

Multiple linear regression

Accessing the data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
churn = pd.read_csv("chennai_house_price_prediction.csv")
```

```
churn
```

	PRT_ID	AREA	INT_SQFT	DIST_MAINROAD	N_BEDROOM
0	P03210	Karapakkam	1004	131	1.0
1	P09411	Anna Nagar	1986	26	2.0
2	P01812	Adyar	909	70	1.0
3	P05346	Velachery	1855	14	3.0
4	P06210	Karapakkam	1226	84	1.0
...
7104	P03834	Karapakkam	598	51	1.0
7105	P10000	Velachery	1897	52	3.0
7106	P09594	Velachery	1614	152	2.0
7107	P06508	Karapakkam	787	40	1.0
7108	P09794	Velachery	1896	156	3.0

	N_ROOM	SALE_COND	PARK_FACIL	BUILDTYPE	UTILITY_AVAIL
0	3	AbNormal	1	Commercial	AllPub
1	5	AbNormal	0	Commercial	AllPub
2	3	AbNormal	1	Commercial	ELO
3	5	Family	0	Others	NoSewr
4	3	AbNormal	1	Others	AllPub
...

...						
7104	2	AdjLand	0	Others	ELO	No
Access						
7105	5	Family	1	Others	NoSeWa	No
Access						
7106	4	Normal Sale	0	House	NoSeWa	
Gravel						
7107	2	Partial	1	Commercial	ELO	
Paved						
7108	5	Partial	1	Others	ELO	
Paved						

	MZZONE	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	QS_OVERALL	COMMIS	\
0	A	4.0	3.9	4.9	4.330	144400	
1	RH	4.9	4.2	2.5	3.765	304049	
2	RL	4.1	3.8	2.2	3.090	92114	
3	I	4.7	3.9	3.6	4.010	77042	
4	C	3.0	2.5	4.1	3.290	74063	
...	
7104	RM	3.0	2.2	2.4	2.520	107060	
7105	RH	3.6	4.5	3.3	3.920	205551	
7106	I	4.3	4.2	2.9	3.840	167028	
7107	RL	4.6	3.8	4.1	4.160	119098	
7108	I	3.1	3.5	4.3	3.640	79812	

	SALES_PRICE
0	7600000
1	21717770
2	13159200
3	9630290
4	7406250
...	...
7104	5353000
7105	10818480
7106	8351410
7107	8507000
7108	9976480

[7109 rows x 19 columns]

churn.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7109 entries, 0 to 7108
Data columns (total 19 columns):
#   Column      Non-Null Count  Dtype
---  -
0   PRT_ID      7109 non-null   object
1   AREA        7109 non-null   object
2   INT_SQFT    7109 non-null   int64
```

```

3  DIST_MAINROAD  7109 non-null  int64
4  N_BEDROOM      7108 non-null  float64
5  N_BATHROOM     7104 non-null  float64
6  N_ROOM         7109 non-null  int64
7  SALE_COND      7109 non-null  object
8  PARK_FACIL     7109 non-null  int64
9  BUILDTYPE      7109 non-null  object
10 UTILITY_AVAIL  7109 non-null  object
11 STREET         7109 non-null  object
12 MZZONE         7109 non-null  object
13 QS_ROOMS       7109 non-null  float64
14 QS_BATHROOM    7109 non-null  float64
15 QS_BEDROOM     7109 non-null  float64
16 QS_OVERALL     7061 non-null  float64
17 COMMIS        7109 non-null  int64
18 SALES_PRICE    7109 non-null  int64
dtypes: float64(6), int64(6), object(7)
memory usage: 1.0+ MB

```

data preprocessing

```
churn.iloc[0:10,0:15]
```

	PRT_ID	AREA	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM
N_ROOM \						
0	P03210	Karapakkam	1004	131	1.0	1.0
1	P09411	Anna Nagar	1986	26	2.0	1.0
2	P01812	Adyar	909	70	1.0	1.0
3	P05346	Velachery	1855	14	3.0	2.0
4	P06210	Karapakkam	1226	84	1.0	1.0
5	P00219	Chrompet	1220	36	2.0	1.0
6	P09105	Chrompet	1167	137	1.0	1.0
7	P09679	Velachery	1847	176	3.0	2.0
8	P03377	Chrompet	771	175	1.0	1.0
9	P09623	Velachery	1635	74	2.0	1.0
	SALE_COND	PARK_FACIL	BUILDTYPE	UTILITY_AVAIL	STREET	MZZONE
QS_ROOMS \						
0	AbNormal	1	Commercial	AllPub	Paved	A
1	AbNormal	0	Commercial	AllPub	Gravel	RH

4.9						
2	AbNormal	1	Commercial	EL0	Gravel	RL
4.1						
3	Family	0	Others	NoSewr	Paved	I
4.7						
4	AbNormal	1	Others	AllPub	Gravel	C
3.0						
5	Partial	0	Commercial	NoSeWa	No Access	RH
4.5						
6	Partial	0	Other	AllPub	No Access	RL
3.6						
7	Family	0	Commercial	AllPub	Gravel	RM
2.4						
8	AdjLand	0	Others	NoSewr	Paved	RM
2.9						
9	AbNormal	0	Others	EL0	No Access	I
3.1						

QS_BATHROOM	
0	3.9
1	4.2
2	3.8
3	3.9
4	2.5
5	2.6
6	2.1
7	4.5
8	3.7
9	3.1

```
churn.iloc[0:10,15:]
```

	QS_BEDROOM	QS_OVERALL	COMMIS	SALES_PRICE
0	4.9	4.330	144400	7600000
1	2.5	3.765	304049	21717770
2	2.2	3.090	92114	13159200
3	3.6	4.010	77042	9630290
4	4.1	3.290	74063	7406250
5	3.1	3.320	198316	12394750
6	2.5	2.670	33955	8488790
7	2.1	3.260	235204	16800250
8	4.0	3.550	33236	8308970
9	3.3	3.160	121255	8083650

```
# target
```

```
y=churn['SALES_PRICE']
```

```
y
```

0	7600000
1	21717770
2	13159200

```

3          9630290
4          7406250
...
7104      5353000
7105      10818480
7106      8351410
7107      8507000
7108      9976480
Name: SALES_PRICE, Length: 7109, dtype: int64

```

features

```

X= churn.drop(['SALES_PRICE'], axis=1)
X

```

	PRT_ID	AREA	INT_SQFT	DIST_MAINROAD	N_BEDROOM
N_BATHROOM \					
0	P03210	Karapakkam	1004	131	1.0
1	P09411	Anna Nagar	1986	26	2.0
2	P01812	Adyar	909	70	1.0
3	P05346	Velachery	1855	14	3.0
4	P06210	Karapakkam	1226	84	1.0
...
7104	P03834	Karapakkam	598	51	1.0
7105	P10000	Velachery	1897	52	3.0
7106	P09594	Velachery	1614	152	2.0
7107	P06508	Karapakkam	787	40	1.0
7108	P09794	Velachery	1896	156	3.0

	N_ROOM	SALE_COND	PARK_FACIL	BUILDTYPE	UTILITY_AVAIL
STREET \					
0	3	AbNormal	1	Commercial	AllPub
Paved					
1	5	AbNormal	0	Commercial	AllPub
Gravel					
2	3	AbNormal	1	Commercial	EL0
Gravel					
3	5	Family	0	Others	NoSewr
Paved					

4	3	AbNormal	1	Others	AllPub	
Gravel						
...	
...						
7104	2	AdjLand	0	Others	EL0	No
Access						
7105	5	Family	1	Others	NoSeWa	No
Access						
7106	4	Normal Sale	0	House	NoSeWa	
Gravel						
7107	2	Partial	1	Commercial	EL0	
Paved						
7108	5	Partial	1	Others	EL0	
Paved						

	MZZONE	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	QS_OVERALL	COMMIS
0	A	4.0	3.9	4.9	4.330	144400
1	RH	4.9	4.2	2.5	3.765	304049
2	RL	4.1	3.8	2.2	3.090	92114
3	I	4.7	3.9	3.6	4.010	77042
4	C	3.0	2.5	4.1	3.290	74063
...
7104	RM	3.0	2.2	2.4	2.520	107060
7105	RH	3.6	4.5	3.3	3.920	205551
7106	I	4.3	4.2	2.9	3.840	167028
7107	RL	4.6	3.8	4.1	4.160	119098
7108	I	3.1	3.5	4.3	3.640	79812

[7109 rows x 18 columns]

Drop irrelevant features

```
X_1 =X.drop(['PRT_ID','SALE_COND','UTILITY_AVAIL'],axis=1)
```

X_1

	AREA	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM
N_ROOM \					
0	Karapakkam	1004	131	1.0	1.0
3					
1	Anna Nagar	1986	26	2.0	1.0
5					
2	Adyar	909	70	1.0	1.0
3					
3	Velachery	1855	14	3.0	2.0
5					
4	Karapakkam	1226	84	1.0	1.0
3					
...
..					

7104 2	Karapakkam	598	51	1.0	1.0
7105 5	Velachery	1897	52	3.0	2.0
7106 4	Velachery	1614	152	2.0	1.0
7107 2	Karapakkam	787	40	1.0	1.0
7108 5	Velachery	1896	156	3.0	2.0

	PARK_FACIL	BUILDTYPE	STREET	MZZONE	QS_ROOMS	QS_BATHROOM
\						
0	1	Commercial	Paved	A	4.0	3.9
1	0	Commercial	Gravel	RH	4.9	4.2
2	1	Commercial	Gravel	RL	4.1	3.8
3	0	Others	Paved	I	4.7	3.9
4	1	Others	Gravel	C	3.0	2.5
...
7104	0	Others	No Access	RM	3.0	2.2
7105	1	Others	No Access	RH	3.6	4.5
7106	0	House	Gravel	I	4.3	4.2
7107	1	Commercial	Paved	RL	4.6	3.8
7108	1	Others	Paved	I	3.1	3.5

