

PML_lab-4_205229118_Mahalakshmi.S

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0.0.1 Lab4. House Price Prediction using LR with Regularization

<https://www.dataquest.io/blog/kaggle-getting-started/>

0.0.2 Step1. [Import dataset]. Using Pandas, import “Ames_House_Sales_Cropped.csv” file and print properties such as head, shape, columns, dtype, info and value_counts.

```
[31]: import pandas as pd
import csv
```

```
[32]: house=pd.read_csv("Ames_House_Sales_Cropped.csv")
house
```

```
[32]:
```

	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	
...	
1374	1Fam	Y	953.0	694.0	0.0	3	
1375	1Fam	Y	2073.0	0.0	0.0	3	
1376	1Fam	Y	1188.0	1152.0	0.0	4	
1377	1Fam	Y	1078.0	0.0	0.0	2	
1378	1Fam	Y	1256.0	0.0	0.0	3	

	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	...	OverallQual	\
0	706.0	0.0	1	0	...	7	
1	978.0	0.0	0	1	...	6	
2	486.0	0.0	1	0	...	7	
3	216.0	0.0	1	0	...	7	
4	655.0	0.0	1	0	...	8	
...	
1374	0.0	0.0	0	0	...	6	
1375	790.0	163.0	1	0	...	6	
1376	275.0	0.0	0	0	...	7	
1377	49.0	1029.0	1	0	...	5	

```

1378      830.0      290.0      1      0 ...      5

      PoolArea  ScreenPorch  TotRmsAbvGrd  TotalBsmtSF  WoodDeckSF  YearBuilt  \
0      0.0      0.0      8      856.0      0.0      2003
1      0.0      0.0      6      1262.0      298.0      1976
2      0.0      0.0      6      920.0      0.0      2001
3      0.0      0.0      7      756.0      0.0      1915
4      0.0      0.0      9      1145.0      192.0      2000
...      ...      ...      ...      ...      ...
1374      0.0      0.0      7      953.0      0.0      1999
1375      0.0      0.0      7      1542.0      349.0      1978
1376      0.0      0.0      9      1152.0      0.0      1941
1377      0.0      0.0      5      1078.0      366.0      1950
1378      0.0      0.0      6      1256.0      736.0      1965

```

```

      YearRemodAdd  YrSold  SalePrice
0      2003      2008      208500.0
1      1976      2007      181500.0
2      2002      2008      223500.0
3      1970      2006      140000.0
4      2000      2008      250000.0
...      ...      ...
1374      2000      2007      175000.0
1375      1988      2010      210000.0
1376      2006      2010      266500.0
1377      1996      2010      142125.0
1378      1965      2008      147500.0

```

[1379 rows x 39 columns]

```
[33]: house.head()
```

```

[33]:  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

      BsmtFinSF1  BsmtFinSF2  BsmtFullBath  BsmtHalfBath  ...  OverallQual  \
0      706.0      0.0              1              0 ...              7
1      978.0      0.0              0              1 ...              6
2      486.0      0.0              1              0 ...              7
3      216.0      0.0              1              0 ...              7
4      655.0      0.0              1              0 ...              8

```

```

      PoolArea  ScreenPorch  TotRmsAbvGrd  TotalBsmtSF  WoodDeckSF  YearBuilt  \

```

0	0.0	0.0	8	856.0	0.0	2003
1	0.0	0.0	6	1262.0	298.0	1976
2	0.0	0.0	6	920.0	0.0	2001
3	0.0	0.0	7	756.0	0.0	1915
4	0.0	0.0	9	1145.0	192.0	2000

	YearRemodAdd	YrSold	SalePrice
0	2003	2008	208500.0
1	1976	2007	181500.0
2	2002	2008	223500.0
3	1970	2006	140000.0
4	2000	2008	250000.0

[5 rows x 39 columns]

```
[34]: house.shape
```

```
[34]: (1379, 39)
```

```
[35]: df=pd.read_csv("Ames_House_Sales_Cropped.csv")
df
```

```
[35]:
```

	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	
...	
1374	1Fam	Y	953.0	694.0	0.0	3	
1375	1Fam	Y	2073.0	0.0	0.0	3	
1376	1Fam	Y	1188.0	1152.0	0.0	4	
1377	1Fam	Y	1078.0	0.0	0.0	2	
1378	1Fam	Y	1256.0	0.0	0.0	3	

	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	...	OverallQual	\
0	706.0	0.0	1	0	...	7	
1	978.0	0.0	0	1	...	6	
2	486.0	0.0	1	0	...	7	
3	216.0	0.0	1	0	...	7	
4	655.0	0.0	1	0	...	8	
...	
1374	0.0	0.0	0	0	...	6	
1375	790.0	163.0	1	0	...	6	
1376	275.0	0.0	0	0	...	7	
1377	49.0	1029.0	1	0	...	5	
1378	830.0	290.0	1	0	...	5	

	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	WoodDeckSF	YearBuilt	\
0	0.0	0.0	8	856.0	0.0	2003	
1	0.0	0.0	6	1262.0	298.0	1976	
2	0.0	0.0	6	920.0	0.0	2001	
3	0.0	0.0	7	756.0	0.0	1915	
4	0.0	0.0	9	1145.0	192.0	2000	
...	
1374	0.0	0.0	7	953.0	0.0	1999	
1375	0.0	0.0	7	1542.0	349.0	1978	
1376	0.0	0.0	9	1152.0	0.0	1941	
1377	0.0	0.0	5	1078.0	366.0	1950	
1378	0.0	0.0	6	1256.0	736.0	1965	

	YearRemodAdd	YrSold	SalePrice
0	2003	2008	208500.0
1	1976	2007	181500.0
2	2002	2008	223500.0
3	1970	2006	140000.0
4	2000	2008	250000.0
...
1374	2000	2007	175000.0
1375	1988	2010	210000.0
1376	2006	2010	266500.0
1377	1996	2010	142125.0
1378	1965	2008	147500.0

[1379 rows x 39 columns]

```
[36]: d=df.columns
      d
```

```
[36]: 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')
```

```
[37]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1379 entries, 0 to 1378
Data columns (total 39 columns):
#   Column              Non-Null Count  Dtype
#   ...
```

```

---      -----      -----      -----
0  BldgType      1379 non-null  object
1  CentralAir    1379 non-null  object
2  1stFlrSF      1379 non-null  float64
3  2ndFlrSF      1379 non-null  float64
4  3SsnPorch     1379 non-null  float64
5  BedroomAbvGr  1379 non-null  int64
6  BsmtFinSF1    1379 non-null  float64
7  BsmtFinSF2    1379 non-null  float64
8  BsmtFullBath  1379 non-null  int64
9  BsmtHalfBath  1379 non-null  int64
10 BsmtUnfSF      1379 non-null  float64
11 EnclosedPorch 1379 non-null  float64
12 Fireplaces    1379 non-null  int64
13 FullBath      1379 non-null  int64
14 GarageArea    1379 non-null  float64
15 GarageCars    1379 non-null  int64
16 GarageYrBlt   1379 non-null  float64
17 GrLivArea     1379 non-null  float64
18 HalfBath      1379 non-null  int64
19 KitchenAbvGr  1379 non-null  int64
20 LotArea       1379 non-null  float64
21 LotFrontage   1379 non-null  float64
22 LowQualFinSF  1379 non-null  float64
23 MSSubClass    1379 non-null  int64
24 MasVnrArea    1379 non-null  float64
25 MiscVal       1379 non-null  float64
26 MoSold        1379 non-null  int64
27 OpenPorchSF   1379 non-null  float64
28 OverallCond   1379 non-null  int64
29 OverallQual    1379 non-null  int64
30 PoolArea      1379 non-null  float64
31 ScreenPorch   1379 non-null  float64
32 TotRmsAbvGrd  1379 non-null  int64
33 TotalBsmtSF   1379 non-null  float64
34 WoodDeckSF    1379 non-null  float64
35 YearBuilt     1379 non-null  int64
36 YearRemodAdd  1379 non-null  int64
37 YrSold        1379 non-null  int64
38 SalePrice     1379 non-null  float64
dtypes: float64(21), int64(16), object(2)
memory usage: 420.3+ KB

```

```
[38]: df.dtypes
```

```
[38]: 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

```

```
[39]: df.dtypes.value_counts()
```

```

[39]: float64    21
      int64     16
      object     2
      dtype: int64

```

0.0.3 Step2. [Predict Sale Price without Categorical features].

Drop both categorical features – BldgType and CentralAir (USE drop() and pop() methods)

```
[40]: house.drop(['BldgType'],axis=1)  ###drop() method
```

```
[40]:
```

