

NM DATA ANALYTICS ASSIGNMENT 3 - House Price dataset of India

DONE BY Jacinth Susanna S

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 plt 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
Out[5]: df=df.drop(['Date'],axis=1)
```

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

		number	number		number	condition	grade	number of living	lot	waterfront	Built	Renovation		
	id	of of	of	of the	of the	...bathrooms	area	area	present	Year	Year	bedrooms	floors	views
		house	house											
0	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] :

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

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

```
Out[9] 0
```

```
]:
```

```
In [10] : df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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.

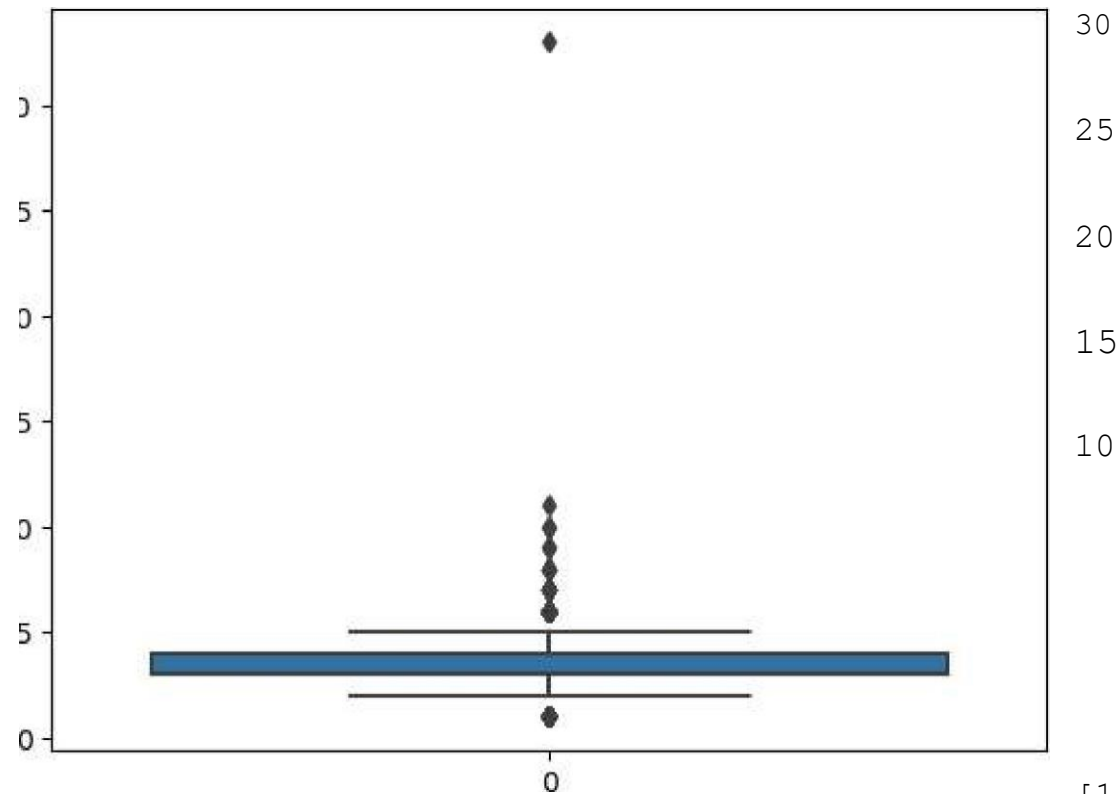
8 rows x 22 columns

UNIVARIATE ANALYSIS

Checking for outliers

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

```
Out [12] : <AxesSubplot : >
```



In
of bedrooms.

[13] : `z=np.abs(stats.zscore(df.number`

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, 3532, 3600, 4207, 4486,
        3322,
        4658, 4680, 6591, 6596, 6982, 6998, 7003, 7454,
        6730,
        8559, 8650, 9282, 9629, 9955, 10168, 10177, 10676,
        9810,
        10748, 10916, 10944, 11247, 11547, 11877, 12273, 13048,
        11441, ],
      )
```

```
13444,13825,14220, 14481]),  
    ) 49
```

```
In [15] : print(np.where(z<-3))
```

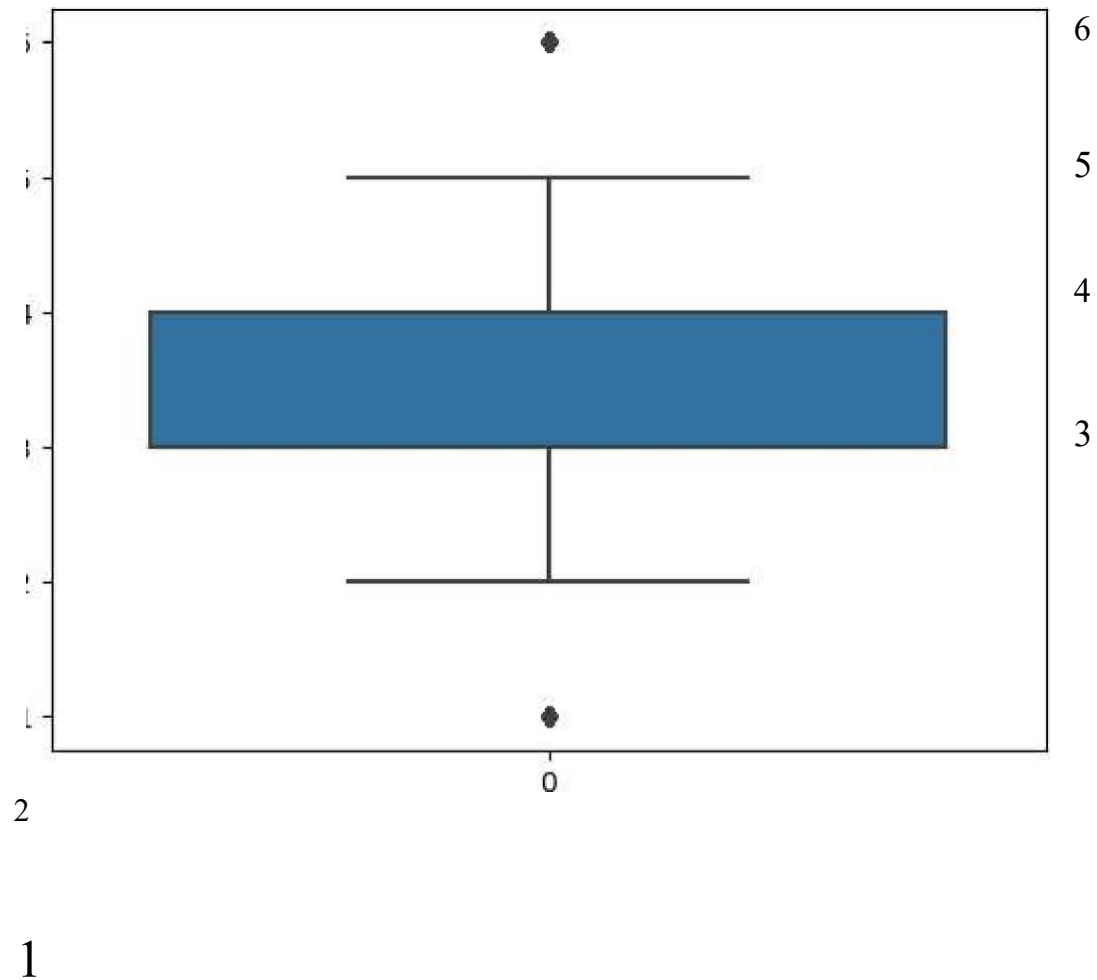
```
(array([], dtype=int64), )
```

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] : <AxesSubplot : >
```

In [18]: dfl

Out[18]:

id	number of	number of	number of	condition of the	grade of the	number of living	lot	waterfront	Built	Renovatio
1	3	2	2	1	1	1	1	1	1	1

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(df['number of bathrooms'])
```

Out[19]: <AxesSubplot: >


$$: \langle \text{AxesSubp10t} : \rangle$$

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), )
```

