NM DATA ANALYTICS ASSIGNMENT 3 - House Price dataset of India

DONE BY Camila V

Importing the necessary libraries for EDA and data preprocessing

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

---

Converting csv file into dataframe

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

In
```
df=df.drop([
```
'Date'] , axis-I)

Out[5] :

	id	number of floors	number of views	number of the	condition of the ...	grade number of bedrooms	number of bathrooms	living area	lot area	waterfront present	house house	Built Year	Renovatio Yee
o	6762810145	5	2.50	3650	9050	2.0			4	5	10...1921		
1	6762810635	4	2.50	2920	4000	1.5	5	8...1909					
2	6762810998	5	2.75	2910	9480	1.5	3	8...1939					

3	6762812605	4	2.50	3310	42998	2.0	3	9...2001	
4	6762812919	3	2.00	2710	4500	1.5	4	8...1929	
14615	6762830250	2	1.50	1556	20000	1.0	4	7...1957	
14616	6762830339	3	2.00	1680	7000	1.5	4	7...1968	
14617	6762830618	2	1.00	1070	6120	1.0	3	6...1962	
14618	6762830709	4	1.00	1030	6621	1.0	4	6...1955	
14619	6762831463	3	1.00	900	4770	1.0	3	6...1969	200

14620 rows x 22 columns

```
[6]: df.head()
```

Out[6]:

	id	number of of house	number of house	number of the	condition of the ...	grade bathrooms	number of living area	lot area	waterfront present	Built Year	Renovation Year	bedrooms	floors	views
o	6762810145	5	2.50	3650	9050	2.0			4	5	10 ... 1921			
1	6762810635	4	2.50	2920	4000	1.5	0	5	8...1909					
2	6762810998	5	2.75	2910	9480	1.5	3	8...1939						

3	6762812605	4	2.50	3310	42998	2.0	0	3	9...2001 o 1:
4	6762812919	3	2.00	2710	4500	1.5	4	8	... 1929

5 rows x 22 columns

```
[7]: df.tail()
```

Out [7] :

	id	number of floors	number of views	number of the	condition of the	...	grade bedrooms	number of bathrooms	living area	lot area	waterfront present	house	house	Built Year	Renovatio Yee
14615	6762830250	2	1.5	1556	20000	1.0	4	71957				...			
14616	6762830339	3	2.0	1680	7000	1.5	4	7...1968							
14617	6762830618	2	1.0	1070	6120	1.0	3	6...1962							
14618	6762830709	4	1.0	1030	6621	1.0	4	6...1955							
14619	6762831463	3	1.0	900	4770	1.0	3	6...1969 200							

5 rows x 22 columns

Checking for null and duplicated values

In [8] : df.isna() .sum()

Out [8] :

```
id                                      0
number of bedrooms                      0
number of bathrooms         basement)   0
living area 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             0
Area of the basement Built              0
Year                                    0
Renovation Year                         0
Postal Code                             0
L attitude                              0
Longitude living                        0
area renov lot area                     0
renov                                   0
Number of schools nearby                0
Distance from the airport               0
Price dtype: int64                      0
                                        0
```

[9]: df.duplicated() . sum()

Out[9] : 0

In [10] : df.info()

```
<class 'pandas. core. frame. DataFrame'>
Rangelndex: 14620 entries, 0 to 14619
Data columns (total 22 columns) :
```

```
#   Column                                    Non-Null Count Dtype
    ------                                    -------------- -----
e   id                                        14620non-null  int64
1   number of bedrooms                        14620non-null  int64
2   number of bathrooms                       14620non-null  float64
3   living area                               14620non-null  int64
4   lot area                                  14620non-null  int64
5   number of floors                          14620non-null  float64
6   waterfront present                        14620non-null  int64
7   number of views                           14620non-null  int64
8   condition of the house                    14620non-null  int64
9   grade of the house                        14620non-null  int64
10  Area of the house(excluding  basement)    14620non-null  int64
11  Area of the basement                      14620non-null  int64
12  Built Year                                14620non-null  int64
13  Renovation Year                           14620non-null  int64
14  Postal Code                               14620non-null  int64
15  L attitude                                14620non-null  float64
16  Longitude                                 14620non-null  float64
17  living area renov                         14620non-null  int64
18  lot area renov                            14620non-null  int64
19  Number of schools nearby                  14620non-null  int64
20  Distance from the airport                 14620non-null  int64
21  Price                                     14620non-null  int64
dtypes: float64(4), int64(18)
memory usage: 2.5 MB
```

In[11] : df.describe()

Out[11] :

	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condi the

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	o.
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.

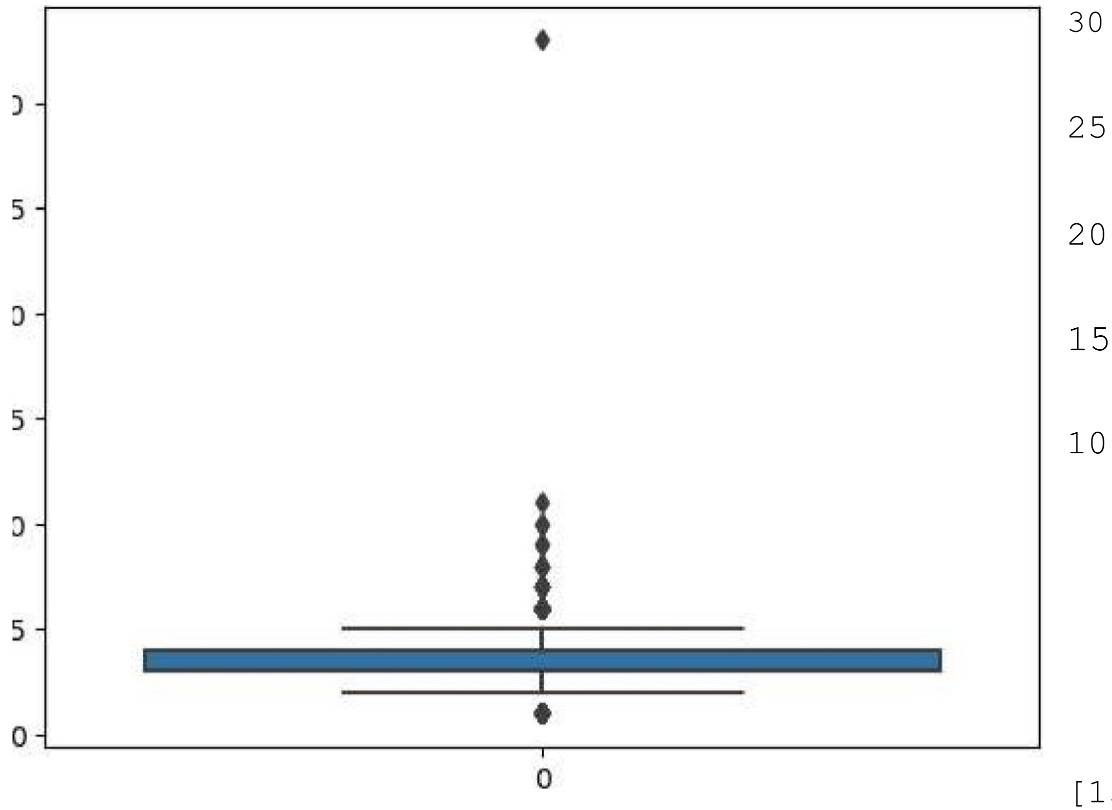
8 rows x 22 columns

UNIVARIATE ANALYSIS

Checking for outliers

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

Out [12] : <AxesSubp10t : >



In [13] : z=np.abs(stats.zscore(df'number of bedrooms.

In[14] : threshold-3

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

```
(array([   76,   243,   268,   275,   624,   785, 1512, 1519, 1553,
        1706,  2814,  3109,  3114,  3322,  3532,  3600,  4207,  4486,
        4658,  4680,  6591,  6596,  6730,  6982,  6998,  7003,  7454,
        8559,  8650,  9282,  9629,  9810,  9955, 10168, 10177, 10676,
       10748, 10916, 10944, 11247, 11441, 11547 11877, 12273, 13048,
```

```
        13444,13825,14220, 14481]),
                           ) 49
In [15] : print(np.where(z<-3))
```

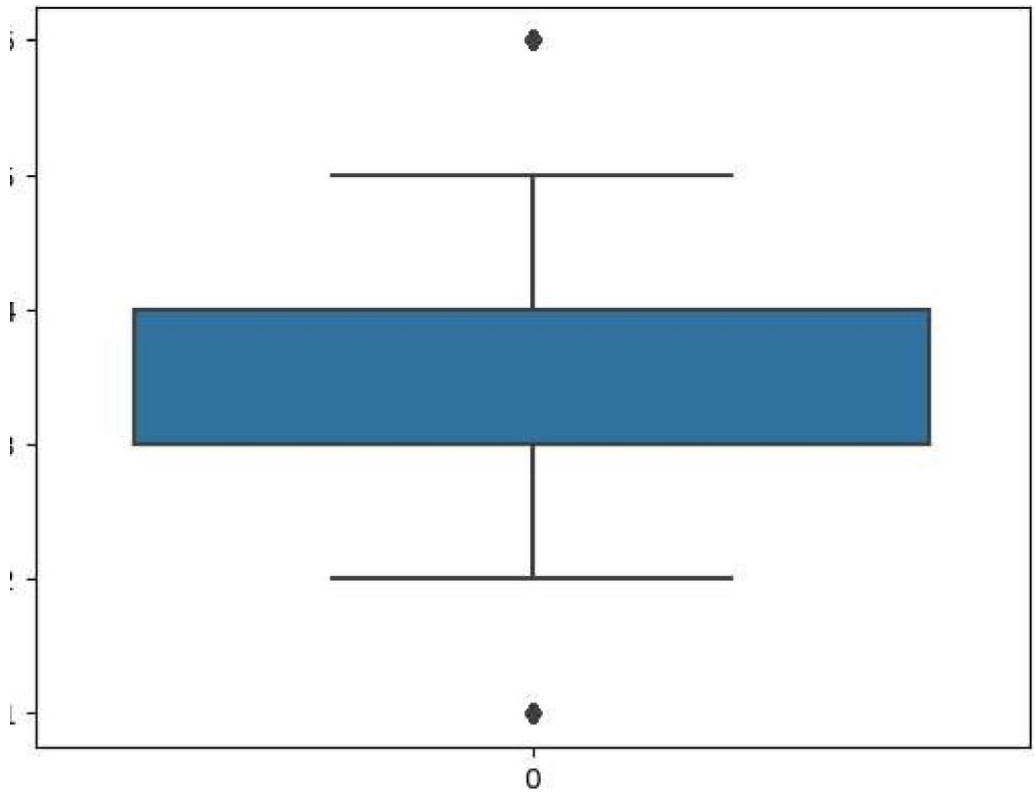
(array([], dtype=int64),)