	QS_BEDROOM	QS_OVERALL	COMMIS
0	4.9	4.330	144400
1	2.5	3.765	304049
2	2.2	3.090	92114
3	3.6	4.010	77042
4	4.1	3.290	74063
...
7104	2.4	2.520	107060
7105	3.3	3.920	205551
7106	2.9	3.840	167028
7107	4.1	4.160	119098
7108	4.3	3.640	79812

```

[7109 rows x 15 columns]
X_1['AREA'].unique()
array(['Karapakkam', 'Anna Nagar', 'Adyar', 'Velachery', 'Chrompet',
      'KK Nagar', 'TNagar', 'T Nagar', 'Chrompt', 'Chrmpt',
      'Karapakkam',
      'Ana Nagar', 'Chormpet', 'Adyr', 'Velchery', 'Ann Nagar',
      'KKNagar'], dtype=object)
X_1['BUILDTYPE'].unique()
array(['Commercial', 'Others', 'Other', 'House', 'Comercial'],
      dtype=object)
X_1['STREET'].unique()
array(['Paved', 'Gravel', 'No Access', 'Pavd', 'NoAccess'],
      dtype=object)
X_1['MZZONE'].unique()
array(['A', 'RH', 'RL', 'I', 'C', 'RM'], dtype=object)
# Conver categorical to numeric using one hot encoding
X_1 =
pd.get_dummies(X_1,columns=['AREA','BUILDTYPE','STREET','MZZONE'])
X_1

```

	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM	N_ROOM
PARK_FACIL \					
0	1004	131	1.0	1.0	3
1					
1	1986	26	2.0	1.0	5
0					
2	909	70	1.0	1.0	3
1					
3	1855	14	3.0	2.0	5
0					
4	1226	84	1.0	1.0	3
1					
...
..					
7104	598	51	1.0	1.0	2
0					
7105	1897	52	3.0	2.0	5
1					
7106	1614	152	2.0	1.0	4
0					

7107	787	40	1.0	1.0	2
1					
7108	1896	156	3.0	2.0	5
1					

	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	QS_OVERALL	...	STREET_No
Access \						
0	4.0	3.9	4.9	4.330	...	
0						
1	4.9	4.2	2.5	3.765	...	
0						
2	4.1	3.8	2.2	3.090	...	
0						
3	4.7	3.9	3.6	4.010	...	
0						
4	3.0	2.5	4.1	3.290	...	
0						
...	
...						
7104	3.0	2.2	2.4	2.520	...	
1						
7105	3.6	4.5	3.3	3.920	...	
1						
7106	4.3	4.2	2.9	3.840	...	
0						
7107	4.6	3.8	4.1	4.160	...	
0						
7108	3.1	3.5	4.3	3.640	...	
0						

	STREET_NoAccess	STREET_Pavd	STREET_Paved	MZZONE_A	
MZZONE_C \					
0	0	0	1	1	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	1	0	0
4	0	0	0	0	1
...
7104	0	0	0	0	0
7105	0	0	0	0	0
7106	0	0	0	0	0

7107	0	0	1	0	0
7108	0	0	1	0	0

	MZZONE_I	MZZONE_RH	MZZONE_RL	MZZONE_RM
0	0	0	0	0
1	0	1	0	0
2	0	0	1	0
3	1	0	0	0
4	0	0	0	0
...
7104	0	0	0	1
7105	0	1	0	0
7106	1	0	0	0
7107	0	0	1	0
7108	1	0	0	0

[7109 rows x 44 columns]

X_1.iloc[0:10,0:15]

	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM	N_ROOM	PARK_FACIL
0	1004	131	1.0	1.0	3	1
1	1986	26	2.0	1.0	5	0
2	909	70	1.0	1.0	3	1
3	1855	14	3.0	2.0	5	0
4	1226	84	1.0	1.0	3	1
5	1220	36	2.0	1.0	4	0
6	1167	137	1.0	1.0	3	0
7	1847	176	3.0	2.0	5	0
8	771	175	1.0	1.0	2	0
9	1635	74	2.0	1.0	4	0

	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	QS_OVERALL	COMMIS
AREA_Adyar \					
0	4.0	3.9	4.9	4.330	144400
					0

1	4.9	4.2	2.5	3.765	304049	0
2	4.1	3.8	2.2	3.090	92114	1
3	4.7	3.9	3.6	4.010	77042	0
4	3.0	2.5	4.1	3.290	74063	0
5	4.5	2.6	3.1	3.320	198316	0
6	3.6	2.1	2.5	2.670	33955	0
7	2.4	4.5	2.1	3.260	235204	0
8	2.9	3.7	4.0	3.550	33236	0
9	3.1	3.1	3.3	3.160	121255	0

	AREA_Adyr	AREA_Ana Nagar	AREA_Ann Nagar
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0

X_1.iloc[0:10,15:]

	AREA_Anna Nagar AREA_Chrompt \	AREA_Chormpet	AREA_Chmpet	AREA_Chrompet
0	0	0	0	0
0				
1	1	0	0	0
0				
2	0	0	0	0
0				
3	0	0	0	0
0				
4	0	0	0	0
0				
5	0	0	0	1
0				
6	0	0	0	1

0				
7	0	0	0	0
0				
8	0	0	0	1
0				
9	0	0	0	0
0				

	AREA_KK Nagar	AREA_KKNagar	AREA_Karapakam	AREA_Karapakkam
AREA_T Nagar \				
0	0	0	0	1
0				
1	0	0	0	0
0				
2	0	0	0	0
0				
3	0	0	0	0
0				
4	0	0	0	1
0				
5	0	0	0	0
0				
6	0	0	0	0
0				
7	0	0	0	0
0				
8	0	0	0	0
0				
9	0	0	0	0
0				

	STREET_No Access	STREET_NoAccess	STREET_Pavd	
STREET_Paved \				
0 ...	0	0	0	1
1 ...	0	0	0	0
2 ...	0	0	0	0
3 ...	0	0	0	1
4 ...	0	0	0	0
5 ...	1	0	0	0
6 ...	1	0	0	0
7 ...	0	0	0	0

8	...	0	0	0	1
9	...	1	0	0	0

	MZZONE_A	MZZONE_C	MZZONE_I	MZZONE_RH	MZZONE_RL	MZZONE_RM
0	1	0	0	0	0	0
1	0	0	0	1	0	0
2	0	0	0	0	1	0
3	0	0	1	0	0	0
4	0	1	0	0	0	0
5	0	0	0	1	0	0
6	0	0	0	0	1	0
7	0	0	0	0	0	1
8	0	0	0	0	0	1
9	0	0	1	0	0	0

[10 rows x 29 columns]

y

0	7600000
1	21717770
2	13159200
3	9630290
4	7406250

...	
7104	5353000
7105	10818480
7106	8351410
7107	8507000
7108	9976480

Name: SALES_PRICE, Length: 7109, dtype: int64

```
import statsmodels.api as sm
X_1 = sm.add_constant(X_1)
X_1
```

	const	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM	N_ROOM	\
0	1.0	1004	131	1.0	1.0	3	
1	1.0	1986	26	2.0	1.0	5	
2	1.0	909	70	1.0	1.0	3	
3	1.0	1855	14	3.0	2.0	5	
4	1.0	1226	84	1.0	1.0	3	
...	
7104	1.0	598	51	1.0	1.0	2	
7105	1.0	1897	52	3.0	2.0	5	
7106	1.0	1614	152	2.0	1.0	4	
7107	1.0	787	40	1.0	1.0	2	
7108	1.0	1896	156	3.0	2.0	5	

Access \	PARK_FACIL	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	...	STREET_No
0	1	4.0	3.9	4.9	...	
0						
1	0	4.9	4.2	2.5	...	
0						
2	1	4.1	3.8	2.2	...	
0						
3	0	4.7	3.9	3.6	...	
0						
4	1	3.0	2.5	4.1	...	
0						
...	
...						
7104	0	3.0	2.2	2.4	...	
1						
7105	1	3.6	4.5	3.3	...	
1						
7106	0	4.3	4.2	2.9	...	
0						
7107	1	4.6	3.8	4.1	...	
0						
7108	1	3.1	3.5	4.3	...	
0						

MZZONE_C \	STREET_NoAccess	STREET_Pavd	STREET_Paved	MZZONE_A		
0	0	0	1	1		0
1	0	0	0	0		0
2	0	0	0	0		0
3	0	0	1	0		0
4	0	0	0	0		1
...
7104	0	0	0	0		0
7105	0	0	0	0		0
7106	0	0	0	0		0
7107	0	0	1	0		0
7108	0	0	1	0		0

	MZZONE_I	MZZONE_RH	MZZONE_RL	MZZONE_RM
0	0	0	0	0
1	0	1	0	0
2	0	0	1	0
3	1	0	0	0
4	0	0	0	0
...
7104	0	0	0	1
7105	0	1	0	0
7106	1	0	0	0
7107	0	0	1	0
7108	1	0	0	0

[7109 rows x 45 columns]

X_1.shape

(7109, 45)

X_1['QS_OVERALL'].fillna(value=5, inplace=True)

X_1['N_BEDROOM'].fillna(value=1, inplace=True)

X_1['N_BATHROOM'].fillna(value=1, inplace=True)

Splitting data into train and test

from sklearn.model_selection import train_test_split

X_train_1, X_test_1, y_train_1, y_test_1
= train_test_split(X_1, y, test_size=0.2, random_state=10)

X_train_1.shape, X_test_1.shape, y_train_1.shape, y_test_1.shape

((5687, 45), (1422, 45), (5687,), (1422,))

X_train_1

	const	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM	N_ROOM	\
591	1.0	764	36	1.0	1.0	2	
2651	1.0	1848	66	2.0	1.0	5	
5737	1.0	1592	95	2.0	2.0	4	
5601	1.0	1303	74	1.0	1.0	3	
1114	1.0	790	200	1.0	1.0	2	
...	
1180	1.0	1042	82	1.0	1.0	3	
3441	1.0	1091	49	1.0	1.0	3	
1344	1.0	1864	46	3.0	2.0	5	
4623	1.0	917	139	1.0	1.0	3	
1289	1.0	897	79	1.0	1.0	3	

PARK_FACIL QS_ROOMS QS_BATHROOM QS_BEDROOM ... STREET_No

Access \					
591	0	3.9	4.8	4.2	...
0					
2651	0	4.0	2.7	4.7	...
0					
5737	1	4.4	4.3	5.0	...
1					
5601	1	3.4	4.6	4.2	...
0					
1114	0	2.7	4.3	2.4	...
0					
...
...					
1180	1	3.0	3.4	2.7	...
0					
3441	1	2.7	4.8	2.4	...
0					
1344	1	2.7	2.0	3.1	...
0					
4623	1	2.1	3.7	3.4	...
1					
1289	1	2.2	2.2	5.0	...
1					

	STREET_NoAccess	STREET_Pavd	STREET_Paved	MZZONE_A	
MZZONE_C \					
591	0	0	0	0	0
2651	0	0	1	0	0
5737	0	0	0	1	0
5601	0	0	0	0	0
1114	0	0	0	0	0
...
1180	0	0	1	0	0
3441	0	0	1	0	0
1344	0	0	0	0	0
4623	0	0	0	0	0
1289	0	0	0	0	0

