.0	3	187.0	627.0	1	0	0.0	252.0	...	5	
1368	1188.0	0.0	0.0	3	593.0	0.0	0	0	595.0	0.0	...	7	
1369	1220.0	870.0	0.0	3	1079.0	0.0	1	0	141.0	0.0	...	5	
1370	796.0	550.0	0.0	2	0.0	0.0	0	0	560.0	0.0	...	7	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	5	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
1372	1072.0	0.0	0.0	2	547.0	0.0	1	0	0.0	0.0	...	0.0	5
1373	1221.0	0.0	0.0	2	410.0	0.0	1	0	811.0	0.0	...	0.0	5
1374	953.0	694.0	0.0	3	0.0	0.0	0	0	953.0	0.0	...	0.0	5
1375	2073.0	0.0	0.0	3	790.0	163.0	1	0	589.0	0.0	...	0.0	6
1376	1188.0	1152.0	0.0	4	275.0	0.0	0	0	877.0	0.0	...	0.0	9
1377	1078.0	0.0	0.0	2	49.0	1029.0	1	0	0.0	112.0	...	0.0	6
1378	1256.0	0.0	0.0	3	830.0	290.0	1	0	136.0	0.0	...	0.0	6

1379 rows × 36 columns

```
In [207]: Y=gd.pop('SalePrice')
Y
```

```
Out[207]: 0      2085000.0
1      1815000.0
2      2235000.0
3      1400000.0
4      2500000.0
5      1430000.0
6      3070000.0
7      2000000.0
8      1299000.0
9      1180000.0
10     1295000.0
11     3450000.0
12     1440000.0
13     279500.0
14     1570000.0
15     1320000.0
16     1490000.0
17     90000.0
18     1590000.0
19     1390000.0
20     325300.0
21     139400.0
22     230000.0
23     129900.0
24     154000.0
25     256300.0
26     134800.0
27     306000.0
28     207500.0
29     68500.0
...
1349    1400000.0
1350    119000.0
1351    182900.0
1352    192140.0
1353    143750.0
1354    64500.0
1355    186500.0
1356    160000.0
1357    174000.0
1358    120500.0
1359    394617.0
1360    149700.0
1361    197000.0
1362    191000.0
1363    149300.0
1364    310000.0
1365    121000.0
1366    179600.0
1367    129000.0
1368    157900.0
1369    240000.0
1370    112000.0
1371    287090.0
1372    145000.0
1373    185000.0
1374    175000.0
1375    210000.0
1376    266500.0
1377    142125.0
1378    147500.0
Name: SalePrice, Length: 1379, dtype: float64
```

```
In [208]: from sklearn.model_selection import train_test_split
```

```
In [209]: X_train,X_test,y_train,y_test=train_test_split(x,Y,test_size=0.25,random_state=42)
```

