NM DATA ANALYTICS ASSIGNMENT 3 - House Price dataset of India

DONE BY Aswathnaraayanan S

Importing the necessary libraries for EDA and data preprocessing

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
from scipy import stats
```

Converting csv file into dataframe

In [3]:
```
df=pd.read_csv('C:/Users/Reshma/Downloads/House Price India.csv')
```

In [4]:
```
df=df.drop(['Date'],axis=1)
```

In [5]:
```
df
```

Out[5]:

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovation Yez
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	1921	
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	1909	
2	6762810998	S	2.75	2910	9480	1.5	0	0	3	8	1939	
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	2001	
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	1929	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.00	1680	7000	15	0	0	4	7	1968	
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	1955	
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	1969	200

14620 rows • 22 columns

In [6] :

```
d-r-. head()
```

Out[6 1

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovation Year	I
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	1921	0	1:
I	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	1909	0	1.
2	67B2810998	5	2.75	2910	9480	1.S	0	0	3	8	1939	0	1.
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	2001	0	1.
4	67g2812919	3	2.00	2710	4500	1.5	0	0	4	8	1929	0	1:

5 rows 22 columns

In [7]: df.tail()

Out[7 1

	id	number y bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovatio Yez
14615	6762830250	2	1.5	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.0	1680	7000	15	0	0	4	7	1968	
14617	6762830618	2	1.0	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.0	1030	6621	1.0	0	0	4	6	1955	
14619	6762831463	3	1.0	900	4770	1.0	0	0	3	6	1969	200

5 rows x 22 columns

Checking for null and duplicated values

```
df.isna().sum()
```

```
id                                       0
number of bedrooms                       0
number of bathrooms                      0
living area                              0
lot area                                 0
number of floors                         0
waterfront present                       0
number of views                          0
condition of the house                   0
grade of the house                       0
Area of the house(excluding basement)    0
Area of the basement                     0
Built Year                               0
Renovation Year                          0
Postal Code                              0
Lattitude                                0
Longitude                                0
living_area_renov                        0
lot_area_renov                           0
Number of schools nearby                 0
Distance from the airport                0
Price                                    0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Rangelndex: 14620 entries, 0 to 14619
Data columns (total 22 columns):
 #   Column                                   Non-Null  Count  Dtype

 0   id                                       14620 non-null  int64
 1   number of bedrooms                       14620  non-null  1nts4
 2   number of bathrooms                      14620 non-null  float64
 3   living area                              14620 non-null  int64
 4   lot area                                 14620 non-null  1nt64
 s   number of floors                         14620 non-null  float64
 6   waterfront present                       14620 non-null  int64
 7   number of views                          14620 non-null  int64
 8   cond1t1on o-F- the house                 14620  non-null  int64
 9   grade of the house                       14620  non - null  1nt64
 10  Area of the house(excluding basement)    14620 non-null  int64
 11  Area of the basement                     14620 non-null  int64
 12  Built Year                               14620 non-null  1nts4
 13  Renovation Year                          14620 non-null  ints4
 14  Postal Code                              14620 non-null  1nt64
 15  Lattitude                                14620 non-null  float64
 16  Longitude                                14620 non-null  float64
 17  living_area_renov                        14620 non-null  1nts4
 18  lot_area_renov                           1462B non-null  lnts4
 19  Number of schools nearby                 14620 non-null  int64
 20  Distance from the airport                14620 non-null  lnt64
 21  Price                                    14620 non-null  1nt64
dtypes: float64(4), int64(18)
memory usage: Z.5 MB
```

```
In [11]:  df.describe()
```

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	cond th
count	1.462000e+04	14620.000000	14620.000000	14620.000000	1.462000e+04	14620.000000	14620.000000	14620.000000	14620.
mean	6.762821e+09	3.379343	2.129583	2098.262996	1.509328e+04	1.502360	0.007661	0.233105	3.
std	6.237575e+03	0.938719	0.769934	928.275721	3.791962e+04	0.540239	0.087193	0.766259	0.
min	6.762810e+09	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000	1.
25%	6.762815e+09	3.000000	1.750000	1440.000000	5.010750e+03	1.000000	0.000000	0.000000	3.
50%	6.762821e+09	3.000000	2.250000	1930.000000	7.620000e+03	1.500000	0.000000	0.000000	3.
75%	6.762826e+09	4.000000	2.500000	2570.000000	1.080000e+04	2.000000	0.000000	0.000000	4.
max	6.762832e+09	33.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.000000	4.000000	5.

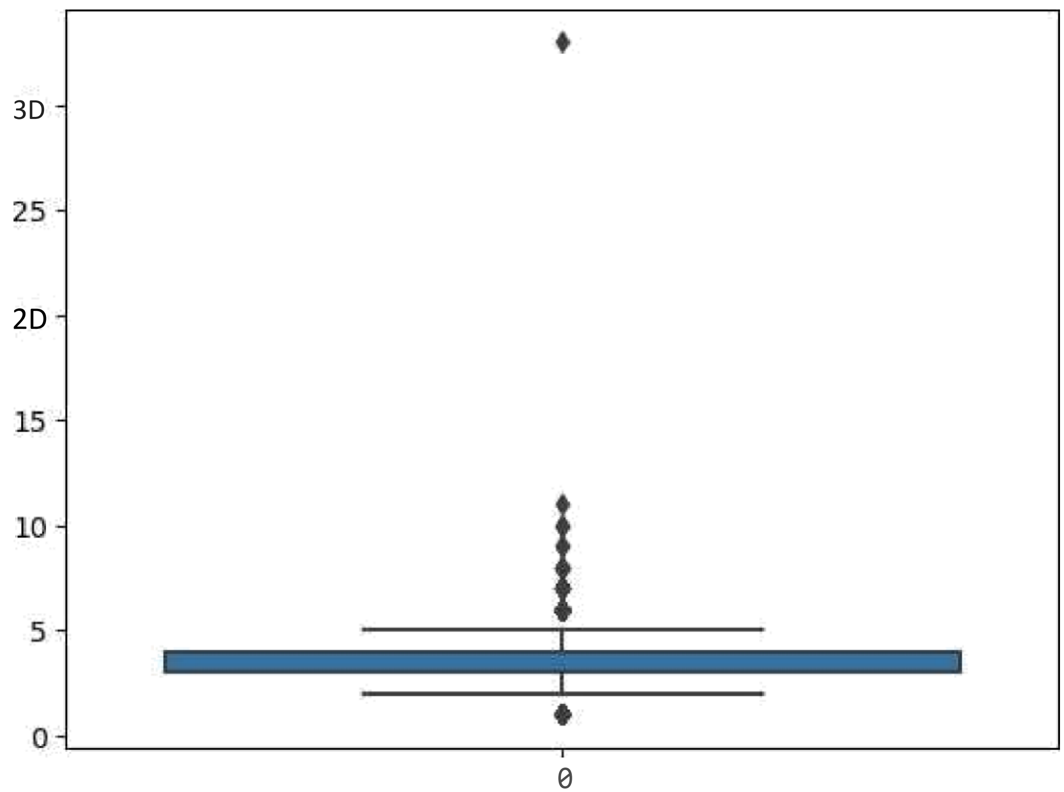
8 rows • 22 columns

UNIVARIATE ANALYSIS

Checking for outliers

In [12]:
```
sns.boxplot(df['number of bedrooms'])
```

Out[12]: <AxesSubplot:>




```
z=np.abs(stats.zscore(df['number of bed ooms']))

threshold=3
prlnt(np.where(z>3),len(np.where(z›3)[0]))
```

```
(an ray ([    76,     243,     268,     275,     624,     785,    1512,    1519,    15 53,
          1706,  2814,  3109,  3114,  3322,  3532,  3600,  4207,  4486,
          465b,  46b6,  6S91,  6556,  67d6,  6962,  6596,  7661,  7454,
          b55S,  b658,  92b2,  9625,  9bl6,  W955, 10166, 16177, 18676,
         1674b, 16916,  lbW44, l1Y47, 11441, 11547,  llb77, 12?74,  ld64b,
         13444,  13825,  14220,  14481]),) 49
```