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
```

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

Out[17] : <AxesSubp10t : >



6

5

4

3

2

1

In [18]: dfl

Out[18] :

number number number condition grade number of living lot waterfront Built Renovatio

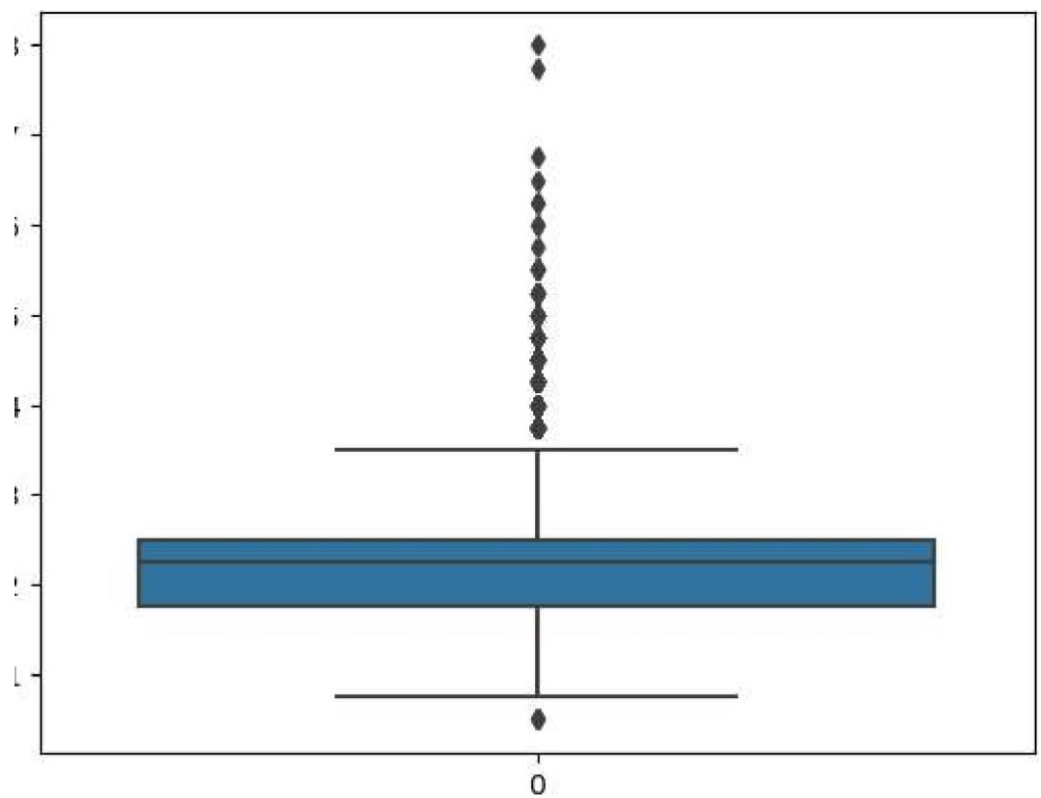
id of of of of the of the ...bedrooms bathrooms area area floors present views house house Year Yee

o	6762810145	5	2.50	3650	9050	2.0			4	5	10...1921	
1	6762810635	4	2.50	2920	4000	1.5	5	8...1909				
2	6762810998	5	2.75	2910	9480	1.5	3	8...1939				
3	6762812605	4	2.50	3310	42998	2.0	3	9...2001				
4	6762812919	3	2.00	2710	4500	1.5	4	8...1929				
14615	6762830250	2	1.50	1556	20000	1.0	4	7...1957				
14616	6762830339	3	2.00	1680	7000	1.5	4	7...1968				
14617	6762830618	2	1.00	1070	6120	1.0	3	6...1962				
14618	6762830709	4	1.00	1030	6621	1.0	4	6...1955				
14619	6762831463	3	1.00	900	4770	1.0	3	6...1969	200			

14571 rows x 22 columns

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

Out[19] : <AxesSubp10t : >



8

7

6

5

4

3

: <AxesSubp10t : >

2

1

In [20] : `z=np.abs(stats.zscore(df1[` 'number of bathrooms']
))

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

Out[21] : 124

In [22] : print(np.where(z<-
3))

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

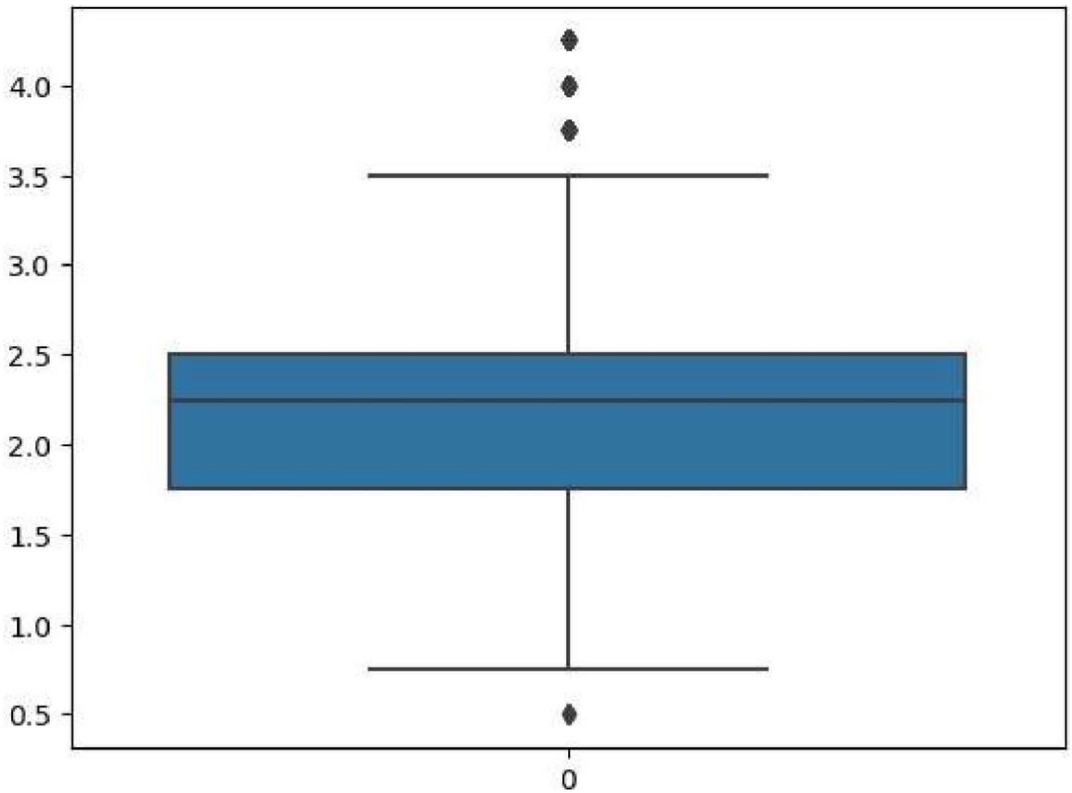
```
df1=df1[(z< 3)]
```

I n [24] : sns.boxplot(dfl['number of bathrooms'])

Out[24]

sns.boxplot(dfl[' living area])

: <AxesSubp10t : >



In[25] : dfl

Out[25] :

	id	number of floors	number of views	number of the	condition of the	...	bedrooms	number of bathrooms	living area	lot area	waterfront present	house	house	Built Year	Renovatio Yee
o	6762810145	5	2.50	3650	9050	2.0	4	5	10...1921						
1	6762810635	4	2.50	2920	4000	1.5	5	8...1909							

2	6762810998	5	2.75	2910	9480	1.5	3	8...1939
3	6762812605	4	2.50	3310	42998	2.0	3	9...2001
4	6762812919	3	2.00	2710	4500	1.5	4	8...1929
14615	6762830250	2	1.50	1556	20000	1.0	4	7...1957
14616	6762830339	3	2.00	1680	7000	1.5	4	7...1968
14617	6762830618	2	1.00	1070	6120	1.0	3	6...1962
14618	6762830709	4	1.00	1030	6621	1.0	4	6...1955
14619	6762831463	3	1.00	900	4770	1.0	3	6...1969 200

14447 rows x 22 columns

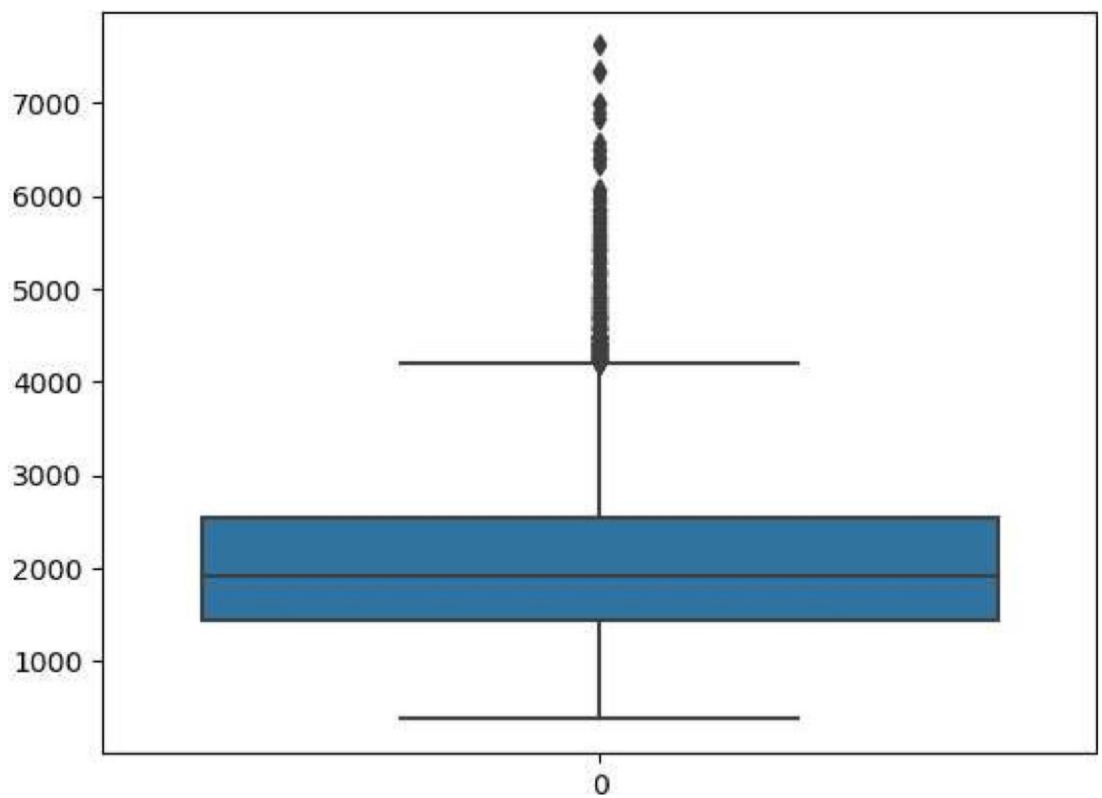
There are 124 outliers in number of bathrooms as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

[26]:
```
sns.boxplot(df1['living area'])
```

Out [26]

sns.boxplot(dfl[' living area])

: <AxesSubp10t : >



