NM ASSIGNMENT 3

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/Res/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 Year	Postal Code	Lat
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	0	122003	52
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	0	122004	52
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

14620 rows × 22 columns

In [6]:

```
df.head()
```

Out[6]:

	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	Postal Code	Lattitud
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	0	122003	52.864
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	0	122004	52.887
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52.885
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52.953
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52.904

5 rows × 22 columns

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

Out[7]:

	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	Postal Code	Lat
14615	6762830250	2	1.5	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.0	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.0	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.0	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.0	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

5 rows × 22 columns

Checking for null and duplicated values

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

Out[8]:
```
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
```

In [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  
---  ------                                 --------------  -----  
 0   id                                     14620 non-null  int64  
 1   number of bedrooms                     14620 non-null  int64  
 2   number of bathrooms                    14620 non-null  float64
 3   living area                            14620 non-null  int64  
 4   lot area                               14620 non-null  int64  
 5   number of floors                       14620 non-null  float64
 6   waterfront present                     14620 non-null  int64  
 7   number of views                        14620 non-null  int64  
 8   condition of the house                 14620 non-null  int64  
 9   grade of the house                     14620 non-null  int64  
 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  int64  
 13  Renovation Year                        14620 non-null  int64  
 14  Postal Code                            14620 non-null  int64  
 15  Lattitude                              14620 non-null  float64
 16  Longitude                              14620 non-null  float64
 17  living_area_renov                      14620 non-null  int64  
 18  lot_area_renov                         14620 non-null  int64  
 19  Number of schools nearby               14620 non-null  int64  
 20  Distance from the airport              14620 non-null  int64  
 21  Price                                  14620 non-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	condition of the house	grade
count	1.462000e+04	14620.000000	14620.000000	14620.000000	1.462000e+04	14620.000000	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	3.430506	7.
std	6.237575e+03	0.938719	0.769934	928.275721	3.791962e+04	0.540239	0.087193	0.766259	0.664151	1.
min	6.762810e+09	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	4.
25%	6.762815e+09	3.000000	1.750000	1440.000000	5.010750e+03	1.000000	0.000000	0.000000	3.000000	7.
50%	6.762821e+09	3.000000	2.250000	1930.000000	7.620000e+03	1.500000	0.000000	0.000000	3.000000	7.
75%	6.762826e+09	4.000000	2.500000	2570.000000	1.080000e+04	2.000000	0.000000	0.000000	4.000000	8.
max	6.762832e+09	33.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.000000	4.000000	5.000000	13.