```
print(np.where(z<-3))
```

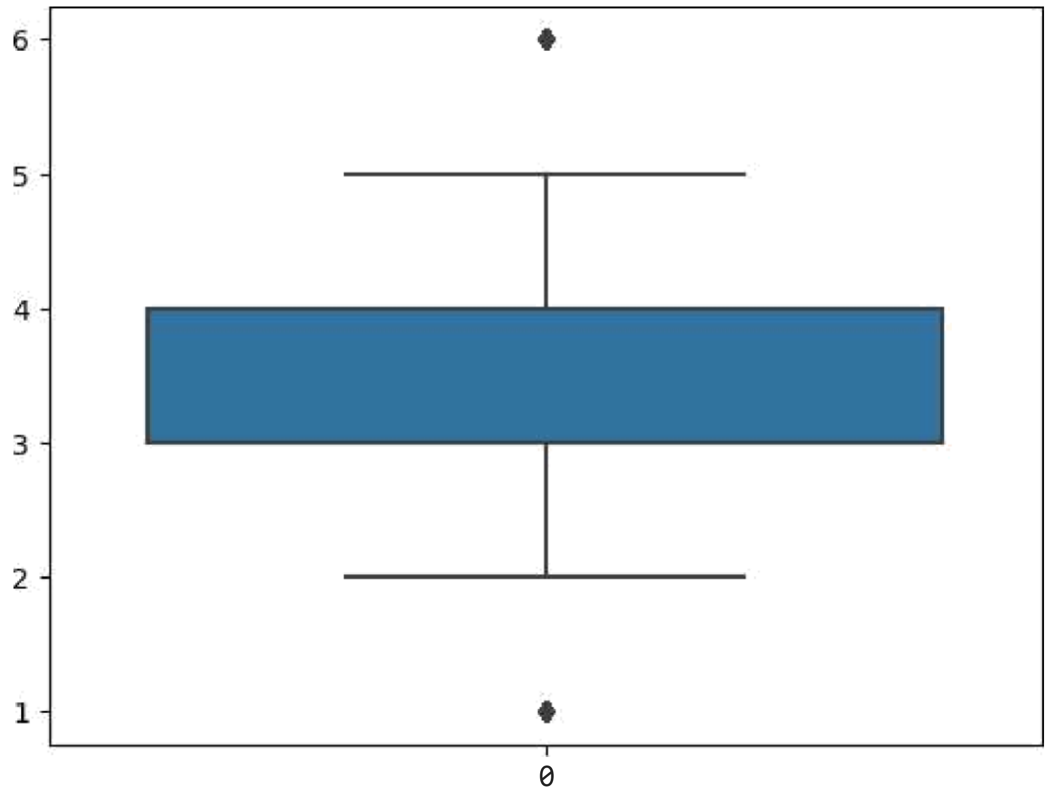
```
(array([],  dtype=int64),)
```

There are 138 outliers in number of bedrooms as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

In [16]:
```
df1=df [ (z‹   3) ]
```

In [17]:
```
sns.boxplot(dfl['number of bedrooms'])
```

Out[17]: ‹AxesSubp1ot:›



df1

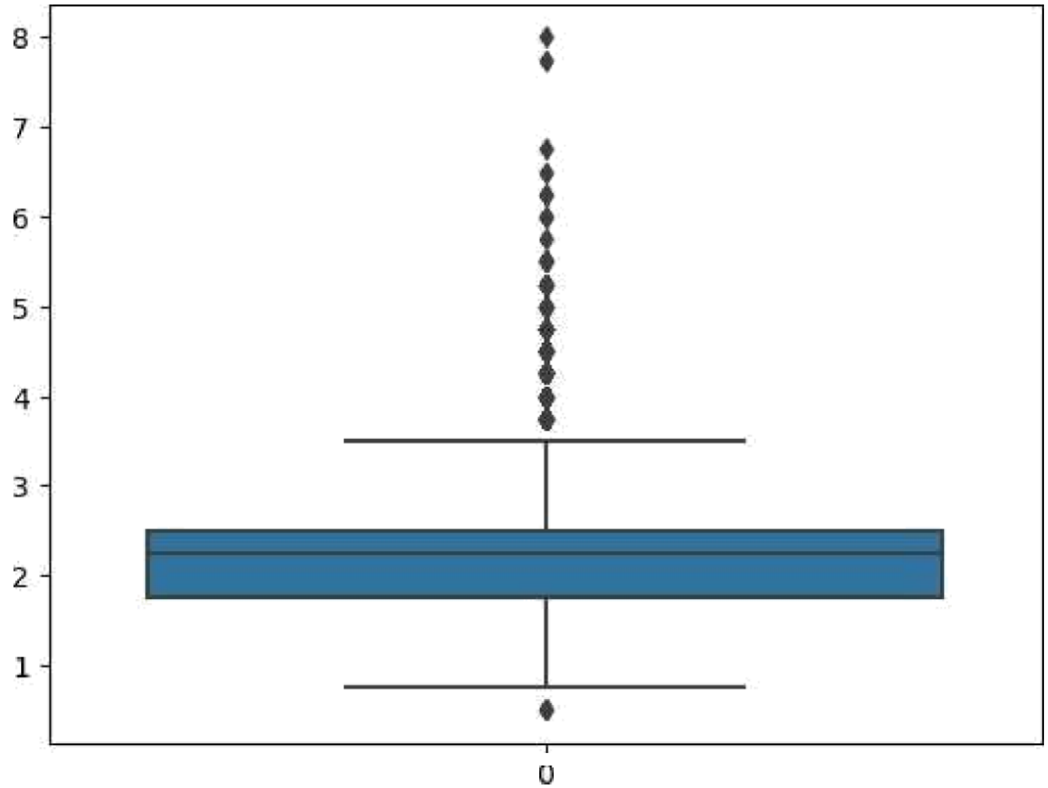
" " ∘ '''

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovatio Yez
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	1921	
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	1909	
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	1939	
3	676281]605	4	2.50	3310	42998	2.0	0	0	3	9	2001	
4	6762812919	3	2.00	2710	4500	1.S	0	0	4	8	1929	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.00	1680	7000	15	0	0	4	7	1968	
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	1955	
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	1969	200

14571 rows • 22 columns

In [19]: `sns.boxplot(dfl['number of bathrooms'])`

Out [19]: ‹AxesSubp1ot :›




```
z=np.abs(stats.zscore(df1['number of bathrooms']))
```

```
len(np.where(z>3)[0])
```

124

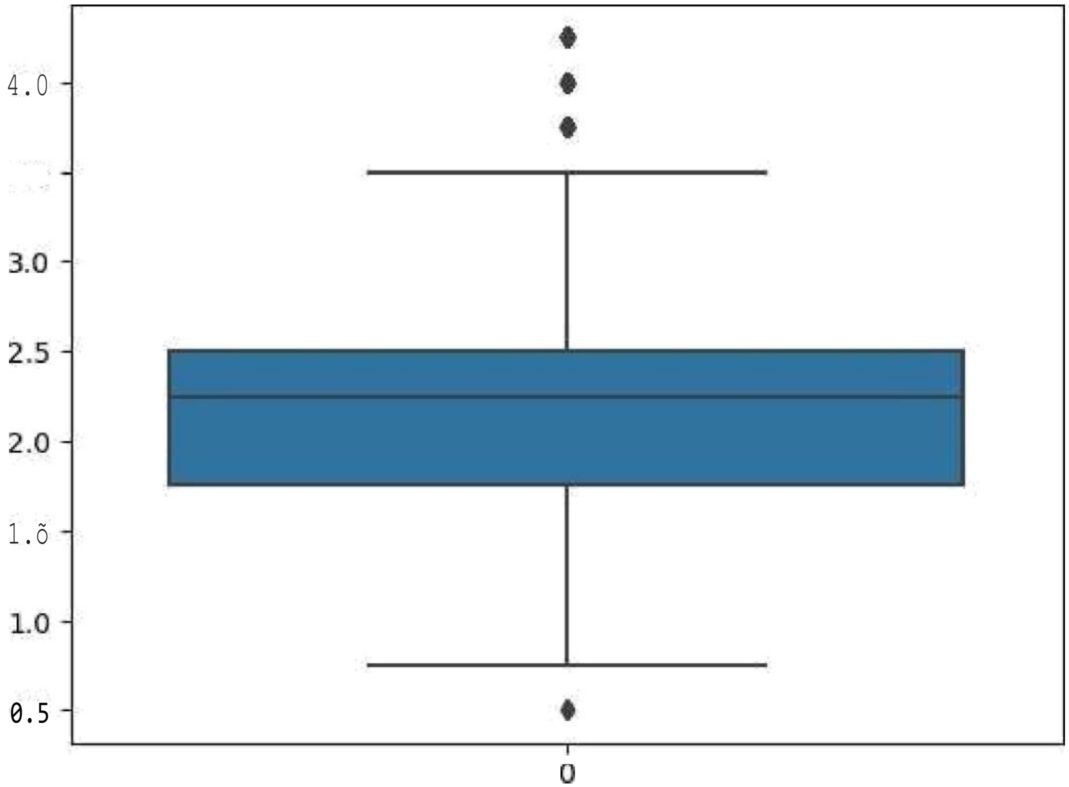
```
prlnt(np.where(z<-3))
```

(array([], dtype=int64),)

```
df1=df1[(z< 3)]
```

```
sns.bOxplot(df1['number of bathrooms'])
```

<AxesSubplot:>



df1

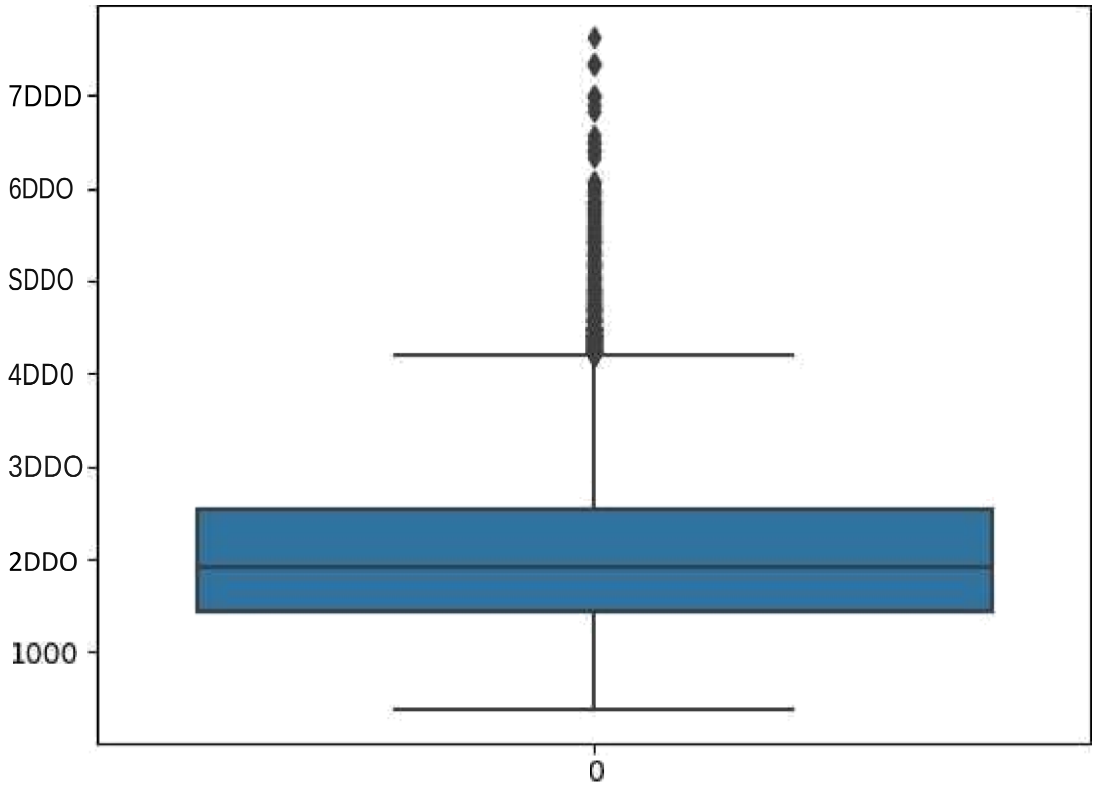
	id	number pt bedrooms	number of bathrooms	living area	lot area	number y floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovatio Yes
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	1921	
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	1909	
Z	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	1939	
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	2001	
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	1929	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.00	1680	7000	1.S	0	0	4	7	1968	
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	1955	
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	1969	200

14447 rows x 22 columns

There are 124 outliers in number of bathrooms as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

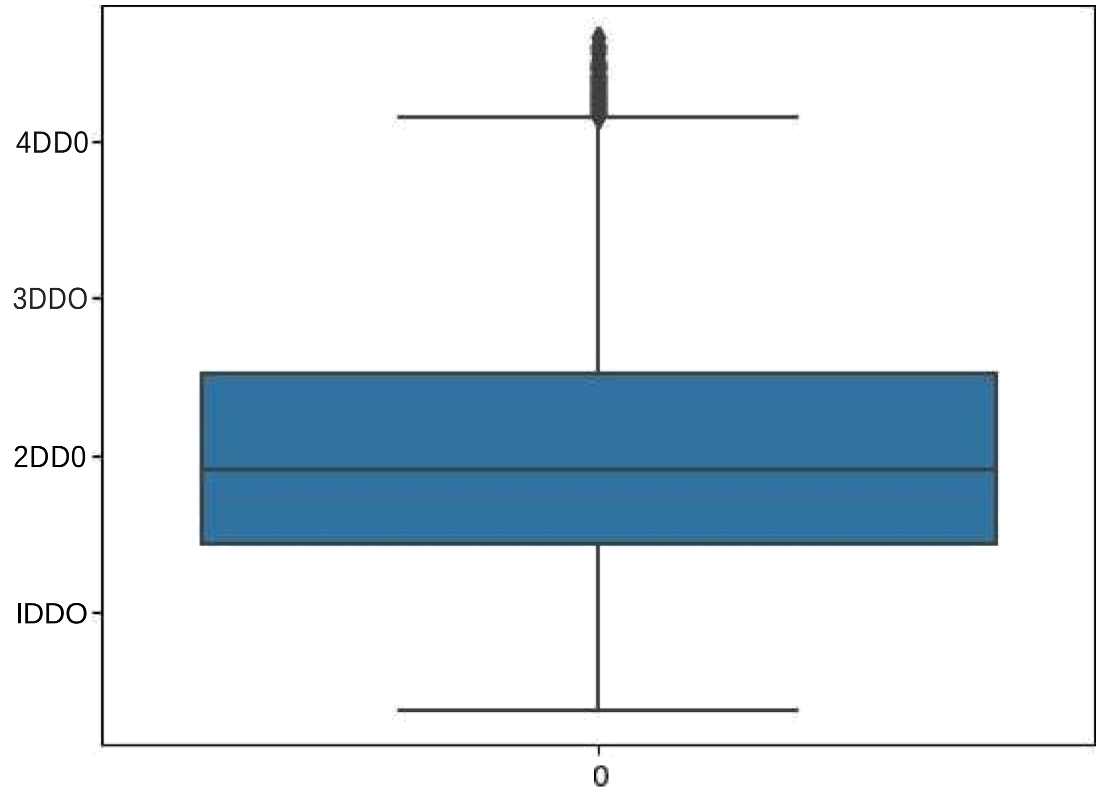
```
sns.boxplot(df1['living area'])
```