```
In [27] :z=np.abs(stats.zscore(df1[' living area' ] ) )
```

```
In [28] : len(np.where(z>3) [0] )
```

```
Out[28] : 136
```

```
In [29] : len(np.where(z<-3) [e])
```

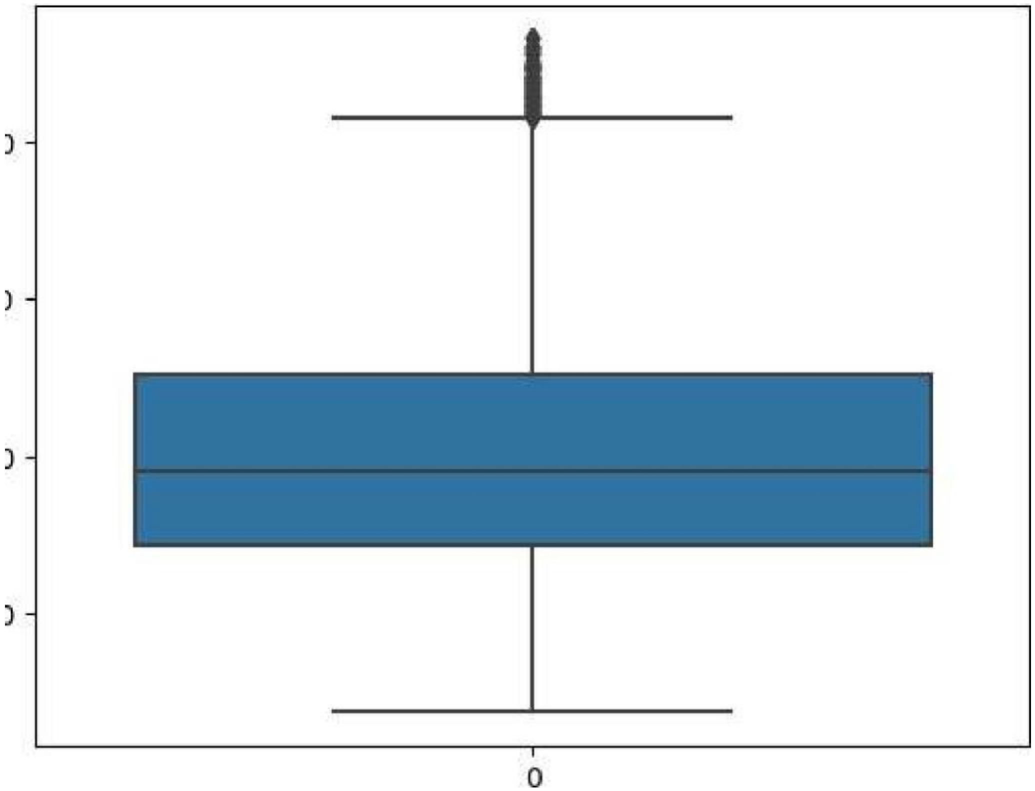
```
sns.boxplot(dfl[ ' living area ] )
```

```
: <AxesSubp10t : >
```

Out[29] : 0

[30]: df1=df1[(z<3)]

In [31] :



Out[31]

4000

sns.boxplot(dfl[' living area])

: <AxesSubp10t : >

3000

2000

1000

In [32]:
```
z=np.abs(stats.zscore(df1[' living area']))
```

In [33]:
```
len(np.where(z>3) [0] )
```

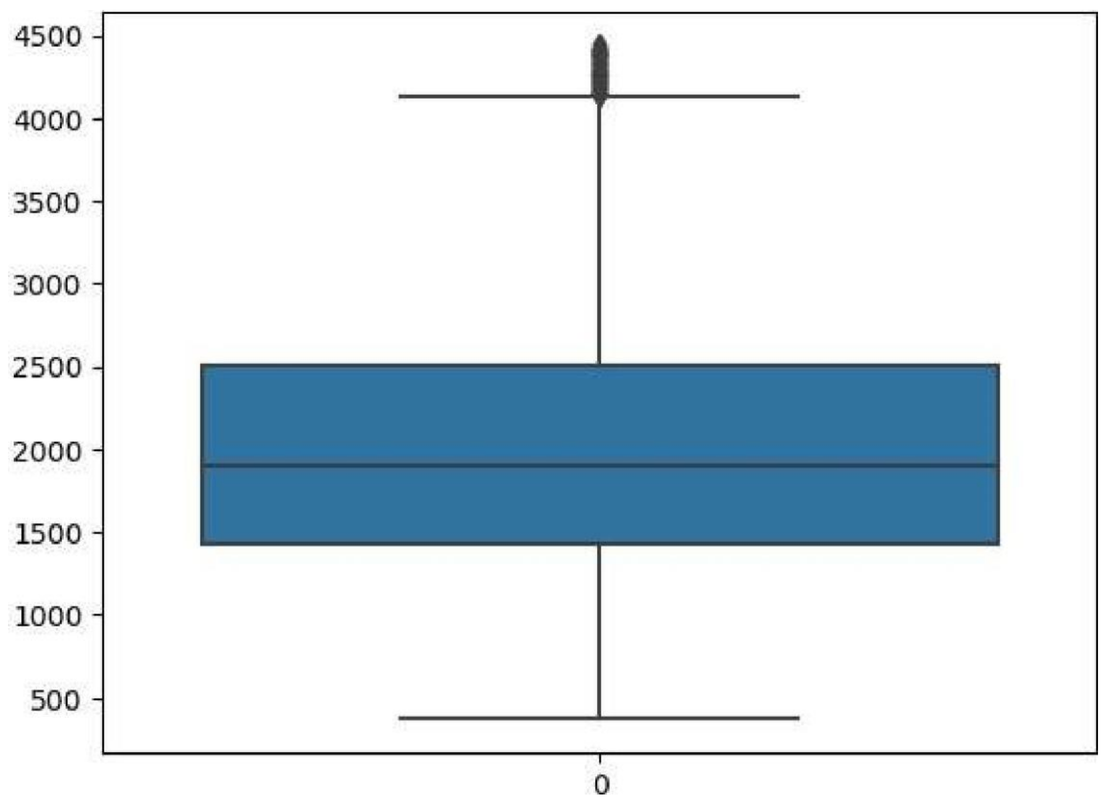
Out[33] : 67

In [34]:
```
df1=df1[(z<3)]
```

In [35]:

'

Out[35]



Iη [36] : df1

sns.boxplot(dfl[' living area])

: <AxesSubp10t : >

Out[36] :

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

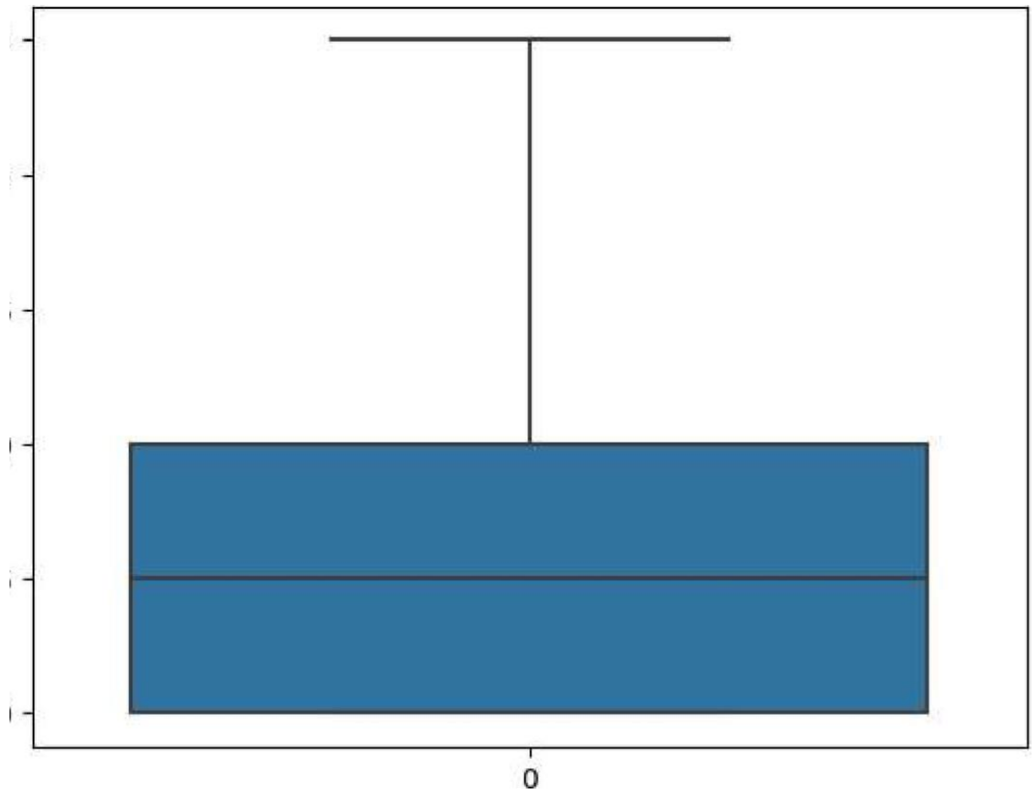
14244 rows x 22 columns

: <AxesSubp10t : >

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

In [37] : sns.boxplot(dfl['number of floors'])

Out[37]



3.5

3.0

2.5

2.0

1.5

1.0

In [38] : `z=np.abs(stats.zscore(df1[` 'number of floors']))

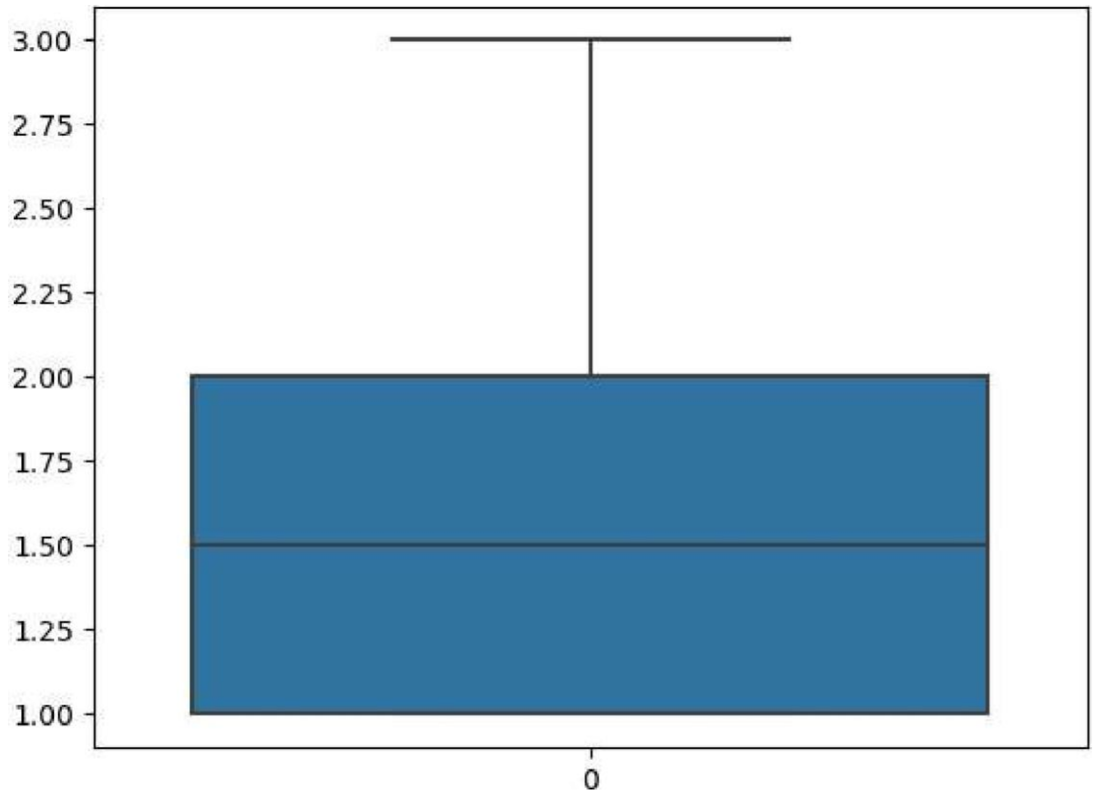
In [39] : len(np.where(z>3) [0])

Out[39] : 3

In [40] : `df1=df1[(z<3)]`

[41]: sns.boxplot(dfl['number of floors'])

Out[41] : <AxesSubp10t : >



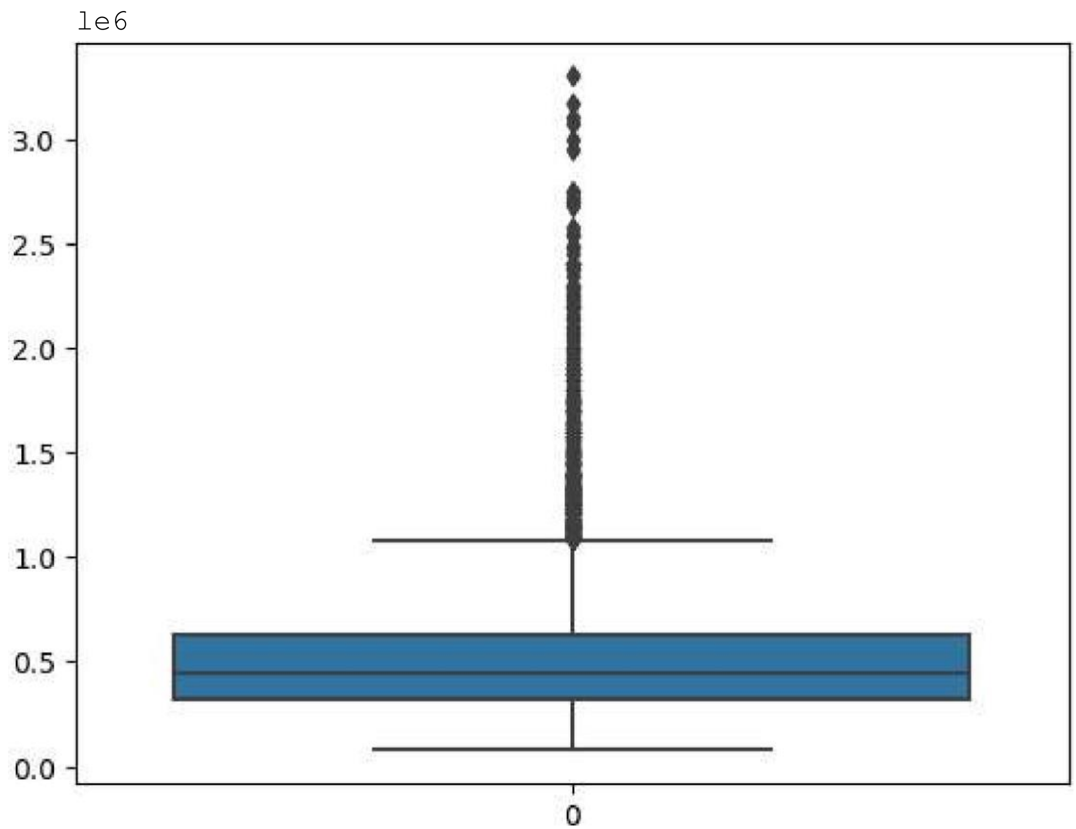
There are 3 outliers in number of floors

I n [42 :

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

sns .

Out[42] : <AxesSubp10t : >




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

In [43] :