In [210]: X\_train

Out[210]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
1193	1337.0	0.0	0.0	2	266.0	0.0	1	0	1139.0	0.0	...	5	
910	1800.0	0.0	0.0	2	0.0	0.0	0	0	1800.0	0.0	...	5	
1068	1328.0	653.0	0.0	4	622.0	0.0	1	0	500.0	0.0	...	3	
1196	2018.0	0.0	0.0	3	0.0	0.0	0	0	2002.0	0.0	...	5	
1102	959.0	712.0	0.0	3	786.0	0.0	1	0	173.0	0.0	...	5	
447	970.0	0.0	0.0	2	630.0	0.0	1	0	340.0	0.0	...	6	
796	1701.0	0.0	0.0	3	1390.0	0.0	1	0	0.0	0.0	...	5	
543	1320.0	0.0	0.0	3	328.0	551.0	1	0	285.0	240.0	...	6	
901	768.0	0.0	0.0	2	660.0	0.0	0	1	108.0	0.0	...	8	
968	1264.0	0.0	0.0	3	697.0	0.0	1	0	571.0	0.0	...	5	
411	904.0	0.0	0.0	2	0.0	0.0	0	0	884.0	105.0	...	7	
96	1535.0	0.0	0.0	4	0.0	0.0	0	0	0.0	0.0	...	5	
429	624.0	720.0	0.0	4	0.0	0.0	0	0	624.0	96.0	...	5	
361	784.0	0.0	0.0	2	0.0	0.0	0	0	784.0	91.0	...	3	
933	778.0	798.0	0.0	3	0.0	0.0	0	0	770.0	0.0	...	5	
588	1422.0	0.0	0.0	3	0.0	0.0	0	0	978.0	36.0	...	5	
156	854.0	0.0	0.0	2	360.0	0.0	0	0	360.0	0.0	...	6	
528	1389.0	0.0	0.0	2	1071.0	123.0	1	0	195.0	0.0	...	5	
654	616.0	0.0	0.0	2	616.0	0.0	0	0	0.0	129.0	...	7	
857	1636.0	0.0	0.0	3	63.0	0.0	1	0	1560.0	0.0	...	5	
1237	1294.0	0.0	0.0	3	1200.0	0.0	1	0	78.0	0.0	...	5	
534	1496.0	636.0	0.0	1	1441.0	0.0	1	0	55.0	0.0	...	8	
1078	1466.0	1362.0	0.0	4	1150.0	0.0	1	0	316.0	0.0	...	5	
1190	1050.0	0.0	0.0	2	504.0	0.0	0	0	546.0	0.0	...	6	
1312	869.0	349.0	0.0	3	375.0	0.0	0	1	360.0	0.0	...	6	
371	1144.0	0.0	0.0	3	739.0	0.0	1	0	405.0	0.0	...	6	
677	848.0	0.0	0.0	1	662.0	0.0	1	0	186.0	0.0	...	5	
308	596.0	596.0	0.0	3	0.0	0.0	0	0	596.0	137.0	...	5	
1371	1578.0	0.0	0.0	3	0.0	0.0	0	0	1573.0	0.0	...	5	
710	866.0	902.0	0.0	3	20.0	0.0	0	0	846.0	0.0	...	5	
...	...	...	...	...	...	...	...	...	...	...	...	...	
474	1801.0	0.0	0.0	1	1247.0	0.0	1	0	254.0	0.0	...	8	
856	1063.0	0.0	0.0	3	354.0	290.0	1	0	412.0	164.0	...	5	
747	1086.0	809.0	0.0	3	0.0	0.0	0	0	712.0	0.0	...	5	
252	1095.0	844.0	0.0	3	0.0	0.0	0	0	1095.0	0.0	...	5	
21	1108.0	0.0	0.0	3	0.0	0.0	0	0	637.0	205.0	...	7	
1337	1569.0	0.0	0.0	1	988.0	0.0	0	1	398.0	0.0	...	5	
459	1484.0	0.0	0.0	3	998.0	0.0	0	0	486.0	0.0	...	6	
1184	760.0	896.0	0.0	3	0.0	0.0	0	0	746.0	0.0	...	5	
276	910.0	648.0	0.0	4	420.0	0.0	0	0	490.0	0.0	...	5	
955	1022.0	0.0	0.0	2	247.0	465.0	1	0	310.0	226.0	...	4	
1215	1582.0	0.0	0.0	4	812.0	0.0	0	1	812.0	0.0	...	5	
385	1050.0	1028.0	0.0	3	789.0	0.0	1	0	245.0	0.0	...	5	
805	1779.0	0.0	0.0	3	306.0	1085.0	1	0	372.0	0.0	...	4	
343	790.0	784.0	0.0	3	712.0	0.0	1	0	84.0	0.0	...	5	
769	1008.0	0.0	0.0	2	486.0	0.0	0	0	522.0	120.0	...	6	
1332	944.0	896.0	0.0	3	666.0	0.0	1	0	278.0	0.0	...	5	
130	928.0	836.0	0.0	3	821.0	0.0	1	0	107.0	0.0	...	5	
871	936.0	785.0	0.0	3	814.0	0.0	0	1	114.0	0.0	...	5	
1123	1622.0	0.0	0.0	3	1159.0	0.0	1	0	90.0	0.0	...	4	
87	964.0	0.0	0.0	2	713.0	0.0	1	0	163.0	44.0	...	7	
330	1453.0	0.0	0.0	2	1082.0	0.0	1	0	371.0	0.0	...	5	
1238	1902.0	0.0	0.0	3	1406.0	0.0	1	0	496.0	162.0	...	8	
466	886.0	0.0	0.0	2	0.0	0.0	0	0	190.0	80.0	...	8	

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	Ov
121	1216.0	941.0	0.0	4	445.0	0.0	0	0	479.0	0.0	...	6	
1044	1500.0	1122.0	0.0	3	1032.0	0.0	1	0	431.0	0.0	...	5	
1095	855.0	601.0	0.0	3	311.0	0.0	0	0	544.0	0.0	...	5	
1130	815.0	875.0	0.0	3	0.0	0.0	0	0	815.0	330.0	...	6	
1294	1661.0	0.0	0.0	3	831.0	0.0	1	0	161.0	0.0	...	6	
860	742.0	742.0	0.0	3	0.0	0.0	0	0	742.0	0.0	...	5	
1126	1224.0	0.0	0.0	2	883.0	0.0	1	0	341.0	0.0	...	5	

1034 rows × 36 columns

```
In [211]: from sklearn.linear_model import LinearRegression
lrr=LinearRegression()
lrr.fit(X_train,y_train)
```

```
Out[211]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