```
<AxesSubplot:>
```




```
z=np.abs(stats.zscore(df1['living area']))

len(np.where(z>3)[0])

136

len(np.where(z<-3)[0])

0

df1=df1[(z<3)]

sns.boxplot(df1['living area'])
```

‹AxesSubplot:›




```
z=np.abs(stats.zscore(df1['living area']))
```

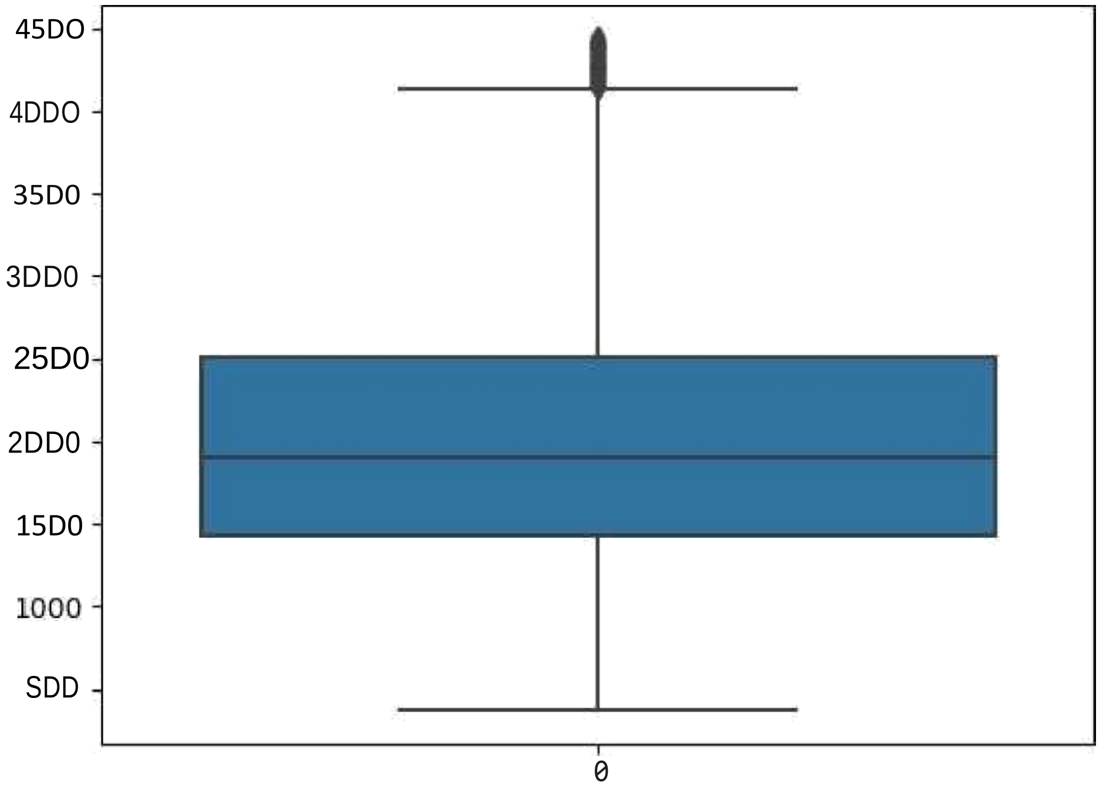
```
len(np.where(z>3)[0])
```

```
67
```

```
df1=df1[(z<3)]
```

```
sns.boxplot(df1['living area'])
```

```
<AxesSubplot:>
```




```
df1
```

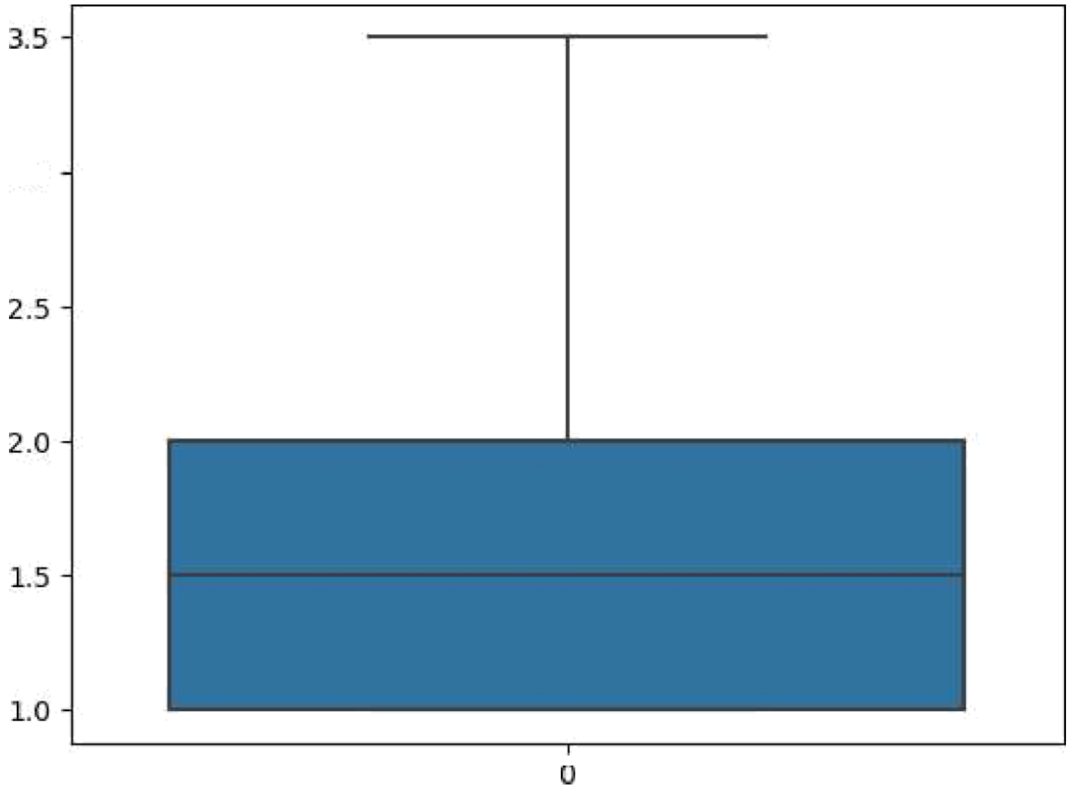
	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovation Yes
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	1921	
1	6762810635	4	2.50	2920	4000	1.S	0	0	5	8	1909	
Z	6762810998	5	2.7s	2910	9480	1.S	0	0	3	8	1939	
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	2001	
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	1929	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	1968	
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.00	1030	6621	1 0	0	0	4	6	1955	
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	1969	200

14244 rows x 22 columns

There are 205 outliers in living as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

```
sns.boxplot(df1['number of floors'])
```

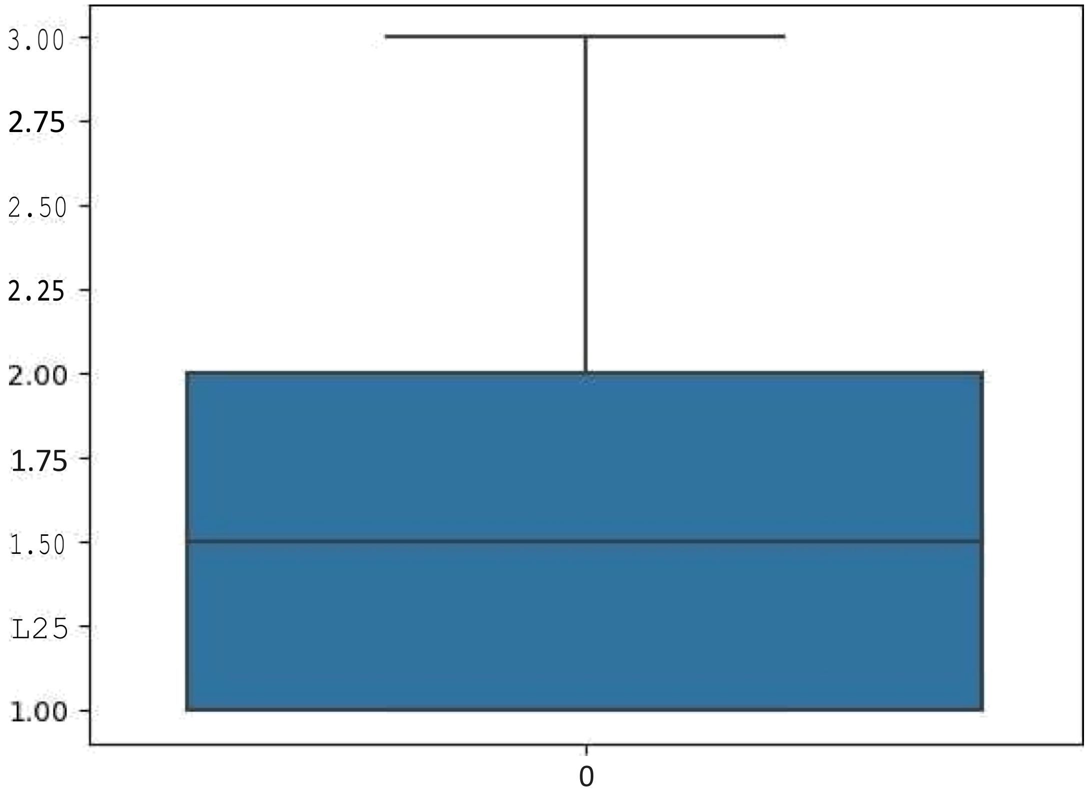
```
<AxesSubplot:>
```