	CentralAir	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	\
0	Y	856.0	854.0	0.0	3	706.0	
1	Y	1262.0	0.0	0.0	3	978.0	
2	Y	920.0	866.0	0.0	3	486.0	
3	Y	961.0	756.0	0.0	3	216.0	
4	Y	1145.0	1053.0	0.0	4	655.0	
...	
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	...	OverallQual	\
0	0.0	1	0	150.0	...	7	
1	0.0	0	1	284.0	...	6	
2	0.0	1	0	434.0	...	7	
3	0.0	1	0	540.0	...	7	
4	0.0	1	0	490.0	...	8	
...	
1374	0.0	0	0	953.0	...	6	
1375	163.0	1	0	589.0	...	6	
1376	0.0	0	0	877.0	...	7	
1377	1029.0	1	0	0.0	...	5	
1378	290.0	1	0	136.0	...	5	

	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	WoodDeckSF	YearBuilt	\
0	0.0	0.0	8	856.0	0.0	2003	
1	0.0	0.0	6	1262.0	298.0	1976	
2	0.0	0.0	6	920.0	0.0	2001	
3	0.0	0.0	7	756.0	0.0	1915	
4	0.0	0.0	9	1145.0	192.0	2000	
...	
1374	0.0	0.0	7	953.0	0.0	1999	
1375	0.0	0.0	7	1542.0	349.0	1978	
1376	0.0	0.0	9	1152.0	0.0	1941	
1377	0.0	0.0	5	1078.0	366.0	1950	
1378	0.0	0.0	6	1256.0	736.0	1965	

	YearRemodAdd	YrSold	SalePrice
0	2003	2008	208500.0
1	1976	2007	181500.0

```

2          2002    2008    223500.0
3          1970    2006    140000.0
4          2000    2008    250000.0
...
1374       2000    2007    175000.0
1375       1988    2010    210000.0
1376       2006    2010    266500.0
1377       1996    2010    142125.0
1378       1965    2008    147500.0

```

[1379 rows x 38 columns]

```
[41]: df.pop('CentralAir')
```

```

[41]: 0      Y
      1      Y
      2      Y
      3      Y
      4      Y
      ..
1374   Y
1375   Y
1376   Y
1377   Y
1378   Y
Name: CentralAir, Length: 1379, dtype: object

```

Prepare X matrix (36 feature columns) and y vector (ie., SalePrice column)

```

[42]: data1 = ['1stFlrSF', '2ndFlrSF', '3SsnPorch', 'BedroomAbvGr', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtFullBath', 'BsmtHalfBath', 'BsmtUnf',
               'GrLivArea', 'HalfBath', 'KitchenAbvGr', 'LotArea', 'LotFrontage', 'LowQualFinSF', 'MSSubClass', 'MoSold', 'OpenPorchSF', 'OverallCond', 'OverallQual', 'PoolArea', 'ScreenPorch', 'TotRmsAbvGrd',
               'YearBuilt', 'YearRemodded']
X=house[data1]
data2 = ['SalePrice']
y=house.SalePrice

```

```
[43]: X
```

```

[43]:   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
...
1374    953.0    694.0         0.0              3         0.0         0.0
1375   2073.0         0.0         0.0              3      790.0      163.0

```


1376	1188.0	1152.0	0.0	4	275.0	0.0
1377	1078.0	0.0	0.0	2	49.0	1029.0
1378	1256.0	0.0	0.0	3	830.0	290.0

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	\
0	1	0	150.0	0.0	...	5	
1	0	1	284.0	0.0	...	8	
2	1	0	434.0	0.0	...	5	
3	1	0	540.0	272.0	...	5	
4	1	0	490.0	0.0	...	5	
...	
1374	0	0	953.0	0.0	...	5	
1375	1	0	589.0	0.0	...	6	
1376	0	0	877.0	0.0	...	9	
1377	1	0	0.0	112.0	...	6	
1378	1	0	136.0	0.0	...	6	

	OverallQual	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	\
0	7	0.0	0.0	8	856.0	
1	6	0.0	0.0	6	1262.0	
2	7	0.0	0.0	6	920.0	
3	7	0.0	0.0	7	756.0	
4	8	0.0	0.0	9	1145.0	
...	
1374	6	0.0	0.0	7	953.0	
1375	6	0.0	0.0	7	1542.0	
1376	7	0.0	0.0	9	1152.0	
1377	5	0.0	0.0	5	1078.0	
1378	5	0.0	0.0	6	1256.0	

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
0	0.0	2003	2003	2008
1	298.0	1976	1976	2007
2	0.0	2001	2002	2008
3	0.0	1915	1970	2006
4	192.0	2000	2000	2008
...
1374	0.0	1999	2000	2007
1375	349.0	1978	1988	2010
1376	0.0	1941	2006	2010
1377	366.0	1950	1996	2010
1378	736.0	1965	1965	2008

[1379 rows x 36 columns]

[44]: y

```
[44]: 0      208500.0
      1      181500.0
      2      223500.0
      3      140000.0
      4      250000.0
      ...
      1374    175000.0
      1375    210000.0
      1376    266500.0
      1377    142125.0
      1378    147500.0
      Name: SalePrice, Length: 1379, dtype: float64
```

Split dataset for training and testing as `X_train`, `X_test`, `y_train`, `y_test` (use 25% test size).

```
[45]: from sklearn.model_selection import train_test_split
```

```
[46]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.
      ↪75, test_size=0.25)
```

```
[47]: X_train, X_test, y_train, y_test
```

```
[47]: (      1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  BsmtFinSF1  BsmtFinSF2  \
      903      979.0      979.0          0.0           4         484.0          0.0
      582     1482.0      780.0          0.0           4         871.0          0.0
      151     1149.0      467.0          0.0           3         370.0          0.0
      523     1092.0         0.0          0.0           2         895.0          0.0
      940     1050.0         0.0          0.0           3         915.0          0.0
      ...      ...      ...      ...      ...      ...      ...
      833      808.0      785.0          0.0           3           0.0          0.0
      982     1306.0         0.0          0.0           1         900.0          0.0
      1096    1640.0         0.0        216.0           3         728.0          0.0
      884     2069.0         0.0          0.0           4         425.0          0.0
      1091    1265.0         0.0          96.0           3         633.0          0.0

      BsmtFullBath  BsmtHalfBath  BsmtUnfSF  EnclosedPorch  ...  OverallCond  \
      903           0           0        495.0           0.0  ...           6
      582           1           0        611.0           0.0  ...           5
      151           0           0        779.0          183.0  ...           7
      523           1           0        197.0           0.0  ...           5
      940           1           0        135.0           0.0  ...           6
      ...      ...      ...      ...      ...  ...
      833           0           0        808.0           0.0  ...           5
      982           1           0        406.0           0.0  ...           5
      1096          1           0        568.0           0.0  ...           7
      884           1           0        160.0           0.0  ...           7
      1091          0           1        586.0           0.0  ...           8
```

	OverallQual	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	\
903	6	0.0	0.0	8	979.0	
582	8	0.0	0.0	10	1482.0	
151	6	0.0	0.0	5	1149.0	
523	5	0.0	122.0	6	1092.0	
940	5	0.0	0.0	6	1050.0	
...	
833	6	0.0	0.0	7	808.0	
982	6	0.0	0.0	5	1306.0	
1096	6	0.0	0.0	7	1296.0	
884	7	0.0	0.0	9	585.0	
1091	5	0.0	0.0	6	1219.0	

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
903	0.0	1946	1950	2007
582	168.0	2003	2003	2008
151	0.0	1926	2004	2007
523	268.0	1957	1957	2006
940	0.0	1961	1961	2006
...
833	342.0	1992	1993	2009
982	170.0	2005	2005	2009
1096	108.0	1954	2006	2008
884	0.0	1960	2007	2008
1091	0.0	1965	1999	2008

[1034 rows x 36 columns],

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	\
1173	2076.0	0.0	0.0	2	1386.0	0.0	
759	980.0	0.0	0.0	3	400.0	480.0	
860	742.0	742.0	0.0	3	0.0	0.0	
363	1269.0	0.0	0.0	2	24.0	0.0	
32	1234.0	0.0	0.0	3	0.0	0.0	
...	
788	1559.0	0.0	0.0	2	338.0	0.0	
539	774.0	656.0	0.0	3	0.0	0.0	
818	1120.0	0.0	0.0	3	932.0	0.0	
333	1192.0	403.0	0.0	2	388.0	0.0	
1377	1078.0	0.0	0.0	2	49.0	1029.0	

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	\
1173	1	0	690.0	0.0	...	5	
759	0	0	100.0	0.0	...	5	
860	0	0	742.0	0.0	...	5	
363	0	0	1232.0	0.0	...	5	
32	0	0	1234.0	0.0	...	5	

...
788	1	0	1221.0	230.0	...	6
539	0	0	384.0	0.0	...	5
818	1	0	108.0	0.0	...	5
333	0	0	552.0	108.0	...	5
1377	1	0	0.0	112.0	...	6