```
In [212]: y_pred=lrr.predict(X_test)  
y_pred
```

```
Out[212]: array([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,  
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372429.94726945, 221672.07367609, 119658.75685737, 100039.78137073,  
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146941.7171239 , 283693.48760668, 106694.19786718, 221733.02172508,  
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111041.26737678, 100160.66573767, 193531.44933265, 206050.88712632,  
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171322.66919858, 224459.70210717, 155548.12334499, 111942.7871775 ,  
316624.83474109, 298116.31992277, 335573.77762719, 86738.88506816,  
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217343.21720916, 120569.43114727, 134354.1238425 , 223860.01643704,  
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131283.81966769, 194221.20494195, 156966.39268757, 268340.58471943,  
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121760.19396639, 134138.79148625, 307661.79229119, 170331.68886912,  
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215661.64584809, 22625.30038962, 132391.85608602, 73443.41948308,  
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268303.4442141 , 116075.01592356, 222914.33666726, 102600.4329218 ,  
226400.49839176, 156093.55758651, 112003.82907499, 218089.37220887,  
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```

```
233147.40044683, 125478.90203711, 175060.50167495, 258877.30470763,
229115.65129666])
```

```
In [213]: from sklearn.metrics import mean_squared_error
```

```
In [214]: MSE=mean_squared_error(y_test,y_pred)
MSE
```

```
Out[214]: 1474827325.5975406
```

### Step6.Normalize using StandardScaler and Predict Sale Price

```
In [215]: from sklearn.preprocessing import StandardScaler
```

```
In [216]: scaler=StandardScaler()
```

```
In [217]: scaled_X_train=scaler.fit_transform(X_train)
scaled_X_train
```

```
Out[217]: array([[ 0.39851037, -0.79290427, -0.11340519, ..., 0.84304574,
       0.65341548,  0.11447318],
       [ 1.57467708, -0.79290427, -0.11340519, ..., 1.14796951,
       1.04559751,  0.8683921 ],
       [ 0.37564751,  0.70143387, -0.11340519, ..., -1.52858358,
      -1.74869949,  0.8683921 ],
       ...,
       [ 1.22157303, -0.79290427, -0.11340519, ..., -0.61381227,
       0.50634721,  0.11447318],
       [-1.11297817,  0.90510323, -0.11340519, ..., 1.08020867,
       0.947552 ,  0.8683921 ],
       [ 0.11145456, -0.79290427, -0.11340519, ..., 0.87692616,
       0.65341548,  0.8683921 ]])
```

```
In [218]: scaled_X_train.shape
```

```
Out[218]: (1034, 36)
```

```
In [219]: scaled_X_test=scaler.transform(X_test)
scaled_X_test
```

```
Out[219]: array([[ 0.85830772, -0.79290427, -0.11340519, ..., 1.01244784,
       0.89852925,  0.11447318],
       [-0.64810018, -0.79290427, -0.11340519, ..., -0.27500808,
       -0.01335818,  0.8683921 ],
       [-0.21624632,  0.76093278, -0.11340519, ..., -2.47723531,
      -1.74869949, -1.39336465],
       ...,
       [-0.04350477,  0.37647826, -0.11340519, ..., -1.86738777,
      -1.74869949,  0.11447318],
       [-0.64301955,  1.46805451, -0.11340519, ..., 0.63976323,
       0.31025619, -1.39336465],
       [-0.29499614,  0.81585486, -0.11340519, ..., 0.47036113,
       0.06514242, -1.39336465]])
```

```
In [220]: from sklearn.metrics import mean_squared_error
```

```
In [221]: Scaler=StandardScaler()
scaled_X_train=Scaler.fit_transform(X_train)
scaled_X_train
```

```
Out[221]: array([[ 0.39851037, -0.79290427, -0.11340519, ..., 0.84304574,
       0.65341548,  0.11447318],
       [ 1.57467708, -0.79290427, -0.11340519, ..., 1.14796951,
       1.04559751,  0.8683921 ],
       [ 0.37564751,  0.70143387, -0.11340519, ..., -1.52858358,
      -1.74869949,  0.8683921 ],
       ...,
       [ 1.22157303, -0.79290427, -0.11340519, ..., -0.61381227,
       0.50634721,  0.11447318],
       [-1.11297817,  0.90510323, -0.11340519, ..., 1.08020867,
       0.947552 ,  0.8683921 ],
       [ 0.11145456, -0.79290427, -0.11340519, ..., 0.87692616,
       0.65341548,  0.8683921 ]])
```

```
In [222]: scaled_X_test=Scaler.transform(X_test)
scaled_X_test

Out[222]: array([[ 0.85830772, -0.79290427, -0.11340519, ..., 1.01244784,
       0.89852925,  0.11447318],
      [-0.64810018, -0.79290427, -0.11340519, ..., -0.27500808,
       -1.01335818,  0.8683921 ],
      [-0.21624632,  0.76093278, -0.11340519, ..., -2.47723531,
       -1.74869949, -1.39336465],
      ...,
      [-0.04350477,  0.37647826, -0.11340519, ..., -1.86738777,
       -1.74869949,  0.11447318],
      [-0.64301955,  1.46805451, -0.11340519, ...,  0.63976323,
       0.31025619, -1.39336465],
      [-0.29499614,  0.81585486, -0.11340519, ...,  0.47036113,
       0.06514242, -1.39336465]])
```

```
In [223]: model1=LinearRegression()
model1.fit(scaled_X_train,y_train)
sy_pred=model1.predict(scaled_X_test)
sy_pred
```

```
Out[223]: array([257434.93050748, 111083.73474764, 100018.0583229 , 204028.53821316,
 207319.25418314, 38036.3092894 , 234153.38582869, 205076.12689603,
 187014.12655231, 235636.78799029, 100976.5094378 , 304119.53646984,
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 73639.52734136, 86011.81491626, 110000.03909849, 231518.89807255,
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 203877.63015227, 109803.05085706, 194633.36256922, 99160.35922074,
 230240.81594383, 211484.77477047, 198342.97693778, 109749.28794505,
 95564.23930695, 235396.44527242, 184775.90385426, 188806.96222982,
 265328.01705249, 245862.13668722, 107422.0040252 , 164786.63106781,
 268303.44421406, 116075.01592358, 222914.33666728, 102600.43292176,
 226400.49839176, 156093.55758654, 112003.82907507, 218089.37220885,
 81085.92660268, 85015.51341445, 98208.34263402, 304262.27895917,
 143757.79043401, 195367.35122022, 241835.21911119, 60944.84144924,
 143731.15831783, 110459.58351738, 438412.24654495, 123265.07239639,
 116119.87930815, 277961.71617821, 201687.81739716, 237947.02580915,
 206117.84987327, 99453.60459335, 115124.57035038, 209795.31353812,
 167537.15563228, 162970.2651776 , 151279.43057794, 189724.86274099,
 96455.47006121, 168652.8258692 , 83051.31596961, 171340.42959833,
 176868.3371188 , 175644.68961809, 131414.67048232, 204543.74960378,
```

```
233147.40044682, 125478.90203713, 175060.50167486, 258877.30470761,
229115.6512967 ])
```

```
In [224]: mse_In1=mean_squared_error(y_test, sy_pred)
mse_In1
print("mean square error using standard scalar:",mse_In1)

mean square error using standard scalar: 1474827325.5975823
```