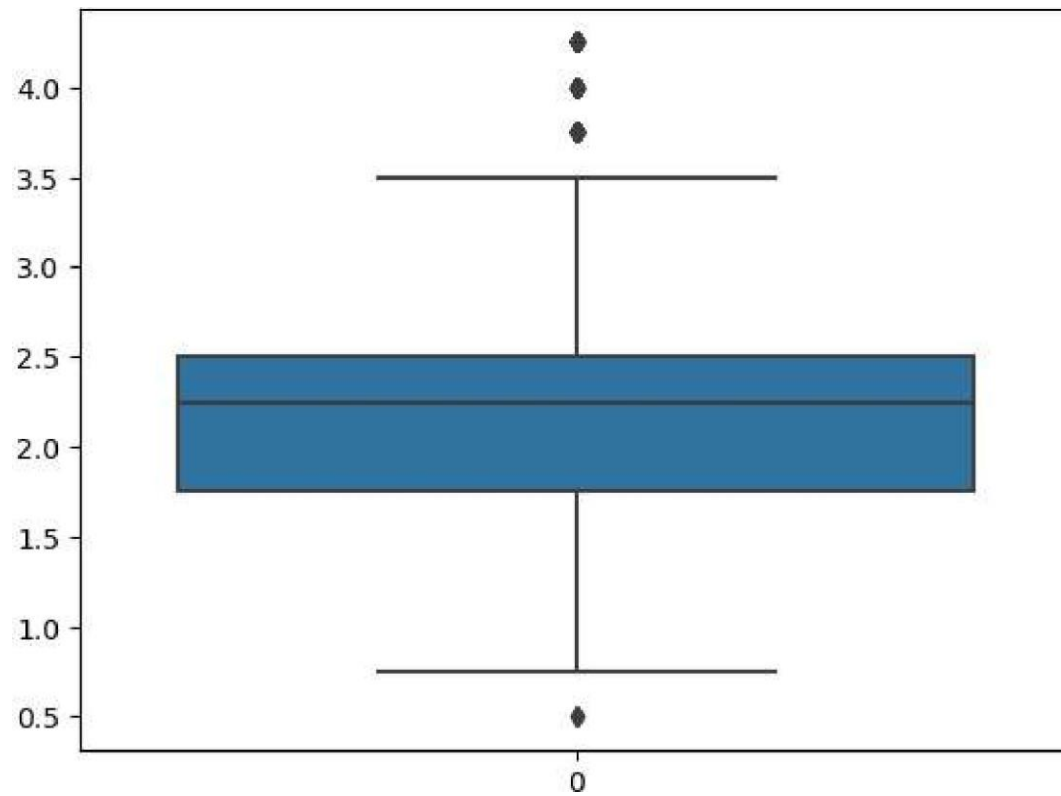
```
df1=df1[(z< 3)]
```

```
In [ 24 ] : sns.boxplot(df1[ 'number of bathrooms' ] )
```

```
Out[24]
```

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

```
: <AxesSubplot : >
```



In[25] : dfl

Out[25] :

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

14447 rows x 22 columns

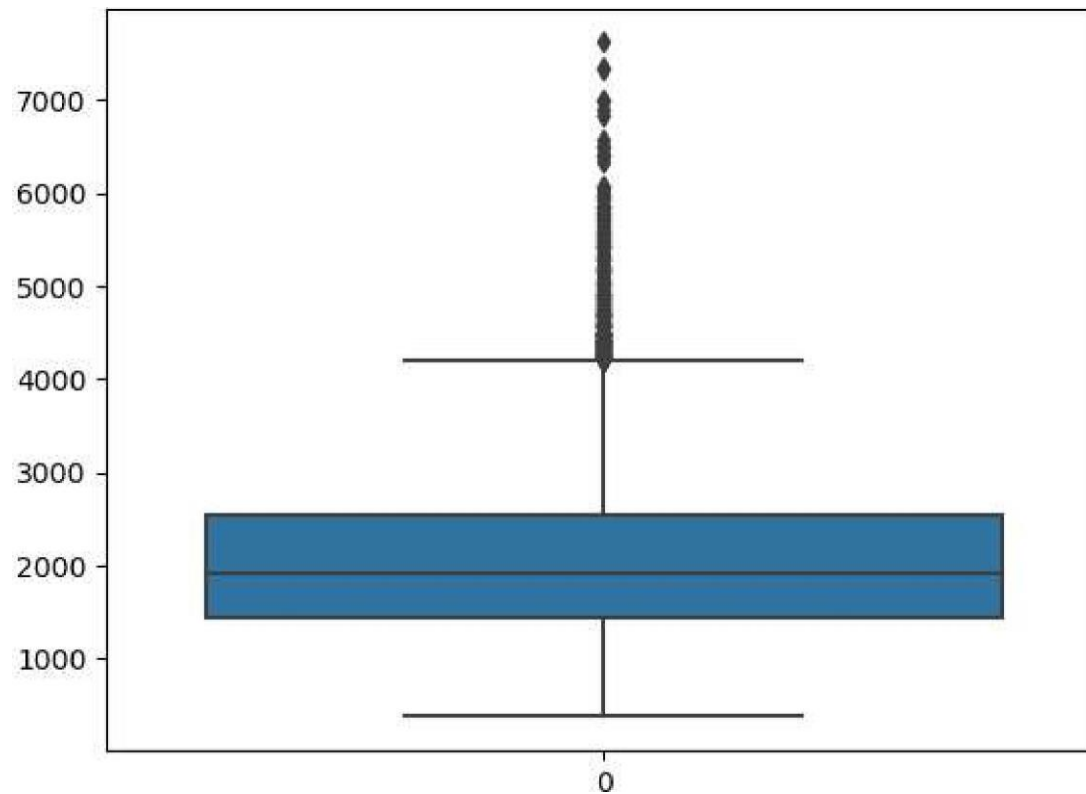
There are 124 outliers in number of bathrooms as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

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

Out [26]

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

```
: <AxesSubplot : >
```



```
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])
```

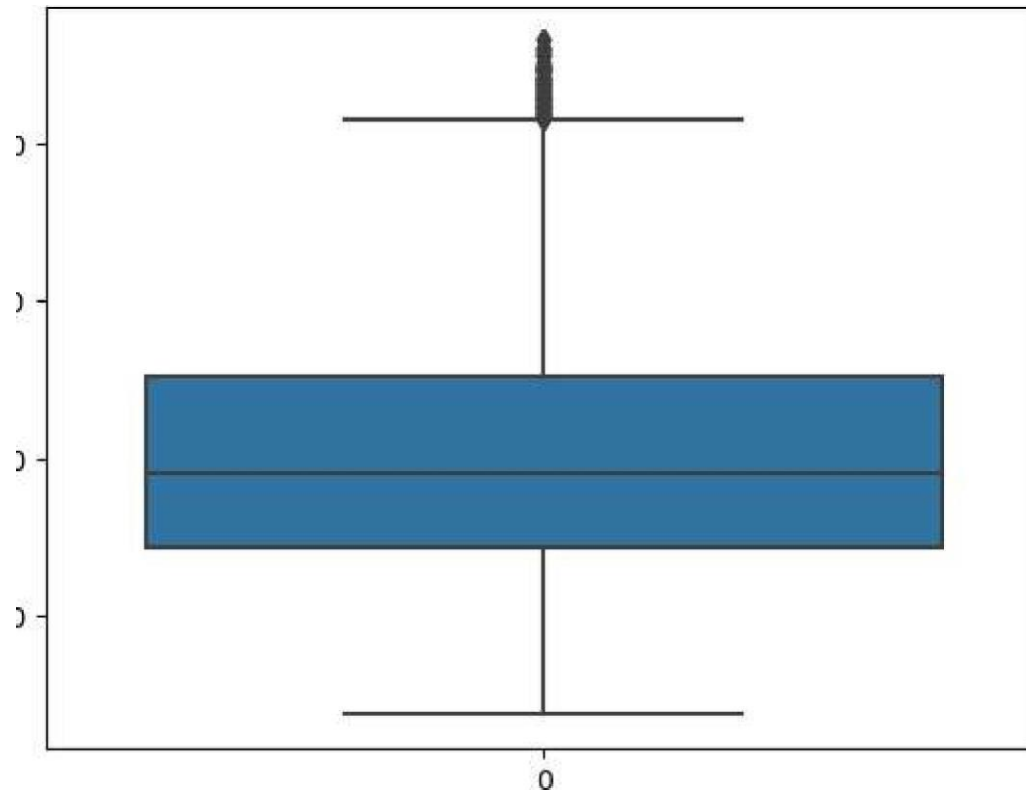
```
sns.boxplot(df1[ 'living area' ] )
```

```
: <AxesSubplot : >
```

Out[29] : 0

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

In [31] :



Out[31]
4000

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

: <AxesSubplot : >

3000

2000

1000

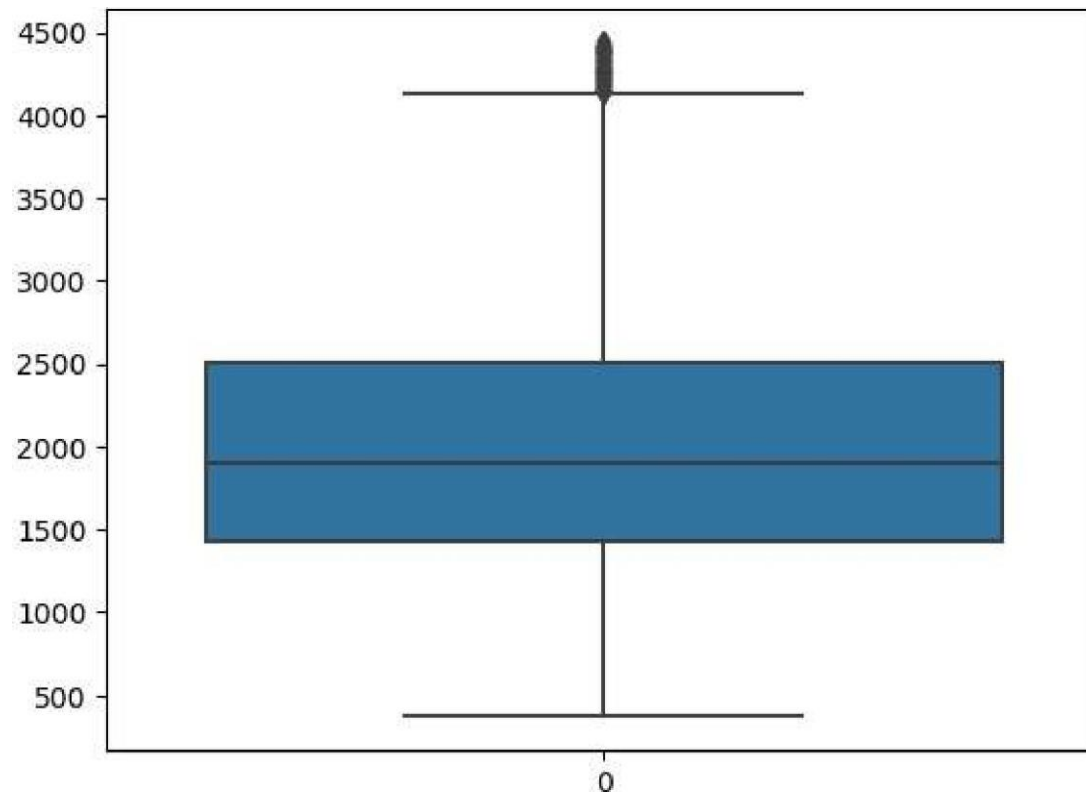
```
In [32] z=np.abs(stats.zscore(df1[' living area']  
:  
))
```