```
z=np.abs(stats.zscore(df1['Price']))
len(np.where(z>3)[0])
```

In [44] :

Out[44] : 259

In [45] :

In [46] :

```
dfl
```

Out [46] :

number number number condition grade number of living lot waterfront Built Renovatio
id of of of of the of the ...bedrooms bathrooms area area floors present views house house Year Yee

2	6762810998	5	2.75	2910	9480	1.5	3	8...1939	
3	6762812605	4	2.50	3310	42998	2.0	3	9...2001	
4	6762812919	3	2.00	2710	4500	1.5	4	8...1929	
5	6762813105	3	2.50	2600	4750	1.0	4	9...1951	
6	6762813157	5	3.25	3660	11995	2.0	2	3	10...2006
14615	6762830250	2	1.50	1556	20000	1.0	4	7...1957	
14616	6762830339	3	2.00	1680	7000	1.5	4	7...1968	
14617	6762830618	2	1.00	1070	6120	1.0	3	6...1962	
14618	6762830709	4	1.00	1030	6621	1.0	4	6...1955	
14619	6762831463	3	1.00	900	4770	1.0	3	6...1969	200

13982 rows x 22 columns

In [47] :

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

In [48] : dfl

number number number condition grade Area of number of living lot waterfront Built

Out [46]:

	id	of house	of basement	of	of the	of the...the	bathrooms	area	area	present	Year	bedrooms	floors	views	house
2	6762810998	5	2.75	2910	9480	1.5	3	8...o	1939						
3	6762812605	4	2.50	3310	42998	2.0	3	9...o	2001						
4	6762812919	3	2.00	2710	4500	1.5	4	8...830	1929						
5	6762813105	3	2.50	2600	4750	1.0	4	9...900	1951						
6	6762813157	5	3.25	3660	11995	2.0	2	3	10...o	2006					