```
z=np.abs(stats.zscore(df1['number of floors']))

len(np.where(z>3)[0])
```

```
df1=df1[(z<3)]

sns .boxplot (d-F1['number at I I oors'])
```

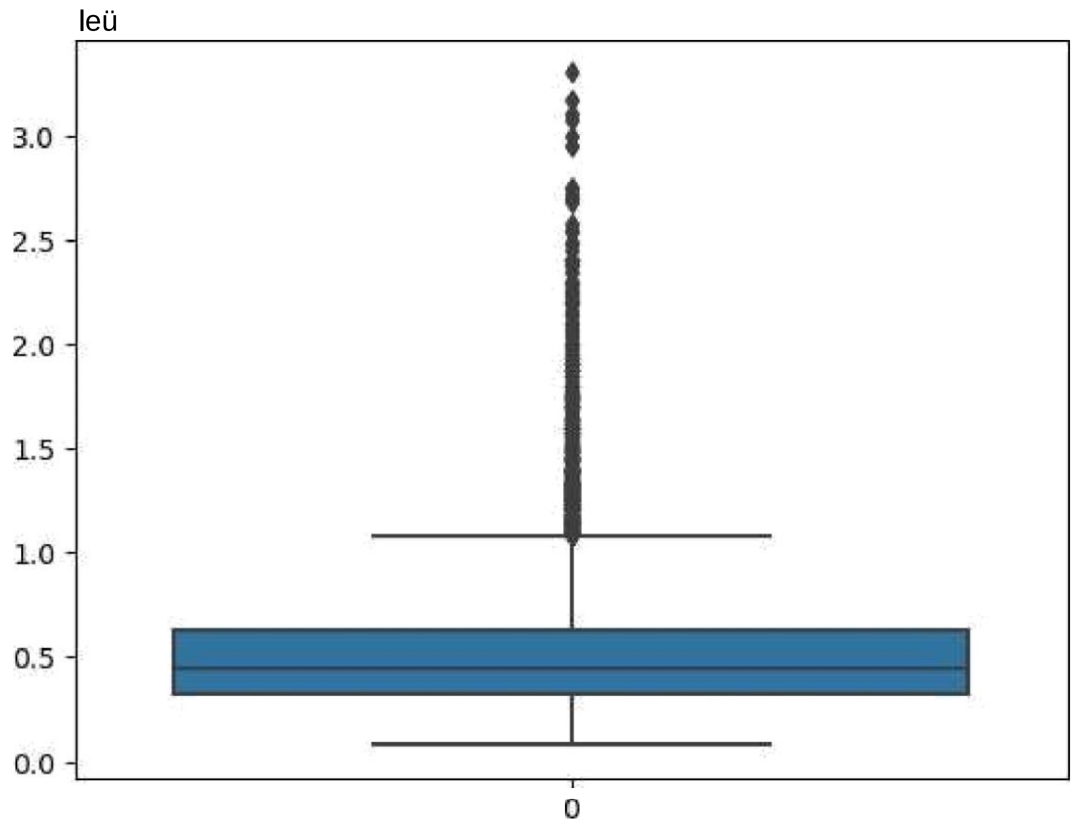
```
<AxesSubplot:>
```



There are 3 outliers in number of floors

```
sns.boxplot(df1['Price'])
```

‹AxesSubplot :›




```
z=np.abs(stats.zscore(df1['Price']))

len(np.where(z›3)[0])

25g

d*1=df1[(z‹3)]

df1
```

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Built Year	Renovatio Yez
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	1939	
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	2001	
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	1929	
5	6762813105	3	2.50	2600	4750	1.0	0	0	4	9	1951	
6	6762813157	5	3.25	3660	11995	2.0	0	2	3	10	2006	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	1957	
14616	6762830339	3	2.00	1680	7000	15	0	0	4	7	1968	
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	1962	
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	1955	
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	1969	200

13982 rows x 22 columns

```
In [47]: df1=df1.drop(['Renovation Year'],axis=1)

In [48]: df1
```

	id	number pt bedrooms	number of ba nrooms	living area	lot area	number 0 fl...	waterfront present	number of views	condition ofthe house	grade ofthe house	Area of the basement	Built Year
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	0	1939
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	0	2001
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	830	1929
5	6762813105	3	2.50	2600	4750	1.0	0	0	4	9	900	1951
6	6762813157	S	3.25	3660	11995	2.0	0	2	3	10	0	2006
14615	6762830Z50	2	1.50	1556	20000	1.0	0	0	4	7	0	1957
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	0	1968
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	b	0	1962
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	0	1955
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	0	1969

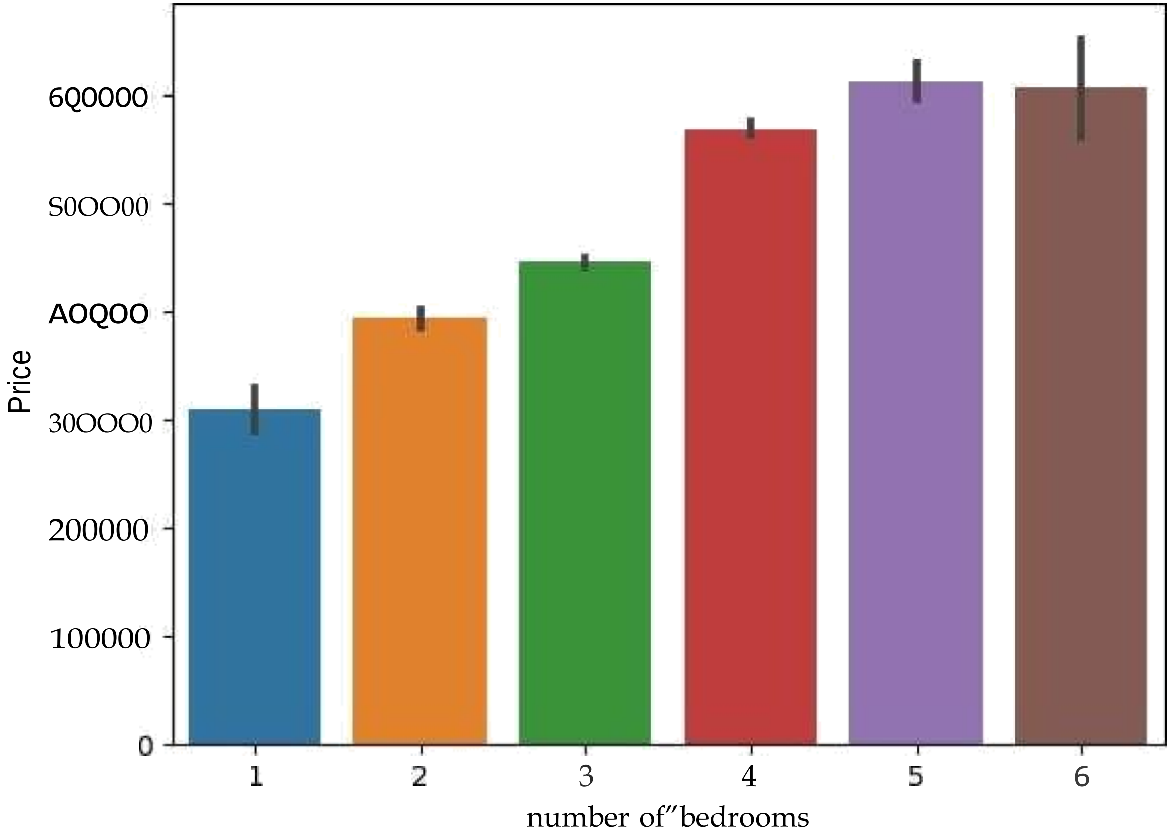
13982 rows x 21 columns

BI - VARIATE ANALYSIS

The column Renovation year have been removed. This is because most of the R vation Year are 0 and proves to be of no use IO the mo‹:e