	MZZONE_I	MZZONE_RH	MZZONE_RL	MZZONE_RM
591	0	0	0	1
2651	0	0	0	1
5737	0	0	0	0
5601	0	1	0	0
1114	1	0	0	0
...
1180	1	0	0	0
3441	1	0	0	0
1344	0	1	0	0
4623	0	0	1	0
1289	0	0	0	1

[5687 rows x 45 columns]

X_test_1

	const	INT_SQFT	DIST_MAINROAD	N_BEDROOM	N_BATHROOM	N_ROOM	\
461	1.0	1563	57	2.0	1.0	4	
3358	1.0	1580	35	1.0	1.0	4	
3751	1.0	1807	83	2.0	1.0	5	
2386	1.0	2495	191	4.0	2.0	6	
1125	1.0	1420	30	2.0	2.0	4	
...
6010	1.0	1738	19	1.0	1.0	4	
4903	1.0	1690	59	2.0	1.0	4	
6806	1.0	1297	0	1.0	1.0	3	
3832	1.0	1934	183	2.0	1.0	5	
364	1.0	802	161	1.0	1.0	3	

	PARK_FACIL	QS_ROOMS	QS_BATHROOM	QS_BEDROOM	...	STREET_No
Access \						
461	1	4.1	4.7	2.7	...	
0						
3358	0	2.9	3.9	5.0	...	
0						
3751	1	3.1	2.4	5.0	...	
0						
2386	0	3.0	3.0	2.7	...	
0						
1125	0	5.0	3.7	2.2	...	
0						
...	
...						
6010	0	3.2	3.4	3.2	...	
0						
4903	1	2.7	3.4	4.3	...	
0						
6806	1	3.1	3.2	3.0	...	
1						

3832	0	4.6	3.2	4.6	...
0					
364	0	3.4	4.2	3.6	...
1					

	STREET_NoAccess	STREET_Pavd	STREET_Paved	MZZONE_A	
MZZONE_C \					
461	0	0	1	0	0
3358	0	0	1	0	0
3751	0	0	1	0	0
2386	0	0	0	0	0
1125	0	0	0	0	0
...
6010	0	0	1	0	0
4903	0	0	0	0	1
6806	0	0	0	0	1
3832	0	0	0	0	0
364	0	0	0	0	0

	MZZONE_I	MZZONE_RH	MZZONE_RL	MZZONE_RM
461	0	0	0	1
3358	0	0	0	1
3751	0	0	0	1
2386	0	0	0	1
1125	0	0	1	0
...
6010	0	0	0	1
4903	0	0	0	0
6806	0	0	0	0
3832	0	0	0	1
364	0	0	0	1

[1422 rows x 45 columns]

X_1.isnull().sum()

const	0
INT_SQFT	0

DIST_MAINROAD	0
N_BEDROOM	0
N_BATHROOM	0
N_ROOM	0
PARK_FACIL	0
QS_ROOMS	0
QS_BATHROOM	0
QS_BEDROOM	0
QS_OVERALL	0
COMMIS	0
AREA_Adyar	0
AREA_Adyr	0
AREA_Ana Nagar	0
AREA_Ann Nagar	0
AREA_Anna Nagar	0
AREA_Chormpet	0
AREA_Chmpet	0
AREA_Chrompet	0
AREA_Chrompt	0
AREA_KK Nagar	0
AREA_KKNagar	0
AREA_Karapakam	0
AREA_Karapakkam	0
AREA_T Nagar	0
AREA_TNagar	0
AREA_Velachery	0
AREA_Velchery	0
BUILDTYPE_Comercial	0
BUILDTYPE_Commercial	0
BUILDTYPE_House	0
BUILDTYPE_Other	0
BUILDTYPE_Others	0
STREET_Gravel	0
STREET_No Access	0
STREET_NoAccess	0
STREET_Pavd	0
STREET_Paved	0
MZZONE_A	0
MZZONE_C	0
MZZONE_I	0
MZZONE_RH	0
MZZONE_RL	0
MZZONE_RM	0
dtype: int64	

```
X_1['QS_OVERALL'].fillna(value=5, inplace=True)
```

```
X_1.isnull().sum()
```

const	0
INT_SQFT	0

DIST_MAINROAD	0
N_BEDROOM	0
N_BATHROOM	0
N_ROOM	0
PARK_FACIL	0
QS_ROOMS	0
QS_BATHROOM	0
QS_BEDROOM	0
QS_OVERALL	0
COMMIS	0
AREA_Adyar	0
AREA_Adyr	0
AREA_Ana Nagar	0
AREA_Ann Nagar	0
AREA_Anna Nagar	0
AREA_Chormpet	0
AREA_Chmpet	0
AREA_Chrompet	0
AREA_Chrompt	0
AREA_KK Nagar	0
AREA_KKNagar	0
AREA_Karapakam	0
AREA_Karapakkam	0
AREA_T Nagar	0
AREA_TNagar	0
AREA_Velachery	0
AREA_Velchery	0
BUILDTYPE_Comercial	0
BUILDTYPE_Commercial	0
BUILDTYPE_House	0
BUILDTYPE_Other	0
BUILDTYPE_Others	0
STREET_Gravel	0
STREET_No Access	0
STREET_NoAccess	0
STREET_Pavd	0
STREET_Paved	0
MZZONE_A	0
MZZONE_C	0
MZZONE_I	0
MZZONE_RH	0
MZZONE_RL	0
MZZONE_RM	0

dtype: int64

```
X_1['N_BEDROOM'].fillna(value=1, inplace=True)
```

```
X_1['N_BATHROOM'].fillna(value=1, inplace=True)
```

```
X_1.isnull().sum()
```

const	0
INT_SQFT	0
DIST_MAINROAD	0
N_BEDROOM	0
N_BATHROOM	0
N_ROOM	0
PARK_FACIL	0
QS_ROOMS	0
QS_BATHROOM	0
QS_BEDROOM	0
QS_OVERALL	0
COMMIS	0
AREA_Adyar	0
AREA_Adyr	0
AREA_Ana Nagar	0
AREA_Ann Nagar	0
AREA_Anna Nagar	0
AREA_Chormpet	0
AREA_Chrmpt	0
AREA_Chrompet	0
AREA_Chrompt	0
AREA_KK Nagar	0
AREA_KKNagar	0
AREA_Karapakam	0
AREA_Karapakkam	0
AREA_T Nagar	0
AREA_TNagar	0
AREA_Velachery	0
AREA_Velchery	0
BUILDTYPE_Comercial	0
BUILDTYPE_Commercial	0
BUILDTYPE_House	0
BUILDTYPE_Other	0
BUILDTYPE_Others	0
STREET_Gravel	0
STREET_No Access	0
STREET_NoAccess	0
STREET_Pavd	0
STREET_Paved	0
MZZONE_A	0
MZZONE_C	0
MZZONE_I	0
MZZONE_RH	0
MZZONE_RL	0
MZZONE_RM	0
dtype: int64	

Building the model

```
m1r_1 = sm.OLS(y_train_1, X_train_1)
```

```
mlr_1 = mlr_1.fit()
```

```
mlr_1.params
```

const	2.700263e+06
INT_SQFT	3.782721e+03
DIST_MAINROAD	-6.888493e+01
N_BEDROOM	2.823435e+05
N_BATHROOM	-4.031941e+05
N_ROOM	1.206859e+05
PARK_FACIL	9.914752e+05
QS_ROOMS	-1.695507e+04
QS_BATHROOM	-1.560937e+04
QS_BEDROOM	2.789208e+03
QS_OVERALL	8.513923e+04
COMMIS	2.840802e+00
AREA_Adyar	4.579575e+05
AREA_Adyr	1.168757e+06
AREA_Ana Nagar	4.596758e+06
AREA_Ann Nagar	1.213446e+06
AREA_Anna Nagar	1.912341e+06
AREA_Chormpet	-9.981541e+03
AREA_Chmpet	5.050556e+05
AREA_Chrompet	-3.400180e+03
AREA_Chrompt	1.940305e+05
AREA_KK Nagar	-1.692252e+06
AREA_KKNagar	-2.066746e+06
AREA_Karapakam	-2.502585e+06
AREA_Karapakkam	-2.033962e+06
AREA_T Nagar	2.051998e+06
AREA_TNagar	2.221258e+06
AREA_Velachery	-1.474939e+06
AREA_Velchery	-1.837474e+06
BUILDTYPE_Comercial	2.026595e+06
BUILDTYPE_Commercial	3.164816e+06
BUILDTYPE_House	-1.349369e+06
BUILDTYPE_Other	-4.606319e+05
BUILDTYPE_Others	-6.811467e+05
STREET_Gravel	1.116480e+06
STREET_No Access	4.600433e+03
STREET_NoAccess	4.874171e+05
STREET_Pavd	4.796557e+05
STREET_Paved	6.121090e+05
MZZONE_A	-9.312163e+05
MZZONE_C	-4.019670e+05
MZZONE_I	1.401905e+05
MZZONE_RH	7.031580e+05
MZZONE_RL	1.286094e+06
MZZONE_RM	1.904003e+06

dtype: float64

Diagnosing the model

```
mlr_1.summary2()
```

```
<class 'statsmodels.iolib.summary2.Summary'>
```

```
"""
```

Results: Ordinary least squares

```
=====
```

```
=====
```

Model:	OLS	Adj. R-squared:
0.952		
Dependent Variable:	SALES_PRICE	AIC:
171092.7797		
Date:	2022-11-10 01:46	BIC:
171365.2632		
No. Observations:	5687	Log-Likelihood:
-85505.		
Df Model:	40	F-statistic:
2827.		
Df Residuals:	5646	Prob (F-
statistic):	0.00	
R-squared:	0.952	Scale:
6.7625e+11		

```
-----
```

```
-----
```