14615	6762830250	2	1.50	1556	20000	1.0	4	7...o	1957						
14616	6762830339	3	2.00	1680	7000	1.5	4	7...o	1968						
14617	6762830618	2	1.00	1070	6120	1.0	3	6...o	1962						
14618	6762830709	4	1.00	1030	6621	1.0	4	6...o	1955						
14619	6762831463	3	1.00	900	4770	1.0	3	6...o	1969						

13982 rows x 21 columns

Bl - VARIATE ANALYSIS

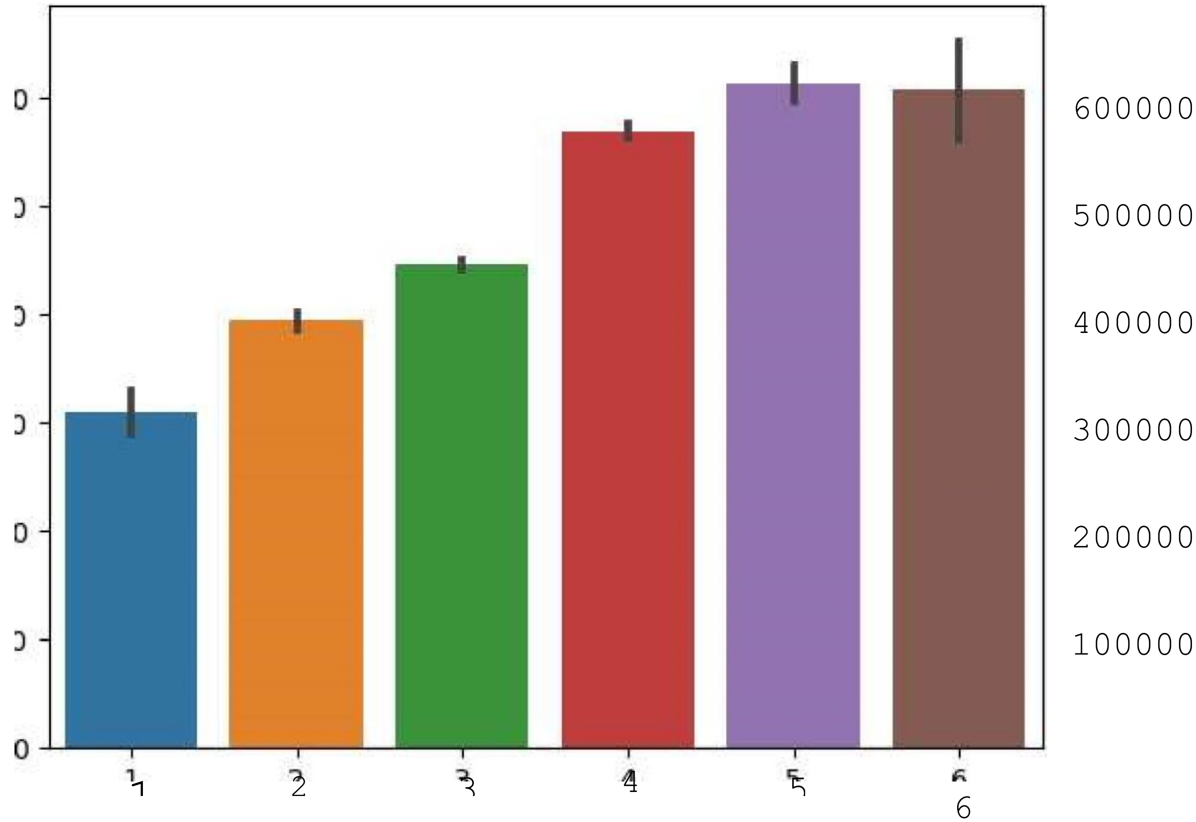
Out [46] :

The column Renovation year have been removed. This is because most of the Renovation Year are O and proves to be of no use to the model

In [49] :

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

<AxesSubp10t:x1abe1='number of bedrooms ' ylabel= ' Price' >



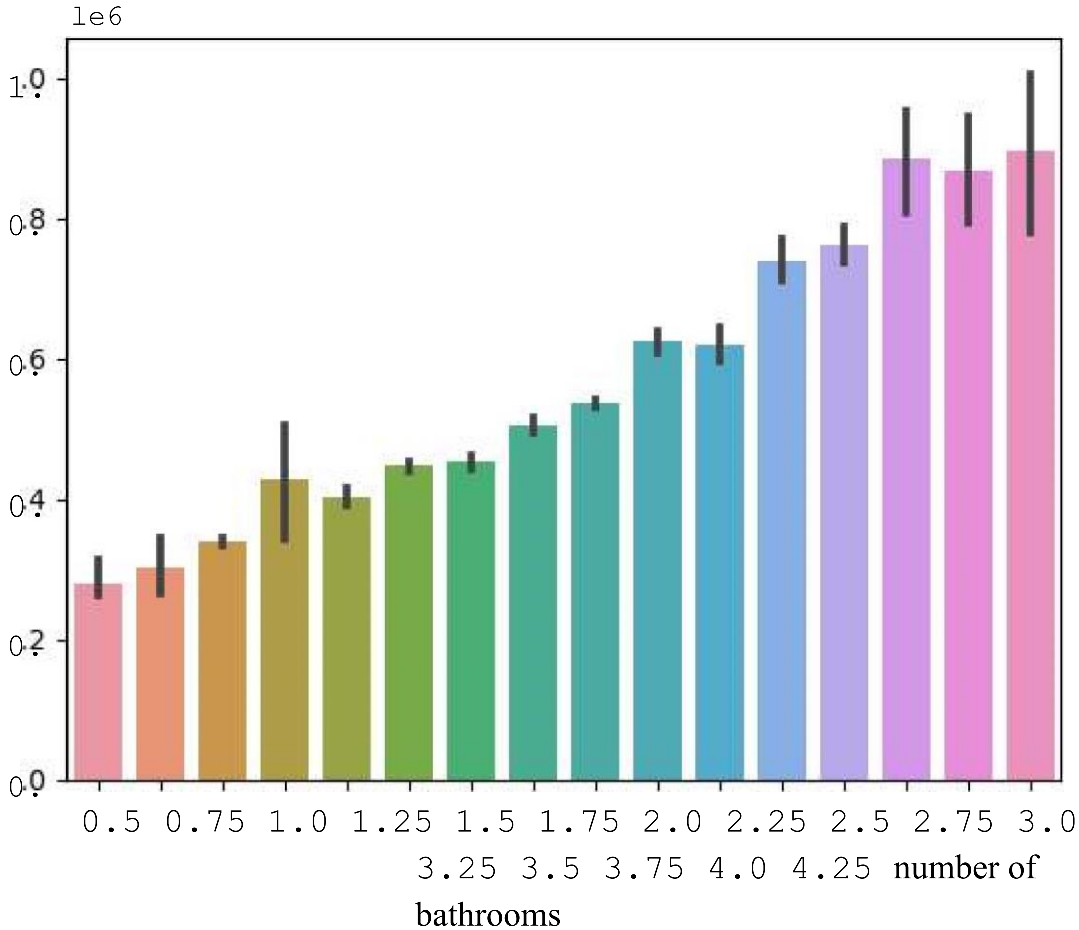
Out [46] :

Clear indication of Price increasing with number of bedrooms

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

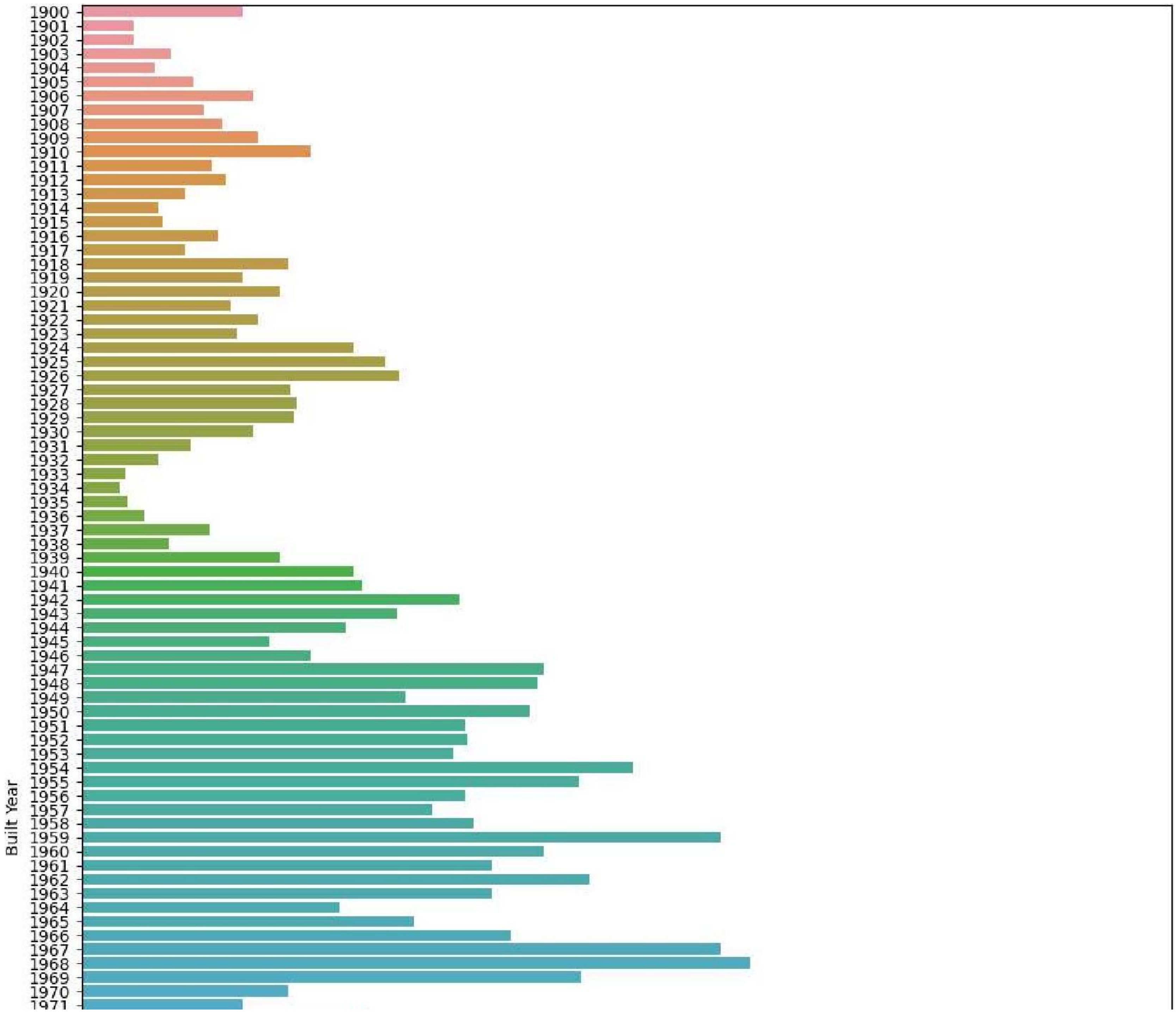
barplot of

Out[50] :<AxesSubplot:xlabel='number of bathrooms' ,ylabel='Price'>



Clear indication of Price increasing with number of bathrooms

In [51]
```
plt.figure(figsize=(12,18 :   18))
sns.countplot(data=df1,y=  ' Built Year' )
PI t . show()
```



Built Year
1900
1901
1902
1903
1904
1905
1906
1907
1908
1909
1910
1911
1912
1913
1914
1915
1916
1917
1918
1919
1920
1921
1922
1923
1924
1925
1926
1927
1928
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1930
1931
1932
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1948
1949