#### Step7.Normalize using MinMaxScaler and Predict Sale Price

```
In [225]: from sklearn.preprocessing import MinMaxScaler
mm_scaler=MinMaxScaler()
```

```
In [226]: mmX_train=mm_scaler.fit_transform(X_train)
mmX_train
```

```
Out[226]: array([[0.21133051, 0.        , 0.        , ..., 0.90769231, 0.81666667,
       0.5        ],
       [0.32016925, 0.        , 0.        , ..., 0.97692308, 0.95        ,
       0.75        ],
       [0.20921486, 0.31622276, 0.        , ..., 0.36923077, 0.        ,
       0.75        ],
       ...,
       [0.28749412, 0.        , 0.        , ..., 0.57692308, 0.76666667,
       0.5        ],
       [0.07146215, 0.35932203, 0.        , ..., 0.96153846, 0.91666667,
       0.75        ],
       [0.18476728, 0.        , 0.        , ..., 0.91538462, 0.81666667,
       0.75        ]])
```

```
In [227]: mmX_test=mm_scaler.transform(X_test)
mmX_test
```

```
Out[227]: array([[0.2538787 , 0.        , 0.        , ..., 0.94615385, 0.9        ,
       0.5        ],
       [0.11448049, 0.        , 0.        , ..., 0.65384615, 0.25        ,
       0.75        ],
       [0.15444288, 0.32881356, 0.        , ..., 0.15384615, 0.        ,
       0.        ],
       ...,
       [0.17042783, 0.24745763, 0.        , ..., 0.29230769, 0.        ,
       0.5        ],
       [0.11495063, 0.47845036, 0.        , ..., 0.86153846, 0.7        ,
       0.        ],
       [0.14715562, 0.34043584, 0.        , ..., 0.82307692, 0.61666667,
       0.        ]])
```

```
In [228]: model3=LinearRegression()
model3.fit(mmX_train,y_train)
```

```
Out[228]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