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

67

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

```
In [35] ,  
:  
Out[35]
```



In [36] : dfl

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

: <AxesSubplot : >

Out[36] :

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

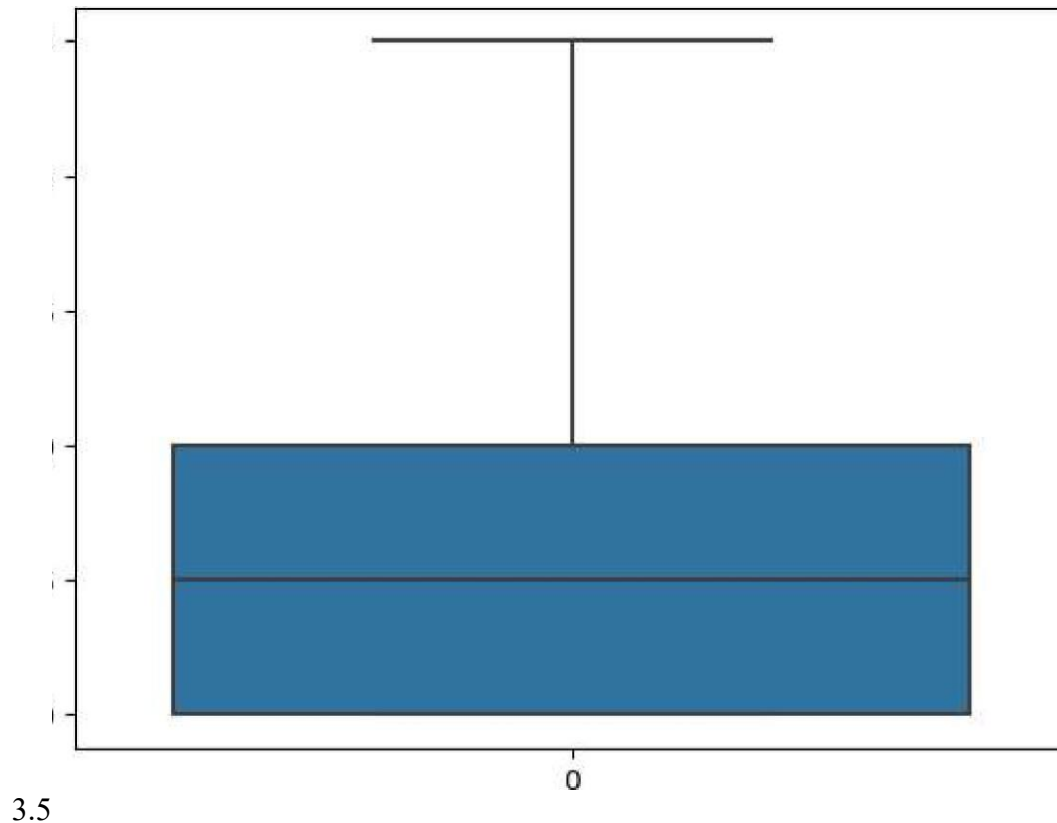
14244 rows x 22 columns

: <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]



3.0

2.5

2.0

1.5

1.0

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

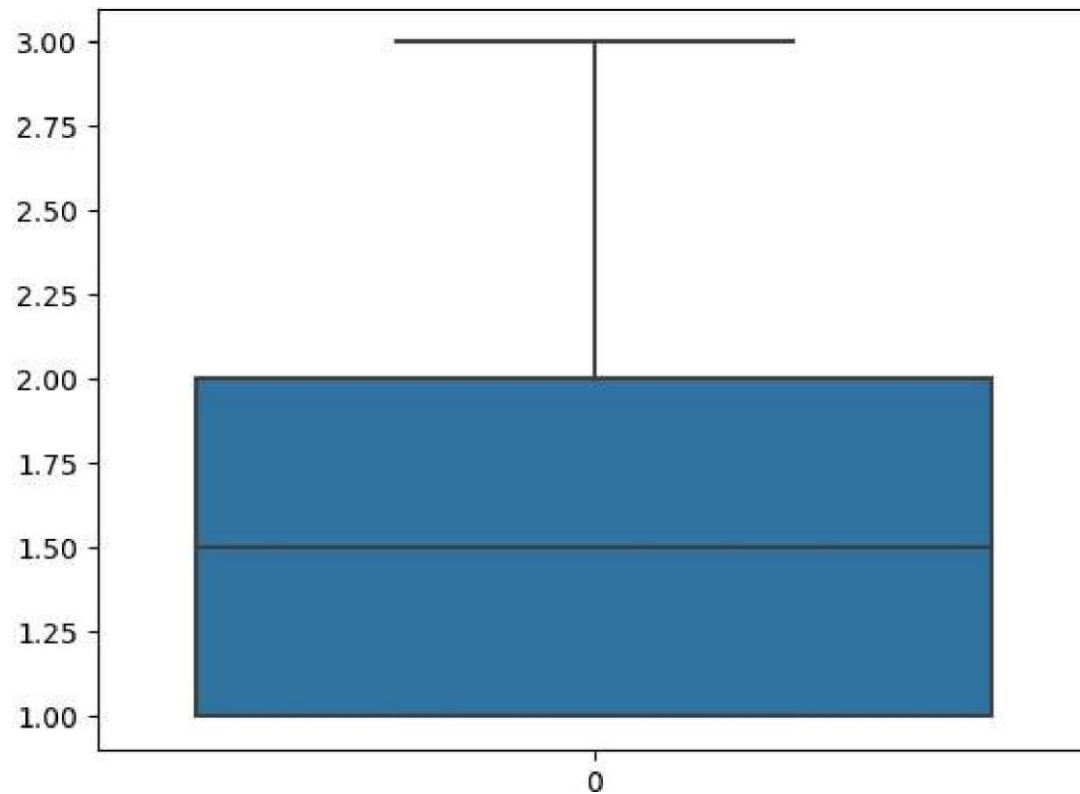
```
In [39] len(np.where(z>3) [0] )
```

```
Out[39]: 3
```

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

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

```
Out[41]: <AxesSubplot: >
```

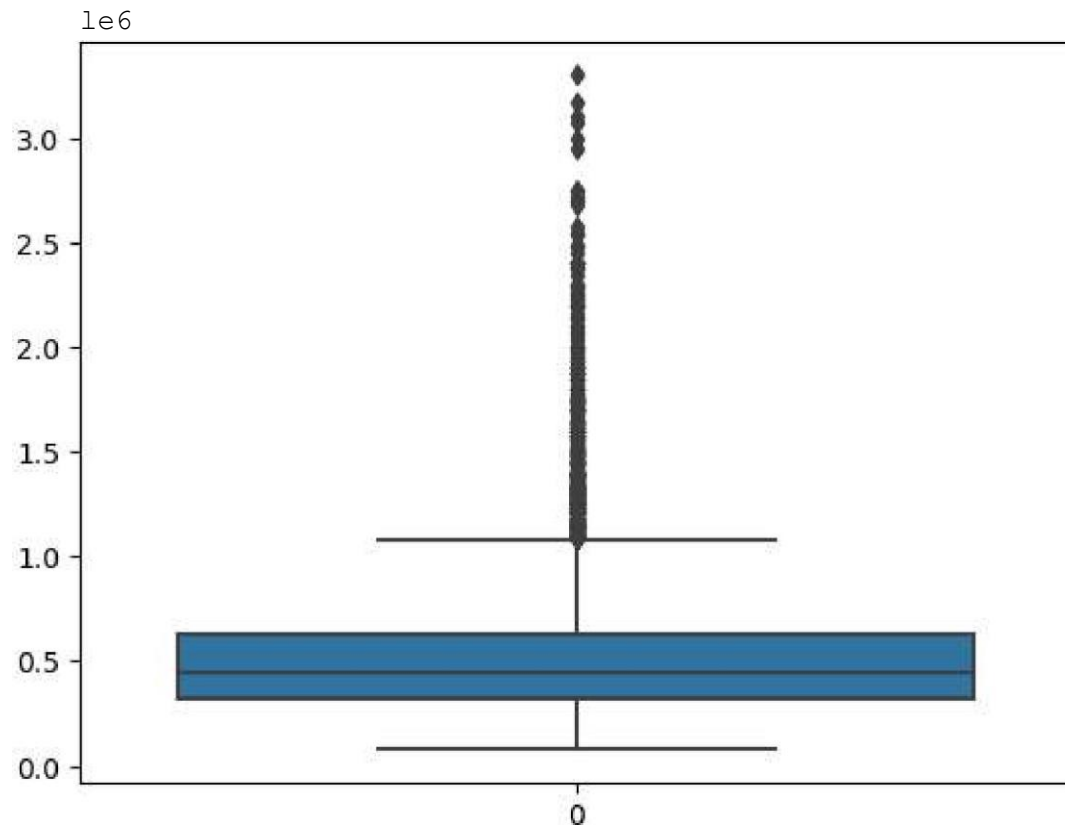


There are 3 outliers in number of floors

```
In [42]:  
sns.boxplot(df1['Price'])
```

sns .