```
sns.ba plot(data=df1,x='number of- bearooms',y:'Price')
```

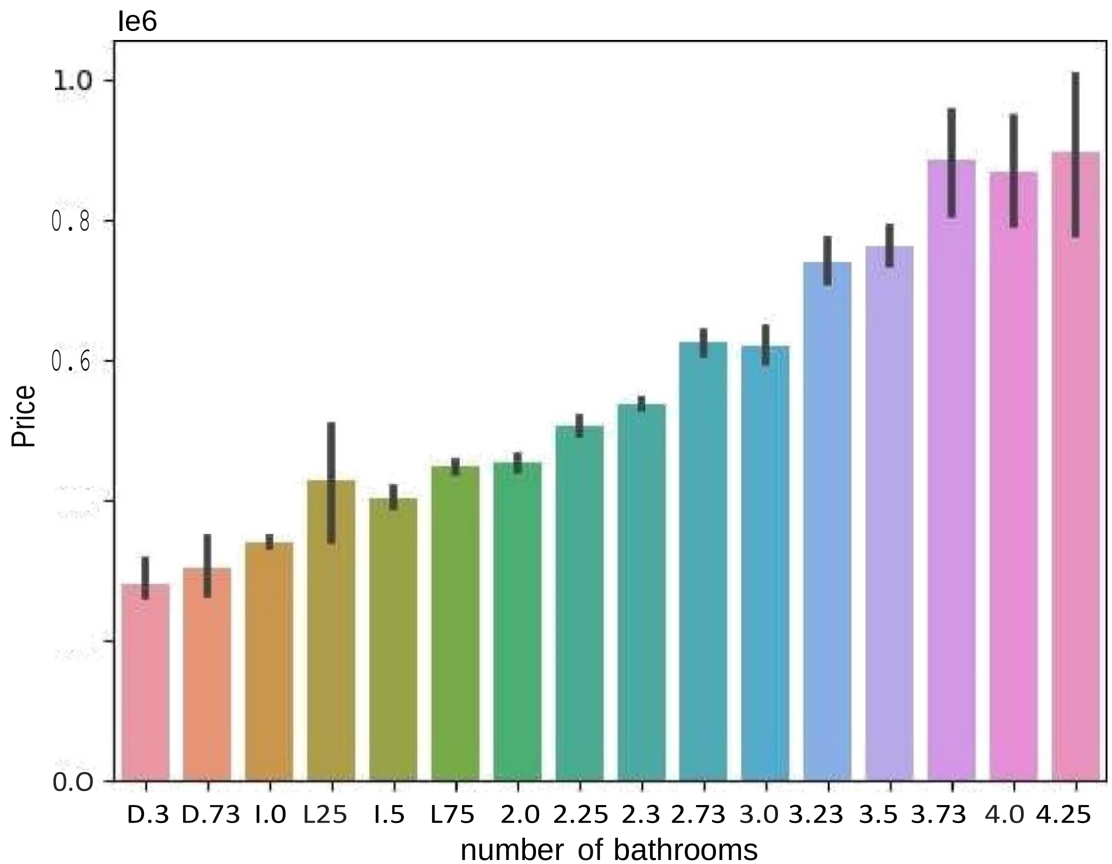
```
‹AxesSubplot:Klabel='number of bedrooms', ylabel='Price'>
```



Clear indication of Price increasing with number of bedrooms

```
sns.barplot(data=df1,x='number of bathrooms',y='Price')
```

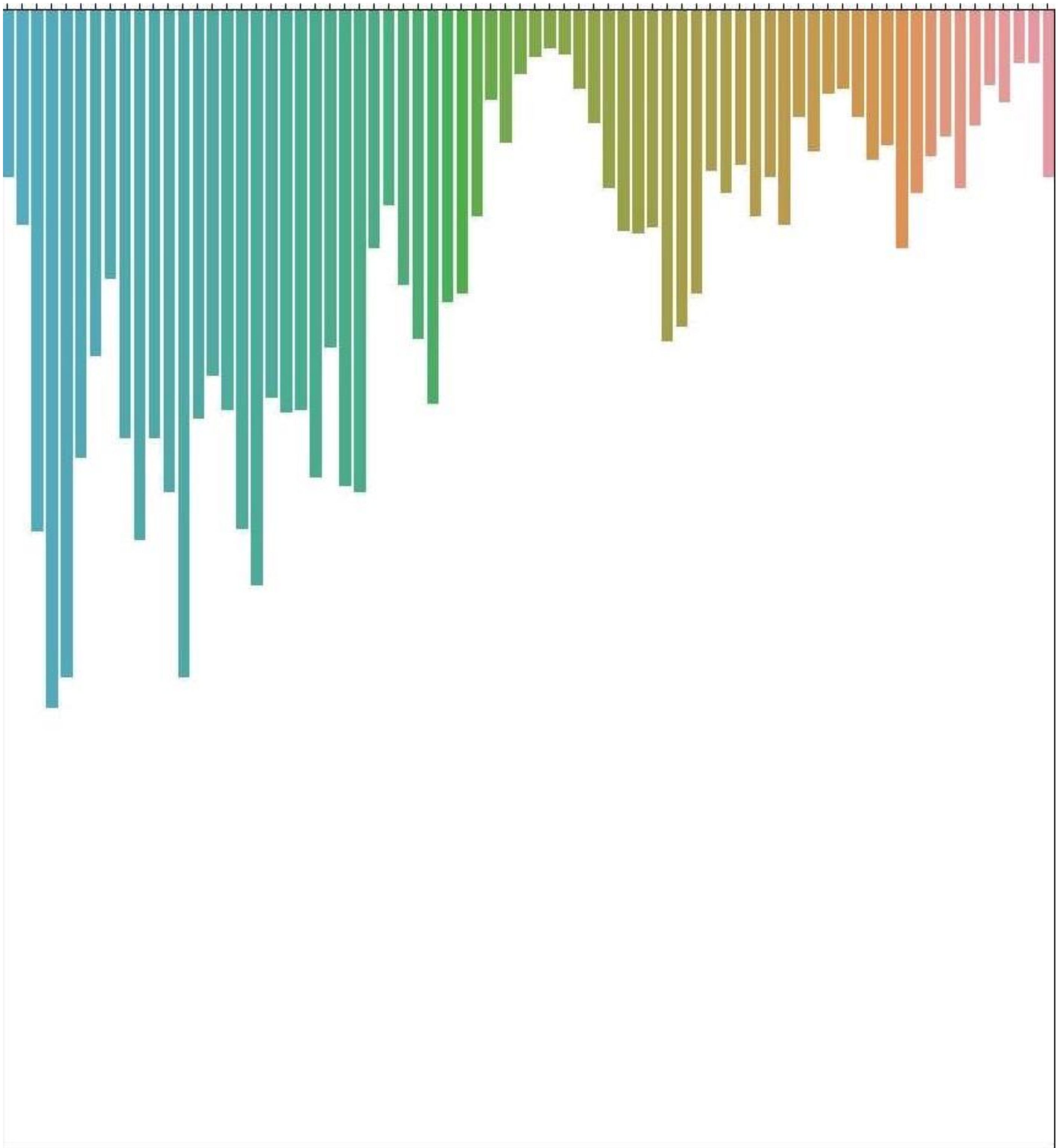
```
‹AxesSubplot:x1abe1='number of bathrooms', y1abel='Price'›
```

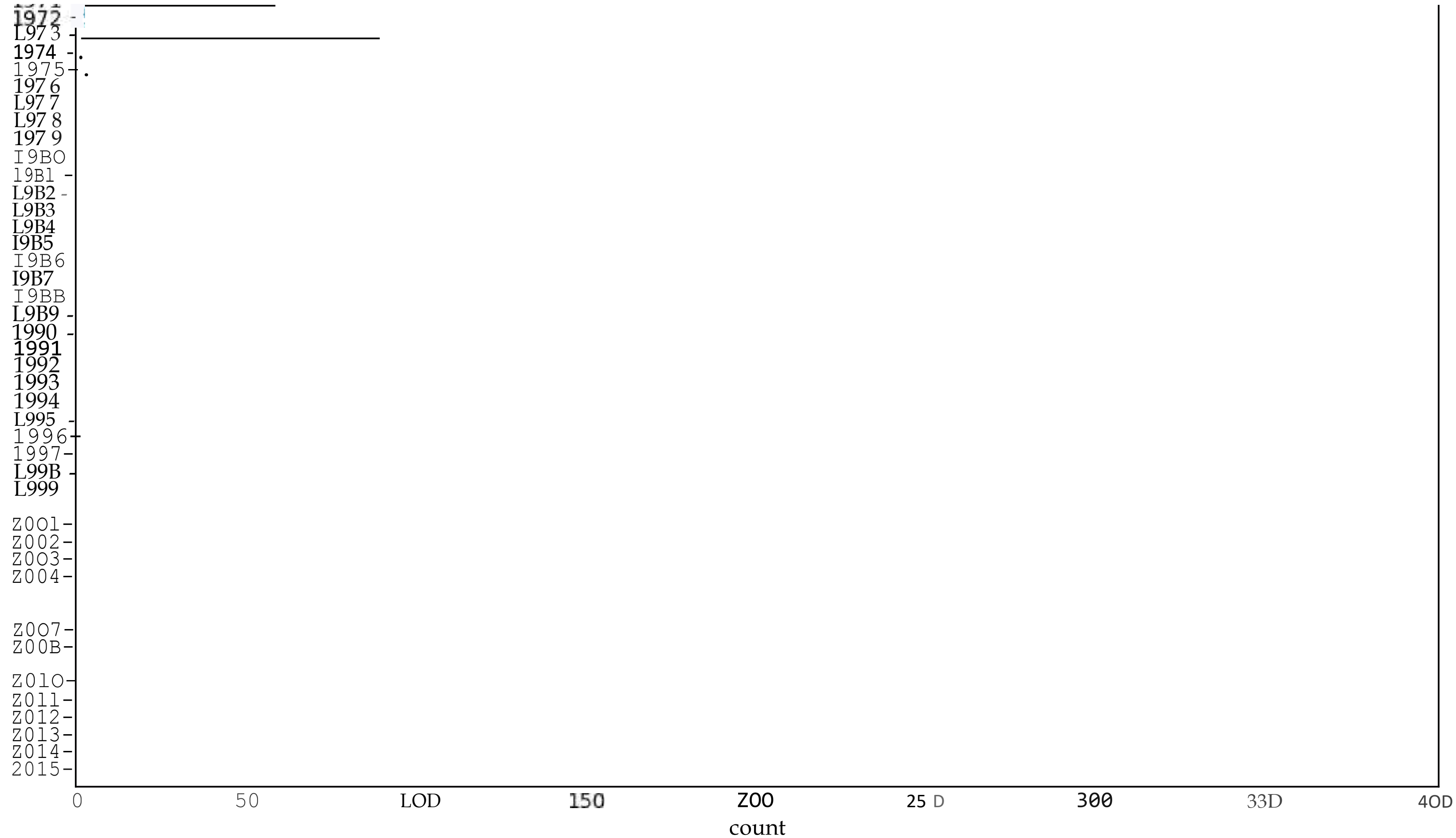


Clear indication of Price increasing with number of bathrooms