```
In [229]: mms_y_pred=model3.predict(mmX_test)  
mms_y_pred
```

```
Out[229]: array([257434.93050748, 111083.73474764, 100018.0583229 , 204028.53821316,
207319.25418314, 38036.3092894 , 234153.38582869, 205076.12689603,
187014.12655231, 235636.78799029, 100976.5094378 , 304119.53646984,
101769.64600715, 288758.46001591, 204767.89338331, 145002.4727962 ,
248322.97436853, 151533.68038638, 209697.39458715, 278312.23574155,
93329.85601463, 153784.1486838 , 163237.87451135, 241495.91212888,
372429.94726951, 221672.07367603, 119658.75685733, 100039.78137072,
319435.02892076, 172088.64665032, 258772.64470115, 199597.36129638,
156349.69283197, 142311.22500108, 204807.33161322, 379608.17785439,
124176.23377553, 141127.25006143, 273832.43247648, 212547.0420556 ,
169474.57176143, 123305.65719309, 200341.24016795, 377957.32307109,
146941.7171239 , 283693.48760665, 106694.19786715, 221733.02172498,
87733.4701401 , 295005.66546303, 125250.6201929 , 53569.11256027,
133831.05086115, 170901.42929711, 213273.17757298, 110818.14723239,
103893.81849705, 200665.21921041, 137764.84464906, 311840.64900749,
53035.52267581, 184866.47797854, 154675.79963876, 298477.53600001,
78162.54074685, 323728.93535801, 169417.44138502, 112718.07937644,
200547.87648959, 205739.30910765, 130292.88475649, 271581.37221157,
119489.76459236, 126635.29232493, 77972.26780485, 138563.37305274,
35555.51251474, 163787.98080894, 271929.1369019 , 115260.62742894,
319958.55004398, 218515.16541523, 291730.97232826, 211176.53228417,
93761.81278832, 263031.10150316, 141886.39666991, 118491.50416098,
143580.34191292, 278395.8537048 , 265558.84177935, 300839.51324223,
182673.3443797 , 168604.54926019, 148322.24627427, 213781.03244608,
247750.58740996, 221693.90686781, 274474.96290584, 242912.73279158,
111041.26737678, 100160.6657377 , 193531.44933267, 206050.88712628,
154584.47386049, 217440.52365088, 210904.23539268, 125864.27688701,
171322.66919868, 224459.70210705, 155548.12334504, 111942.78717749,
316624.83474108, 298116.31992275, 335573.77762719, 86738.8850682 ,
146692.58771907, 228471.54032911, 123374.07354541, 204867.33148188,
217343.2172092 , 120569.43114714, 134354.12384257, 223860.01643707,
138360.76267459, 210765.75439351, 145423.97229839, 291155.26974381,
183089.17904137 , 98716.55524168, 323896.46706842, 178447.30657099,
123643.15346305, 134345.24799852, 309423.49789816, 136836.97808939,
282083.02092585, 132621.22372555, 90821.15043383, 164193.14328597,
147333.60026799, 162030.92949967, 177621.20328223, 254054.45691356,
119092.92298358, 140081.84030887, 236509.39317217, 318578.4396165 ,
105538.81578044, 192023.58779378, 174531.98294676, 146314.75164223,
95146.4623636 , 250936.32825849, 304056.57810764, 55008.42319126,
281810.05395731, 93402.68236917, 138283.44603758, 166415.31922933,
209758.26998557, 205602.16976193, 177026.58819392, 248435.62725108,
145190.55457312, 133283.94785761, 171593.43394517, 344925.23412389,
181194.80288335, 98431.28117765, 131287.46561778, 110849.96802293,
131283.81966778, 194221.20494201, 156966.39268746, 268340.58471954,
211804.83660278, 151971.72881378, 115946.37551381, 243618.89320954,
136292.76068278, 265335.41730192, 302175.59064211, 85054.45272485,
146007.43532806, 150439.28821419, 159145.83079284, 232246.23120847,
231571.1353201 , 139178.99313682, 355030.61932406, 127659.29864187,
235339.23724176, 116707.21916903, 103103.75191053, 159574.2341845 ,
149485.12469047, 408898.40096808, 335368.65026121, 290500.91914897,
281845.43486757, 275341.81718413, 321705.52591335, 307549.31796982,
201661.19536927, 142047.81494963, 157876.45367581, 258695.10810312,
207592.92972056, 146121.60182467, 107032.82242136, 151245.32235212,
100804.20363832, 296980.23153202, 341413.30991675, 255158.86136984,
147006.34954488, 199721.9925516 , 127291.41093952, 264030.58756771,
121760.1939664 , 134138.79148626, 307661.79229112, 178331.68886981,
173593.89056667, 567240.20119423, 182277.7226559 , 144159.48526094,
199515.17896317, 107691.20503763, 181383.00130506, 328401.72330995,
139225.20214767, 197660.10401735, 116340.37479633, 54949.57465393,
199375.67314464, 272915.38777825, 119902.62390782, 197573.81604287,
231881.98496931, 119555.98822724, 128709.54702316, 289158.8058549 ,
200733.61408615, 364228.39366111, 119308.94568442, 124086.72254035,
225161.62739516, 171005.22659816, 93631.9176723 , 178506.48207582,
215661.64584802, 226255.3003896 , 132391.85608605, 73443.41948312,
242913.00968347, 141042.39030918, 114633.38186074, 89093.07024775,
208503.15479643, 172828.98634139, 270797.22136179, 253693.44924279,
103518.85057202, 220521.27460717, 185034.32129264, 169518.90296988,
154846.17459054, 224605.38839966, 85972.23828463, 151323.12661365,
180628.92554339, 200106.98029839, 179499.81727936, 223755.69902623,
73639.52734136, 86011.81491626, 110000.03909849, 231518.89807255,
153369.35976788, 320899.35432164, 194412.83170321, 57741.65743008,
203877.63015227, 109803.05085706, 194633.36256922, 99160.35922074,
230240.81594383, 211484.77477047, 198342.97693778, 109749.28794505,
95564.23930695, 235396.44527242, 184775.90385426, 188806.96222982,
265328.01705249, 245862.13668722, 107422.0040252 , 164786.63106781,
268303.44421406, 116075.01592358, 222914.33666728, 102600.43292176,
226400.49839176, 156093.55758654, 112003.82907507, 218089.37220885,
81085.92660268, 85015.51341445, 98208.34263402, 304262.27895917,
143757.79043401, 195367.35122022, 241835.21911119, 60944.84144924,
143731.15831783, 110459.58351738, 438412.24654495, 123265.07239639,
116119.87930815, 277961.71617821, 201687.81739716, 237947.02580915,
206117.84987327, 99453.60459335, 115124.57035038, 209795.31353812,
167537.15563228, 162970.2651776 , 151279.43057794, 189724.86274099,
96455.47006121, 168652.8258692 , 83051.31596961, 171340.42959833,
176868.3371188 , 175644.68961809, 131414.67048232, 204543.74960378,
```