	OverallQual	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	\
1173	10	0.0	0.0	7	2076.0	
759	5	0.0	0.0	6	980.0	
860	6	0.0	0.0	8	742.0	
363	8	0.0	144.0	6	1256.0	
32	8	0.0	0.0	7	1234.0	
...	
788	5	0.0	0.0	5	1559.0	
539	7	0.0	0.0	8	384.0	
818	4	0.0	0.0	5	1040.0	
333	6	0.0	0.0	6	940.0	
1377	5	0.0	0.0	5	1078.0	

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
1173	216.0	2006	2006	2006
759	68.0	1967	1967	2006
860	36.0	2005	2005	2009
363	146.0	2004	2005	2010
32	0.0	2007	2007	2008
...
788	0.0	1948	1973	2007
539	100.0	2000	2000	2007
818	168.0	1961	1961	2007
333	0.0	1940	2000	2006
1377	366.0	1950	1996	2010

[345 rows x 36 columns],

903	145000.0
582	305000.0
151	152000.0
523	141000.0
940	136500.0

...	
833	178000.0
982	196000.0
1096	224000.0
884	242000.0
1091	179900.0

Name: SalePrice, Length: 1034, dtype: float64,

1173	465000.0
------	----------

```

759      135500.0
860      174000.0
363      192000.0
32       179900.0
...
788      153500.0
539      170000.0
818      129000.0
333      140000.0
1377     142125.0
Name: SalePrice, Length: 345, dtype: float64)

```

Create LinearRegression model, fit on training set and predict on test set

```
[48]: from sklearn.linear_model import LinearRegression
```

```
[49]: #create a linear regression object
model = LinearRegression()
#train a model
model.fit( X_train,y_train)
```

```
[49]: LinearRegression()
```

```
[50]: y_pred = model.predict(X_test)
y_pred
```

```
[50]: array([343843.65754748,  95029.38549773, 169794.24889062, 211304.43611183,
        210398.63861163,  75073.75727441, 111613.78843825, 144962.28248309,
        178539.06759803, 113796.00153267,  91671.80644439, 112023.44969957,
        106306.57435984, 222129.07385228, 174818.66894032, 108839.68591425,
        180008.73409479, 136905.97584528, 101504.92408718, 141319.2703993 ,
        169394.68535725, 141770.09535832,  49816.7114211 , 209753.53862673,
        220739.27697146, 102349.50412943, 100955.66549767,  88788.24616048,
        179979.31978142, 229207.93369507, 241499.59810583, 188573.8133879 ,
        138375.20136656, 112016.38806082, 198329.03194489, 213189.51413244,
        231224.16110581, 154516.5968845 , 128722.31576005, 151342.18758167,
        173073.15762992, 194854.4806387 , 283405.38148664, 117922.26895843,
        73247.28522753, 112162.98929892, 170780.47241076, 324588.27230496,
        240759.96079044, 376707.91509053, 265351.68182457,  52797.83793952,
        207565.38162927, 137146.55832762, 191801.41285861, 204542.17349544,
        240015.20819539, 191464.28519076,  88148.39470493, 223662.22798159,
        218008.19170056, 252613.22316689, 211216.46271609, 121252.1408625 ,
        189858.25835928, 114656.39533588, 311195.87421964, 160167.35381274,
        161506.36275148, 145894.30802898, 209508.32111458, 244821.78260324,
        44364.86688781, 142116.28241324, 219838.56665944, 127267.1121915 ,
        129126.64201766,  71205.84496587, 316361.93753265, 111323.07906176,
        172203.96169718, 118218.47248644, 375364.49984387, 186482.14424936,
        133975.88760024, 195839.25614804, 252274.12652459,  95868.28330894,
```

96467.0065489 , 193469.76575237, 237346.83053708, 317316.53283583,
 104338.1839894 , 169324.18407076, 147120.54908734, 162379.31436992,
 114252.41919604, 241078.17358412, 180049.15726857, 374334.07520483,
 182872.24886861, 389594.21545611, 100083.54193546, 179894.28103745,
 86343.17988349, 161582.77420357, 190120.30064037, 370966.34888382,
 217181.34609185, 193768.54543017, 268317.70720833, 180129.69249009,
 84368.38112288, 203167.6505222 , 136923.11025027, 120723.16582559,
 78874.36006872, 240952.34883125, 302603.0658477 , 197655.47810502,
 132960.04668215, 227244.22062148, 145305.85479897, 160068.57599372,
 263402.82296716, 223641.15730607, 233353.84989055, 236842.74634309,
 123161.64295409, 318429.78602217, 236085.05579585, 125656.71370325,
 201346.2142906 , 212772.07888998, 232278.40725318, 241399.84028217,
 339662.57382198, 165932.85963536, 249188.74082173, 148432.75729727,
 313322.94694106, 281458.57291332, 198250.88898276, 307062.99875764,
 212830.2678777 , 195185.84256723, 198296.71248287, 241384.50337242,
 278124.91272708, 293537.34106261, 138422.97188358, 199705.71261725,
 122685.60179981, 134101.98706842, 233156.2788514 , 173867.95240058,
 127079.30119989, 275272.46587755, 149614.4985271 , 116838.56773206,
 179349.89036903, 205296.45988448, 280704.42302814, 220472.76452976,
 181736.32767933, 72906.5192921 , 209955.36277415, 162241.12368289,
 168417.29546066, 187516.28570373, 178130.39219583, 283402.3917727 ,
 266787.97378909, 235228.03906513, 175463.25683058, 208772.99037848,
 181954.46424814, 96087.44546314, 97373.3039676 , 156479.21529055,
 246842.73204126, 84439.97994498, 207358.2905316 , 183480.20272491,
 295485.06817171, 110016.25396967, 280948.15927398, 150143.37721436,
 140699.35578697, 111522.96936896, 203426.31539381, 309617.66605417,
 222605.94078697, 152126.4755989 , 208944.97909766, 200269.93244918,
 129421.54124901, 327464.78729045, 150540.69768937, 138957.65876576,
 240236.91935131, 120076.1806853 , 152807.2110174 , 116919.20757723,
 269626.12282073, 193157.06313123, 109296.41387479, 155573.91414951,
 168412.70691209, 192130.8872861 , 258759.02562345, 146189.29338464,
 193676.5935051 , 185695.54792075, 205471.4708046 , 204388.63726063,
 147153.80828935, 149691.45422258, 127272.57565986, 109813.26239063,
 97890.08593742, 66559.03971253, 182196.79195973, 121240.38793064,
 124492.85617282, 187414.63011091, 233925.97634536, 121505.6186186 ,
 151713.93743585, 248904.82020454, 223745.3477359 , 206925.87759428,
 311348.59321594, 114916.79869721, 98359.79222636, 104630.75578839,
 238044.2406506 , 127425.30219648, 107660.43604895, 139091.94792935,
 161006.3049412 , 149546.31747296, 191680.71710645, 212247.00270499,
 71997.50881137, 253388.24859653, 161542.76759104, 163304.93672006,
 164299.49390882, 81040.29144344, 130689.37322539, 175833.68795763,
 312826.74380163, 261361.54029388, 222710.0253466 , 236803.75840854,
 125591.75631497, 118622.07676837, 185032.35923665, 156047.64563767,
 181953.94767967, 185024.21450639, 159390.20954353, 217728.91375373,
 173461.00212053, 149525.83708286, 271526.4382511 , 189721.30939484,
 247996.35077442, 123758.83075548, 146413.20190542, 206782.80814967,
 145757.39891842, 235760.080671 , 255195.70046381, 83013.32995505,

```
274441.95664722, 152272.98095611, 173640.58390295, 122195.40672676,
96642.84610201, 112395.07266538, 155844.40737419, 234640.57994914,
82659.12415209, 165264.69402393, 123807.15190975, 117234.8014548 ,
63526.9835117 , 164142.7821134 , 119562.68646113, 133563.35601578,
180300.01635249, 194468.87415699, 112137.51810579, 175908.09300241,
198497.30947856, 211527.53277822, -887.83369126, 149940.98575298,
223437.7602771 , 322575.87534534, 214588.14225161, 269683.6773258 ,
250148.10809315, 210958.46363519, 221064.3637554 , 145134.69029348,
314669.0756796 , 202093.96054347, 153567.04196271, 195343.53299302,
187135.53691539, 212421.32205353, 131766.79441047, 160504.86756532,
221870.87604526, 180381.69525633, 181513.70086275, 270279.43930549,
376513.47803224, 215030.37472794, 227078.69915926, 271347.61961927,
307094.34305625, 124269.9338672 , 198860.50918028, 132753.38157498,
154140.18509407, 240226.46491656, 253087.2949071 , 223504.51287066,
212863.77291139, 191172.96194414, 225182.43049873, 202435.23860725,
225215.69134337, 168757.20189302, 89133.2624629 , 113800.09896732,
164258.34732077, 192132.29723948, 116433.33223496, 159725.8773468 ,
134803.88016751])
```