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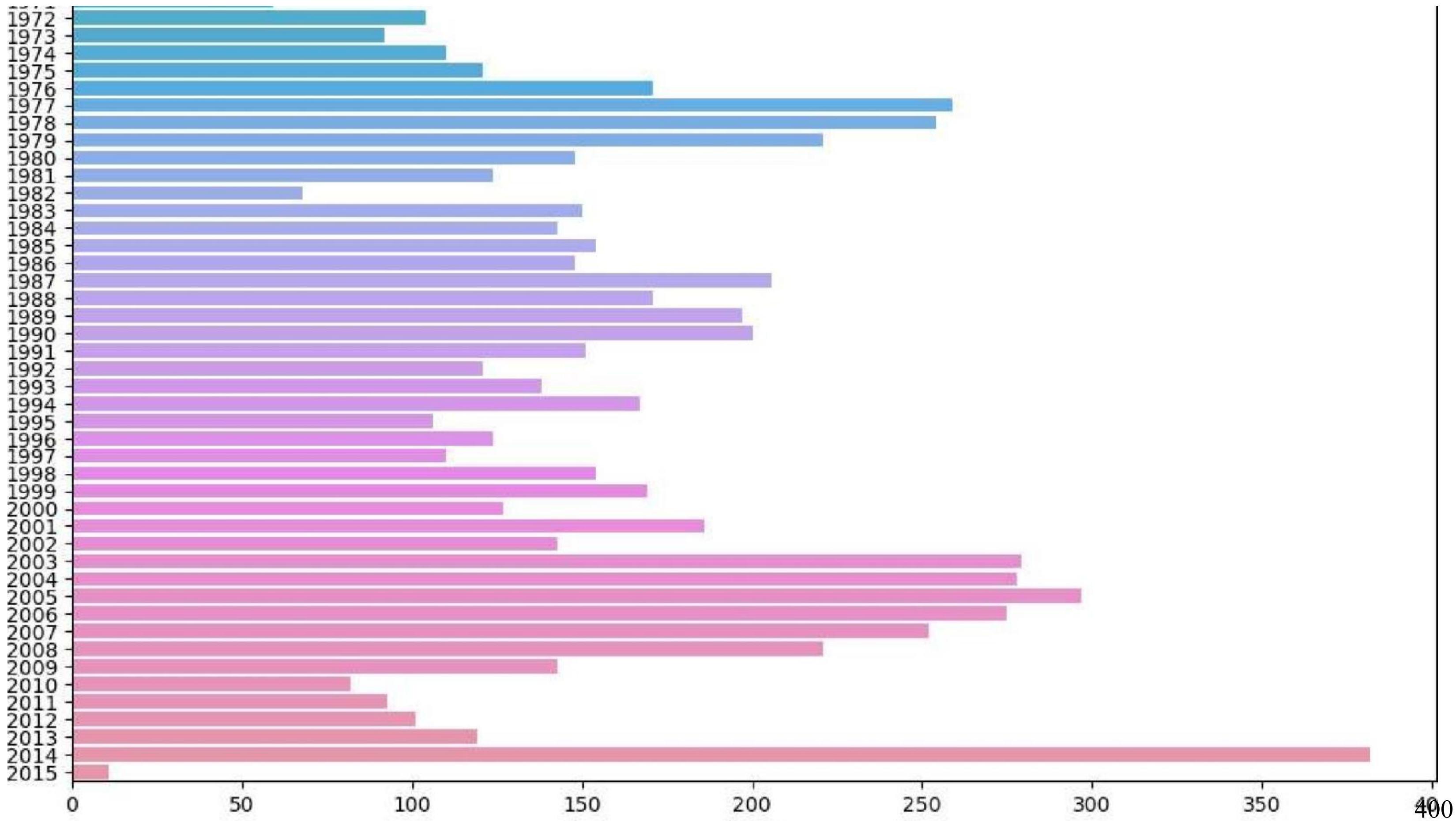
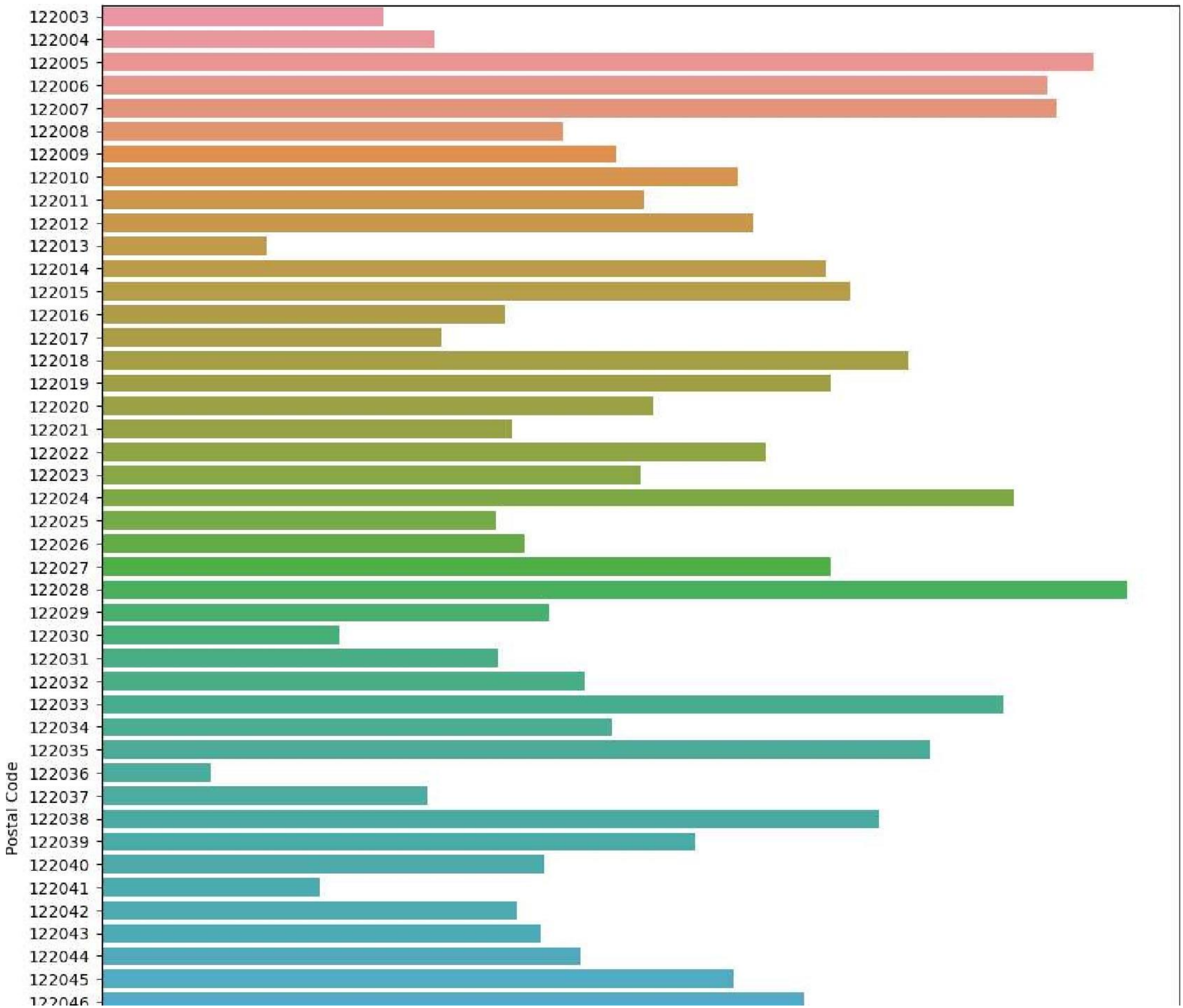
1951
1952
1953
1954
1955
1956
1957
1958
1959
1960
1961
1962
1963
1964
1965
1966
1967
1968
1969
1970
1971

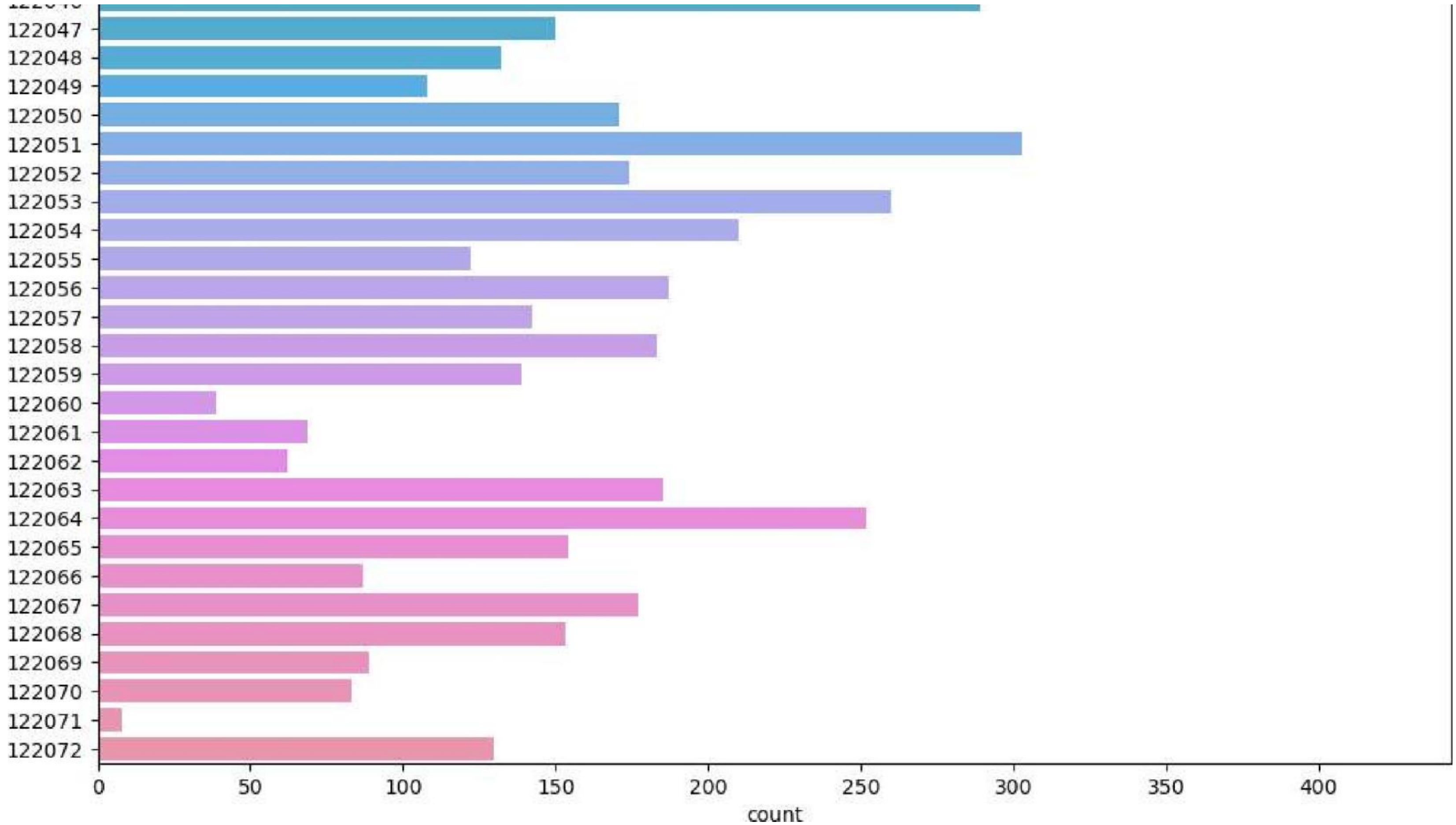


Most of the houses were listed for sale in 2017

---

ln [52] : plt.figure(figsize=(12,18)) sns.countplot
(data=dfl,y='Posta1 Code') Pl t . show()


Postal Code
122003
122004
122005
122006
122007
122008
122009
122010
122011
122012
122013
122014
122015
122016
122017
122018
122019
122020
122021
122022
122023
122024
122025
122026
122027
122028
122029
122030
122031
122032
122033
122034
122035
122036
122037
122038
122039
122040
122041
122042
122043
122044
122045



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

In [53] : df1[d .Bu1.l t Year -2014] [' L attitude'] .
mean()

Out[54] :

Out [53]

: 52.77583376963351

In [54] :

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

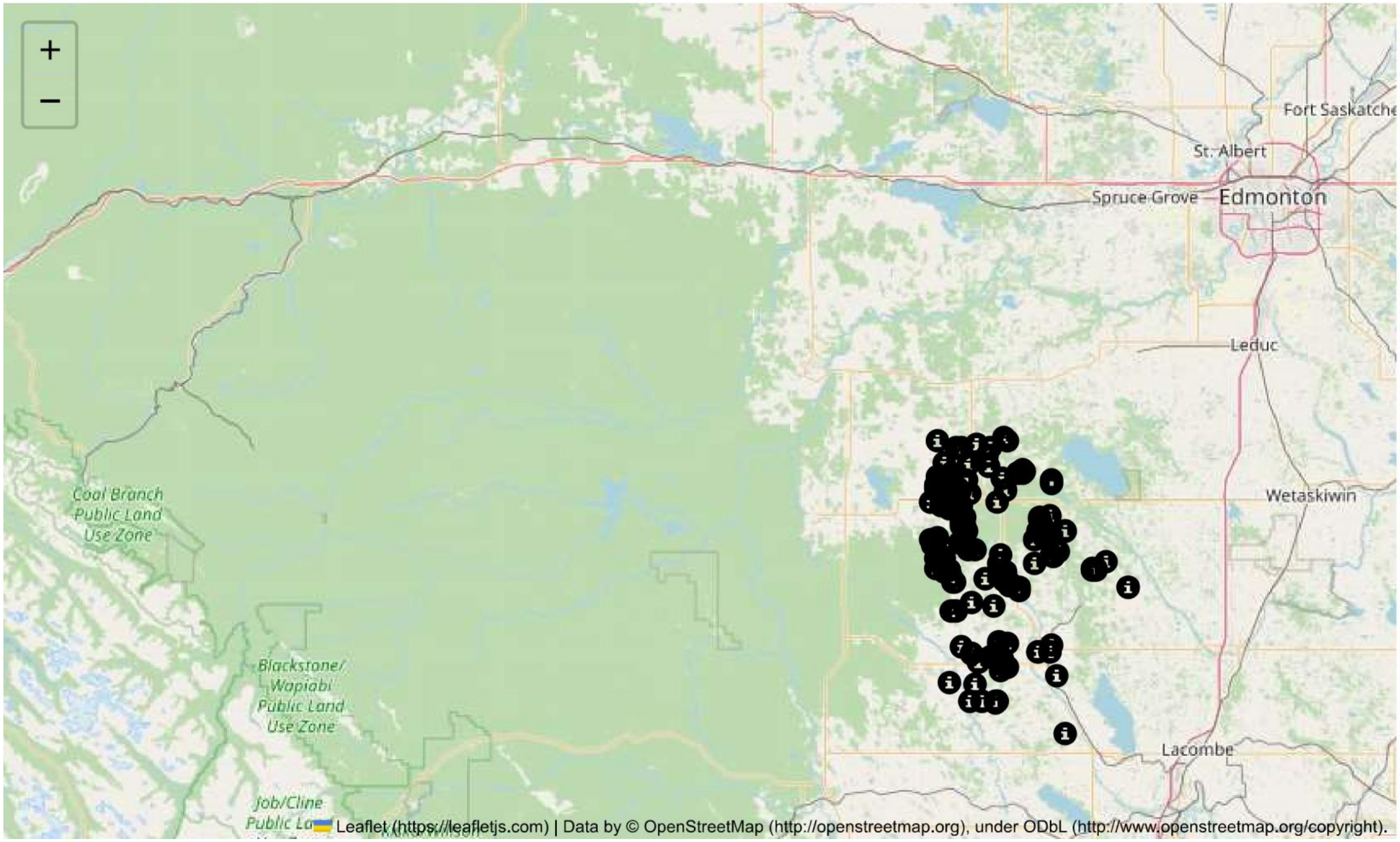
-114.38898952879582

[55] :m = folium. Map(location [52.77, -114.4], tiles = 'OpenStreetMap' , zoom_start=8)

Out[54] :

Out[55] :

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



In [56] :

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

52 .77850305343512

Out[54] :

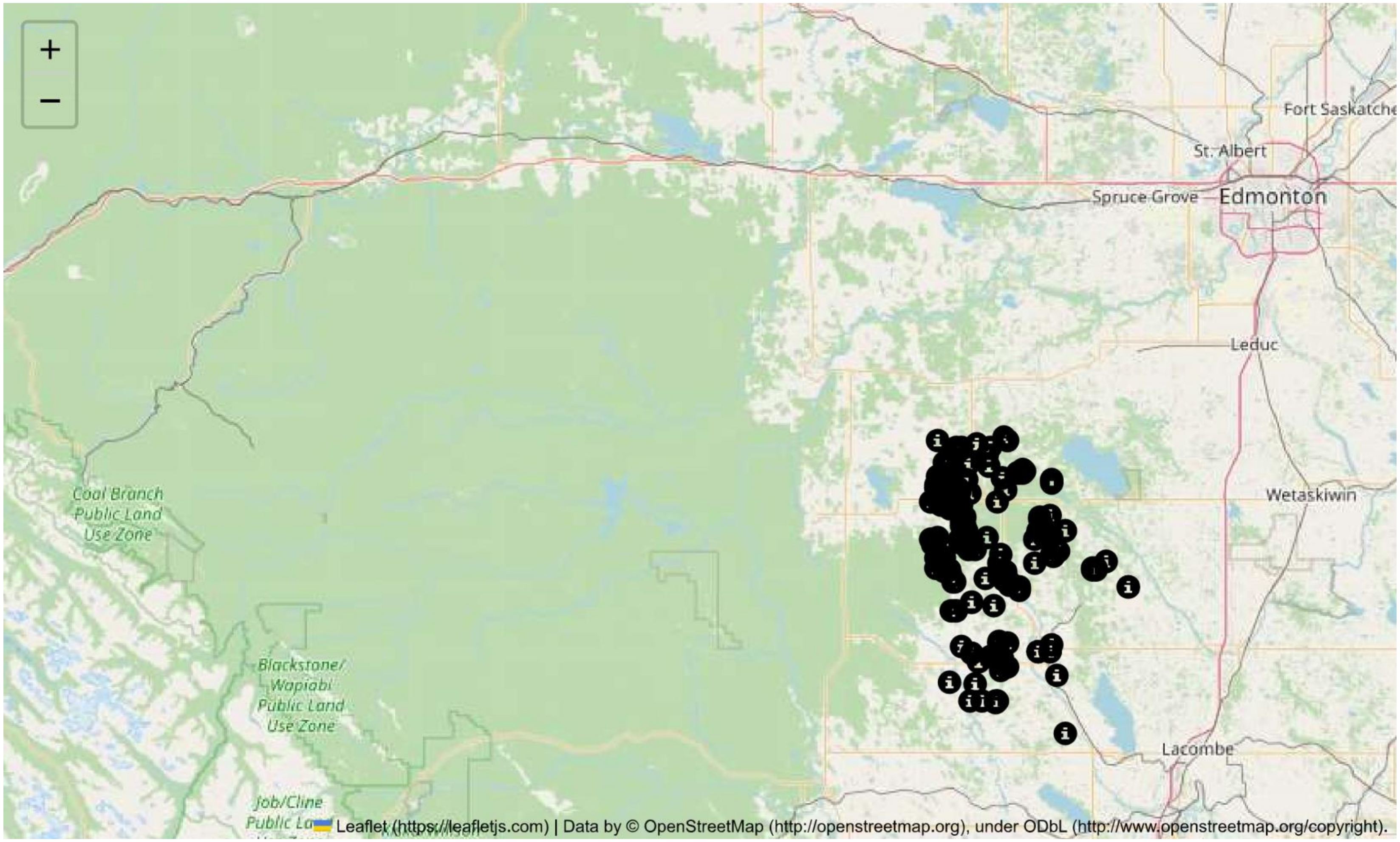
In [57] :
```
df1[df1 ['Built Year']>=2014]['Longitude'].mean()
```
-114.39186768447837

Out[57] :