```
233147.40044682, 125478.90203713, 175060.50167486, 258877.30470761,  
229115.6512967 ])
```

```
In [230]: mmMSE=mean_squared_error(y_test,mms_y_pred)
```

```
In [231]: print("Mean sqaure error using MinMaxScaler:",mmMSE)
```

```
Mean sqaure error using MinMaxScaler: 1474827325.5975811
```

#### Step8.Predict using Ridge and SGD Regression

```
In [239]: from sklearn.linear_model import SGDRegressor
sgd=SGDRegressor()
sgd.fit(scaled_X_train, y_train)
sgd_y_pred=sgd.predict(scaled_X_test)
print("Predictions of scaled data using SGDRegressor:", sgd_y_pred)
```

Predictions of scaled data using SGDRegressor: [250851.08701713 113046.15345709 110215.57231865 200690.21553301  
 208255.36365841 47034.73843394 233831.98270146 203942.89751742  
 194157.43704549 224848.84415329 104786.90478342 285927.60031221  
 112247.39033602 284506.85909405 207296.47131102 155213.02630626  
 238672.53242113 153962.43406735 211228.46968196 261423.72279589  
 102083.28516987 159508.27265748 169538.87624881 244375.06010953  
 357650.91616614 218668.96522354 128385.35232838 103249.78111936  
 312982.4591815 175061.28026342 240682.60998631 200821.70956329  
 147153.21088862 147074.20825085 209860.62512088 361489.66473804  
 124028.33879649 145942.81316447 261494.13296702 210485.55011114  
 172223.15038761 129287.01359267 190049.40028832 366128.94264503  
 154790.3800747 280102.19680578 110626.22891403 215574.05135203  
 91387.12921027 292956.23675168 129378.29586996 58512.92146235  
 147302.83961466 170103.96783047 208611.35774562 120608.36551101  
 110598.49859265 197978.31856349 143974.35357487 303499.19716547  
 55792.63348257 186101.28978829 156979.00619636 285569.92561712  
 88046.32972286 316345.2947259 167366.85389997 120377.04830319  
 200130.20238792 208966.77505062 136069.7255166 268811.26584678  
 129880.91612209 132967.66660034 80465.8903749 137372.56289361  
 44326.47550692 170022.01948623 267422.33019354 121571.02025789  
 317872.21119126 213457.14156838 284491.83489067 208188.5658527  
 104589.08681713 254259.40900486 142080.207281 114679.12174299  
 138771.34892194 279943.95166722 264542.67429881 287029.7359947  
 181642.84115515 163919.30623042 156782.17218052 212155.13636597  
 243886.96738247 216779.633019 271146.21510057 239350.94874882  
 114853.2412123 105878.50295633 194687.61629086 204326.44333928  
 155142.24170734 211848.77363691 214405.69140606 133673.21024797  
 177332.33942174 226588.61585729 160694.13400918 115570.62170025  
 310936.62379005 284274.70825307 320061.67925837 94696.046271  
 150924.18558875 228288.84251664 128640.1859062 202629.943196  
 218200.2209175 118158.78250045 132032.03214889 218754.26448825  
 141270.17951156 209133.38881404 146056.69851842 285455.12082552  
 180738.92546607 101071.55452799 310780.42733594 169374.92026214  
 126888.52337069 138261.50936761 293510.68119291 145830.26697951  
 275828.38379144 136348.70989642 96988.89570827 167741.12827323  
 149815.22656343 166610.29401491 179073.4604493 246900.41121939  
 126200.39958332 142955.01301409 231462.85665889 306077.22825801  
 110960.46012431 195376.74523845 170904.51359999 149589.47488674  
 96793.03093433 247305.30162233 301858.59424996 58470.47056675  
 274701.74202198 99891.46462489 145400.82483068 170138.67703668  
 212144.89527954 189688.88783278 180060.78829098 250137.04470811  