	Coef.	Std.Err.	t	P> t
--	-------	----------	---	------

[0.025	0.975]
--------	--------

```
-----
```

const	2700262.6253	133901.4227	20.1660	0.0000	
2437764.3863	2962760.8642				
INT_SQFT	3782.7207	101.9670	37.0975	0.0000	
3582.8262	3982.6152				
DIST_MAINROAD	-68.8849	190.3813	-0.3618	0.7175	-
442.1055	304.3356				
N_BEDROOM	282343.4565	50202.0172	5.6241	0.0000	
183928.2131	380758.6998				
N_BATHROOM	-403194.0971	50465.7131	-7.9895	0.0000	-
502126.2859	-304261.9084				
N_ROOM	120685.8893	49649.9672	2.4307	0.0151	
23352.8760	218018.9026				
PARK_FACIL	991475.2304	22074.5239	44.9149	0.0000	
948200.6817	1034749.7791				
QS_ROOMS	-16955.0748	24316.7456	-0.6973	0.4857	-
64625.2397	30715.0901				
QS_BATHROOM	-15609.3741	26057.3976	-0.5990	0.5492	-
66691.8856	35473.1375				
QS_BEDROOM	2789.2083	29137.5059	0.0957	0.9237	-
54331.4990	59909.9156				
QS_OVERALL	85139.2250	70710.7591	1.2040	0.2286	-
53481.0328	223759.4829				

COMMIS		2.8408	0.2011	14.1231	0.0000	
2.4465	3.2351					
AREA_Adyar		457957.5015	119915.1918	3.8190	0.0001	
222877.6492	693037.3538					
AREA_Adyr		1168756.9164	784444.8204	1.4899	0.1363	-
369056.3478	2706570.1806					
AREA_Ana Nagar		4596757.6997	784668.4589	5.8582	0.0000	
3058506.0179	6135009.3814					
AREA_Ann Nagar		1213446.1788	560789.6282	2.1638	0.0305	
114083.0288	2312809.3289					
AREA_Anna Nagar		1912341.4195	122213.1100	15.6476	0.0000	
1672756.7645	2151926.0745					
AREA_Chormpet		-9981.5407	464024.4963	-0.0215	0.9828	-
919647.8510	899684.7697					
AREA_Chrmpt		505055.5965	337033.3664	1.4985	0.1341	-
155659.3039	1165770.4970					
AREA_Chrompet		-3400.1804	115578.4249	-0.0294	0.9765	-
229978.3033	223177.9425					
AREA_Chrompt		194030.5498	296549.9201	0.6543	0.5129	-
387321.2404	775382.3400					
AREA_KK Nagar		-1692251.6215	119992.7799	-14.1029	0.0000	-
1927483.5764	-1457019.6667					
AREA_KKNagar		-2066746.4053	783928.1856	-2.6364	0.0084	-
3603546.8668	-529945.9439					
AREA_Karapakam		-2502585.1522	463351.4545	-5.4011	0.0000	-
3410932.0419	-1594238.2625					
AREA_Karapakkam		-2033961.5584	117218.1490	-17.3519	0.0000	-
2263754.1706	-1804168.9462					
AREA_T Nagar		2051997.7054	124485.9407	16.4838	0.0000	
1807957.4290	2296037.9818					
AREA_TNagar		2221257.9227	405559.9557	5.4770	0.0000	
1426204.5765	3016311.2689					
AREA_Velachery		-1474938.7710	118305.6171	-12.4672	0.0000	-
1706863.2385	-1243014.3035					
AREA_Velchery		-1837473.6355	784870.6218	-2.3411	0.0193	-
3376121.6342	-298825.6369					
BUILDTYPE_Comercial		2026594.7061	481654.6730	4.2076	0.0000	
1082366.4752	2970822.9370					
BUILDTYPE_Commercial		3164815.8045	111404.3121	28.4084	0.0000	
2946420.5467	3383211.0624					
BUILDTYPE_House		-1349369.2327	110654.0102	-12.1945	0.0000	-
1566293.6105	-1132444.8549					
BUILDTYPE_Other		-460631.9271	181581.7847	-2.5368	0.0112	-
816601.9965	-104661.8578					
BUILDTYPE_Others		-681146.7255	110814.9170	-6.1467	0.0000	-
898386.5426	-463906.9085					
STREET_Gravel		1116480.4732	78695.8205	14.1873	0.0000	
962206.4269	1270754.5196					
STREET_No Access		4600.4335	79117.7594	0.0581	0.9536	-
150500.7753	159701.6422					


```

STREET_NoAccess      487417.0973 282303.8921    1.7266 0.0843  -
66007.0040 1040841.1987
STREET_Pavd          479655.6547 214706.0734    2.2340 0.0255
58749.2519 900562.0575
STREET_Paved         612108.9664 78715.8453    7.7762 0.0000
457795.6638 766422.2690
MZZONE_A             -931216.3144 43206.4938 -21.5527 0.0000  -
1015917.6440 -846514.9848
MZZONE_C             -401967.0306 42368.1625  -9.4875 0.0000  -
485024.9087 -318909.1525
MZZONE_I             140190.5487 43827.7971    3.1987 0.0014
54271.2260 226109.8714
MZZONE_RH            703158.0169 32263.5037   21.7942 0.0000
639909.1527 766406.8811
MZZONE_RL            1286094.4877 32511.6068   39.5580 0.0000
1222359.2461 1349829.7294
MZZONE_RM            1904002.9169 32809.7085   58.0317 0.0000
1839683.2814 1968322.5524
-----
-----
Omnibus:              132.790                Durbin-Watson:
2.043
Prob(Omnibus):        0.000                Jarque-Bera (JB):
192.697
Skew:                 0.255                Prob(JB):
0.000
Kurtosis:             3.743                Condition No.:
11448429555476168
=====
=====
* The condition number is large (1e+16). This might indicate
strong
multicollinearity or other numerical problems.
"""

```

Note

only ODI_WKTS and BASE PRICE are relevant features.

Multicollinearity

```

from statsmodels.stats.outliers_influence import
variance_inflation_factor

def var_inf_factor(data):
    vif=pd.DataFrame()
    vif['Feature']=data.columns
    vif['VIF_Value']= [variance_inflation_factor(data.values,i) for i
in range(data.shape[1])]
    print(vif)

var_inf_factor(X_1)

```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\regression\
linear_model.py:1736: RuntimeWarning: divide by zero encountered in
double_scalars
```

```
    return 1 - self.ssr/self.centered_tss
```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\stats\
outliers_influence.py:195: RuntimeWarning: divide by zero encountered
in double_scalars
```

```
    vif = 1. / (1. - r_squared_i)
```

	Feature	VIF_Value
0	const	0.000000
1	INT_SQFT	18.539409
2	DIST_MAINROAD	1.006672
3	N_BEDROOM	13.567914
4	N_BATHROOM	3.577235
5	N_ROOM	21.475609
6	PARK_FACIL	1.023800
7	QS_ROOMS	4.012710
8	QS_BATHROOM	4.620034
9	QS_BEDROOM	5.649446
10	QS_OVERALL	12.293831
11	COMMIS	2.110629
12	AREA_Adyar	inf
13	AREA_Adyr	inf
14	AREA_Ana Nagar	inf
15	AREA_Ann Nagar	inf
16	AREA_Anna Nagar	inf
17	AREA_Chormpet	inf
18	AREA_Chmpet	inf
19	AREA_Chrompet	inf
20	AREA_Chrompt	inf
21	AREA_KK Nagar	inf
22	AREA_KKNagar	inf
23	AREA_Karapakam	inf
24	AREA_Karapakkam	inf
25	AREA_T Nagar	inf
26	AREA_TNagar	inf
27	AREA_Velachery	inf
28	AREA_Velchery	inf
29	BUILDTYPE_Comercial	inf
30	BUILDTYPE_Commercial	inf
31	BUILDTYPE_House	inf
32	BUILDTYPE_Other	inf
33	BUILDTYPE_Others	inf
34	STREET_Gravel	inf
35	STREET_No Access	inf
36	STREET_NoAccess	inf
37	STREET_Pavd	inf
38	STREET_Paved	inf
39	MZZONE_A	inf

```

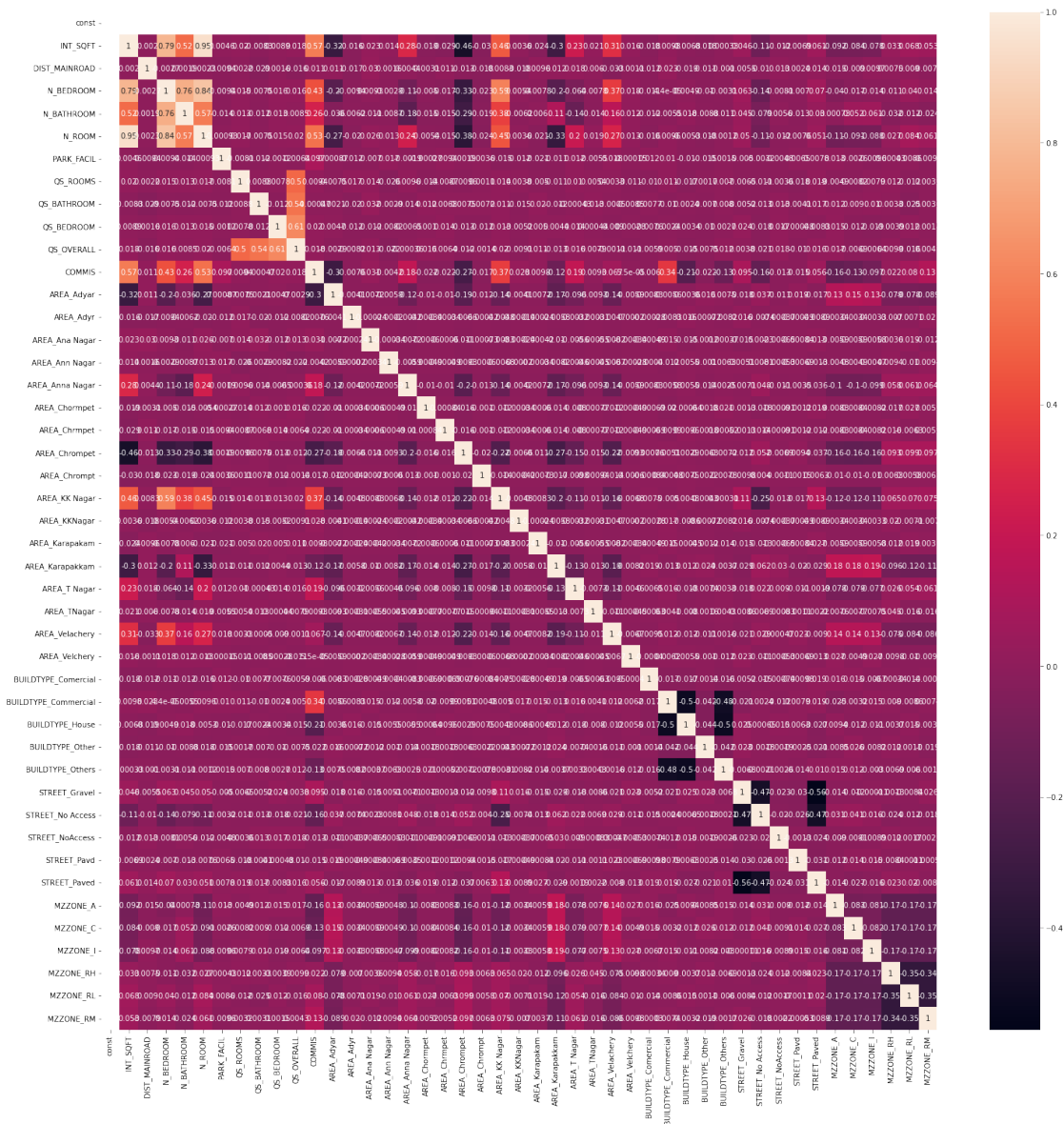
40      MZZONE_C      inf
41      MZZONE_I      inf
42      MZZONE_RH     inf
43      MZZONE_RL     inf
44      MZZONE_RM     inf