```
plt.figure(figsize:(12,18))
sns.countplot(data=df1,y:'Built Year')
plt.show()
```

Built Sear

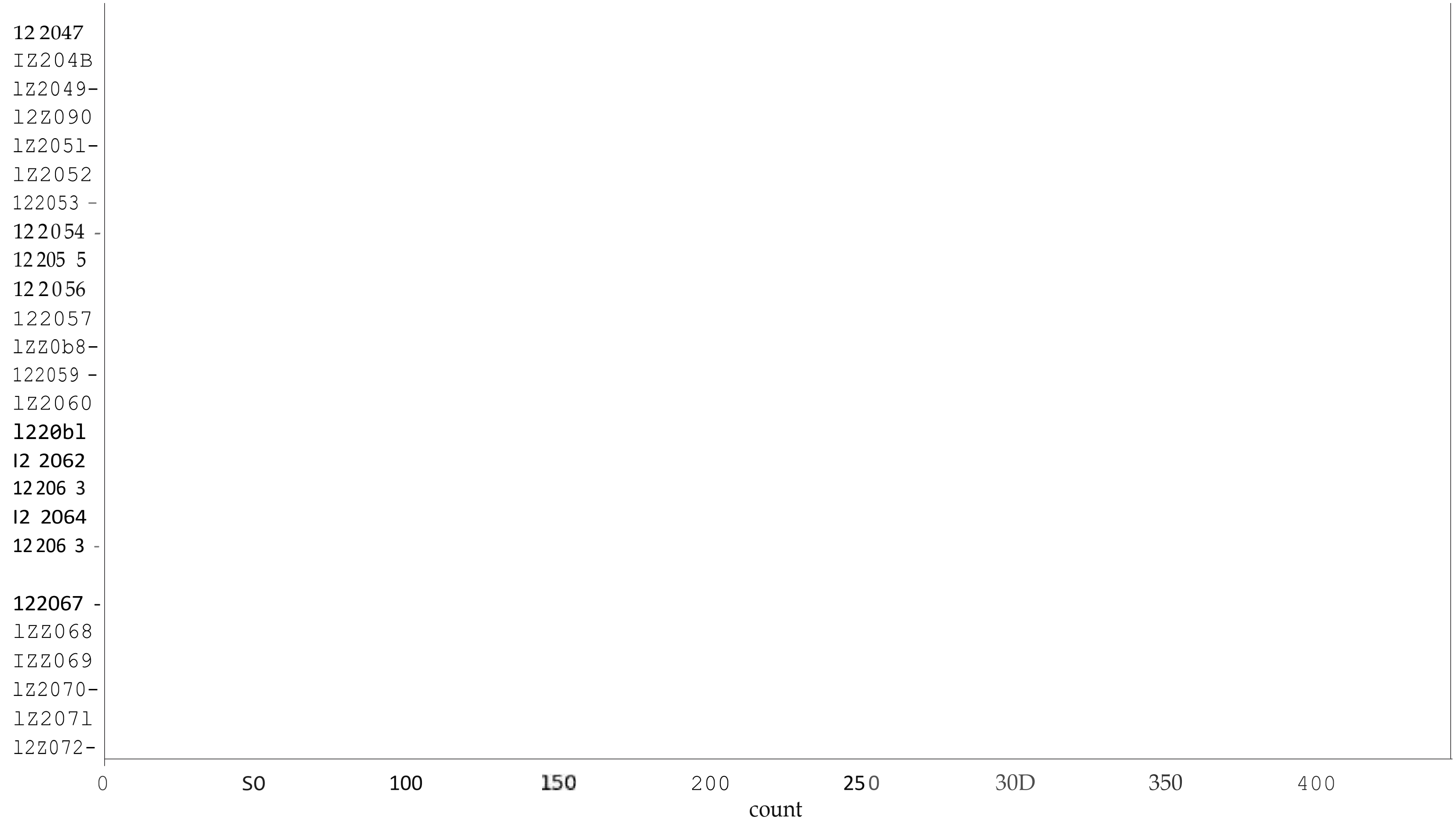




Most of the houses were listed for sale in 2017

```
plt.figure(figsize=(12,18))
sns.countplot(data=d*l,y='Postal Code')
plt.show()
```

12 2 00 3
12 2 004
12 2 005
12 2 006
12 2 00 7
12 2 008
12 2 009
12 2 010
12 2 011
12 2 012
12 2 013
12 2 014
12 2 015
12 2 0 lfi
12 2 017
12 2 018
12 2 019
12 2 0 20
12 2 021
12 2 0 22
12 2 02 3
12 2 0 24
12 2 025
12 2 0 26
12 2 027
12 2 028
12 2 029
12 2 0 30
12 2 0 31
12 2 0 32
12 2 0 33
12 2 0 34
12 2 0 35
12 2 0 36
12 2 0 37
12 2 0 38
12 2 0 39
12 2 040
12 2 041
12 2 042
12 2 043
12 2 044
122045
122046



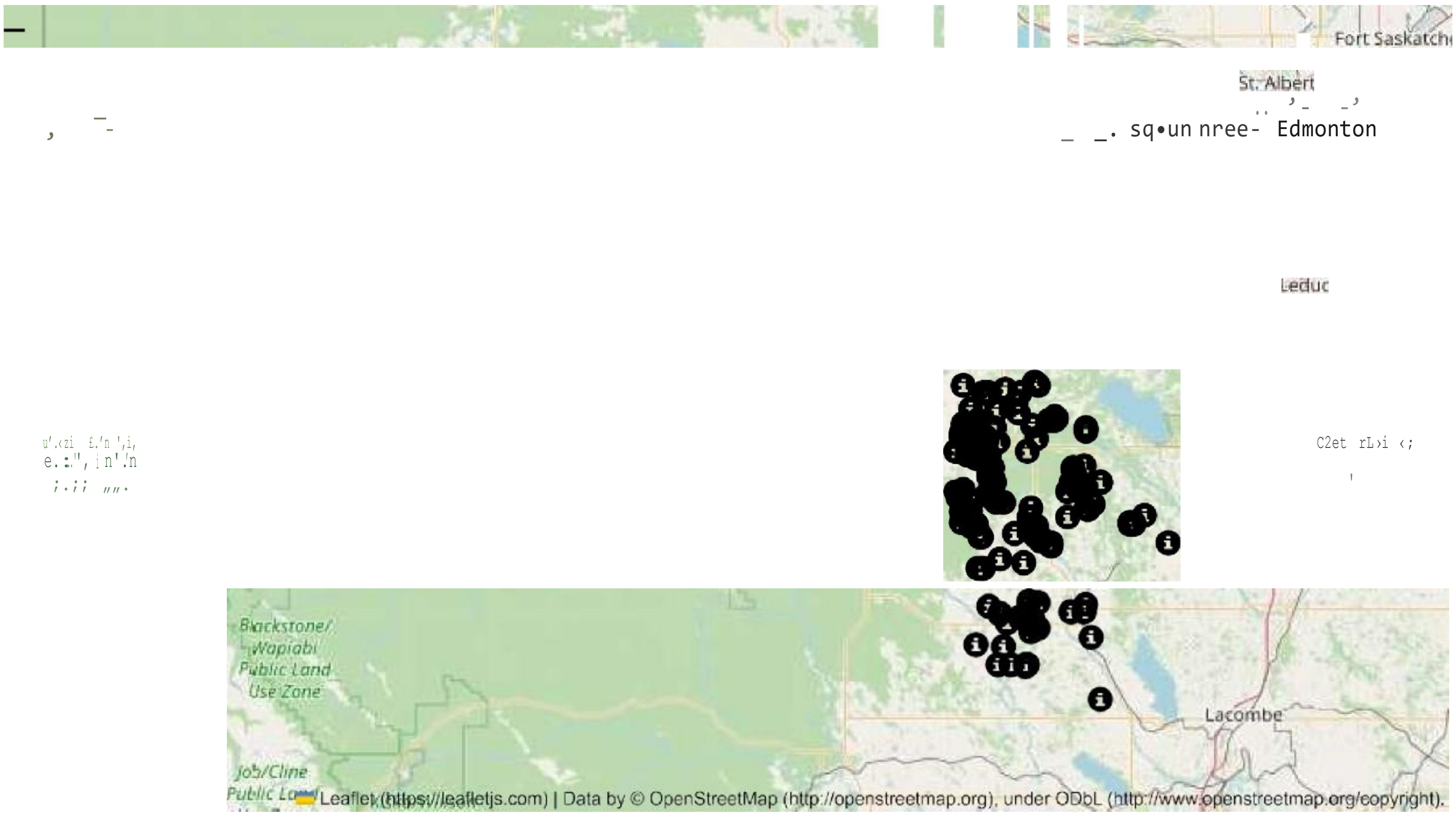
Most of the houses listed for sale are from the Pincode 122028

```
df1[df1['Built Year']==2014]['Lattitude'].mean()
```

52.77583376963351

```
d+1[df1['Built  Year']--2014]['Longitude'].mean()
```

```
-114.3889g9s2879582

m = folium.Map(location:  [5Z.77, -114.4], tiles ='Open5treetMap',
    zoom_start=8)

for index, location info in df1[(df1 'Built Year' ]==2014) & (df1['Distance from the ai*Dont' ]<=70)].iterrows():
    folium.Marker([location_info["Lattitude"], location_info["Longitude"]], popup=location_info["Price"],icon=folium.
```




```
del[df1['Built Year']>-2014]['Lattitude'].mean()
```

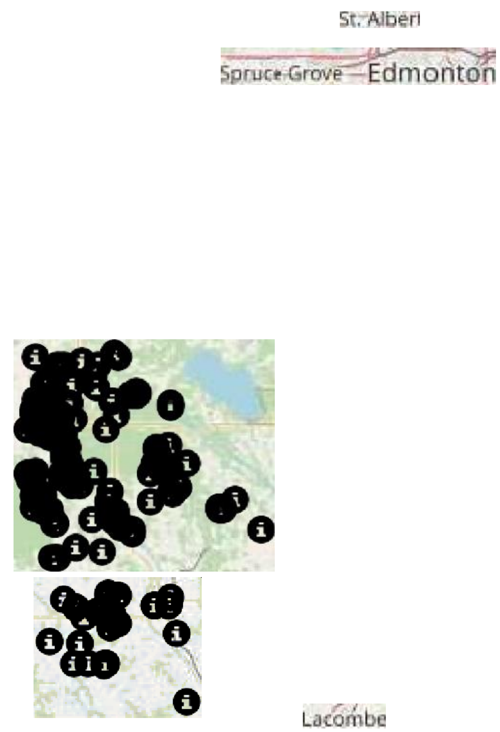
```
52.77850305343512
```

```
dfl[df1['Built  Year']>:2014]['Longitude'].mean()
```

```
-114.39186768447837
```

```
m = folium.Map(location = [5Z.77, -114.4], tiles ='0penStreetMap',
    zoom start=8)
```