 157893.77079671 135786.93208563 172092.81054341 322348.4373301  
 177172.62907044 101467.71004957 128655.54678455 116644.14179487  
 137300.92472209 188613.36402934 154389.34085197 262371.97406526  
 208622.63232356 156261.96436979 115702.98827925 239987.23007589  
 130205.14232415 262167.65778449 299207.69551207 93631.80238483  
 143812.42373437 147260.99307113 163858.03328841 229811.39827074  
 229155.50182926 145113.73390798 332648.82143072 130508.017802  
 231574.34262925 119983.96267855 106500.12535036 168175.92844473  
 149668.44573733 392875.07989813 328598.44653042 285366.70587729  
 279372.54190014 271810.43323098 306855.13295791 296116.34997407  
 203371.65069488 140470.43179008 160529.00474037 210736.52969394  
 207209.28551848 147602.14042871 111316.76043823 161285.20938472  
 109156.41329861 289430.46676731 335434.9364487 252977.85402853  
 154075.15442073 198118.83308252 133422.89679149 260348.87335848  
 138776.50799071 137913.3293974 301154.41307913 174043.83617789  
 175488.36260327 514438.52637105 185566.93886465 147067.38826808  
 194694.40296533 117018.58512198 178628.65636224 319560.00822801  
 144699.83290919 199587.86153301 128118.42668569 68106.31436715  
 197171.74587675 264074.55286023 124186.09050836 195989.55037768  
 235074.02511108 122527.754431 133908.798196 273588.63869008  
 206487.11255228 354315.22637195 122153.54673697 131217.51102153  
 219384.95779473 174230.80708777 90791.36866263 180106.06094426  
 214215.31947767 222484.26050932 141160.05421634 84739.65963394  
 241383.14013834 136253.74122713 123577.63933239 97108.53691404  
 209659.54305957 166997.7954833 272209.03224303 245662.56819911  
 108992.12672892 228370.63307283 192757.17716878 169588.48264611  
 161519.6287375 224453.25831433 91784.83682114 147818.66273271  
 176408.10853678 198188.73533599 180300.47915672 215136.68965183  
 28166.47470073 87168.40624526 116267.31356404 224008.35965364  
 159548.28831737 303915.06645982 195997.88771663 64205.57781099  
 207200.03099167 116344.76631827 195391.16665352 108370.69429338  
 229711.97394503 208230.28607324 203300.59127753 112307.69302091  
 101480.66718546 234651.71796636 178810.17637122 192263.38093019  
 260863.18861466 238577.82545967 114247.79571307 158203.11788476  
 261235.26266404 120018.84887211 214334.98726304 110589.04301375  
 228812.33833055 159172.44159021 119745.2266805 215120.62661922  
 91540.09096617 92658.23396281 101173.49068194 298492.5273976  
 70175.60494488 187866.82349679 243849.19006854 68821.63500256  
 145323.57229819 119357.88695377 420387.35497599 124631.63993908  
 120143.45558428 267021.09989005 197973.50867811 238467.96943022  
 210208.41791904 107050.33702569 122827.66352525 207193.6237502  
 159442.62093416 163117.12613184 152691.33855964 193423.73169172  
 98312.30708896 170324.771287 83724.66561554 159883.02163719  
 181373.67130207 169625.21294556 132549.3443558 208320.59720371

```
227792.9349017 129907.80790589 180653.05812503 257177.14200734  
224898.19144258]
```

```
C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:128: FutureWarning: max_iter and tol parameters have been added in <class 'sklearn.linear_model.stochastic_gradient.SGDRegressor'> 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 [240]: sgd_mse=mean_squared_error(y_test, sgd_y_pred)  
print("SGD_MSE:",sgd_mse)
```