Compute Mean Squared Error (MSE) on actual values and predicted values (you will get output as 1474827326.0).

```
[51]: from sklearn.metrics import mean_squared_error
```

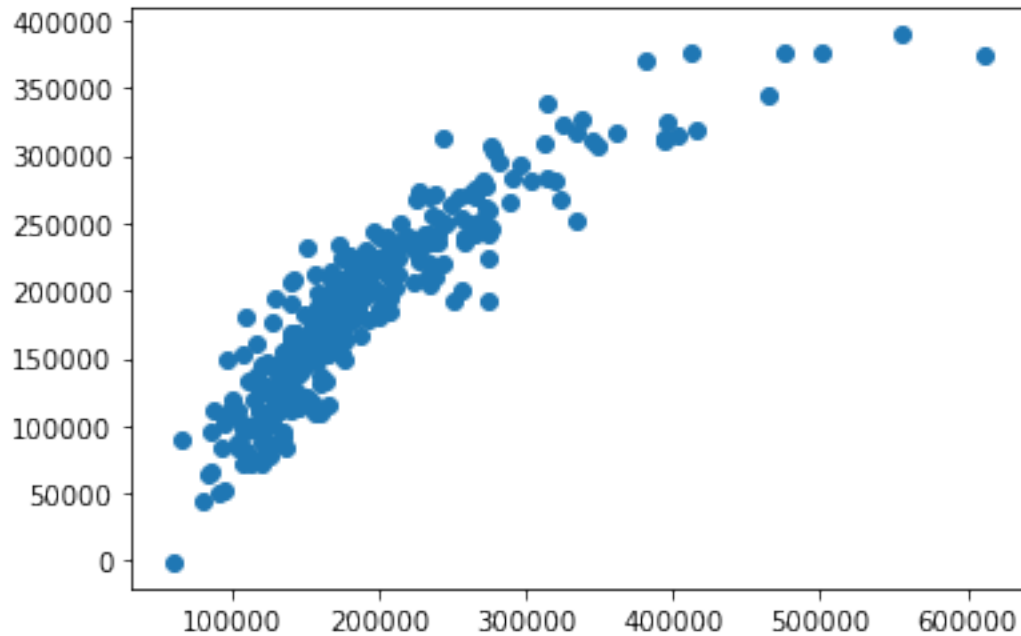
```
[52]: mse=mean_squared_error(y_test,y_pred)
mse
```

```
[52]: 1127595525.476533
```

0.0.4 Step3. [Create Scatter Plot]. Plot Scatterplot between y_test and y_pred.

```
[53]: import matplotlib.pyplot as plt
plt.scatter(y_test,y_pred)
```

```
[53]: <matplotlib.collections.PathCollection at 0x1f1906ff7c0>
```



0.0.5 Step4. [Encode Categorical columns]. Using `get_dummies()` method, perform one hot encoding on the two categorical columns, `BldgType` and `CentralAir`. Now, you will get 5 columns for `BldgType` variable and 2 columns for `CentralAir` column. So, now you have 43 independent variables and 1 dependent variable.

```
[62]: house=pd.read_csv("Ames_House_Sales_Cropped.csv")
house
```

```
[62]:
```

	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	
...	
1374	1Fam	Y	953.0	694.0	0.0	3	
1375	1Fam	Y	2073.0	0.0	0.0	3	
1376	1Fam	Y	1188.0	1152.0	0.0	4	
1377	1Fam	Y	1078.0	0.0	0.0	2	
1378	1Fam	Y	1256.0	0.0	0.0	3	

	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	...	OverallQual	\
0	706.0	0.0	1	0	...	7	
1	978.0	0.0	0	1	...	6	
2	486.0	0.0	1	0	...	7	

3	216.0	0.0	1	0 ...	7
4	655.0	0.0	1	0 ...	8
...
1374	0.0	0.0	0	0 ...	6
1375	790.0	163.0	1	0 ...	6
1376	275.0	0.0	0	0 ...	7
1377	49.0	1029.0	1	0 ...	5
1378	830.0	290.0	1	0 ...	5

	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	WoodDeckSF	YearBuilt	\
0	0.0	0.0	8	856.0	0.0	2003	
1	0.0	0.0	6	1262.0	298.0	1976	
2	0.0	0.0	6	920.0	0.0	2001	
3	0.0	0.0	7	756.0	0.0	1915	
4	0.0	0.0	9	1145.0	192.0	2000	
...	
1374	0.0	0.0	7	953.0	0.0	1999	
1375	0.0	0.0	7	1542.0	349.0	1978	
1376	0.0	0.0	9	1152.0	0.0	1941	
1377	0.0	0.0	5	1078.0	366.0	1950	
1378	0.0	0.0	6	1256.0	736.0	1965	

	YearRemodAdd	YrSold	SalePrice
0	2003	2008	208500.0
1	1976	2007	181500.0
2	2002	2008	223500.0
3	1970	2006	140000.0
4	2000	2008	250000.0
...
1374	2000	2007	175000.0
1375	1988	2010	210000.0
1376	2006	2010	266500.0
1377	1996	2010	142125.0
1378	1965	2008	147500.0

[1379 rows x 39 columns]

```
[63]: encode_house=pd.get_dummies(house, columns=["CentralAir","BldgType"])
      encode_house.head()
```

```
[63]:
```

	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	

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	YearRemodAdd	\
0	1	0	150.0	0.0	...	2003	
1	0	1	284.0	0.0	...	1976	
2	1	0	434.0	0.0	...	2002	
3	1	0	540.0	272.0	...	1970	
4	1	0	490.0	0.0	...	2000	

	YrSold	SalePrice	CentralAir_N	CentralAir_Y	BldgType_1Fam	\
0	2008	208500.0	0	1	1	
1	2007	181500.0	0	1	1	
2	2008	223500.0	0	1	1	
3	2006	140000.0	0	1	1	
4	2008	250000.0	0	1	1	

	BldgType_2fmCon	BldgType_Duplex	BldgType_Twnhs	BldgType_TwnhsE
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 44 columns]

```
[64]: encode_house.columns
```

```
[64]: Index(['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', 'CentralAir_N', 'CentralAir_Y',
        'BldgType_1Fam', 'BldgType_2fmCon', 'BldgType_Duplex', 'BldgType_Twnhs',
        'BldgType_TwnhsE'],
        dtype='object')
```

```
[65]: encode_house.shape
```

```
[65]: (1379, 44)
```

0.0.6 Step5. [Predict Sale Price with Categorical features]

Prepare X matrix (43 feature columns) and y vector (ie., SalePrice column)

```
[75]: data3 = ['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', 'CentralAir_N', 'CentralAir_Y',
'BldgType_1Fam', 'BldgType_2fmCon', 'BldgType_Duplex', 'BldgType_Twnhs',
'BldgType_TwnhsE']
encode_X=house[data1]
data4 = ['SalePrice']
encode_y=house.SalePrice

```

[76]: encode_X

```

[76]:      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
...      ...      ...      ...      ...      ...      ...
1374       953.0    694.0         0.0             3          0.0         0.0
1375      2073.0         0.0         0.0             3         790.0        163.0
1376      1188.0   1152.0         0.0             4         275.0         0.0
1377      1078.0         0.0         0.0             2          49.0       1029.0
1378      1256.0         0.0         0.0             3         830.0        290.0

      BsmtFullBath  BsmtHalfBath  BsmtUnfSF  EnclosedPorch  ...  OverallCond  \
0                 1             0       150.0           0.0  ...             5
1                 0             1       284.0           0.0  ...             8
2                 1             0       434.0           0.0  ...             5
3                 1             0       540.0          272.0  ...             5
4                 1             0       490.0           0.0  ...             5
...      ...      ...      ...      ...      ...
1374              0             0       953.0           0.0  ...             5
1375              1             0       589.0           0.0  ...             6
1376              0             0       877.0           0.0  ...             9
1377              1             0          0.0          112.0  ...             6
1378              1             0       136.0           0.0  ...             6

      OverallQual  PoolArea  ScreenPorch  TotRmsAbvGrd  TotalBsmtSF  \
0                7         0.0         0.0             8         856.0
1                6         0.0         0.0             6        1262.0
2                7         0.0         0.0             6         920.0
3                7         0.0         0.0             7         756.0
4                8         0.0         0.0             9        1145.0
...      ...      ...      ...      ...      ...
1374              6         0.0         0.0             7         953.0

```

1375	6	0.0	0.0	7	1542.0
1376	7	0.0	0.0	9	1152.0
1377	5	0.0	0.0	5	1078.0
1378	5	0.0	0.0	6	1256.0

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
0	0.0	2003	2003	2008
1	298.0	1976	1976	2007
2	0.0	2001	2002	2008
3	0.0	1915	1970	2006
4	192.0	2000	2000	2008
...
1374	0.0	1999	2000	2007
1375	349.0	1978	1988	2010
1376	0.0	1941	2006	2010
1377	366.0	1950	1996	2010
1378	736.0	1965	1965	2008