```
for index, location_info in df1[(df1 'Built Year'] ›=2014) & (df1['Distance from the ai port' ]‹=70)].iterrows():
    folium.Marker([location_info["Lattitude"],  location_info["Longitude”]],  popup=location_info[”Price”],icon=folium.
m
```



"" ' -' -" Leafle} ($tt'pS //j.qg{[etjs com] | Data by OpenStreetMap (http:.'/openstreetma g.org), under ODDL (http:,'/www.openstreetmap.org/copyrignt).

The houses listed for sale in this dataset are located in Alberta, Canada

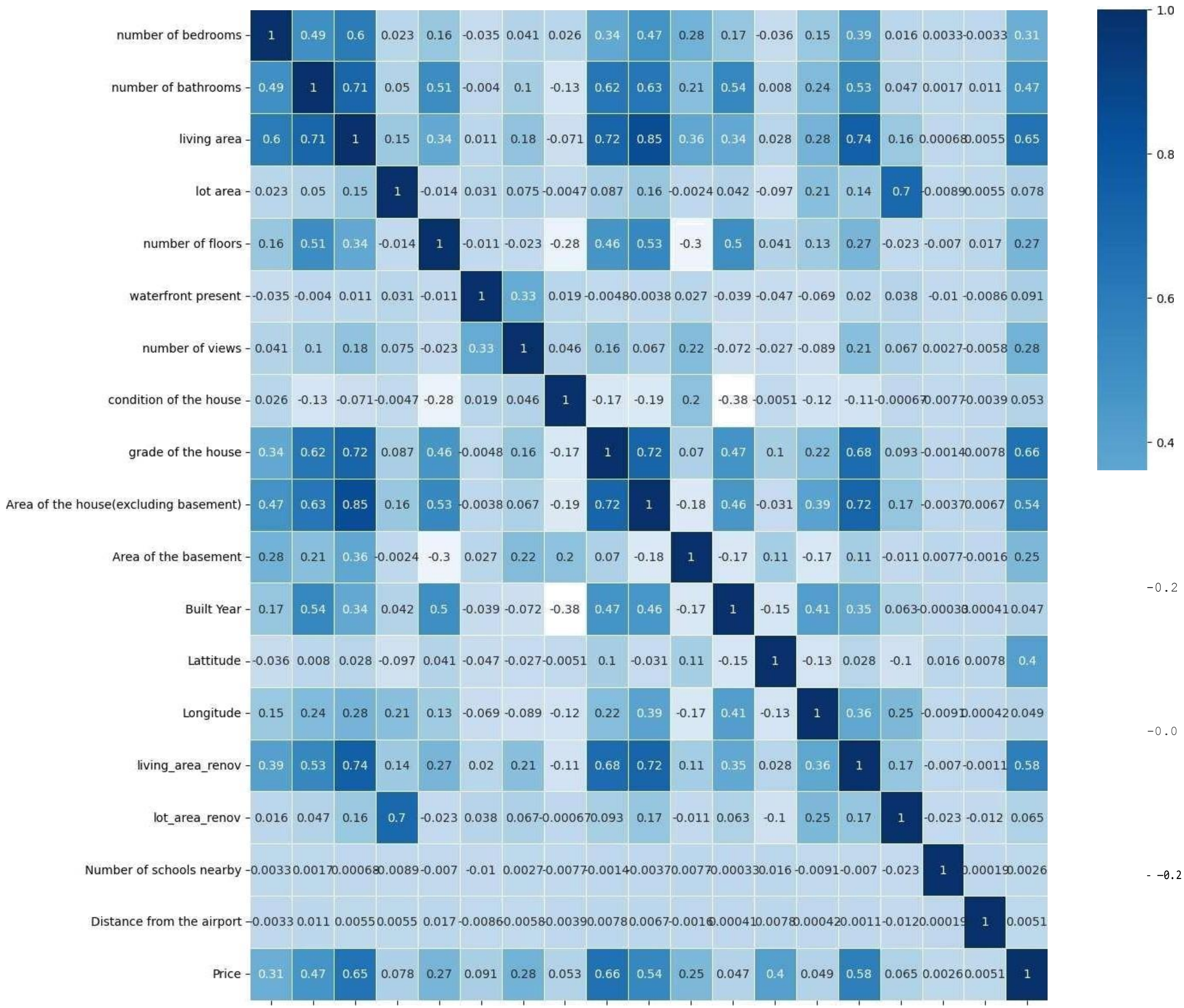
```
d+1=d+1. d op([ i d'],ax is - 1)
```

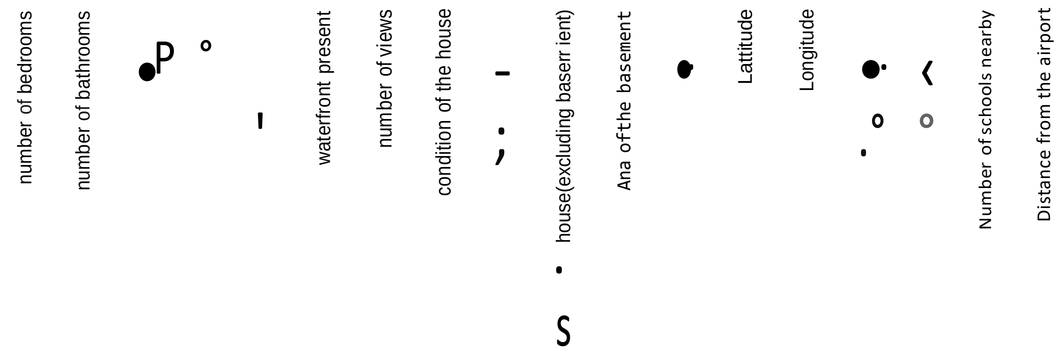
```
df1=d*1.drop(['POstal COde'],axis=l)
```

MULTI - VARIATE ANALYSIS

Columns ID and Postal Code have been dropped from df as an increase or decrease in Postal Code shall not directly impact the Price of the property

```
plt.figure(figsize=(15,15))
sns.heatmap(df1.corr(),linewidths-0.5,annot=True,cmap='Blues')
plt.show()
```

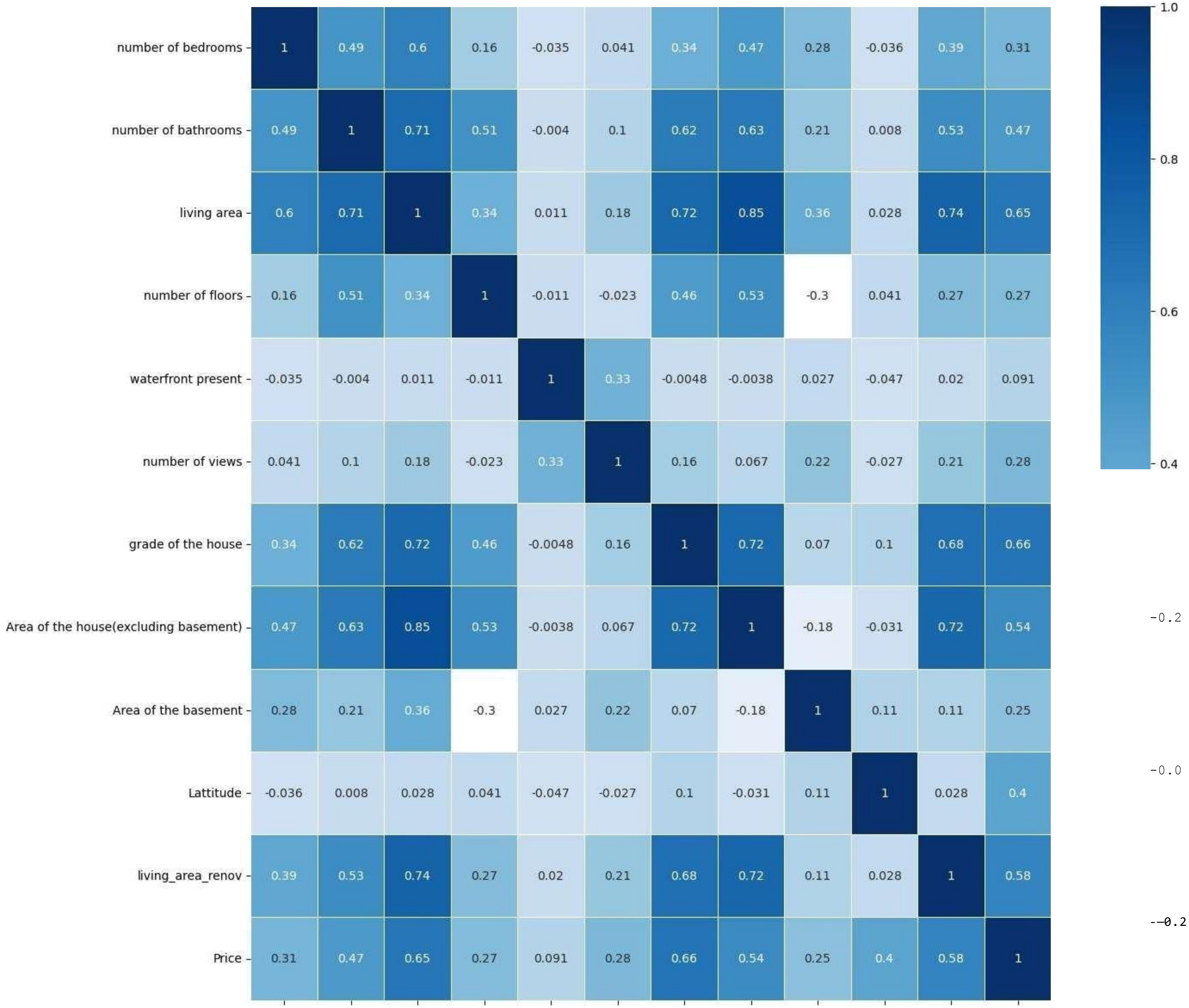




Columns like 'lot area','condition of the house','Built Year','lot_area_renov','Number of schools nearby','Distance from the airport','Longitude' contribute minimal to Price which is the Target variable. Hence it is removed before training

```
In [62]: df1=df1 d op([  o  a ea   condition o  the house   Buil  Yea    lo  a ea  enov   Number o  schools nearby   istance
```