```
SGD_MSE: 1487957680.751117
```

```
In [241]: from sklearn.linear_model import Ridge
ridge=Ridge()
ridge.fit(scaled_X_train, y_train)
ridge_y_pred=ridge.predict(scaled_X_test)
print("Predictions of scaled data using RIDGERegression:", ridge_y_pred)
```

Predictions of scaled data using RIDGERegression: [257421.40327467 111048.93900918 100148.22166502 204007.69016285  
 207318.26438778 38130.16627273 234150.19679274 205083.79807217  
 186990.35389928 235496.28665193 100966.52935332 303934.63164847  
 101890.94872879 288779.98473831 204801.28875069 145108.44985327  
 248228.38505616 151485.3620995 209733.2274515 278197.4394422  
 93455.6609326 153804.93005254 163194.49635267 241430.2463605  
 372368.42646834 221632.71135779 119760.90284387 100047.58843771  
 319413.64552184 172029.21920287 258742.7512024 199493.44526659  
 156253.40634584 142260.62082583 204826.1806726 379453.76863261  
 124049.03967105 140938.68021813 273742.38050574 212502.29963116  
 169496.97954299 123279.27640286 200131.43501379 377624.34223268  
 147067.67507791 283730.24445742 186654.11168627 221721.98335033  
 87859.6015935 294987.18055758 125202.71399397 53519.12559123  
 133851.65120566 170814.11457786 213257.89409118 110890.21052619  
 103962.51733658 200705.10120865 137825.92554828 311801.15478353  
 53110.79651703 184799.6096954 154734.86644008 298380.40493944  
 78246.19078408 323702.02510789 169466.06274122 112823.93682159  
 200532.47961727 205732.7434815 130430.98213571 271576.54141384  
 119517.69643887 126813.06031022 77948.07913159 138459.94428071  
 35594.69872621 163851.24303414 271911.16049004 115170.8409182  
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 281794.68069314 93471.49702787 138431.7751144 166584.56732248  
 209797.30479015 205691.94925356 177054.65626513 248576.02992629  
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 181892.55310315 98456.02843269 131282.04325445 110934.36779116  
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 147042.32133388 199835.1635117 127396.28236212 264028.87507205  
 121842.35752249 134224.48204824 387690.96067651 170299.19516249  
 173634.61888396 566895.37162083 182267.3152515 144230.71243381  
 199542.41967282 107725.24929291 181340.3055302 328346.05768061  
 139169.93510577 197676.26414789 116515.40028976 54920.97367886  
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 226446.39169676 156039.73352165 112118.2621359 218009.48577344  
 81138.79394674 85183.53240143 98120.58664156 304221.85064095  
 143825.10439664 195254.9013155 241807.65208589 60898.21659707  
 143757.7855566 110569.79788548 438249.62394314 123258.66869765  
 116123.99585904 277966.01915293 201690.38568323 237978.5356511  
 206247.6433917 99449.19364681 115124.23894833 209778.46658561  
 167434.01104678 162852.00375468 151360.56894059 189760.65510995  
 96349.80598172 168767.97321727 83076.25780314 171281.0121331  
 176931.55688827 175568.0530263 131382.65018492 204547.73197275

```
233033.33528768 125501.91800535 175116.80170643 258825.79733597
228967.00891845]
```

```
In [242]: ridge_mse=mean_squared_error(y_test, ridge_y_pred)
print("RIDGE_MSE:",ridge_mse)

RIDGE_MSE: 1473019452.6343954
```

```
In [ ]: from sklearn.linear_model import Lasso
lasso=Lasso()
lasso.fit(scaled_X_train, y_train)
lasso_y_pred=lasso.predict(scaled_X_test)
print("Predictions of scaled data using LASSORegression:", lasso_y_pred)
```

```
In [243]: lasso_mse=mean_squared_error(y_test, lasso_y_pred)
print("LASSO_MSE:",lasso_mse)

LASSO_MSE: 1474731226.7767062
```

### Step9.RMSE

```
In [246]: import numpy as np
#RMSE without CD
print("RMSE without one hot encoding: ",np.sqrt(mse_In))
#RMSE with CD
print("RMSE with one hot encoding: ",np.sqrt(MSE))
#RMSE with CD and Standard Scaling
print("RMSE with OHE and SS: ",np.sqrt(mse_In1))
#RMSE with CD and MinMaxScaling
print("RMSE with OHE and MinMaxScaling: ",np.sqrt(mmMSE))
#RMSE of SGDRegressor with CD and StandardScaler
print("RMSE of SGDRegressor with OHE and StandardScaler: ",np.sqrt(sgd_mse))
#RMSE of Ridgecv with CD and Standard Scaler
print("RMSE of Ridgecv with OHE and Standard Scaler: ",np.sqrt(ridge_mse))
#RMSE of LassoCV with CD and StandardScaler
print("RMSE of LassoCV with OHE and StandardScaler",np.sqrt(lasso_mse))

RMSE without one hot encoding: 38403.48064430541
RMSE with one hot encoding: 38403.48064430541
RMSE with OHE and SS: 38403.48064430596
RMSE with OHE and MinMaxScaling: 38403.48064430594
RMSE of SGDRegressor with OHE and StandardScaler: 38574.054502361
RMSE of Ridgecv with OHE and Standard Scaler: 38379.93554755395
RMSE of LassoCV with OHE and StandardScaler 38402.229450602295
```