[1379 rows x 36 columns]

```
[77]: encode_y
```

```
[77]: 0      208500.0
      1      181500.0
      2      223500.0
      3      140000.0
      4      250000.0
      ...
      1374    175000.0
      1375    210000.0
      1376    266500.0
      1377    142125.0
      1378    147500.0
```

Name: SalePrice, Length: 1379, dtype: float64

Split dataset for training and testing

```
[78]: encode_X_train, encode_X_test, encode_y_train, encode_y_test =
      ↪ train_test_split(encode_X, encode_y, train_size=0.75, test_size=0.25)
      encode_X_train, encode_X_test, encode_y_train, encode_y_test
```

```
[78]: (   1stFlrSF  2ndFlrSF  3SsnPorch  BedroomAbvGr  BsmtFinSF1  BsmtFinSF2  \
      223    798.0    689.0        0.0           3         94.0         0.0
      673   1178.0         0.0        0.0           3        1084.0         0.0
      718   1494.0         0.0        0.0           2         437.0        1057.0
      136    875.0         0.0        0.0           2         209.0         0.0
      684   1776.0         0.0        0.0           4          0.0         0.0
      ..     ...     ...     ...     ...     ...     ...
      ...     ...     ...     ...     ...     ...     ...
```

965	1504.0	0.0	0.0	2	16.0	0.0
482	1368.0	0.0	0.0	2	0.0	0.0
562	1402.0	0.0	0.0	2	0.0	0.0
581	1828.0	0.0	0.0	3	48.0	0.0
949	985.0	0.0	0.0	3	595.0	0.0

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	\
223	0	0	641.0	0.0	...		4
673	0	1	92.0	0.0	...		6
718	1	0	0.0	0.0	...		5
136	1	0	506.0	0.0	...		7
684	1	0	1584.0	0.0	...		5
..		
965	0	0	1330.0	0.0	...		5
482	0	0	1368.0	0.0	...		5
562	0	2	1258.0	0.0	...		5
581	0	0	1774.0	0.0	...		5
949	0	0	390.0	0.0	...		8

	OverallQual	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	\
223	6	0.0	0.0	7	735.0	
673	5	0.0	0.0	5	1176.0	
718	8	0.0	216.0	6	1494.0	
136	5	0.0	0.0	5	715.0	
684	5	0.0	0.0	9	1584.0	
..	
965	7	0.0	0.0	7	1346.0	
482	7	0.0	0.0	6	1368.0	
562	7	0.0	0.0	7	1258.0	
581	9	0.0	260.0	9	1822.0	
949	5	0.0	0.0	6	985.0	

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
223	0.0	1945	1950	2010
673	224.0	1973	2000	2008
718	0.0	1995	1996	2006
136	48.0	1931	1993	2009
684	0.0	1958	1958	2009
..
965	156.0	2005	2006	2008
482	132.0	2005	2006	2006
562	120.0	2006	2007	2007
581	0.0	2007	2007	2007
949	210.0	1977	1977	2008

[1034 rows x 36 columns],

1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	\
----------	----------	-----------	--------------	------------	------------	---

646	1419.0	0.0	0.0	2	945.0	0.0
571	1040.0	0.0	0.0	3	732.0	0.0
262	1175.0	807.0	196.0	3	421.0	0.0
285	2000.0	0.0	0.0	3	1464.0	0.0
1360	1236.0	0.0	0.0	2	600.0	0.0
...
1184	760.0	896.0	0.0	3	0.0	0.0
1372	1072.0	0.0	0.0	2	547.0	0.0
1167	847.0	1101.0	0.0	4	0.0	0.0
432	979.0	224.0	0.0	3	185.0	0.0
1269	960.0	0.0	0.0	2	250.0	0.0

	BsmtFullBath	BsmtHalfBath	BsmtUnfSF	EnclosedPorch	...	OverallCond	\
646	1	0	474.0	0.0	...	6	
571	1	0	308.0	0.0	...	5	
262	0	0	386.0	0.0	...	6	
285	1	0	536.0	0.0	...	5	
1360	1	0	312.0	158.0	...	7	
...	
1184	0	0	746.0	0.0	...	5	
1372	1	0	0.0	0.0	...	5	
1167	0	0	847.0	0.0	...	5	
432	1	0	524.0	248.0	...	4	
1269	0	0	710.0	168.0	...	4	

	OverallQual	PoolArea	ScreenPorch	TotRmsAbvGrd	TotalBsmtSF	\
646	8	0.0	0.0	7	1419.0	
571	5	0.0	0.0	6	1040.0	
262	7	0.0	0.0	7	807.0	
285	8	0.0	0.0	8	2000.0	
1360	6	0.0	0.0	6	912.0	
...	
1184	7	0.0	0.0	7	746.0	
1372	5	0.0	0.0	5	547.0	
1167	7	0.0	0.0	8	847.0	
432	5	0.0	0.0	5	709.0	
1269	4	0.0	0.0	5	960.0	

	WoodDeckSF	YearBuilt	YearRemodAdd	YrSold
646	140.0	2007	2007	2007
571	168.0	1996	1996	2009
262	0.0	1989	1989	2007
285	168.0	2004	2005	2007
1360	0.0	1957	1996	2010
...
1184	178.0	2003	2004	2008
1372	0.0	2005	2005	2006

1167	100.0	2004	2005	2006
432	0.0	1950	1950	2009
1269	0.0	1920	1950	2007

```
[345 rows x 36 columns],
223    113000.0
673    157000.0
718    270000.0
136    105000.0
684    110000.0
...
965    191000.0
482    202665.0
562    194201.0
581    314813.0
949    149900.0
Name: SalePrice, Length: 1034, dtype: float64,
646    392000.0
571    152000.0
262    228500.0
285    305900.0
1360   149700.0
...
1184   165400.0
1372   145000.0
1167   195000.0
432    110000.0
1269   108500.0
Name: SalePrice, Length: 345, dtype: float64)
```

Create LinearRegression model, fit on training set and predict on test set

```
[79]: #create a linear regression object
model3 = LinearRegression()
#train a model
model3.fit( encode_X_train,encode_y_train)
```

```
[79]: LinearRegression()
```

```
[80]: encode_y_pred3 = model3.predict(encode_X_test)
encode_y_pred3
```

```
[80]: array([263011.17348096, 151278.69406732, 237521.15280445, 306444.83659023,
179589.12045248, 115295.24967863, 203596.65767938, 176617.38472468,
268631.19291751, 182056.65942805, 280772.96016023, 107016.90710112,
116173.93325518, 120909.63455584, 165041.44922353, 176959.05623095,
168691.0385779 , 297130.05957958, 211041.07273794, 229225.62046386,
204372.74722721, 125472.33582051, 210250.28184771, 128133.06143696,
```

160466.20410665, 143316.83598233, 113662.70546705, 128384.85053326,
 204005.67809678, 254170.40185392, 111373.05179766, 117721.75287262,
 89979.83990709, 53289.42641272, 227546.2766431, 174599.88447911,
 363855.5618764, 112180.99083582, 174408.02921482, 320263.70850029,
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 172222.59936543, 90329.90726443, 134316.70375444, 134398.98814105,
 170693.92853795, 295137.06691152, 192412.42730159, 202648.90969701,
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 279912.95630235, 345131.7259968, 354245.95943962, 124802.71354199,
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 125903.62241077, 200033.66968395, 188384.13418649, 187014.74534527,
 366840.92399515, 171340.68202929, 180659.96318462, 241796.97393946,
 178984.99265562, 256187.75060533, 238896.11051133, 127986.90388687,
 127945.75954876, 136560.17497404, 347308.27837608, 220818.50833088,
 319258.77269899, 151892.02301402, 332118.0268508, 200334.08430189,
 96927.44804144, 258774.95707355, 134845.09515714, 236906.54301218,
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 219695.3821903, 109280.55617755, 256299.31063149, 113250.09453629,
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 157226.47275121, 234567.00576567, 244633.4325637, 203512.75897764,
 188172.48748111, 300578.67352358, 125936.78644275, 152772.71209275,
 317321.56611107, 204630.72168036, 265764.30817731, 318292.02460144,
 218103.1205221, 227570.84723725, 144899.41628243, 162528.96358485,
 113675.08061916, 99646.87295535, 175831.98050102, 279607.81356017,
 80388.45142476, 157558.57514864, 168716.53749412, 158511.1143292,
 268159.52493592, 236030.91601818, 259218.29023872, 306769.60415783,
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 136728.36963521, 195616.73994141, 307220.9427874, 135630.1097641,


```

123819.66544811, 233493.80313421, 126293.91297419, 269723.82669657,
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130697.29943982, 322330.7171025 , 206494.67765573, 217801.94377649,
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108413.50885758, 175793.81847454, 190290.43772055, 276491.19707614,
90684.53922019, 178990.13616749, 204272.18383693, 395103.81203293,
250330.88058944, 216749.38023034, 338149.81739905, 129065.56432815,
114852.59813526, 183704.56915614, 77724.39581912, 119295.61866632,
85125.19311684, 112336.27193449, 136734.87988703, 189230.78678898,
140351.79140137, 167472.87343677, 255651.38742537, 250560.48788194,
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204156.88903463, 118201.02786527, 259503.7059336 , 210497.32464545,
144318.01028186, 218206.35075101, 168758.05219649, 192116.25796623,
84124.35128754, 174483.07513333, 114455.60670438, 162952.99027018,
163370.15493512, 185867.67412221, 143442.1821607 , 133335.64273741,
232920.80084234, 130420.20688356, 265221.32286707, 180656.98578366,
268759.68205338, 187263.82446352, 128223.98511918, 209432.10302999,
229927.56623541, 100692.22043756, 167147.5715183 , 204197.84577366,
222393.52363762, 237642.86126765, 188461.28661532, 266329.18727241,
184233.43166737, 154538.6997815 , 211658.36389192, 246958.88902765,
332224.4655521 , 198189.98332438, 139392.87862161, 130614.43000603,
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171526.78910715, 153455.57979293, 113005.2184186 , 211979.73979886,
308238.95500522, 145949.37373025, 134900.0070884 , 95068.31565341,
211776.03931884, 122288.44223574, 222255.09745693, 107166.74408712,
56209.2667581 ] )