Out[42]: <AxesSubplot: >



```
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 Renovation							
	id	of	of	of	of the	...	bedrooms	bathrooms	area	area	floors	present	views	house	house	Year	Year
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] : df1

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

Out [46] :

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



B1 - VARIATE ANALYSIS

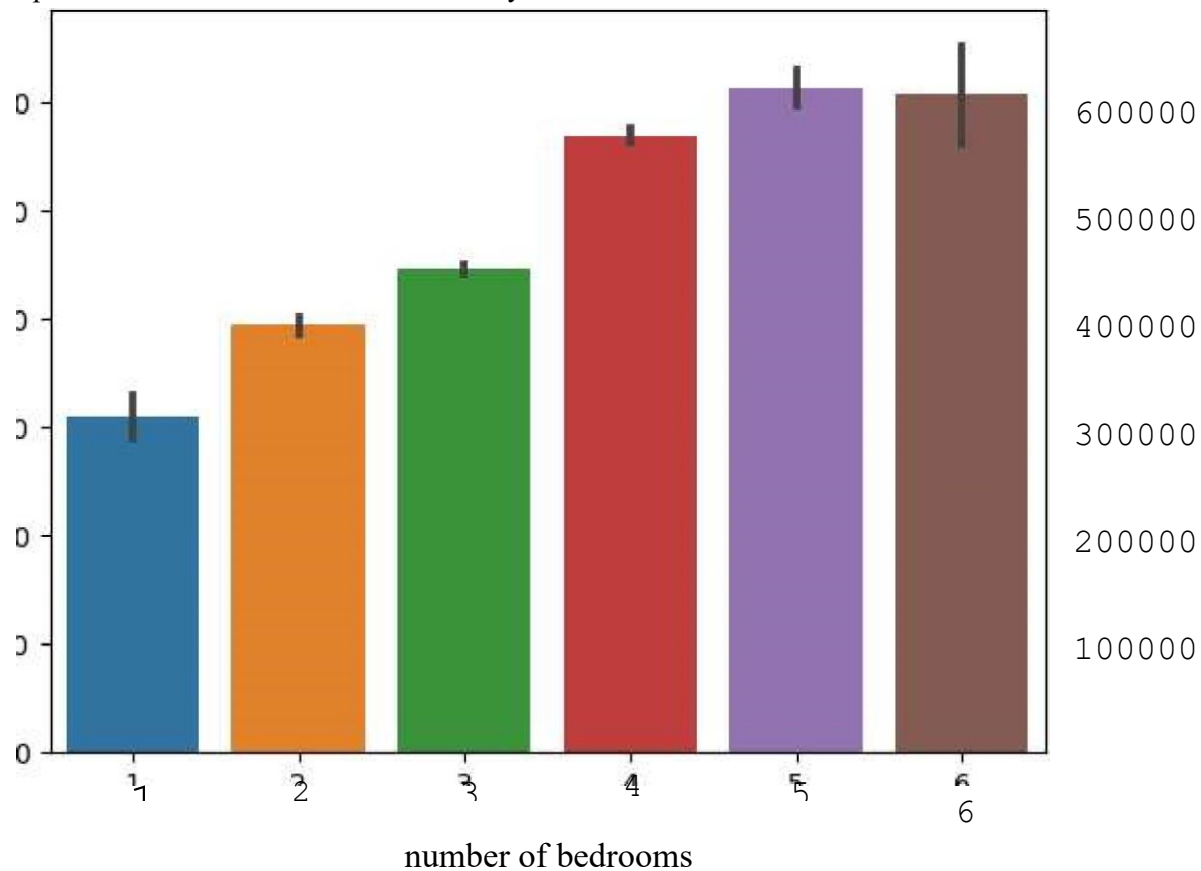
Out [46] :

The column Renovation year have been removed. This is because most of the Renovation Year are 0 and proves to be of no use to the model

In [49] :

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