```
m =folium. Map (location = [52.77, -114.4], tiles = 'OpenStreetMap' ,
    zoom_start=8)

for index, location _info in df1[(df1[ 'Bui1t Year' ]>=2014) & (dfl[ 'Distance from the airport'
folium.Marker([10cation_info["Lattitude"], location_info["Longitude"] ], m
```

Out[54]:



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

```
df1=df1.drop(['id'],axis=1)
```

Out[54] :

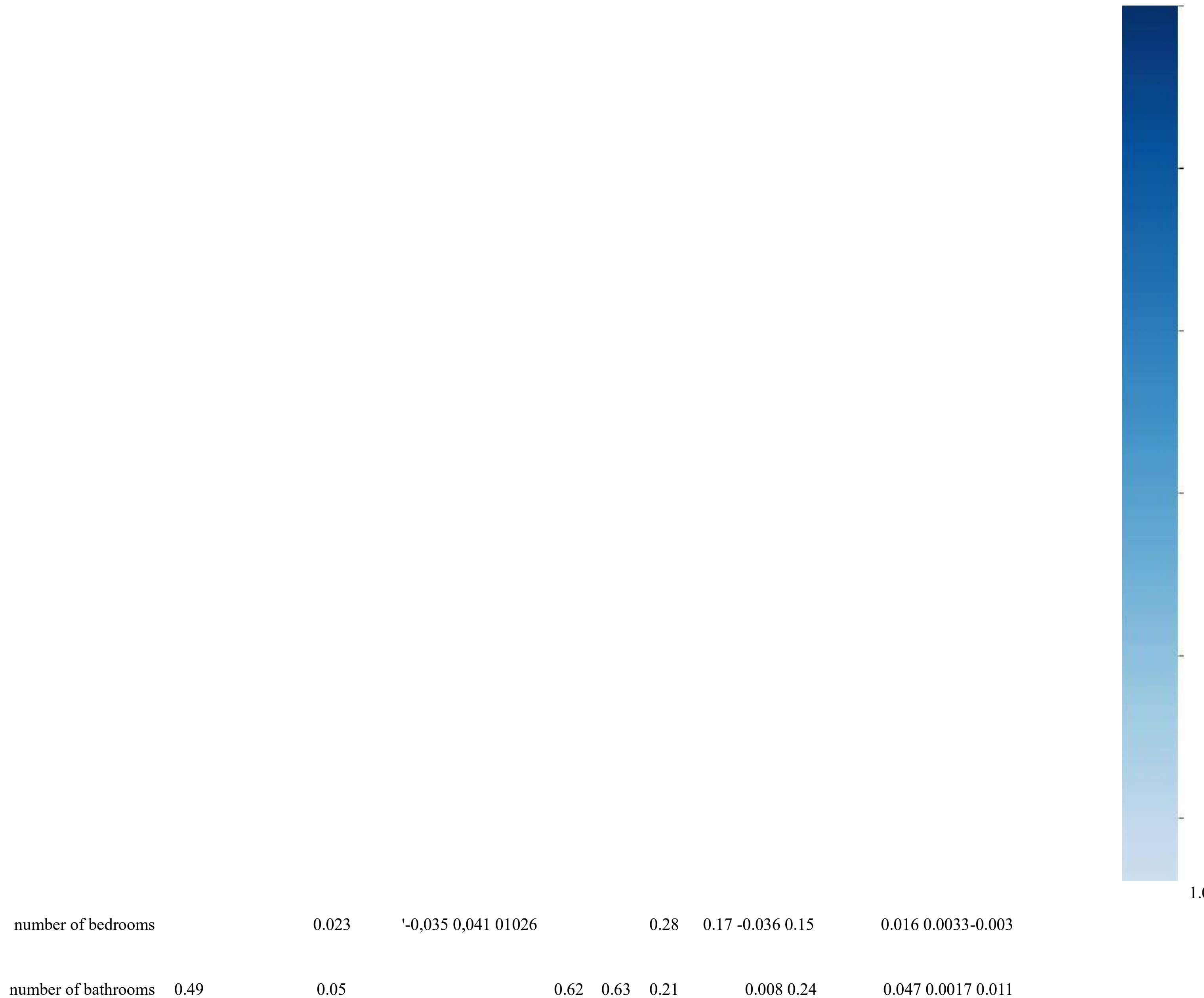
In [60] :

```
df1=df1.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

In [61] : plt.figure(figsize=(15,15)) sns . heatmap(dfl . corr() , linewidths=0.5, annot=True, cmap= ' Blues ') PIt . show()


1.0
number of bedrooms 0.023 '-0,035 0,041 01026 0.28 0.17 -0.036 0.15 0.016 0.0033-0.003
number of bathrooms 0.49 0.05 0.62 0.63 0.21 0.008 0.24 0.047 0.0017 0.011

liVing area 0.6 0.71 0.15 0.72 0.85 .36 0.34 0.16 0.00060.0055

0.8

o. 05 0.15 -0.014 0.031 0.075 -0.0047 0.087 0.16 -0.00240.042 -0.097 0.21 0.14 0.00890.0055 0.078

number of floors 0.16 -0,014 -0,011 40.023 0.28 -0.3 0,041 0.13 0.27 -0.023 -0,007 0,017 0.2

waterfront present•-O.035 -0.004 0.011 0.03i -0.011 01019-0.00460.0038 0.02? -0.039 -0.047 -0.0" 0.02 0.038 -0.01 -0.0086 0.090.6

number of views - 0.041 0-1 0.18 0.075 -0.023 0.046 0.16 0,067 0.22 -0.072-0.027 -O.OB9 0.21 0.067 0.0027-0.0058 0.2

condition of the house - 0.02& -0.13 -0.071-0.0047 -0.23 0,019 0,046 -0.17 -0.19 0.2 -0.38 -0.0051 -0.12

0.4 grade of the house 0.34 0.62 0.72 0.004& o.lí -0.17 0.72 0.07 0.1 o. 093 -0.00140.0078

Area of the house(excluding basement) 0116 0,0038 0,067 -0.19 -0.18 -0,031 0.17 -0.00370.0067

Area of the basement .28 0.21 .0024 -0.3 0,027 0.22 0.2 0.07 -0.18 -0.17 0.1L -0.17 '0.11 -0.011 0.0077-0.0016, 0.2

0.2

Built year 0.17 0.042 *0.039 -0.38 0.47 0.46 0.06+0.00038000410.047

Lattitude -90.036 0.008 0028 -0,097 0.041 -0,047 0.1 -0.031 0.11 -0.15 -0.13 0.028 -0.1 O.OL6 0.0078

Longitude 0.15 0.24 0.28 0.21 0.13 0069 -0.089 -0.12 0.22 0.39 0.41 0.25 -0.00911000420.04

0.0

livi 0.39 0.53 0.74 0.68 0.72 0,028 0,17 -0.007-0.001

IOt area renov -0.016 0.047 0.16 -0.023 0,038 0,067-0.000670.093 0.17 -0,011 0.063 -0.1 0.25 0.17 -0.023 -0.012 0.065

Number ot schools nearbY -0.00330.00170.00058).0089-0.007-0.01 0.023 -000100026

Distance from the airport -0.0033 0.011 0.00550.0055 0.017 0.0051

Price 0.07B 0.27 0.091 00.28 0.053 0.065 0.00260.0051 5' 0.2S o.