```

```

plt.figure(figsize=(25,25))
sns.heatmap(X_1.corr(),annot=True);

```



```

features_to_drop_1=['N_BEDROOM', 'N_BATHROOM', 'N_ROOM']
features_2=list(set(X_1.columns)-set(features_to_drop_1))
features_2

```

```
[ 'STREET_NoAccess',
  'AREA_Chmpet',
  'AREA_Adyr',
  'AREA_Velachery',
  'BUILDTYPE_Others',
  'QS_ROOMS',
  'QS_BATHROOM',
  'BUILDTYPE_Comercial',
  'AREA_TNagar',
  'AREA_Karapakkam',
  'AREA_Adyar',
  'AREA_Chrompt',
  'STREET_Gravel',
  'AREA_Chrompt',
  'MZZONE_C',
  'MZZONE_RL',
  'AREA_Ana Nagar',
  'MZZONE_RM',
  'STREET_No Access',
  'DIST_MAINROAD',
  'AREA_KK Nagar',
  'MZZONE_I',
  'BUILDTYPE_Commercial',
  'QS_OVERALL',
  'AREA_Anna Nagar',
  'INT_SQFT',
  'COMMIS',
  'AREA_Chormpet',
  'BUILDTYPE_Other',
  'BUILDTYPE_House',
  'AREA_Velchery',
  'MZZONE_RH',
  'AREA_KKNagar',
  'PARK_FACIL',
  'STREET_Pavd',
  'AREA_Karapakam',
  'STREET_Paved',
  'const',
  'AREA_Ann Nagar',
  'QS_BEDROOM',
  'AREA_T Nagar',
  'MZZONE_A']
```

```
len(features_2)
```

```
42
```

The new feature set

```
X_2=X_1[features_2]
```

```
X_2
```

	STREET_NoAccess	AREA_Chmpet	AREA_Adyr	AREA_Velachery	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	1	
4	0	0	0	0	
...	
7104	0	0	0	0	
7105	0	0	0	1	
7106	0	0	0	1	
7107	0	0	0	0	
7108	0	0	0	1	

	BUILDTYPE_Others	QS_ROOMS	QS_BATHROOM	BUILDTYPE_Comercial	\
0	0	4.0	3.9		0
1	0	4.9	4.2		0
2	0	4.1	3.8		0
3	1	4.7	3.9		0
4	1	3.0	2.5		0
...	
7104	1	3.0	2.2		0
7105	1	3.6	4.5		0
7106	0	4.3	4.2		0
7107	0	4.6	3.8		0
7108	1	3.1	3.5		0

	AREA_TNagar	AREA_Karapakkam	...	AREA_KKNagar	PARK_FACIL	\
0	0	1	...	0		1
1	0	0	...	0		0
2	0	0	...	0		1
3	0	0	...	0		0
4	0	1	...	0		1
...	
7104	0	1	...	0		0
7105	0	0	...	0		1
7106	0	0	...	0		0
7107	0	1	...	0		1
7108	0	0	...	0		1

	STREET_Pavd	AREA_Karapakkam	STREET_Paved	const	AREA_Ann	Nagar
\						
0	0	0	1	1.0		0
1	0	0	0	1.0		0
2	0	0	0	1.0		0
3	0	0	1	1.0		0

4	0	0	0	1.0	0
...
7104	0	0	0	1.0	0
7105	0	0	0	1.0	0
7106	0	0	0	1.0	0
7107	0	0	1	1.0	0
7108	0	0	1	1.0	0

	QS_BEDROOM	AREA_T	Nagar	MZZONE_A
0	4.9		0	1
1	2.5		0	0
2	2.2		0	0
3	3.6		0	0
4	4.1		0	0
...
7104	2.4		0	0
7105	3.3		0	0
7106	2.9		0	0
7107	4.1		0	0
7108	4.3		0	0

[7109 rows x 42 columns]

Splitting X_2 to train and test

```
X_train_2,X_test_2,y_train_2,y_test_2=train_test_split(
    X_2,y,test_size=0.2, random_state=10)
```

```
X_train_2.shape,X_test_2.shape,y_train_2.shape,y_test_2.shape
```

```
((5687, 42), (1422, 42), (5687,), (1422,))
```

```
X_train_2
```

	STREET_NoAccess	AREA_Chrmptet	AREA_Adyr	AREA_Velachery	\
591	0	0	0	0	
2651	0	0	0	0	
5737	0	0	0	0	
5601	0	0	0	0	
1114	0	0	0	0	
...	
1180	0	0	0	0	
3441	0	0	0	0	

1344	0	0	0	1
4623	0	0	0	0
1289	0	0	0	0

	BUILDTYPE_Others	QS_ROOMS	QS_BATHROOM	BUILDTYPE_Comercial	\
591	1	3.9	4.8	0	
2651	0	4.0	2.7	0	
5737	0	4.4	4.3	0	
5601	1	3.4	4.6	0	
1114	0	2.7	4.3	0	
...	
1180	0	3.0	3.4	0	
3441	0	2.7	4.8	0	
1344	0	2.7	2.0	0	
4623	0	2.1	3.7	0	
1289	0	2.2	2.2	0	

	AREA_TNagar	AREA_Karapakkam	...	AREA_KKNagar	PARK_FACIL	\
591	0	0	...	0	0	
2651	0	0	...	0	0	
5737	0	1	...	0	1	
5601	0	0	...	0	1	
1114	0	0	...	0	0	
...	
1180	0	1	...	0	1	
3441	0	1	...	0	1	
1344	0	0	...	0	1	
4623	0	0	...	0	1	
1289	0	0	...	0	1	

	STREET_Pavd	AREA_Karapakam	STREET_Paved	const	AREA_Ann	Nagar
\						
591	0	0	0	1.0		0
2651	0	0	1	1.0		0
5737	0	0	0	1.0		0
5601	0	0	0	1.0		0
1114	0	0	0	1.0		0
...
1180	0	0	1	1.0		0
3441	0	0	1	1.0		0
1344	0	0	0	1.0		0

4623	0	0	0	1.0	0
1289	0	0	0	1.0	0

	QS_BEDROOM	AREA_T	Nagar	MZZONE_A
591	4.2		0	0
2651	4.7		0	0
5737	5.0		0	1
5601	4.2		0	0
1114	2.4		0	0
...
1180	2.7		0	0
3441	2.4		0	0
1344	3.1		0	0
4623	3.4		0	0
1289	5.0		0	0

[5687 rows x 42 columns]

Building the model

```
mlr_2=sm.OLS(y_train_2,X_train_2)
```

Fit

```
mlr_2=mlr_2.fit()
```

Diagnosis

```
mlr_2.summary2()
```

```
<class 'statsmodels.iolib.summary2.Summary'>
"""
```

```

                                Results: Ordinary least squares
=====
=====
Model:                            OLS                               Adj. R-squared:
0.951
Dependent Variable:                SALES_PRICE                       AIC:
171190.4518
Date:                             2022-11-10 01:46                   BIC:
171442.9974
No. Observations:                  5687                             Log-Likelihood:
-85557.
Df Model:                          37                               F-statistic:
2999.
Df Residuals:                      5649                             Prob (F-
statistic):                      0.00
```


R-squared:
6.8833e+11

0.952

Scale:

[0.025 0.975]		Coef.	Std.Err.	t	P> t	
STREET_NoAccess	457365.8240	284693.8407	1.6065	0.1082	-	
100743.4313	1015475.0794					
AREA_Chmpet	533891.4931	339315.5303	1.5734	0.1157	-	
131297.2496	1199080.2358					
AREA_Adyr	1064968.5697	790815.7195	1.3467	0.1781	-	
485333.9281	2615271.0676					
AREA_Velachery	-1410884.3476	117940.7831	-11.9627	0.0000	-	
1642093.5739	-1179675.1213					
BUILDTYPE_Others	-694861.8194	111581.8528	-6.2274	0.0000	-	
913605.1004	-476118.5383					
QS_ROOMS	-17817.0027	24531.5459	-0.7263	0.4677	-	
65908.2533	30274.2478					
QS_BATHROOM	-15864.7060	26287.0808	-0.6035	0.5462	-	
67397.4791	35668.0671					
BUILDTYPE_Comercial	2024077.3383	485922.5623	4.1654	0.0000		
1071482.5129	2976672.1636					
AREA_TNagar	2193080.4458	407799.8187	5.3778	0.0000		
1393636.1986	2992524.6931					
AREA_Karapakkam	-2182255.6491	116351.3429	-18.7557	0.0000	-	
2410348.9623	-1954162.3359					
AREA_Adyar	369299.4733	119363.2056	3.0939	0.0020		
135301.7526	603297.1939					
AREA_Chrompt	167866.6891	298896.2801	0.5616	0.5744	-	
418084.8015	753818.1797					
STREET_Gravel	1115206.0058	79219.8938	14.0773	0.0000		
959904.5921	1270507.4194					
AREA_Chrompet	-23031.3189	116138.4901	-0.1983	0.8428	-	
250707.3588	204644.7210					
MZZONE_C	-403677.5243	42435.3928	-9.5128	0.0000	-	
486867.1901	-320487.8585					
MZZONE_RL	1283375.1264	32425.7394	39.5789	0.0000		
1219808.2251	1346942.0276					
AREA_Ana Nagar	4717499.3646	790964.8076	5.9642	0.0000		
3166904.5966	6268094.1326					
MZZONE_RM	1894055.6775	32682.0972	57.9539	0.0000		
1829986.2164	1958125.1386					
STREET_No Access	6562.3025	79666.3930	0.0824	0.9344	-	
149614.4211	162739.0262					
DIST_MAINROAD	-73.1462	192.0718	-0.3808	0.7033	-	
449.6807	303.3883					
AREA_KK Nagar	-1592795.0856	118915.0614	-13.3944	0.0000	-	
1825914.2715	-1359675.8997					