<AxesSubplot:xlabel='number of bedrooms' ylabel=' Price' >

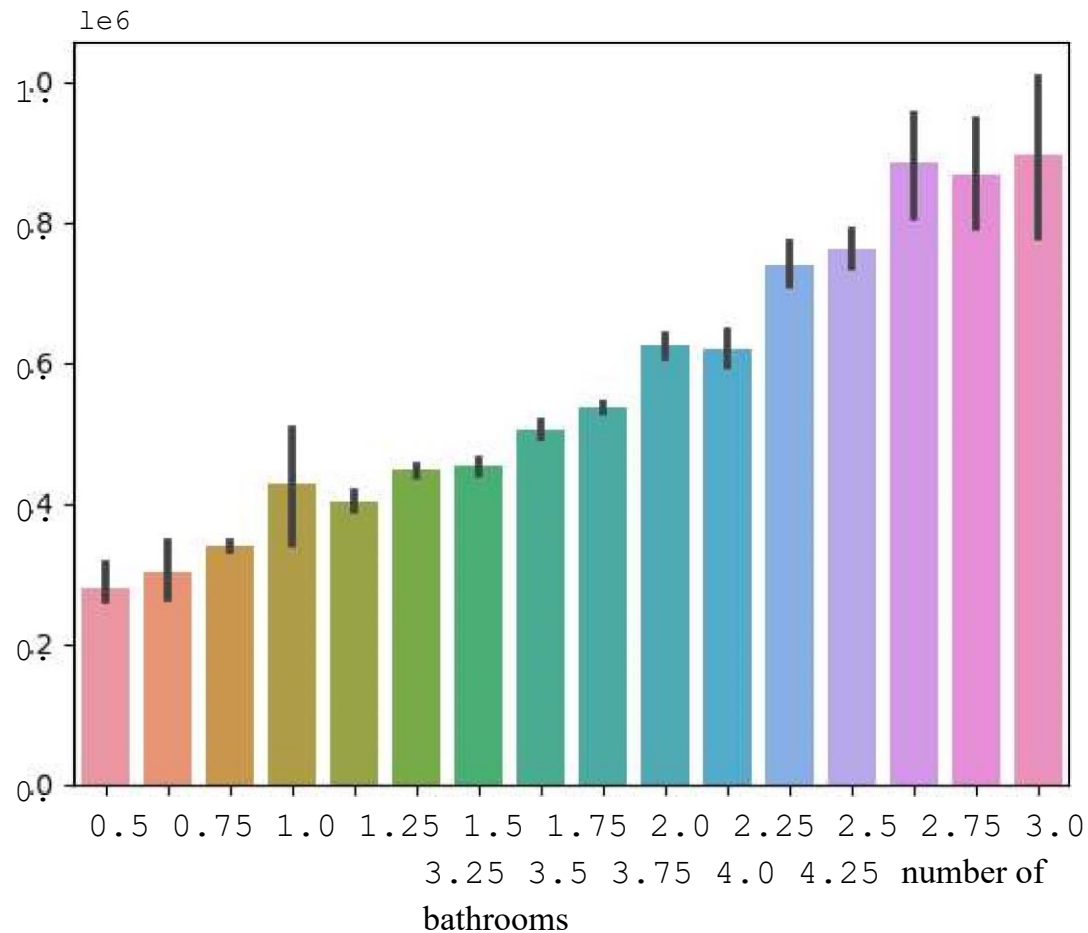


Out [46] :

Clear indication of Price increasing with number of bedrooms

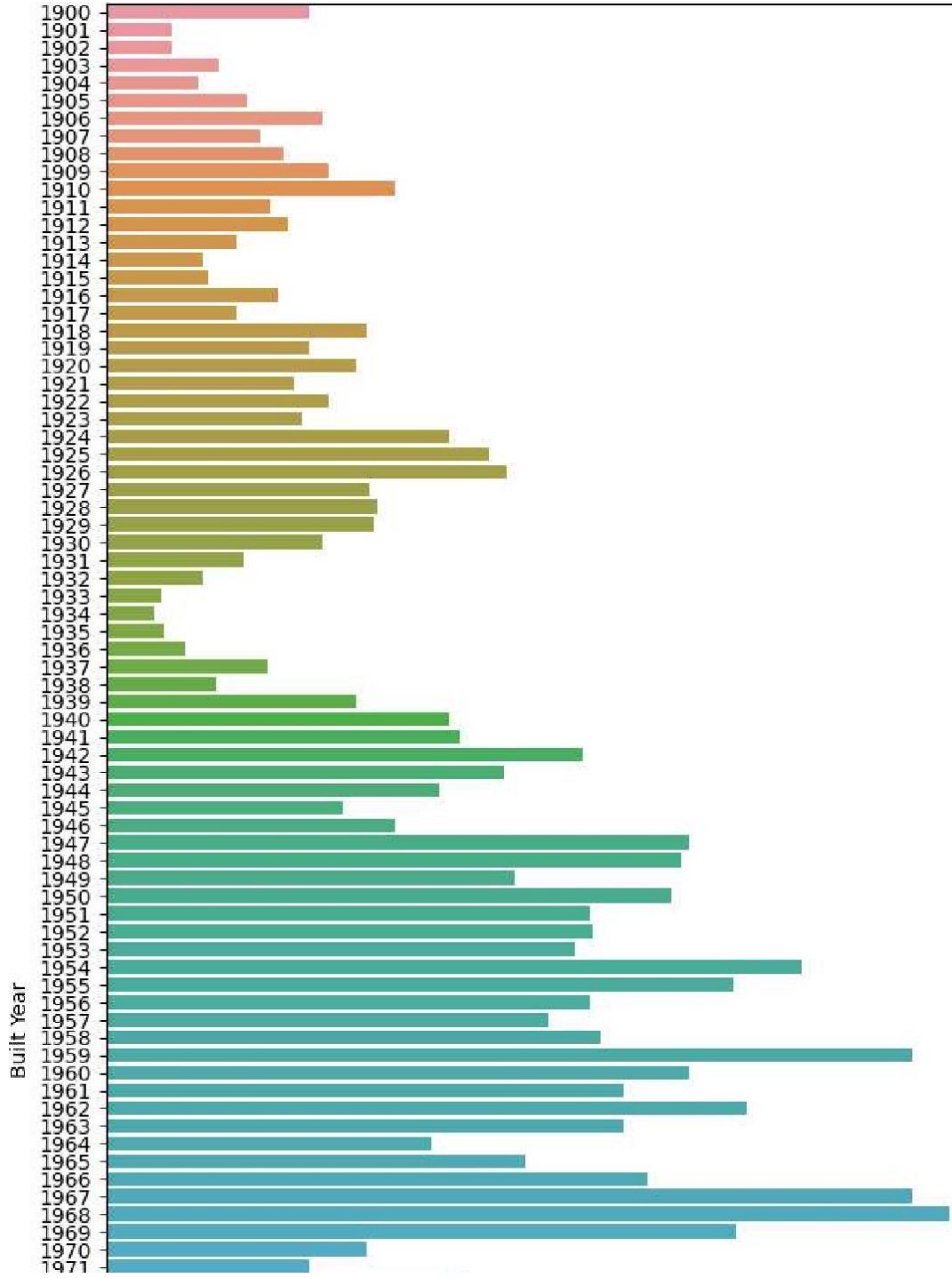
```
[50]: sns.barplot(data=df1,x='number of bathrooms',y='Price')
```

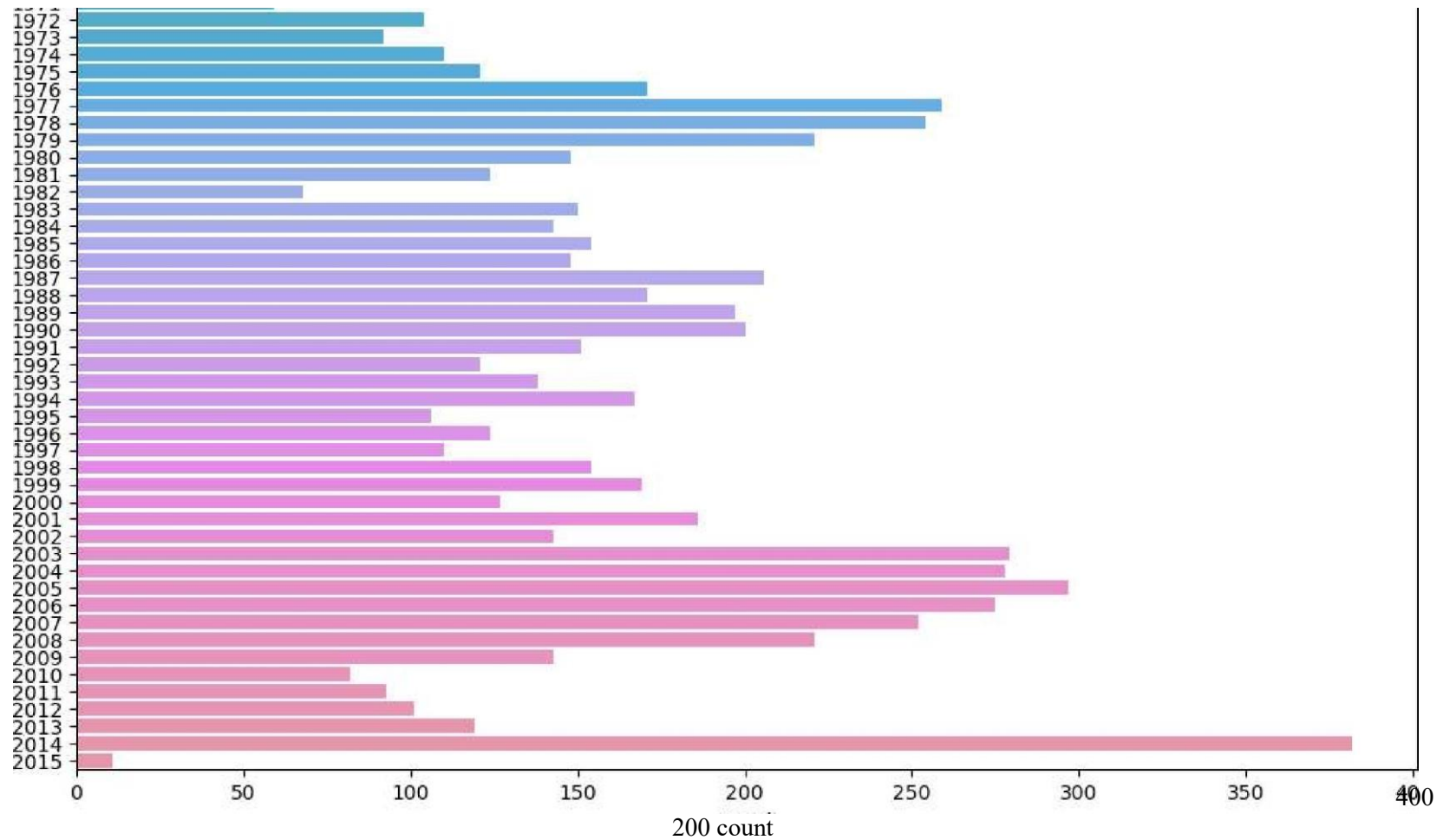
Out[50] :<AxesSubplot:xlabel= 'number of bathrooms' ,ylabel='Price'>



Clear indication of Price increasing with number of bathrooms

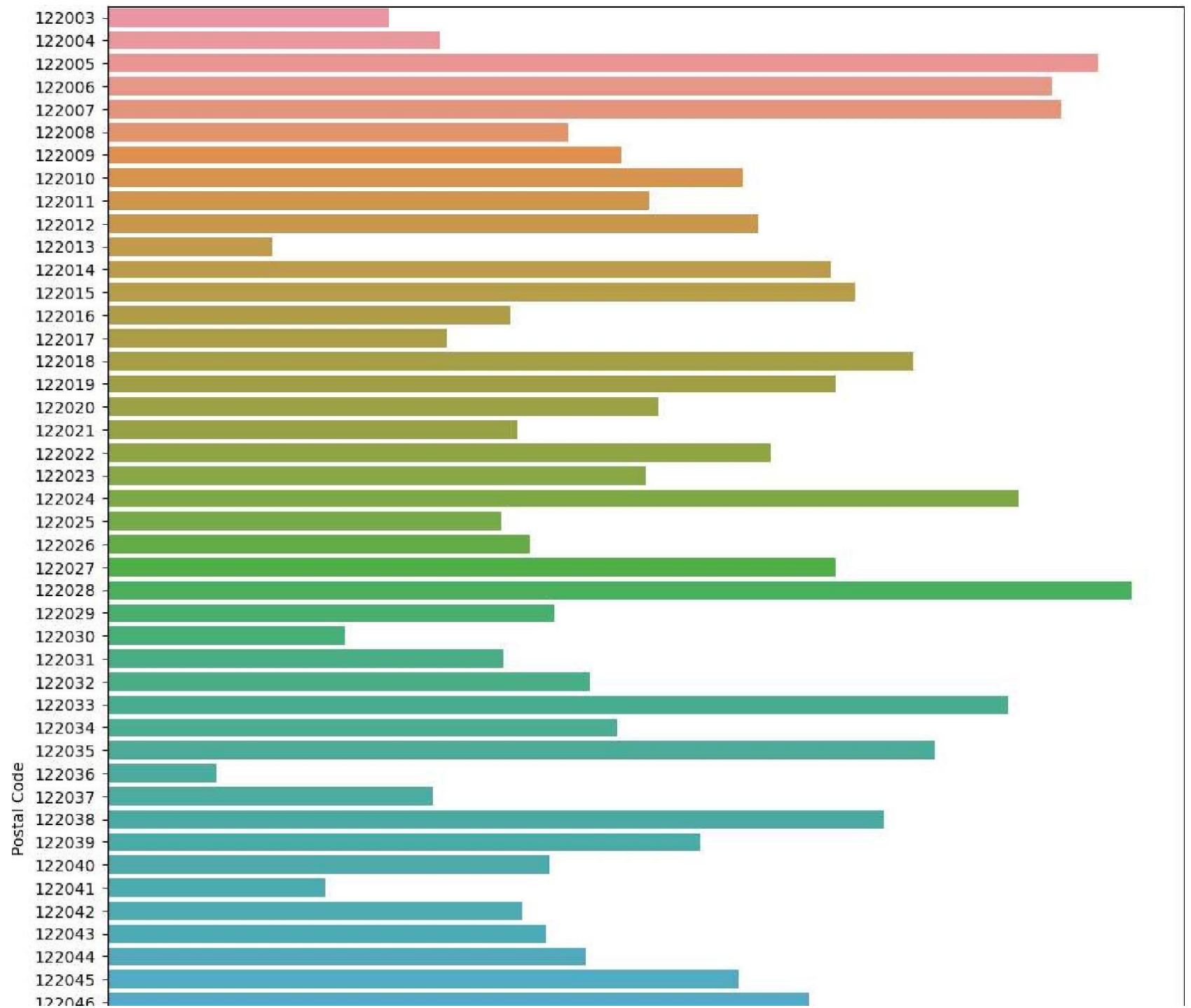
```
In [51] plt.figure(figsize=(12,18 : 18))
sns.countplot(data=df1,y= ' Built Year')
plt.show()
```

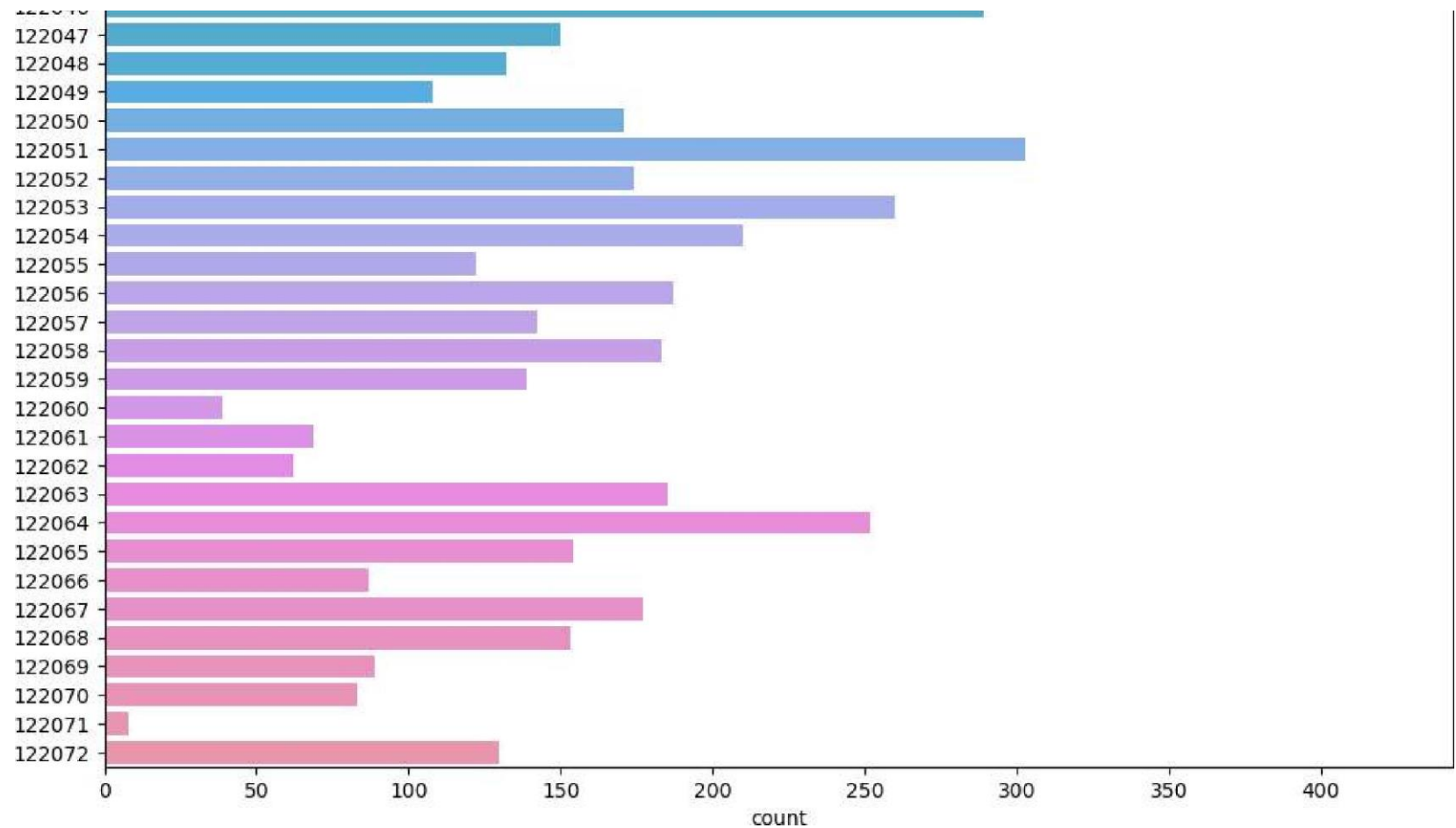




Most of the houses were listed for sale in 2017