047 0.049

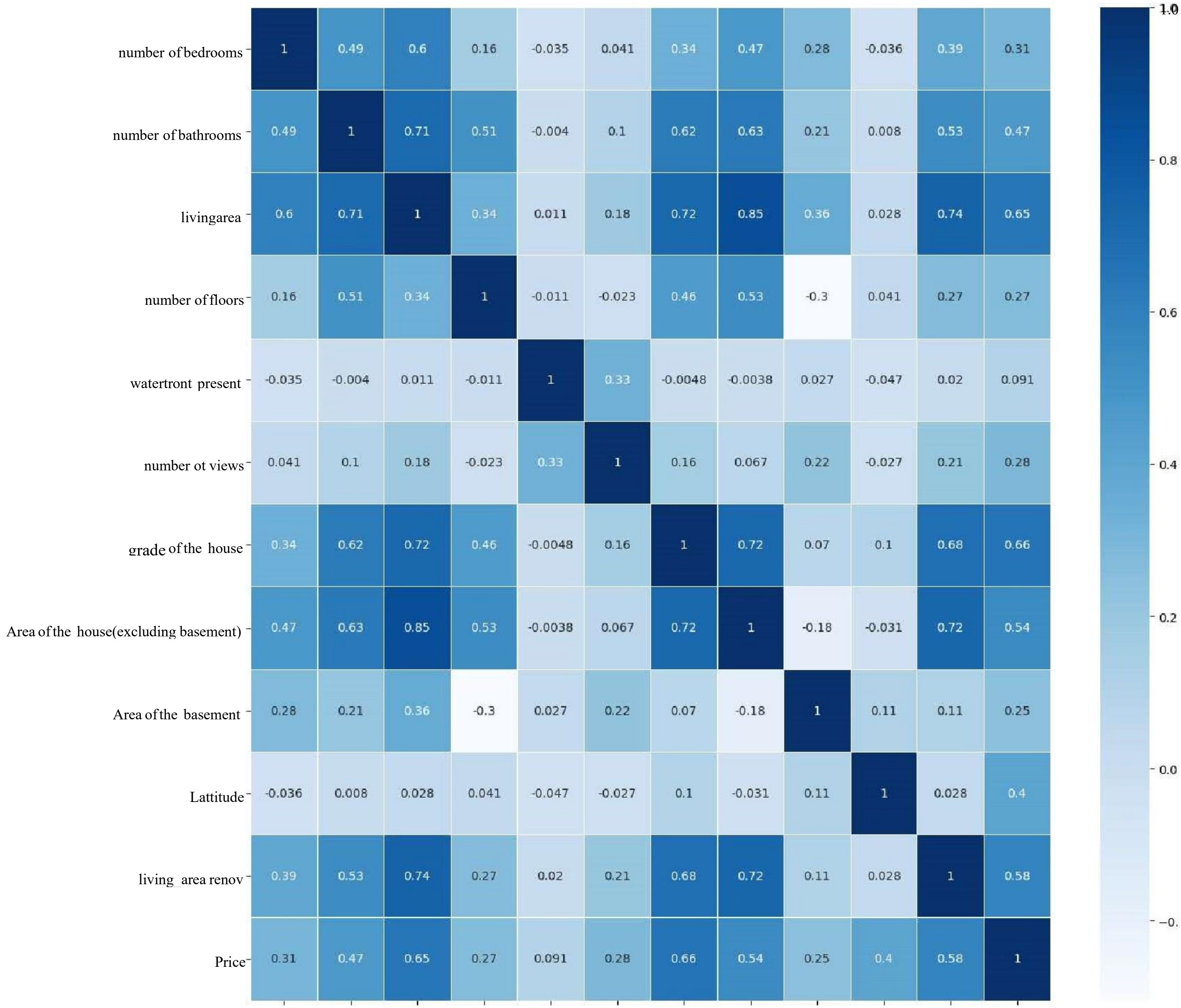
number of bedrooms
number of bathrooms
living area
lot area
number of floors
waterfront present
number of views
condition of the house
grade of the house
Area of the house(excluding basement)
Area of the basement
Built Year
Lattitude
Longitude
living_area_renov
lot_area_renov
Number of schools nearby
Distance from the airport
Price

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.drop(['lot area' , ' condition of the house' , ' Built Year' , 'lot area renov' , 'Number of schools nearby' , 'Distance

---

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


number of bedrooms
number of bathrooms
livingarea
number of floors
watertront present
number ot views
grade of the house
Area of the house(excluding basement)
Area of the basement
Lattitude
living area renov
Price
1.0
0.8
0.6
0.4
0.2
0.0
−0.
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

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

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

In [65] :
```
X=df1.drop( [ ' Price' ],axis =1)
```

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

Out[66] :
```
(13982, 11)
```

In [67] :
```
y_df1[ ' Price ' ]
```

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

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

In [69] :
```
X_train, X_test, y_train,    train_test_split    (X,    y,
test_size=0.2, random_state=11)
```

Out[71] : (2797, 11)

72] :

```
from sklearn.pipeline import make_pipeline from sklearn.preprocessing import
StandardSca1er from sklearn.linear_model import ElasticNet, Lasso,
LinearRegression, RidgeCV from catboost import CatBoostRegressor from
sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor f rom
xgboost import XGBRegressor from sklearn.tree import DecisionTreeRegressor from
sklearn.ensemble import StackingRegressor from sklearn.svm import SVR
```

In [73] :

```
pipelines __ {en' :make_pipe1ine(StandardSca1er(),
    ElasticNet()),
    ' lasso' :make_pipe1ine(StandardSca1er(), Lasso())'
    'Rcv ' :make_pipe1ine(StandardSca1er(), RidgeCV()),
    'CatB' : make_ pipeline(StandardSca1er(), CatBoostRegressor(eva1_metr1c• ='RMSE ' ,verbose-
    1000) ) ,
    ' Ir ' :make_pipe1ine(StandardSca1er(), LinearRegression()),
    ' rf' :make_pipe1ine(StandardSca1er(), RandomForestRegressor()),
    'gb'  :make_pipe1ine(StandardSca1er(),  GradientBoostingRegressor()),  '
    dtc :make_pipeline (StandardSca1er()  ,  DecisionTreeRegressor()), , xg'
    :make_pipe1ine(StandardSca1er() ,XGBRegressor())
```

In [74] :

```
fit_models = {}
```

In [70] : X_train . shape

Out[70] : (11185, 11)

In [71] : X_test . shape

```
for algo, pipeline in pipelines. items() :
    model       pipeline.fit(X_train, y_train)
    fit_models[algo] - model
```

/opt/conda/1ib/python3.7/site-packages/sk1earn/1inear_mode1/_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 reasing regularisation. Duality gap: 4.781e+12, tolerance: 5.929e+1e coef 11_ reg, 12_ reg, X, y, max_iter, tol, rng, random, positive Learning rate set to 0.05996 e: learn: 221490.1496581 total: 61.4ms remaining: 1m Is
999: learn: 77595.2298921 total: 2.85s remaining: eus

[75] : from sklearn . metrics import mean_absolute_error, mean_ squared _error

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

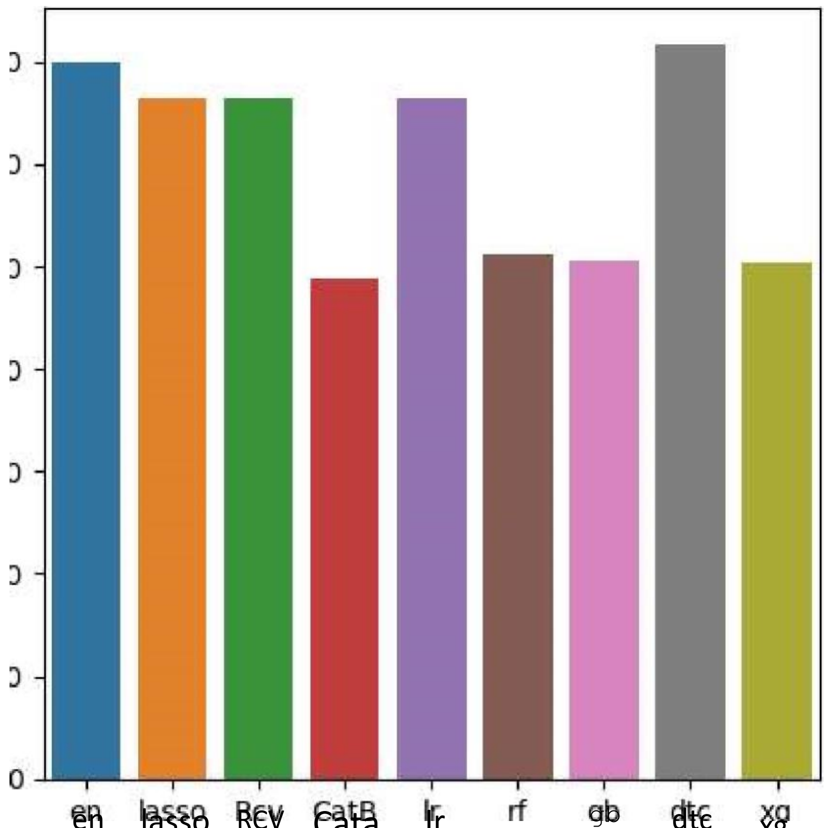
Rcv ROOT MEAN SQUARED ERROR 132918.333682342

CatB MEAN ABSOLUTE ERROR 66637.30790160663

CatB ROOT MEAN SQUARED ERROR
97508.34029611414 Ir MEAN ABSOLUTE ERROR
97574.48622571728 Ir ROOT MEAN SQUARED ERROR
132952.7515959945 rf MEAN ABSOLUTE ERROR
69217.89879907611 rf ROOT MEAN SQUARED ERROR
102292.3632979867 gb MEAN ABSOLUTE ERROR
69874.84067217445 gb ROOT MEAN SQUARED ERROR
101056.41447857216 dtc MEAN ABSOLUTE ERROR
96944.72285782386 dtc ROOT MEAN SQUARED ERROR
143316.21683052482 xg MEAN ABSOLUTE ERROR
69035.05210660976 xg ROOT MEAN SQUARED ERROR
100694.41040458805

In [76] : plt.figure(figsize=(5, 5)) plt.xlabel('ML Algorithms. . .') plt.ylabel(

'Root Mean Squared Errors. ')



en lasso RCV Cata lr gb dtc xg

ax=sns . barplot (x=al, y=maes) Pl t .
show()

140000

120000

2 100000

LLI

a 80000

a 60000

Root Me

40000

200001

ML Algorithmsv..

[ ]:

```
CatB = CatBoostRegressor(verbose=1000,eval_metric= ' RMSE
'      )      rf      =      RandomForestRegressor()      gb      =
GradientBoostingRegressor() xg = XGBRegressor()
1r=LinearRegression()

stregr - StackingRegressor(estimators=[( 'catb' ,CatB), ( 'xg' , xg),('gb',gb)],
                                    final_estimator=lr)

pipeline - make_pipeline(
     StandardSca1er(),
     stregr

pipeline. fit (X_train, y_train)
```

```
# Generate predictions on the test set y_pred
pipeline. predict (X_test)

# Evaluate the model print( " Root Mean Squared Error: %.4f" %
mean_squared_error(y_test,y_pred)**0.5)
```

```
Learning rate set to 0.05996
e :     learn : 221490. 1496581    total : 4.18ms    remaining: 4.18s
999:    learn : 77595.2298921      total : 2.81s     remaining: eus
Learning rate set to 0.057883
e:      learn: 222091.4863333      total : 3. 52ms   remaining: 3. 51s
999 :   learn : 76337 . 1933964    total : 2.52s     remaining: eus
Learning rate set to 0.057883
e :     learn : 222546. 8538661    total : 2 .94ms   remaining: 2. 94s
999 :   learn : 75466. 5961681     total : 2. 51s    remaining: eus
Learning rate set to 0.057883
e :     learn : 223455 . 5230951   total : 3.2ms     remaining: 3.2s
999:    learn : 75656. 3661258     total : 2.52s     remaining: eus
Learning rate set to 0.057883
e:      learn : 221606.9467960     total : 3.71ms    remaining: 3.7s
999:    learn : 75195 .9699196     total : 2.46s     remaining: eus
Learning rate set to 0.057883
e:      learn : 219316.0911020     total : 2.47ms    remaining: 2.47s
```

```
[ ]:mean_ squared _error (y_test , y_pred)      .5
```

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

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

```
[ ]:plt.figure(figsize=(9,5))
    plt.xlabel( 'ML Algorithms . . .
    ')
    plt.ylabel( ' Root Mean Squared Errors . ' ) ax=sns
    . barplot (x=al, y=maes) PI t . show()
```

ALL DONE BY CAMILA V AS NAAN MUDALVAN IBM SMARTINTERNZ ASSIGNMENT 3