```

Compute Mean Squared Error on actual values and predicted values (you will get output as 1461036570.0).

```
[82]: msel=mean_squared_error(encode_y_test,encode_y_pred3)
      msel
```

```
[82]: 840762442.6361699
```

0.0.7 Step6. [Normalize using StandardScaler and Predict Sale Price]

Using StandardScaler, perform fit_transform() on X_train and transform() on X_test matrix that you already splitted.

```
[83]: from sklearn.preprocessing import StandardScaler
```

```
[84]: scaler = StandardScaler()
      ss3=scaler.fit_transform(encode_X_train)    # scale X_train using
      ↪fit_transform() method
      print(ss3)
```

```
[[-0.97719621  0.76025618 -0.13151388 ... -0.96495393 -1.72036703
   1.68452317]
 [-0.01783362 -0.79993851 -0.13151388 ...  0.00341162  0.72527132
   0.16130764]
 [ 0.77995212 -0.79993851 -0.13151388 ...  0.76427027  0.52962025
  -1.36190789]
 ...
 [ 0.54768539 -0.79993851 -0.13151388 ...  1.1446996   1.06766068
  -0.60030012]
 [ 1.62318135 -0.79993851 -0.13151388 ...  1.17928408  1.06766068
  -0.60030012]
 [-0.50508883 -0.79993851 -0.13151388 ...  0.14174956 -0.39972232
   0.16130764]]
```

```
[85]: ss5=scaler.transform(encode_X_test)    #X_test using transform() method
      print(ss5)
```

```
[ [ 0.59060424 -0.79993851 -0.13151388 ...  1.17928408  1.06766068
   -0.60030012]
 [-0.36623372 -0.79993851 -0.13151388 ...  0.79885476  0.52962025
   0.9229154 ]
 [-0.02540753  1.02745933  5.70578985 ...  0.55676337  0.18723088
  -0.60030012]
 ...
 [-0.85348893  1.69320278 -0.13151388 ...  1.07553063  0.96983515
  -1.36190789]
 [-0.52023666 -0.29270541 -0.13151388 ... -0.79203151 -1.72036703
   0.9229154 ]
 [-0.56820479 -0.79993851 -0.13151388 ... -1.82956604 -1.72036703
  -0.60030012]]
```

Create a new Linear Regression model, fit on scaled X_train and y_train and predict on scaled X_test.

```
[90]: #create a linear regression object
      model4 = LinearRegression()
      #train a model
      model4.fit(ss3,encode_y_train)
```

```
[90]: LinearRegression()
```

```
[91]: s_y_pred = model4.predict(encode_X_test)
      s_y_pred
```

```
[91]: array([9.16641201e+07, 1.01960588e+08, 1.17921652e+08, 1.18784635e+08,
            8.13404241e+07, 8.94732382e+07, 9.40521718e+07, 8.47305101e+07,
            1.11879748e+08, 6.47857271e+07, 1.39809605e+08, 8.72764978e+07,
            9.85254414e+07, 7.72023423e+07, 9.66862338e+07, 1.11663252e+08,
            9.90062546e+07, 1.29149393e+08, 1.53985324e+08, 1.13938057e+08,
            9.44874523e+07, 8.04543375e+07, 9.55535295e+07, 1.12715683e+08,
            8.45654831e+07, 9.46792646e+07, 9.30213017e+07, 9.51049792e+07,
            1.00308638e+08, 1.01110706e+08, 8.46569143e+07, 7.87684559e+07,
            9.51238547e+07, 8.44224001e+07, 9.64064389e+07, 7.14143473e+07,
            2.99870872e+08, 9.00930628e+07, 7.98589158e+07, 1.23314146e+08,
            9.47740853e+07, 1.36703065e+08, 8.92381830e+07, 8.29015280e+07,
            6.47684408e+07, 7.28783855e+07, 8.35825411e+07, 9.62460522e+07,
            1.56130989e+08, 1.30085628e+08, 9.41808575e+07, 1.37399172e+08,
            9.56875697e+07, 6.71284621e+07, 1.39568890e+08, 7.19868076e+07,
            1.40921072e+08, 1.36362965e+08, 1.27910779e+08, 1.02474794e+08,
            1.24479957e+08, 8.92606595e+07, 1.09407801e+08, 1.25688788e+08,
            9.02957006e+07, 9.37778793e+07, 9.30732934e+07, 9.02820844e+07,
            1.99388307e+08, 9.42320616e+07, 8.34053312e+07, 7.72624437e+07,
            1.10582394e+08, 9.87283474e+07, 1.15513216e+08, 7.25534410e+07,
            1.09310637e+08, 9.20374785e+07, 1.31179967e+08, 1.02381062e+08,
            1.24246165e+08, 9.98933331e+07, 1.22981220e+08, 1.14885993e+08,
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            8.07059974e+07, 9.80360183e+07, 1.01462812e+08, 9.19190997e+07,
            1.20607654e+08, 8.94451470e+07, 7.92758343e+07, 5.21040469e+07,
            9.70979648e+07, 1.33645982e+08, 9.75844215e+07, 1.16932286e+08,
            9.05383680e+07, 1.13395704e+08, 8.17611341e+07, 9.26553145e+07,
            7.30816587e+07, 1.02899776e+08, 9.39256261e+07, 1.10572573e+08,
            7.98994838e+07, 1.38512152e+08, 7.28357281e+07, 6.07388723e+07,
            1.20411275e+08, 1.24206979e+08, 1.15181569e+08, 1.56402983e+08,
            8.07768788e+07, 1.04060733e+08, 6.61875041e+07, 9.07279922e+07,
            7.65473156e+07, 8.37475103e+07, 9.16628008e+07, 1.14966565e+08,
            6.68177663e+07, 1.17358911e+08, 6.85002864e+07, 9.43845460e+07,
            1.65833402e+08, 1.04614663e+08, 1.14491876e+08, 1.13956884e+08,
            1.56405781e+08, 1.26236143e+08, 5.36109947e+07, 1.12691125e+08,
            9.23031865e+07, 2.28469833e+08, 1.16744290e+08, 7.67268299e+07,
            1.05680716e+08, 1.00118862e+08, 1.25669415e+08, 8.39872429e+07,
            1.09373936e+08, 7.01473628e+07, 1.09704528e+08, 1.01774303e+08,
            7.16728335e+07, 1.00959615e+08, 1.08175447e+08, 1.26176587e+08,
            1.99590228e+08, 5.92470972e+07, 9.66054120e+07, 9.24548203e+07,
            1.15713043e+08, 9.89009719e+07, 6.46164542e+07, 1.38205260e+08,
            8.06373480e+07, 1.10955137e+08, 6.51196433e+07, 6.58506181e+07,
            1.45993206e+08, 1.19771278e+08, 8.07381134e+07, 1.05959802e+08,
            8.59720795e+07, 8.23026924e+07, 6.08504443e+07, 6.63097150e+07,
            1.07485905e+08, 1.08918601e+08, 1.01261217e+08, 1.02021569e+08,
            7.29412137e+07, 5.95393189e+07, 8.83747718e+07, 7.86319076e+07,
            1.01661929e+08, 6.87087724e+07, 8.55632040e+07, 1.33760274e+08,
            7.09432761e+07, 7.60087911e+07, 7.35824812e+07, 1.03657494e+08,
```

```

6.49093376e+07, 8.58657662e+07, 7.44920196e+07, 1.07741758e+08,
6.97833653e+07, 1.04687913e+08, 8.21479326e+07, 1.18079129e+08,
6.32165786e+07, 1.02204371e+08, 6.36160742e+07, 8.38877131e+07,
9.87039930e+07, 9.19352380e+07, 1.30043791e+08, 7.07709388e+07,
5.18607555e+07, 1.04338825e+08, 1.64968639e+08, 7.17895141e+07,
6.00582080e+07, 8.67773943e+07, 1.62080488e+08, 7.24391264e+07,
8.89251420e+07, 8.16662594e+08, 8.81034385e+07, 1.34670048e+08,
9.22457377e+07, 1.19223531e+08, 1.18382877e+08, 9.39139341e+07,
1.19511333e+08, 9.68588909e+07, 1.21804997e+08, 7.92371538e+07,
9.11865528e+07, 1.15920774e+08, 1.05730375e+08, 1.26427349e+08,
7.99437311e+07, 9.32777696e+07, 1.04156997e+08, 8.48304495e+07,
8.72083166e+07, 1.15087361e+08, 7.97450318e+07, 1.08030183e+08,
1.07363092e+08, 1.29637269e+08, 1.17782376e+08, 9.84558173e+07,
1.07157171e+08, 1.59256698e+08, 1.68249069e+08, 9.85401439e+07,
1.23929236e+08, 1.05170368e+08, 1.49520016e+08, 9.43043341e+07,
7.32764182e+07, 1.06782692e+08, 1.05960393e+08, 9.59927249e+07,
9.08892952e+07, 1.04143658e+08, 1.02963385e+08, 7.80821520e+07,
1.05110574e+08, 1.08717449e+08, 1.02391918e+08, 1.05734320e+08,
4.89999891e+07, 7.22827480e+07, 9.74740462e+07, 1.29681685e+08,
7.46262426e+07, 1.06663755e+08, 9.31611382e+07, 1.52783153e+08,
9.97074504e+07, 1.14506874e+08, 1.18258264e+08, 7.47109510e+07,
7.50098534e+07, 9.95254797e+07, 9.28027774e+07, 8.30553627e+07,
7.24690740e+07, 7.14928073e+07, 7.99921243e+07, 1.00937130e+08,
5.94354435e+07, 6.58244375e+07, 1.10367044e+08, 1.22011916e+08,
7.93460638e+07, 3.03733902e+08, 8.47470568e+07, 1.39044001e+08,
1.07214468e+08, 8.95826846e+07, 2.82530972e+08, 9.23072760e+07,
8.85673716e+07, 1.17266244e+08, 9.41489065e+07, 9.01380777e+07,
8.43275899e+07, 1.01344499e+08, 7.35218838e+07, 1.11560783e+08,
8.01922500e+07, 9.94324541e+07, 1.00859252e+08, 7.45208247e+07,
8.12282741e+07, 6.89538819e+07, 1.30218132e+08, 9.01186100e+07,
9.29986175e+07, 1.06019768e+08, 6.49795908e+07, 7.83716852e+07,
1.15652778e+08, 8.66608872e+07, 9.38367180e+07, 1.17935343e+08,
1.02700950e+08, 1.02576625e+08, 9.58117017e+07, 2.03837209e+08,
9.78755175e+07, 6.52359539e+07, 9.76479776e+07, 1.07303616e+08,
1.18225721e+08, 1.11322943e+08, 6.19466718e+07, 9.03351056e+07,
6.86394862e+07, 6.87814966e+07, 2.00793971e+08, 9.00403543e+07,
9.94373605e+07, 6.15647734e+07, 2.03275965e+08, 1.01790898e+08,
1.36709677e+08, 7.66373011e+07, 8.83327752e+07, 7.92059860e+07,
8.90455807e+07, 5.96399320e+07, 1.19966136e+08, 7.85258597e+07,
6.77285855e+07])