```
In [52] : plt.figure(figsize=(12,18) ) sns.countplot  
         (data=df,y='Postal Code' ) Pl t . show()
```





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

```
In [53]: df1.groupby('Year -2014') ['L attitude'].
          mean()
```


Out[54] :

Out [53]

: 52.77583376963351

In [54] :

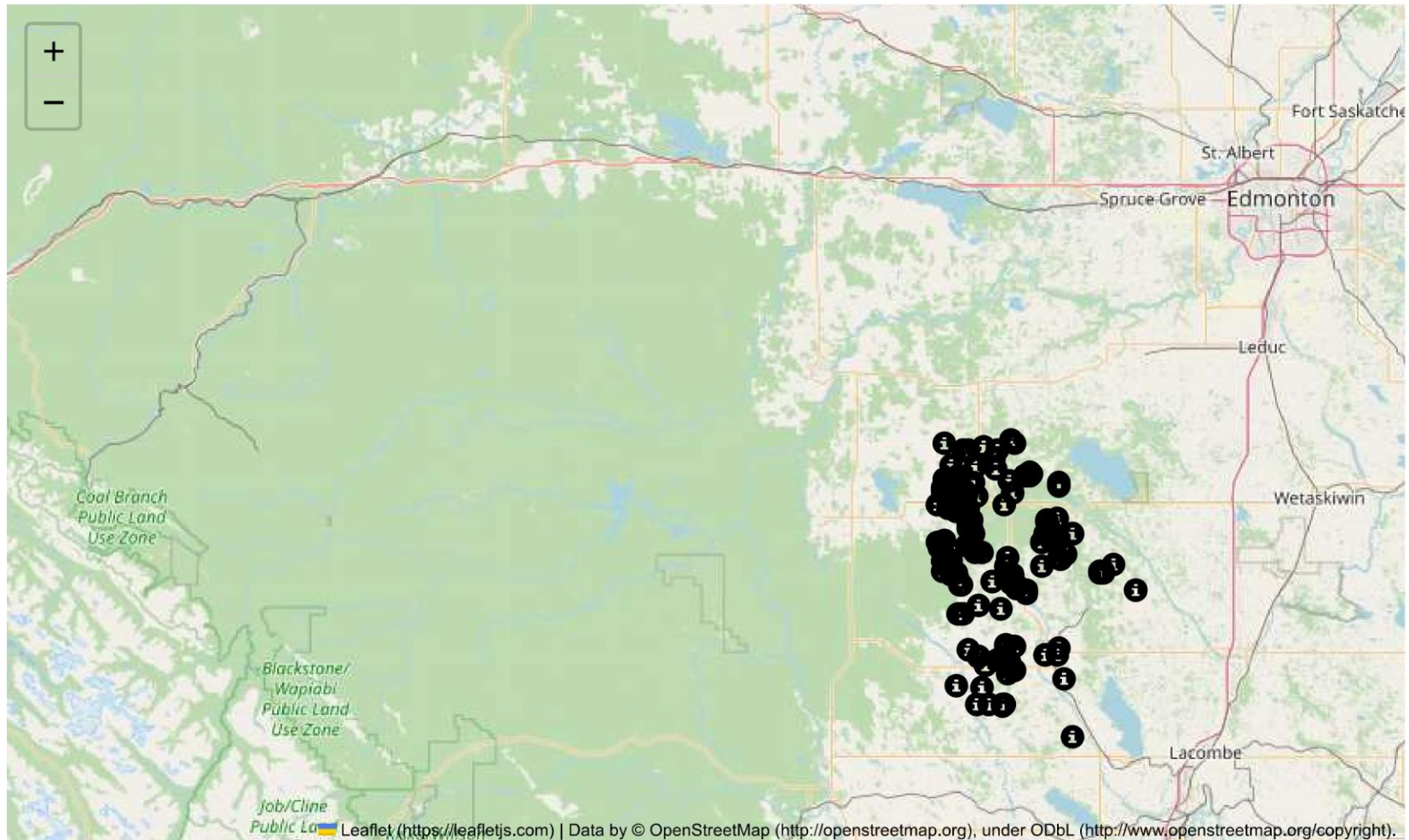
```
df1[df1['Built Year']==2014]['Longitude'].mean()  
-114.38898952879582
```

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

Out[54] :

Out[55] :

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



In [56] :

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

52.77850305343512

Out[54] :

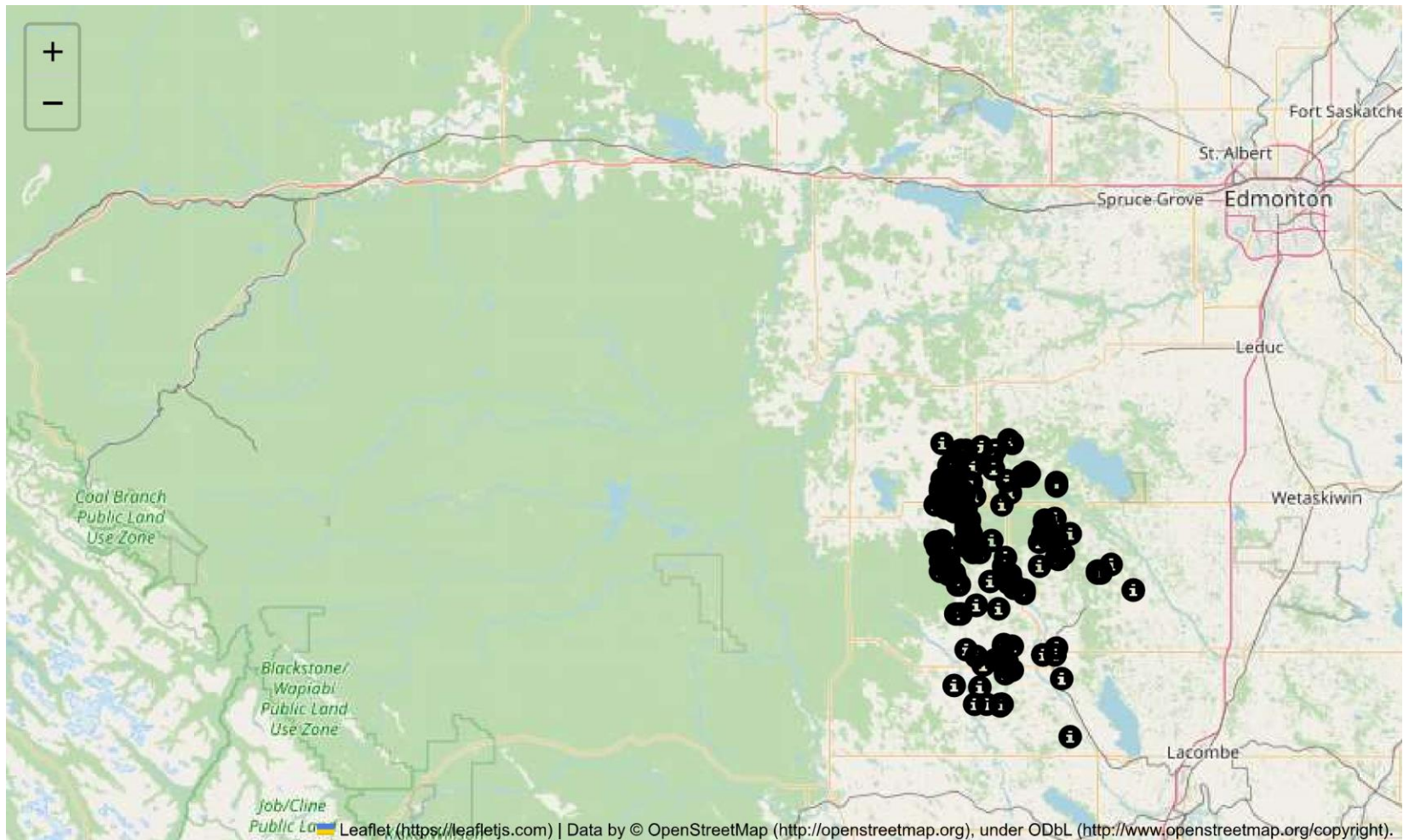
```
In [57] : df1[df1['Built Year']>=2014]['Longitude'].mean()  
-114.39186768447837
```

Out[57] :

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