MZZONE_I	133679.4603	43999.0069	3.0382	0.0024	
47424.5104	219934.4102				
BUILDTYPE_Commercial	3149982.5340	112110.9485	28.0970	0.0000	
2930202.0223	3369763.0458				
QS_OVERALL	84157.9464	71337.2284	1.1797	0.2382	-
55690.4161	224006.3089				
AREA_Anna Nagar	1854703.1179	118474.8331	15.6548	0.0000	
1622446.9485	2086959.2873				
INT_SQFT	4145.0527	47.0418	88.1142	0.0000	
4052.8327	4237.2728				
COMMIS	2.8435	0.2029	14.0165	0.0000	
2.4458	3.2412				
AREA_Chormpet	135147.3100	467725.5387	0.2889	0.7726	-
781774.3611	1052068.9810				
BUILDTYPE_Other	-440033.9664	183053.9274	-2.4038	0.0163	-
798889.9602	-81177.9727				
BUILDTYPE_House	-1367109.8480	111428.5860	-12.2689	0.0000	-
1585552.6672	-1148667.0287				
AREA_Velchery	-1853425.3538	791470.6019	-2.3417	0.0192	-
3405011.6727	-301839.0349				
MZZONE_RH	687374.7461	32149.9106	21.3803	0.0000	
624348.5752	750400.9169				
AREA_KKNagar	-1913331.1232	790634.2068	-2.4200	0.0156	-
3463277.7866	-363384.4598				
PARK_FACIL	988397.8002	22262.7629	44.3969	0.0000	
944754.2357	1032041.3648				
STREET_Pavd	480414.7334	216396.3959	2.2201	0.0265	
56194.6973	904634.7696				
AREA_Karapakam	-2597074.5012	466350.7250	-5.5689	0.0000	-
3511301.0094	-1682847.9930				
STREET_Paved	612505.3728	79259.7216	7.7278	0.0000	
457125.8813	767884.8643				
const	2672054.2386	131633.0004	20.2993	0.0000	
2414003.0083	2930105.4689				
AREA_Ann Nagar	1196810.8868	564824.3208	2.1189	0.0341	
89538.3152	2304083.4584				
QS_BEDROOM	4701.5959	29394.3617	0.1599	0.8729	-
52922.6410	62325.8329				
AREA_T Nagar	2011584.2670	121029.2920	16.6206	0.0000	
1774320.3773	2248848.1567				
MZZONE_A	-922753.2473	43119.4426	-21.3999	0.0000	-
1007283.9134	-838222.5812				

Omnibus:	215.321	Durbin-Watson:
2.042		
Prob(Omnibus):	0.000	Jarque-Bera (JB):
317.681		
Skew:	0.366	Prob(JB):
0.000		

Kurtosis: 3.897 Condition No.:
22487865609621064

```
=====
* The condition number is large (2e+16). This might indicate
strong
multicollinearity or other numerical problems.
"""
```

VIF

var_inf_factor(X_2)

C:\Users\hp\anaconda3\lib\site-packages\statsmodels\stats\outliers_influence.py:195: RuntimeWarning: divide by zero encountered in double_scalars

vif = 1. / (1. - r_squared_i)

	Feature	VIF_Value
0	STREET_NoAccess	inf
1	AREA_Chmpet	inf
2	AREA_Adyr	inf
3	AREA_Velachery	inf
4	BUILDTYPE_Others	inf
5	QS_ROOMS	4.011797
6	QS_BATHROOM	4.619991
7	BUILDTYPE_Comercial	inf
8	AREA_TNagar	inf
9	AREA_Karapakkam	inf
10	AREA_Adyar	inf
11	AREA_Chrompt	inf
12	STREET_Gravel	inf
13	AREA_Chrompt	inf
14	MZZONE_C	inf
15	MZZONE_RL	inf
16	AREA_Ana Nagar	inf
17	MZZONE_RM	inf
18	STREET_No Access	inf
19	DIST_MAINROAD	1.006590
20	AREA_KK Nagar	inf
21	MZZONE_I	inf
22	BUILDTYPE_Commercial	inf
23	QS_OVERALL	12.293344
24	AREA_Anna Nagar	inf
25	INT_SQFT	3.835332
26	COMMIS	2.108649
27	AREA_Chormpet	inf
28	BUILDTYPE_Other	inf
29	BUILDTYPE_House	inf
30	AREA_Velchery	inf
31	MZZONE_RH	inf

```

32         AREA_KKNagar          inf
33         PARK_FACIL      1.023054
34         STREET_Pavd          inf
35         AREA_Karapakam        inf
36         STREET_Paved          inf
37         const      0.000000
38         AREA_Ann Nagar        inf
39         QS_BEDROOM      5.648738
40         AREA_T Nagar          inf
41         MZZONE_A            inf

```

```

C:\Users\hp\anaconda3\lib\site-packages\statsmodels\regression\
linear_model.py:1736: RuntimeWarning: divide by zero encountered in
double_scalars

```

```

    return 1 - self.ssr/self.centered_tss

```

```

## now there is no multicollinearity

```

```

# Features with p < 0.05

```

```

features_3=['INT_SQFT', 'PARK_FACIL', 'DIST_MAINROAD']

```

```

X_3=X_2[features_3]

```

```

X_3

```

	INT_SQFT	PARK_FACIL	DIST_MAINROAD
0	1004	1	131
1	1986	0	26
2	909	1	70
3	1855	0	14
4	1226	1	84
...
7104	598	0	51
7105	1897	1	52
7106	1614	0	152
7107	787	1	40
7108	1896	1	156

```

[7109 rows x 3 columns]

```

```

# Splitting

```

```

X_train_3,X_test_3,y_train_3,y_test_3=train_test_split(X_3,

```

```

y,train_size=0.8,random_state=10)

```

```

X_train_3.shape,X_test_3.shape,y_train_3.shape,y_test_3.shape

```

```

((5687, 3), (1422, 3), (5687,), (1422,))

```

```

# Buidling the model

```

```

mlr_3=sm.OLS(y_train_3,X_train_3)

```

```

mlr_3=mlr_3.fit()
mlr_3.summary2()
<class 'statsmodels.iolib.summary2.Summary'>
"""
                                Results: Ordinary least squares
=====
=====
Model:                        OLS                        Adj. R-squared (uncentered):
0.930
Dependent Variable:          SALES_PRICE                  AIC:
185971.2208
Date:                        2022-11-10 01:46             BIC:
185991.1586
No. Observations:           5687                        Log-Likelihood:
-92983.
Df Model:                    3                          F-statistic:
2.518e+04
Df Residuals:                5684                      Prob (F-statistic):
0.00
R-squared (uncentered):      0.930                      Scale:
9.3156e+12
-----
-----
                                Coef.      Std.Err.      t      P>|t|      [0.025
0.975]
-----
-----
INT_SQFT                     6565.4930      52.8530  124.2218  0.0000      6461.8810
6669.1051
PARK_FACIL                   1518613.2545    78038.3975   19.4598  0.0000    1365628.2292
1671598.2799
DIST_MAINROAD                8108.3462      622.4316   13.0269  0.0000      6888.1428
9328.5495
-----
-----
Omnibus:                     93.877                        Durbin-Watson:
1.988
Prob(Omnibus):               0.000                        Jarque-Bera (JB):
98.255
Skew:                        0.320                        Prob(JB):
0.000
Kurtosis:                    2.934                        Condition No.:
2817
=====
=====
* The condition number is large (3e+03). This might indicate
strong
multicollinearity or other numerical problems.
"""

```

```
var_inf_factor(X_3)
```

```
      Feature  VIF_Value
0      INT_SQFT    3.626530
1     PARK_FACIL    1.872617
2  DIST_MAINROAD    3.154200
```

```
features_4=['INT_SQFT', 'PARK_FACIL']
X_4=X_3[features_4]
```

```
X_4
```

```
      INT_SQFT  PARK_FACIL
0         1004           1
1         1986           0
2          909           1
3         1855           0
4         1226           1
...         ...         ...
7104        598           0
7105        1897          1
7106        1614           0
7107         787           1
7108        1896           1
```

```
[7109 rows x 2 columns]
```

```
# Splitting
```

```
X_train_4,X_test_4,y_train_4,y_test_4=train_test_split(X_4,
                                                         y,
                                                         train_size=0.8,random_state=10)
```

```
X_train_4.shape,X_test_4.shape,y_train_4.shape,y_test_4.shape
((5687, 2), (1422, 2), (5687,), (1422,))
```

```
# Building
```

```
mlr_4=sm.OLS(y_train_4,X_train_4)
mlr_4=mlr_4.fit()
```

```
mlr_4.summary2()
```

```
<class 'statsmodels.iolib.summary2.Summary'>
"""
```

```
Results: Ordinary least squares
```

```
=====
=====
Model:                                OLS                                Adj. R-squared (uncentered):
0.928
Dependent Variable:    SALES_PRICE    AIC:
186136.5249
```

Date: 2022-11-10 01:46 BIC: 186149.8168
 No. Observations: 5687 Log-Likelihood: -93066.
 Df Model: 2 F-statistic: 3.660e+04
 Df Residuals: 5685 Prob (F-statistic): 0.00
 R-squared (uncentered): 0.928 Scale: 9.5920e+12

	Coef.	Std.Err.	t	P> t	[0.025
INT_SQFT	7045.6051	38.4409	183.2843	0.0000	6970.2463
PARK_FACIL	1658157.6922	78438.2336	21.1397	0.0000	1504388.8413

Omnibus: 1.983 Prob(Omnibus): 58.749 Skew: 0.000 Kurtosis: 2784
 Durbin-Watson: 59.799 Jarque-Bera (JB): 0.000 Prob(JB): 0.227 Condition No.: 2.796

* The condition number is large (3e+03). This might indicate strong multicollinearity or other numerical problems.

var_inf_factor(X_4)

	Feature	VIF_Value
0	INT_SQFT	1.838724
1	PARK_FACIL	1.838724

mlr_4.params

INT_SQFT 7.045605e+03
 PARK_FACIL 1.658158e+06
 dtype: float64

The model is:

SOLD PRICE = INT_SQFT * 7.045605 + PARK_FACIL * 1.658158

Residual Analysis

Normality

mlr_4.resid

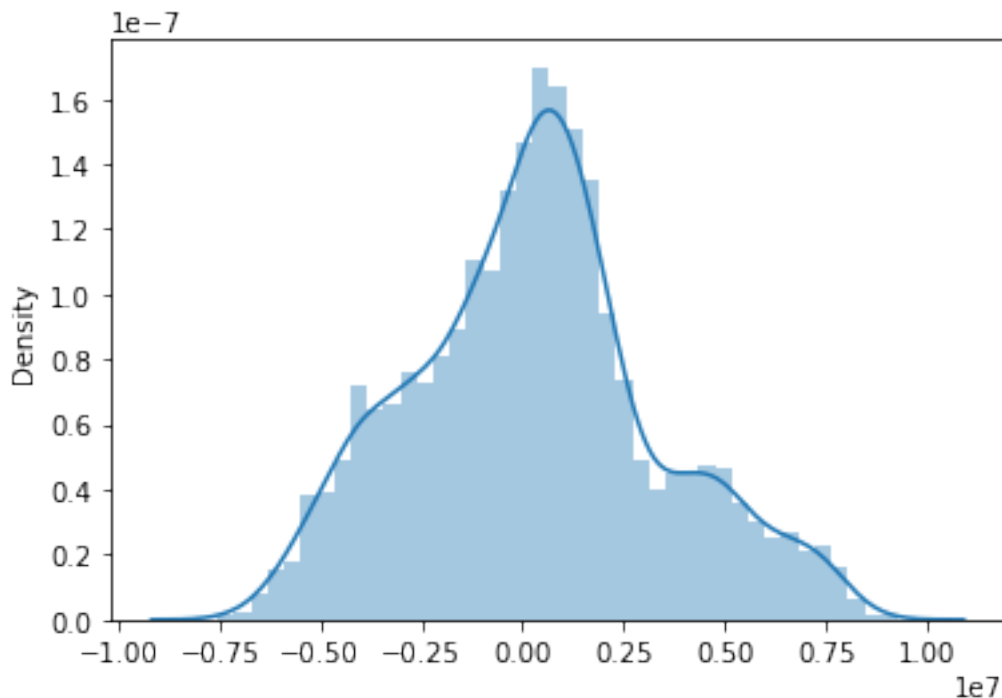
```
591      3.093338e+06
2651     2.186518e+05
5737    -6.441511e+06
5601    -1.482561e+06
1114     4.192007e+06
```

```
...
1180    -2.630428e+06
3441    -2.635413e+06
1344     1.122404e+06
4623     3.577222e+06
1289     9.189846e+05
```

Length: 5687, dtype: float64

```
sns.distplot(mlr_4.resid);
```

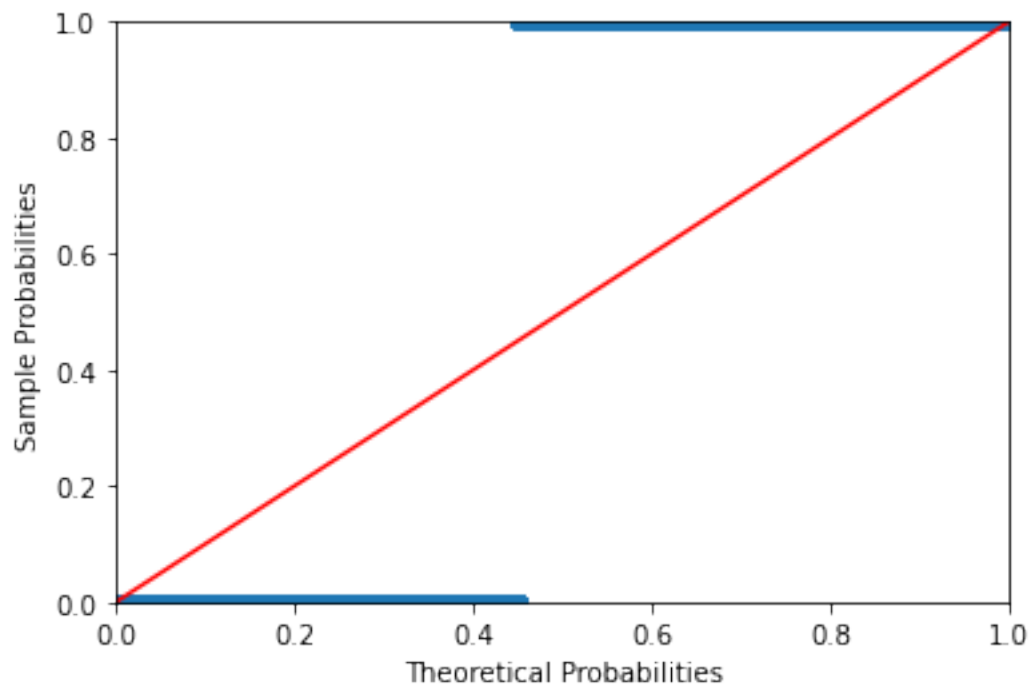
C:\Users\hp\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an
axes-level function for histograms).
warnings.warn(msg, FutureWarning)




```
## Prob prob plot
```

```
def prob_prob_plot(model):  
    probplot=sm.ProbPlot(model.resid)  
    probplot.ppplot(line='45')  
    plt.show();
```

```
prob_prob_plot(mlr_4)
```



```
X_train_4
```

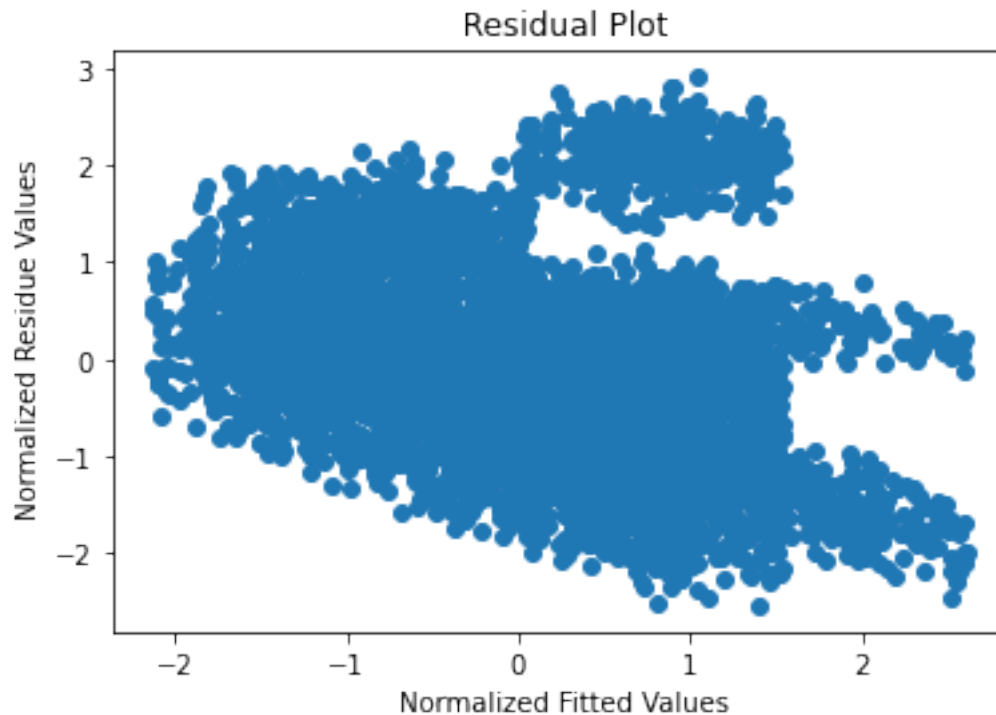
	INT_SQFT	PARK_FACIL
591	764	0
2651	1848	0
5737	1592	1
5601	1303	1
1114	790	0
...
1180	1042	1
3441	1091	1
1344	1864	1
4623	917	1
1289	897	1

```
[5687 rows x 2 columns]
```

The residuals are not fully normally distributed

Homoscedasticity

```
def standard(data):  
    return (data-data.mean())/data.std()  
  
# Plotting residual plot  
  
def residual_plot(model):  
    plt.scatter(standard(model.fittedvalues),  
                standard(model.resid))  
    plt.xlabel(' Normalized Fitted Values')  
    plt.ylabel(' Normalized Residue Values')  
    plt.title(' Residual Plot')  
    plt.show();  
  
# Calling the function  
  
residual_plot(mlr_4)
```



Checking the outliers

Z Score

```
from scipy.stats import zscore  
  
z_score=zscore(X_4)
```

```

z_score[z_score>3].count()

INT_SQFT      0
PARK_FACIL    0
dtype: int64

z_score[z_score < -3].count()

INT_SQFT      0
PARK_FACIL    0
dtype: int64

```

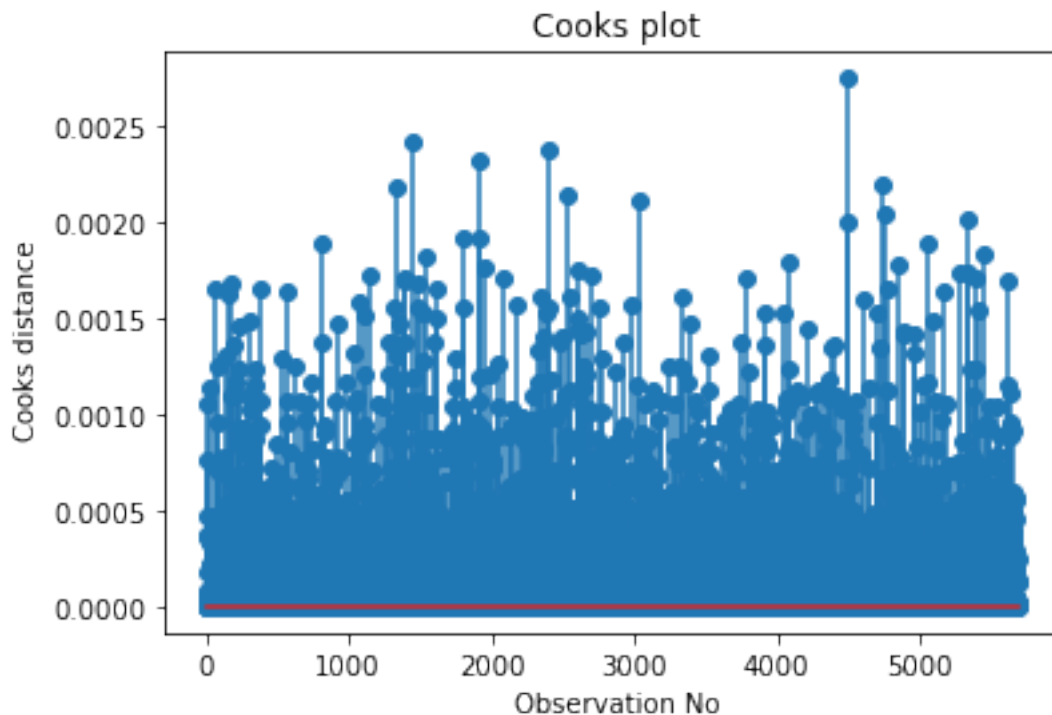
Cooks Distance

```

def cooks_dist(model):
    model_influence=model.get_influence()
    (c,_)=model_influence.cooks_distance
    plt.stem(np.arange(len(X_train_4)),c)
    plt.xlabel(' Observation No')
    plt.ylabel(' Cooks distance')
    plt.title(' Cooks plot')
    plt.show();

cooks_dist(mlr_4)

```



There is no observation with cooks distance > 1 .