```
In [63]: plt.figure(figsize=(15,15))
         sns.heatmap(df1.corr(),linewidths=0.5,annot=True,cmap='Blues')
         plt.show()
```


number of bedrooms
number of bathrooms
living area
number of floors
waterfront present
number of views
grade of the house
Area of the house(excluding basement)
Area of the basement
Lattitude
living_area_renov
Price
1 0.49 0.6 0.16 -0.035 0.041 0.34 0.47 0.28 -0.036 0.39 0.31
0.49 1 0.71 0.51 -0.004 0.1 0.62 0.63 0.21 0.008 0.53 0.47
0.6 0.71 1 0.34 0.011 0.18 0.72 0.85 0.36 0.028 0.74 0.65
0.16 0.51 0.34 1 -0.011 -0.023 0.46 0.53 -0.3 0.041 0.27 0.27
-0.035 -0.004 0.011 -0.011 1 0.33 -0.0048 -0.0038 0.027 -0.047 0.02 0.091
0.041 0.1 0.18 -0.023 0.33 1 0.16 0.067 0.22 -0.027 0.21 0.28
0.34 0.62 0.72 0.46 -0.0048 0.16 1 0.72 0.07 0.1 0.68 0.66
0.47 0.63 0.85 0.53 -0.0038 0.067 0.72 1 -0.18 -0.031 0.72 0.54
0.28 0.21 0.36 -0.3 0.027 0.22 0.07 -0.18 1 0.11 0.11 0.25
-0.036 0.008 0.028 0.041 -0.047 -0.027 0.1 -0.031 0.11 1 0.028 0.4
0.39 0.53 0.74 0.27 0.02 0.21 0.68 0.72 0.11 0.028 1 0.58
0.31 0.47 0.65 0.27 0.091 0.28 0.66 0.54 0.25 0.4 0.58 1
1.0
0.8
0.6
0.4
-0.2
-0.0
--0.2

number of bedrooms
m
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o
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waterfront present
mber of views
e of the house
house(excluding
the basement
Lattit d
g_area_renov
.y

Training of Model, Splitting of Dataset into Train and Test Set

In [64]
```
from sklearn.model_selection import train_test_split
```

In [65]:
```
X=dfl.drop(['Price'],axis =1)
```

In [66]:
```
X. shape
```

Out[6G]:
```
(13982, 11)
```

In [67]:
```
y=dfl['Pnice']
```

In [68]:
```
y. shape
```

Out[68]
```
(13982,)
```

In [69]:
```
X_train,X_test,y_train,y_test=  train_test_split(X,y,test_size=0.2,random_state=l1)
```

In [70]:
```
X_train.shape
```

Out[70]:
```
(11185, 11)
```

In [71]
```
X test.shape
```

Out[71]: (2797, 11)

In [72]:
```
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear model import ElasticNet, Lasso,LinearRegression,RidgeCV
from catboost import CatBoostRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import StackingRegressor
from sk1earn.svm import SVR
```

In [73]:
```
pipelines = {
    'en':make_pipeline(StandardScaler(), ElasticNet()),
    'lasso' :make_pipeline(StandardScaler(), Lasso()),
    'Rcv':make_pipeline(StandardSca1er(), RidgeCV()),
    'CatB':make_pipeline(StandardScaler(),  CatBoostRegressor(eval_metric='RMSE',verbose=1000)),
    'lr'            :make_pipeline(StandardScaler(),            LinearRegression()),
    'rf'         :make_pipeline(StandardScaler(),          RandomForestRegressor()),
    'gb' :make_pipeline(StandardScaler(), GradientBoostingRegressor()),
    'dtc':make_pipeline(StandardScaler(),DecisionTreeRegressor()),
    'xg':make_pipeline(StandardScaler(),XGBRegressor())
```

In [74]:
```
fit_models = {}
for algo, pipeline in pipelines.items():
    model = pipeline.fit(x tnain, y tnain)
    fit_models[algo] = model
```

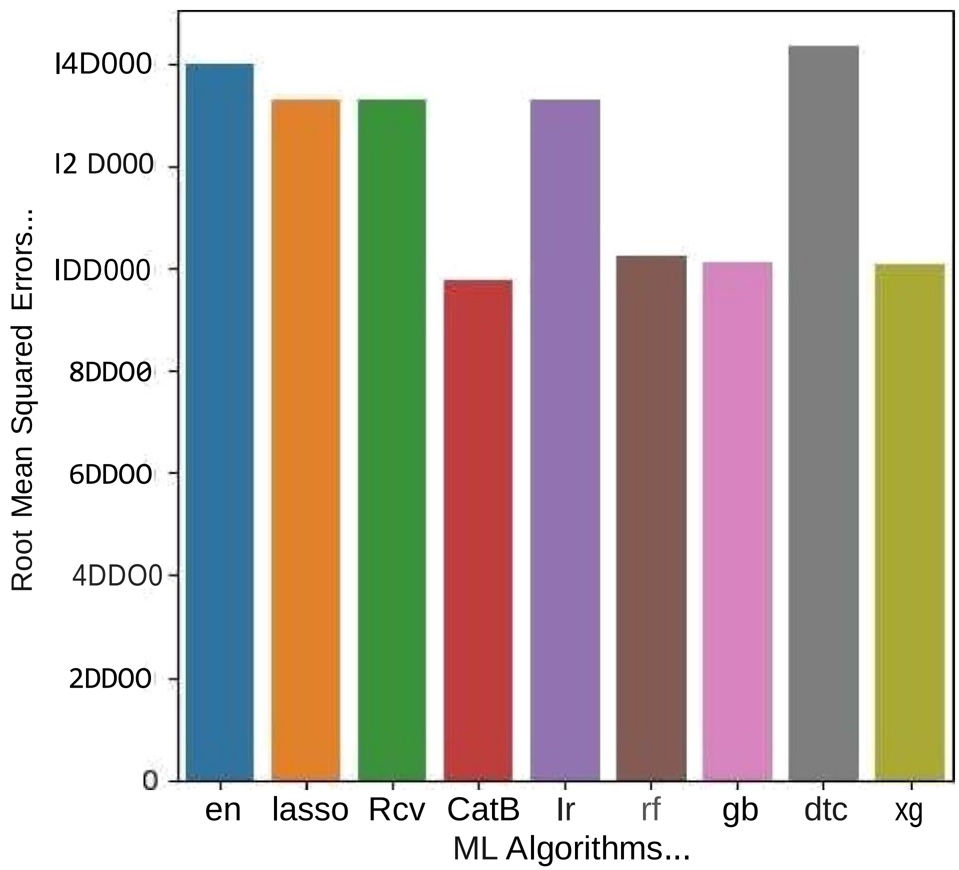
```
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_coordinate_descent.py:648: ConvergenceWarning:  Objective
did not converge. You might want to increase the number of iterations, check the scale of the features or consider inc
rearing regularisation. Duality gap: 4.781e+12, tolerance: 5.929e+10
  coef_, l1_reg, l2_reg, X, y, max_iter, tol, rng, random, positive
Learning rate set to 0.0599g
0:      learn: 221490.1496581   total: 61.4ms   remaining: lm 1s
999:    learn: 77595.2298921    total: 2.85s    remaining: 0us
```

In [75]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
maes=[]
a1=[]
for algo, model in fit_models.items():
```

```
    yhat = model.predict(X_test)
    al.append(algo)
    maes.append(mean_squared_error(y_test,yhat)**0.5)
    print(algo, 'MEAN ABSOLUTE ERROR', mean_absolute_error(y_test,yhat))
    print(algo,'ROOT MEAN SQUARED ERROR',mean_squared_error(y_test,yhat)’*0.5)
```

```
en MEAN ABSOLUTE ERROR 104444.32355671145
en ROOT MEAN SQUARED ERROR 140011.53917862213
lasso MEAN ABSOLUTE ERROR 97479.23118789196
lasso ROOT MEAN SQUARED ERROR 132916.1566456281
RcV MEAN ABSOLUTE ERROR 97481.91673717603
RcV ROOT MEAN SQUARED ERROR 132918.333682342
CatB MEAN ABSOLUTE ERROR 66637.3B790160663
CatB ROOT MEAN SQUARED ERROR 97508.34029611414
Ir MEAN ABSOLUTE ERROR 97574.48622571728
lr ROOT MEAN SQUARED ERROR 132952.7515959945
rf MEAN ABSOLUTE ERROR 69217.89879907611
rf ROOT MEAN SQUARED ERROR 102292.J632979867
gb MEAN ABSOLUTE ERROR 69874.84067217445
gb ROOT MEAN SQUARED ERROR 101056.4iL7gS7216
dtc MEAN ABSOLUTE ERROR 96944.72285782386
dtc ROOT MEAN SQUARED ERROR 143316.21683052482
xg MEAN ABSOLUTE ERROR 69035.05210660976
Xg ROOT MEAN SQUARED ERROR 1066V4.4l64B4ZS66b
```

```
In [76]: plt.figure(figsize=(5,5))
         plt.xlabel('ML Algorithms... ')
         plt.ylabel('Root Mean Squared Errors...')
         ax=sns.barplot(x=al,y=maes)
         plt.show()
```




```
CatB   CatBoostReg essor(verbose=1000,eval_metric='RMSE')
rf = RandomForestRegressor()
gb = Gradi ent Boost ingRegres sor()
xg = XGBRegres sor ()
lr=LinearRegression()

streg    StackingRegressor(estimators=[('catb',CatB),('xg', xg),('gb',gb)],
                          final_estimator:lr)

pipeline = make pipeline(
    StandardScaler(),
    stregr

pipeline.fit(X train, y_train)
```

```
It Generate predict ions on the tee I set
y_pred = pipeline.predict(X_test)

It Evatuate the mode L
print("Root Mean Squared Error: %.4f" % mean_squared_error(y_test,y_pred)**0.5)
```

```
Learning rate set to 0.0s996
0:      learn: 221490.1496581   total: 4.18ms   remaining: 4.18s
999:    learn: 77595.2298921    total: 2.81s    remaining: 0us
Learning rate set to 0.057883
0:      learn: 222091.4863333   total: 3.52ms   remaining: 3.51s
999:    learn: 76337.1933964    total: 2.52s    remaining: 0us
Learning rate set to 0.B57883
0:      learn: 222546.8538661   tota1: 2.94ns   rema1ning: 2.94s
999:    learn: 75466.5961681    total: 2.51s    rema1n1ng: Ous
Learning rate set to 0.057883
0:      learn: 223455.5230951   total: 3.2ms    remaining: 3.2s
999:    learn: 75656.3661258    total: 2.52s    remaining: 0us
Learning rate set to 0.0s7883
0:      learn: 221606.9467960   total: 3.71ms   remaining: 3.7s
999:    learn: 75195.9699196    total: 2.46s    remaining: 0us
Learning rate set to 0.057883
0:      learn: 219316.0911020   total: 2.47ns   rema1n1ng: 2.47s
```

In [ ]:
```
mean_squared_error(y_test,y_pred)**0.5
```

In [ ]:
```
al.append('stacked model')
maes.append(mean_squared_error(y_test,y_pred)**0.5)
```

In [ ]:
```
for i in range(10):
    print("The RMSE of",al[i],'is',maes[i])
```

In [ ]:
```
plt.figure(figsize=(9,5))
plt.xlabel('ML Algorithms...')
plt.ylabel('Root Mean Squared Errors...')
ax=sns.barplot(x=al,y=maes)
plt.show()
```