```
for index, location_info in df1[(df1['Built Year']>=2014) & (df1['Distance from the airport']  
folium.Marker([location_info["Latitude"], 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)
```

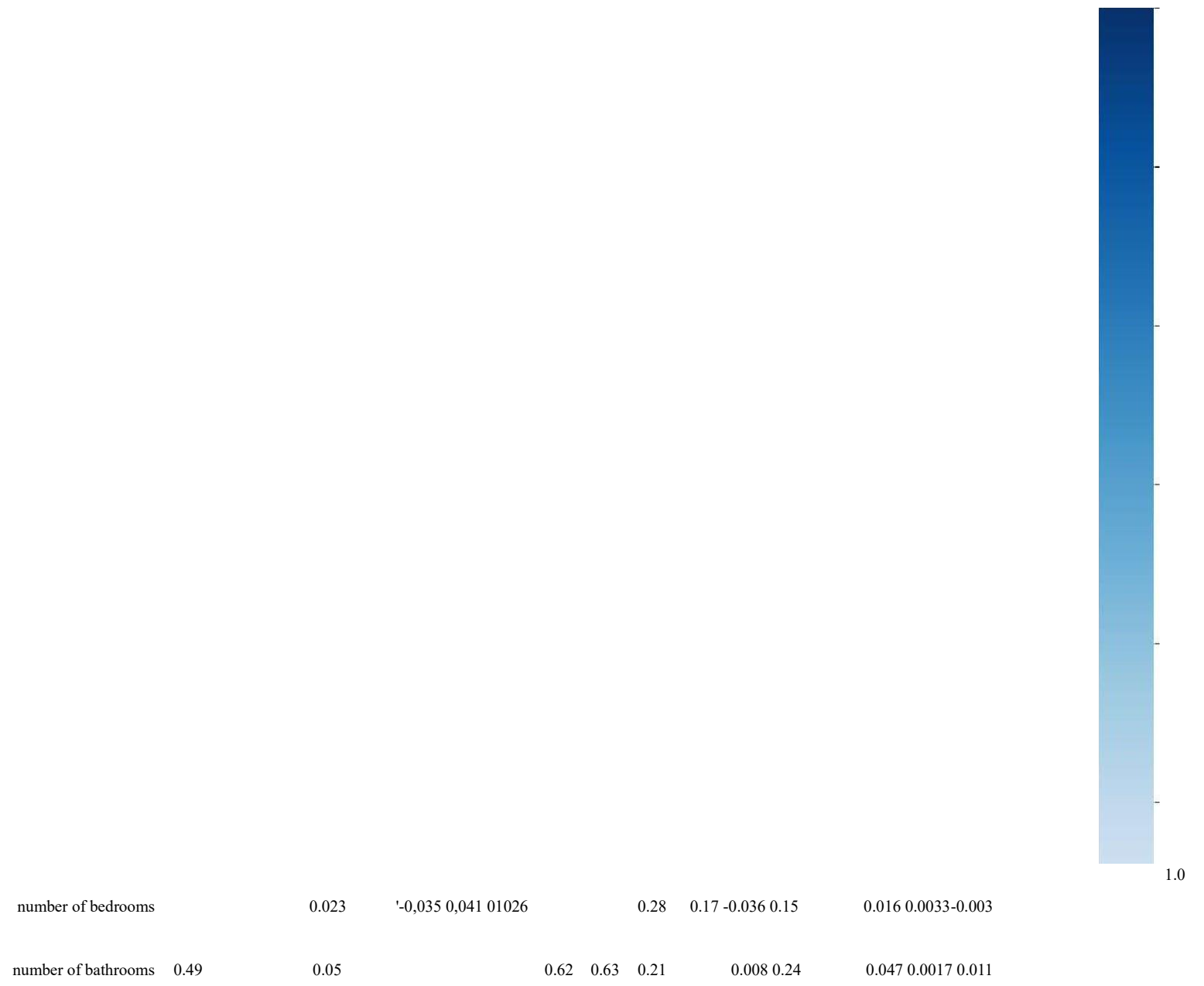
Out[54] :

In [60] : `df1=df1.drop(['Postal Code'],axis=1)`

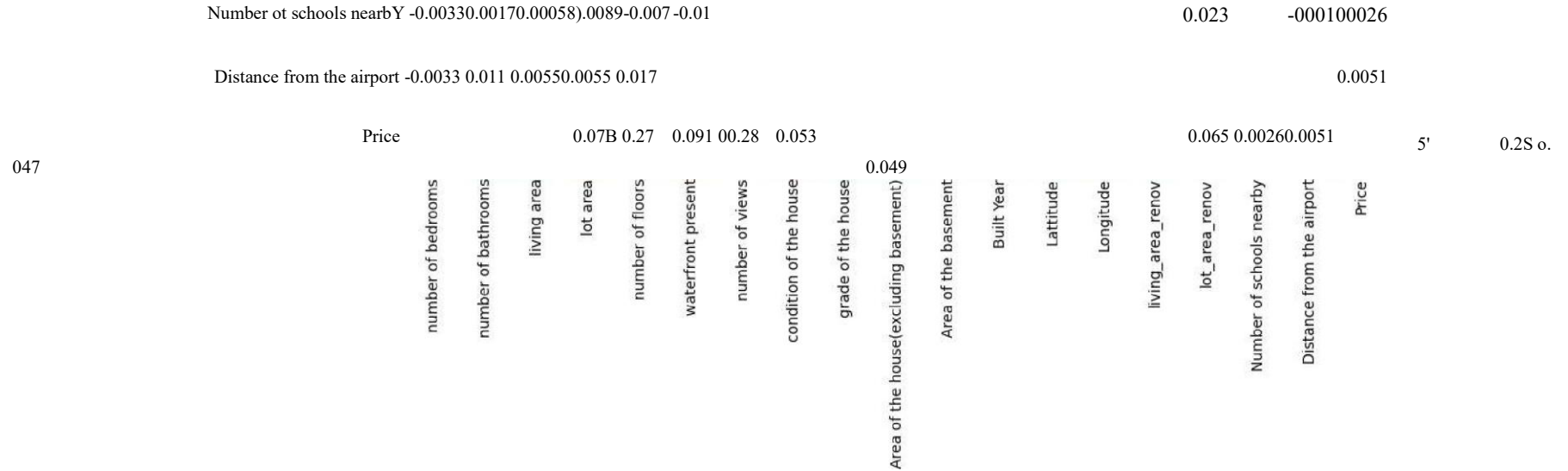
MULTI - VARIATE ANALYSIS

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 ' ) Plt . show()
```