So, the measure says there is no outlier.

Leverage distance

n=5687 # No of training data

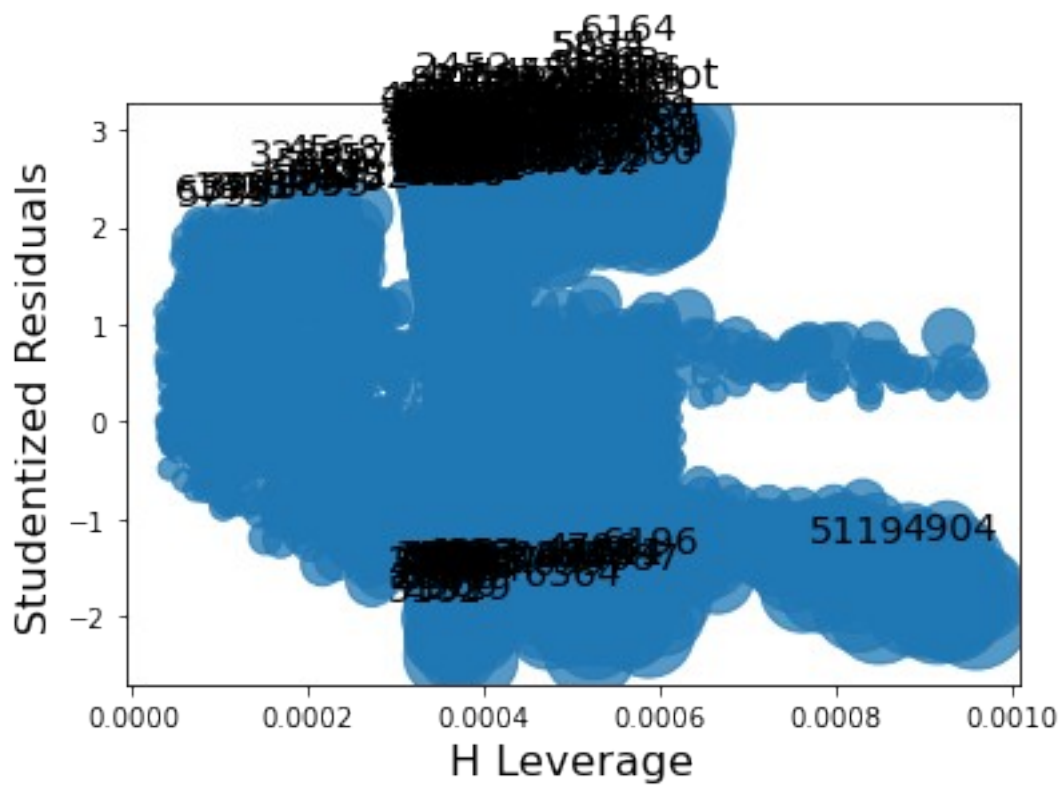
k= 2 # No of features in the model

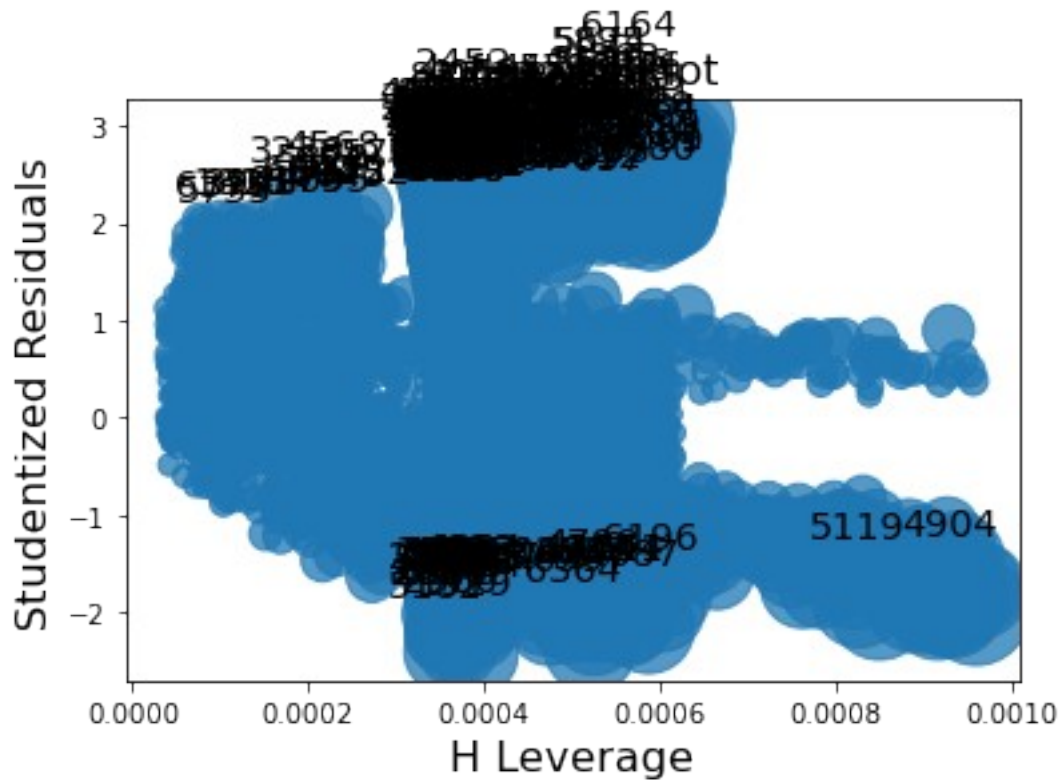
$$\text{lev_cutoff} = (3 * (k + 1)) / n$$

```
print(' The Leverage cut off:',lev_cutoff)
```

The Leverage cut off: 0.0015825567082820467

```
from statsmodels.graphics.regressionplots import influence_plot
influence_plot(mlr_4)
```





```
X_train_4.iloc[4904]
```

```
INT_SQFT      1776
PARK_FACIL      0
Name: 1345, dtype: int64
```

```
y_pred= mlr_4.predict(X_test_4)
y_pred
```

```
461      1.267044e+07
3358      1.113206e+07
3751      1.438957e+07
2386      1.757878e+07
1125      1.000476e+07
```

```
...
6010      1.224526e+07
4903      1.356523e+07
6806      1.079631e+07
3832      1.362620e+07
364       5.650575e+06
```

```
Length: 1422, dtype: float64
```

```
X_train_4['INT_SQFT'].min(),X_train_4['INT_SQFT'].max()
```

```

(500, 2500)
X_5= X_4.drop([5119,4904])
X_5.shape
(7107, 2)
y_5=y.drop([5119,4904])
y_5.shape
(7107,)
X_train_5,X_test_5,y_train_5,y_test_5=train_test_split(X_5,
                                                        y_5,
                                                        train_size=0.8,random_state=10)
X_train_5.shape,X_test_5.shape,y_train_5.shape,y_test_5.shape
((5685, 2), (1422, 2), (5685,), (1422,))
mlr_5=sm.OLS(y_train_5,X_train_5)
mlr_5=mlr_5.fit()
mlr_5.summary2()
<class 'statsmodels.iolib.summary2.Summary'>
"""
                                Results: Ordinary least squares
=====
=====
Model:                        OLS                        Adj. R-squared (uncentered):
0.928
Dependent Variable:          SALES_PRICE                  AIC:
186089.2541
Date:                        2022-11-10 01:49             BIC:
186102.5453
No. Observations:           5685                        Log-Likelihood:
-93043.
Df Model:                    2                          F-statistic:
3.651e+04
Df Residuals:                5683                      Prob (F-statistic):
0.00
R-squared (uncentered):      0.928                      Scale:
9.6227e+12
-----
-----
                                Coef.      Std.Err.      t      P>|t|      [0.025
0.975]
-----
-----

```

INT_SQFT	7043.2743	38.3709	183.5579	0.0000	6968.0527
7118.4958					
PARK_FACIL	1673080.9715	78513.0265	21.3096	0.0000	1519165.4865
1826996.4565					

```
-----
-----
Omnibus:                61.517                Durbin-Watson:
1.992
Prob(Omnibus):          0.000                Jarque-Bera (JB):
60.275
Skew:                   0.229                Prob(JB):
0.000
Kurtosis:               2.789                Condition No.:
2784
=====
=====
```

```
* The condition number is large (3e+03). This might indicate
strong
multicollinearity or other numerical problems.
"""
```

Predicting the value

```
y_pred= mlr_5.predict(X_test_5)
y_pred
```

```
461      1.268172e+07
1798     1.156184e+07
3655     6.814671e+06
5207     1.480879e+07
1125     1.000145e+07
```

```
...
5334     1.391429e+07
4302     9.300947e+06
3831     1.023066e+07
364      5.648706e+06
591      5.381062e+06
```

```
Length: 1422, dtype: float64
```

Performance of the model

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

```
r2= r2_score(y_test_5, y_pred)
print('R2:', r2)
```

```
mse = mean_squared_error(y_test_5, y_pred)
```

```
rmse= np.sqrt(mse)
```

```
print(' RMSE:',rmse)
```

R2: 0.34575389208379126
RMSE: 3093969.0027331156

Transform the target

```
y.min(),y.max()  
(2156875, 23667340)  
y_sq= np.sqrt(y)  
y_sq.min(),y_sq.max()  
(1468.6303142724516, 4864.909043342948)  
# log  
y_log= np.log(y)  
y_log.min(),y_log.max()  
(14.584170972834405, 16.97960659663699)
```