```

Compute Mean Squared Error (MSE) on actual values and predicted values (you will get output as 1461036570.0).

```
[92]: s_mse=mean_squared_error(encode_y_test,s_y_pred)
      s_mse
```

```
[92]: 1.3194590569635376e+16
```

0.0.8 Step7. [Normalize using MinMaxScaler and Predict Sale Price]

Repeat Step6 using MinMaxScaler

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

```
[94]: mm_ss = mm_scaler.fit_transform(encode_X_train)  
mm_ss
```

```
[94]: array([[0.08462623, 0.33365617, 0.          , ..., 0.50387597, 0.          ,  
            1.          ],  
            [0.17395393, 0.          , 0.          , ..., 0.72093023, 0.83333333,  
            0.5          ],  
            [0.24823695, 0.          , 0.          , ..., 0.89147287, 0.76666667,  
            0.          ],  
            ...,  
            [0.22661025, 0.          , 0.          , ..., 0.97674419, 0.95          ,  
            0.25         ],  
            [0.32675129, 0.          , 0.          , ..., 0.98449612, 0.95          ,  
            0.25         ],  
            [0.12858486, 0.          , 0.          , ..., 0.75193798, 0.45          ,  
            0.5          ]])
```

```
[95]: mm_ss5 = mm_scaler.transform(X_test)  
mm_ss5
```

```
[95]: array([[0.12858486, 0.          , 0.          , ..., 0.75193798, 0.45          ,  
            0.5          ],  
            [0.37141514, 0.          , 0.          , ..., 0.99224806, 0.98333333,  
            1.          ],  
            [0.1274095 , 0.          , 0.          , ..., 0.75193798, 0.45          ,  
            0.75         ],  
            ...,  
            [0.20122238, 0.          , 0.          , ..., 0.97674419, 0.93333333,  
            0.          ],  
            [0.14621533, 0.          , 0.          , ..., 0.68217054, 0.85          ,  
            1.          ],  
            [0.07898449, 0.31767554, 0.          , ..., 0.93023256, 0.83333333,  
            0.25         ]])
```

```
[96]: model5 =LinearRegression()  
model5.fit(mm_ss,encode_y_train)
```

```
[96]: LinearRegression()
```

```
[97]: mm_y_pred = model5.predict(mm_ss5)  
mm_y_pred
```

```
[97]: array([131797.95467908, 311704.86657981, 139200.22539657, 313443.20643999,
252797.86648437, 123046.91784846, 117378.5017364 , 222172.6976128 ,
225919.4630138 , 180879.68083942, 173522.13201178, 147080.98290307,
204272.18383693, 100657.93059886, 97695.61667541, 191181.57760294,
308238.9550052 , 132857.42712151, 141577.62792228, 113675.08061916,
133983.75273388, 106062.11127522, 235032.39810745, 125903.62241075,
189230.78678897, 199644.5909249 , 184328.28307383, 147043.47428562,
204828.93843517, 191484.14923426, 114409.9774009 , 171845.43746774,
176599.78087299, 204242.60775792, 250560.48788192, 216913.12810681,
232734.08171018, 211273.28920557, 205569.63752126, 167472.87343678,
58478.58513446, 113005.21841861, 157012.7838008 , 265221.32286705,
168950.64885348, 152213.169075 , 167451.55099716, 328199.39199748,
182010.58031063, 203642.03567921, 147973.13197864, 96325.89094823,
227570.84723723, 87289.27444502, 169799.61515644, 202276.66487611,
158903.08731367, 236695.18810547, 200704.90091373, 70912.58735497,
372414.87062263, 120904.75499932, 96877.38457711, 180410.18529927,
131992.24757059, 112748.40036357, 374947.25696151, 208122.54514936,
245464.72312833, 171561.09113784, 135713.20259672, 201627.87982328,
190963.78357114, 280290.68776881, 134900.00708843, 152486.91542099,
168058.4776116 , 263951.56875983, 208821.17236003, 108191.58736302,
119009.30046201, 229225.62046382, 171340.68202927, 301868.29481478,
168344.11865204, 124946.7784666 , 202924.04278927, 283129.01806473,
90321.09801381, 111434.79492568, 188279.584864 , 310253.08207238,
124177.88215722, 191364.53226893, 240510.01635049, 137097.71622446,
224450.7257173 , 186186.58033816, 174408.02921481, 106497.17048662,
222255.09745691, 187107.9138167 , 171013.26852221, 286300.5193322 ,
151816.48733704, 192330.6818937 , 121339.24136301, 187943.44089951,
69672.21423892, 226013.06200258, 157736.36367454, 125614.14239237,
82370.14313929, 234633.38466123, 174849.87891931, 228994.29928491,
302419.37850495, 372850.36173382, 148534.95382617, 125161.76106928,
160958.73940291, 244633.43256371, 185104.44245956, 109348.07455719,
142219.41722934, 170693.92853793, 289372.03297905, 203836.88086247,
162952.99027016, 87353.3701625 , 217253.70326651, 229022.16508795,
137336.7806884 , 45810.62635894, 83810.06542091, 292457.11129938,
106603.3551778 , 205243.88581606, 241796.97393948, 259925.58173828,
190073.21382609, 60190.08832769, 179326.57329592, 268759.6820534 ,
219695.3821903 , 110159.98639961, 151730.09618353, 189467.95297045,
238896.11051135, 154538.69978151, 179535.24405334, 157226.4727512 ,
206920.7651633 , 87488.18342567, 318281.55475284, 121592.17926646,
225079.95899261, 99206.43007536, 350886.78442964, 64911.93346957,
199162.10444576, 165041.44922353, 198408.78376549, 342284.15682558,
253629.30319572, 141702.38177368, 223936.79704981, 221763.0218073 ,
71748.62376294, 216749.38023036, 209819.305251 , 247398.57461258,
148818.45871333, 134299.956664 , 208529.84307596, 121718.46776888,
246796.42571128, 221822.48322739, 150426.82848835, 91038.74809643,
210250.2818477 , 193469.14479176, 126743.41868673, 159628.50146886,
154222.3116162 , 164828.96002419, 58346.59238042, 236030.91601818,
```