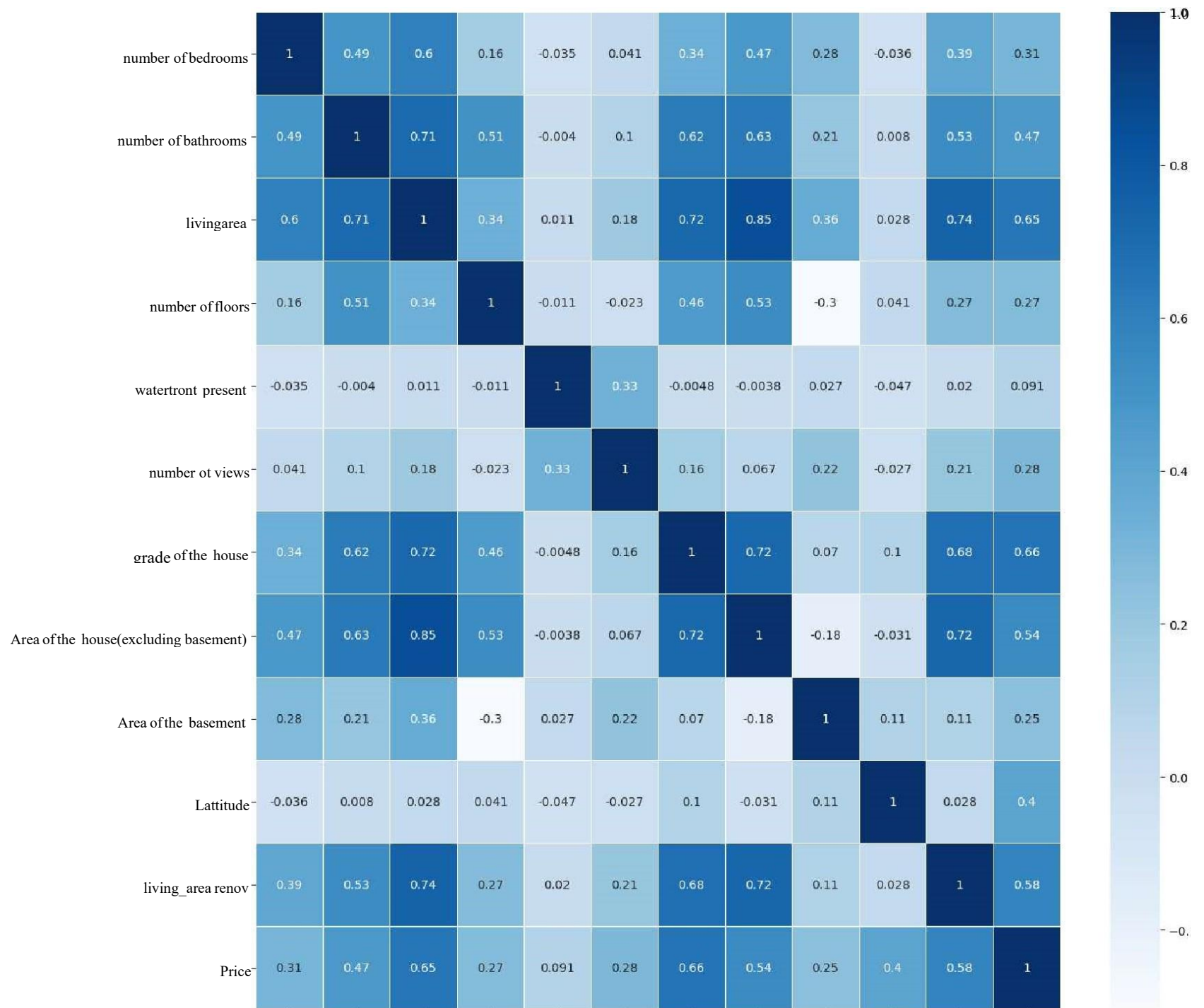
	living area	-0.6	-0.71	-0.15				0.72	0.85	-0.36	-0.34				0.16	0.00060.0055				0.8	
			o. 05	0.15		-0.014	0.031	0.075	-0.0047	0.087	0.16	-0.00240.042	-0.097	0.21	0.14		0.00890.0055	0.078			
	number of floors	0.16			-0,014		-0,011	40.023	0.28			-0.3		0,041	0.13		0.27	-0.023	-0,007	0,017	0.2
	waterfront 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.li	-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.	0.0067			
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		
Built year	0.17			0.042	*	0.039		-0.38	0.47	0.46							0.06+	0.00038000410.	0.047		0.2
Latitude	-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.	0.04		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		



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 ' ) 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	Latitude	living_area_renov
--------------------	---------------------	-------------	------------------	--------------------	-----------------	--------------------	---------------------------------------	----------------------	----------	-------------------

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, train_test_split (X, y,
y_train, test_size=0.2, random_state=11)
```

Out[71]: (2797, 11)

721:

```
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 sklearn.svm import SVR
```

```
In [73]: pipelines = {'en': make_pipeline(StandardScaler(),
    ElasticNet()),
    'lasso': make_pipeline(StandardScaler(), Lasso()),
    'rcv': make_pipeline(StandardScaler(), 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 = {}
```

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/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 increasing 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 1s

999: learn: 77595.2298921 total: 2.85s remaining: 1m 1s

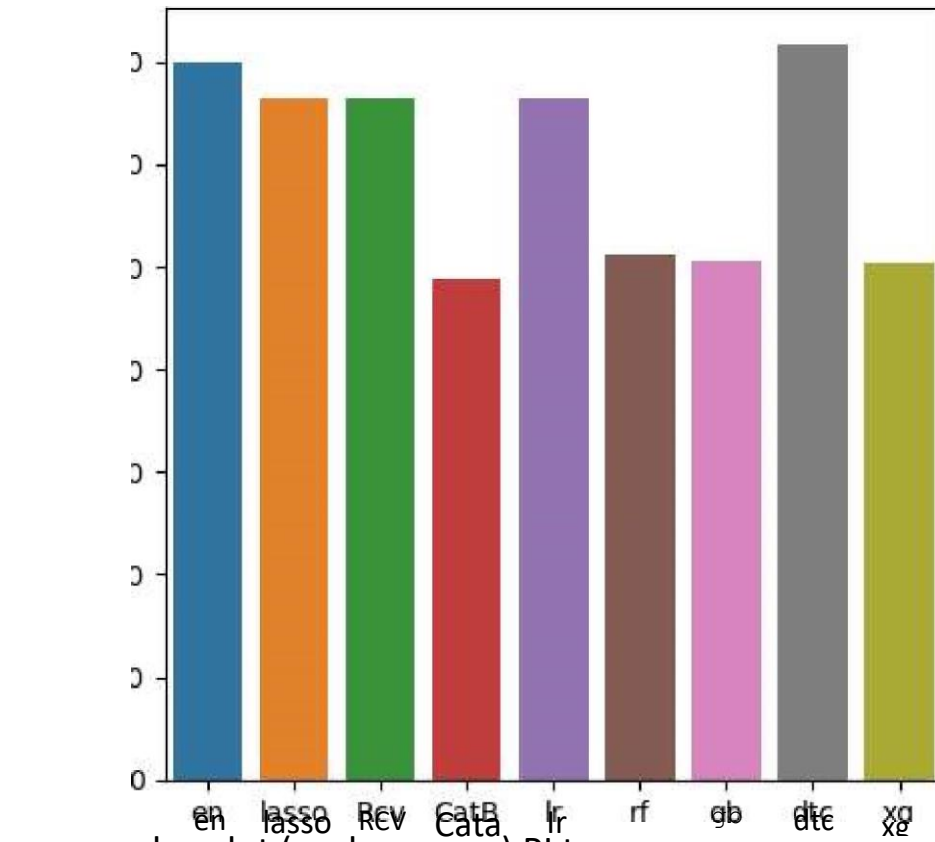
```
[75] from sklearn.metrics import mean_absolute_error, mean_squared_error
```

```
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 lr MEAN ABSOLUTE ERROR
97574.48622571728 lr 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. ')



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

140000

120000

2 100000

LLI

a 80000

a 60000

Root Me a 40000

200001

ML Algorithmsv..

[]:

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

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

pipeline = make_pipeline(
    StandardScaler(),
    streg

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 RESHMA J AS NAAN MUDALVAN IBM SMARTINTERNZ
ASSIGNMENT 3