163337.84431464, 197506.33333978, 189900.67153842, 202065.55393313,
143427.31590278, 91941.75422128, 194033.123235 , 122288.44223573,
219835.3266294 , 203509.58311323, 277486.32626813, 113393.43516722,
71434.11407794, 128133.0614369 , 232835.91042458, 126345.58693362,
213757.2855931 , 188461.28661533, 228138.77777231, 113286.08499329,
199954.19844488, 229168.14499803, 126662.70717147, 151343.46012082,
132467.27566252, 119722.60839977, 166888.64391534, 170015.30933012,
211776.03931884, 249508.84112791, 225821.34852512, 237642.86126766,
134845.09515712, 139693.30522558, 166225.66762986, 167412.08988042,
197306.88021357, 128962.76955742, 149439.48347799, 137780.58869745,
113250.09453629, 211294.82771477, 256438.20380864, 91527.76302953,
315648.3103501 , 153349.04140675, 223484.37770866, 220406.03575001,
176244.49900157, 326154.33124785, 240139.27500634, 246194.02367624,
163370.15493512, 158774.43897576, 168062.08340555, 150938.68882643,
237521.15280443, 118350.86924399, 152772.7120928 , 189182.40557759,
94156.03258368, 136728.36963522, 323253.92392125, 306444.83659023,
197364.56585763, 191515.20856002, 162528.96358485, 158805.30420469,
174483.07513334, 339453.10792647, 259218.29023872, 256269.4913154 ,
81078.92710764, 179216.09079246, 196053.7999349 , 69925.56921821,
77524.44997807, 278729.65010917, 136737.19550606, 159011.75015581,
141549.47303786, 107016.90710112, 56188.48328662, 257486.98554138,
283512.88170101, 110833.17828138, 140185.37989928, 208750.68153392,
146653.62396668, 86351.99804667, 366840.92399517, 210497.32464546,
160332.82904559, 345131.72599683, 209895.385998 , 170754.79172982,
196763.59104331, 183495.97878296, 125440.12321561, 210270.16586046,
157561.02922355, 183617.37524351, 124347.42275114, 209237.40519505,
146365.42082202, 128348.35137953, 228287.30600781, 58502.20696902,
202053.93165781, 60633.65728011, 327693.85423899, 220571.15035579,
266599.32182306, 205775.00759204, 126943.75499451, 328475.86147282,
174599.88447912, 153277.84921259, 198858.71075878, 153370.43576296,
210658.84725672, 42328.15085915, 165274.73178474, 311684.57942758,
282407.75408125, 137053.12462343, 115903.56228679, 201504.45607005,
201221.62291035, 217801.94377652, 143893.6090452 , 117069.72214884,
196117.41625152, 260669.23754427, 120909.63455586, 221838.58604191,
232625.94937109, 181106.71333204, 319054.33392657, 186768.41427705,
286314.57583226, 135045.22806807, 203596.65767939, 199064.41622639,
116994.40277252, 76661.25164569, 203813.8622668 , 186125.05188484,
295016.0751565 , 148796.46199888, 108086.23253092, 232920.80084236,
138691.16327863, 215651.2658567 , 209239.9661726 , 150208.0263511 ,
194551.01171507])

Mean Squared Error will be: 1461036570.0

```
[98]: mse_mm=mean_squared_error(encode_y_test,mm_y_pred)
      mse_mm
```

[98]: 9404508368.107819

0.0.9 Step8. [Predict using SGD Regressor]

Use scaled X_train and X_test using StandardScaler that you computed before

```
[99]: from sklearn.linear_model import SGDRegressor
      from sklearn.pipeline import make_pipeline
```

Create SGDRegressor, fit and predict

```
[100]: seg = make_pipeline(StandardScaler(), SGDRegressor(max_iter=1000, tol=1e-3))
      seg.fit(X, y)
```

```
[100]: Pipeline(steps=[('standardscaler', StandardScaler()),
                        ('sgdregressor', SGDRegressor())])
```

```
[101]: re_y_pred = seg.predict(X)
      re_y_pred
```

```
[101]: array([228671.31817897, 200777.00895064, 222178.96664092, ...,
              229832.92538152, 128254.43107227, 155640.32874484])
```

Compute MSE on y_test and y_pred this time. You will get output as 1592430104.0

```
[103]: mse_seg=mean_squared_error(y,re_y_pred)
      mse_seg
```

```
[103]: 1207136617.6570287
```

0.0.10 Step8. [Predict using Ridge Regression]

Create RidgeCV, fit and predict

```
[118]: from sklearn.linear_model import Ridge
```

```
[119]: RidgeCV = Ridge(alpha=1.0)
      RidgeCV.fit(ss3,encode_y_train)
      rid_y_pred = RidgeCV.predict(ss3)
      rid_y_pred
```

```
[119]: array([129474.25435239, 154299.40507943, 226646.37404798, ...,
              213069.56190215, 319814.40859995, 131879.06092969])
```

Compute MSE on y_test and y_pred this time. You will get output as 1442196000.3367693.

```
[120]: mse_rid=mean_squared_error(encode_y_train,rid_y_pred)
      mse_rid
```

```
[120]: 1316556019.1346939
```


0.0.11 Step8. [Predict using Lasso Regression]

```
[121]: from sklearn.linear_model import Lasso
```

Create LassoCV, fit and predict

```
[122]: LasCV = Lasso(alpha=1.0)
LasCV.fit(ss3,encode_y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\linear_model\_coordinate_descent.py:529: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 305643652788.40485, tolerance: 675327095.0964903
    model = cd_fast.enet_coordinate_descent(
```

```
[122]: Lasso()
```

```
[123]: las_y_pred = LasCV.predict(ss3)
las_y_pred
```

```
[123]: array([129497.73854696, 154226.11412444, 226690.0456038 , ...,
          213090.74498072, 319851.56030583, 131789.02164197])
```

Compute MSE on y_test and y_pred this time. You will get output as **1409368613.5329669**

```
[124]: mse_las=mean_squared_error(encode_y_train,las_y_pred)
mse_las
```

```
[124]: 1316552641.500684
```

0.0.12 Step9.[RMSE]. Print Root Mean Squared Error values (use numpy.sqrt() method) as below and compare error values.

RMSE without one hot encoding: 38403.0

RMSE with One hot encoding: 38224.0

RMSE with OHE and Standard Scaling: 38224.0

RMSE with OHE and MinMax Scaling: 38224.0

RMSE of SGDRegressor with OHE and Standard Scaler: 38528.0

RMSE of RidgeCV with OHE and Standard Scaler: 37976.0

RMSE of LassoCV with OHE and Standard Scaler: 37542.0

```
[125]: from math import sqrt
```

```
[126]: print("RMSE without one hot encoding: ",sqrt(mse))
print("RMSE with one hot encoding: ",sqrt(mse1))
print("RMSE with one and Standard Scaling: ",sqrt(s_mse))
print("RMSE with one and MinMax Scaling: ",sqrt(mse_mm))
print("RMSE of SGDRegressor with one and Standard Scaler: ",sqrt(mse_seg))
print("RMSE of RigidCV with one and Standard Scaler: ",sqrt(mse_rid))
print("RMSE of LassoCV with one and Standard Scaler: ",sqrt(mse_las))
```

```
RMSE without one hot encoding: 33579.689180761234
RMSE with one hot encoding: 28995.903894104937
RMSE with one and Standard Scaling: 114867708.99445751
RMSE with one and MinMax Scaling: 96976.8444944865
RMSE of SGDRegressor with one and Standard Scaler: 34743.87165612129
RMSE of RigidCV with one and Standard Scaler: 36284.37706692363
RMSE of LassoCV with one and Standard Scaler: 36284.3305229776
```