8 rows × 22 columns

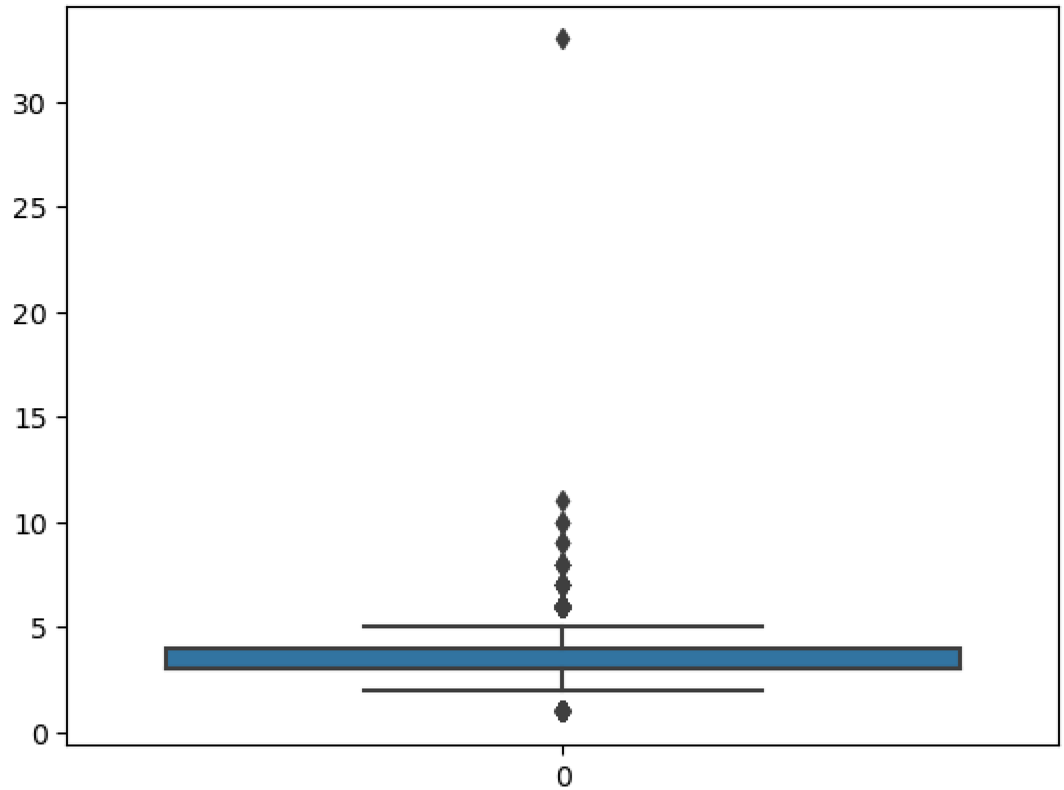
Checking for outliers

In [12]:

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

Out[12]:

```
<AxesSubplot:>
```



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))
```

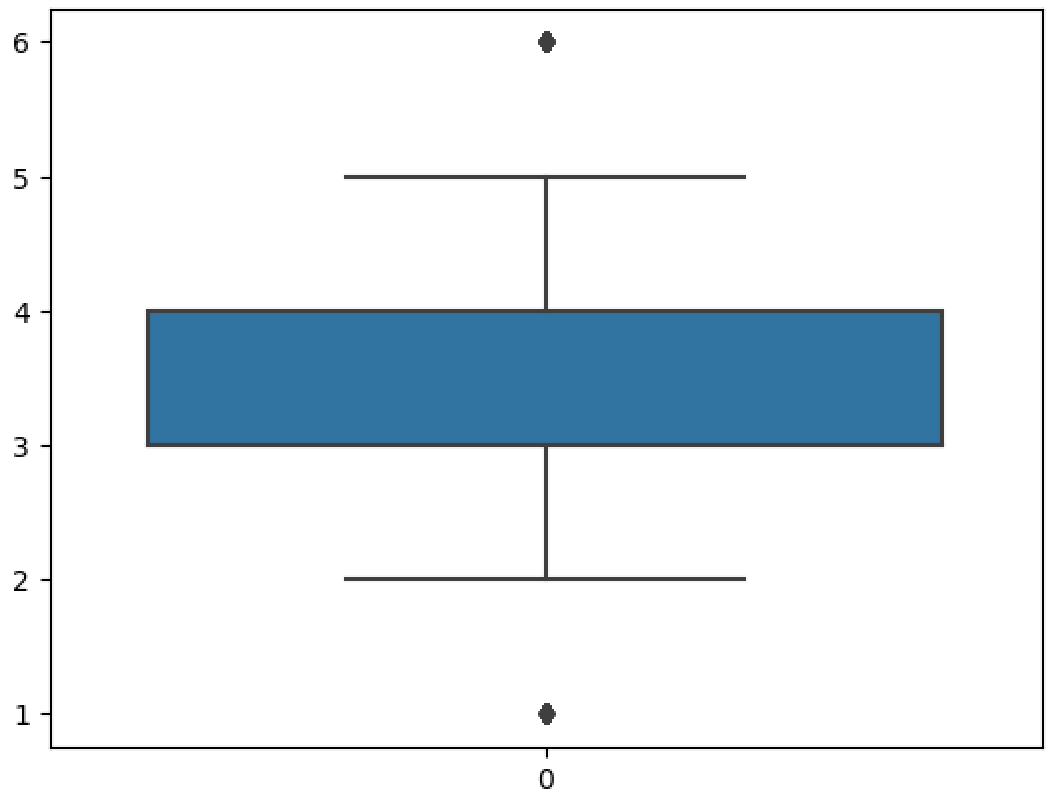
```
(array([], dtype=int64),)
```

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< 3)]
```

In [17]:
```
sns.boxplot(df1['number of bedrooms'])
```

Out[17]: <AxesSubplot:>



In [18]:
```
df1
```

Out[18]:

	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	Postal Code	Latt
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	0	122003	52
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	0	122004	52
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

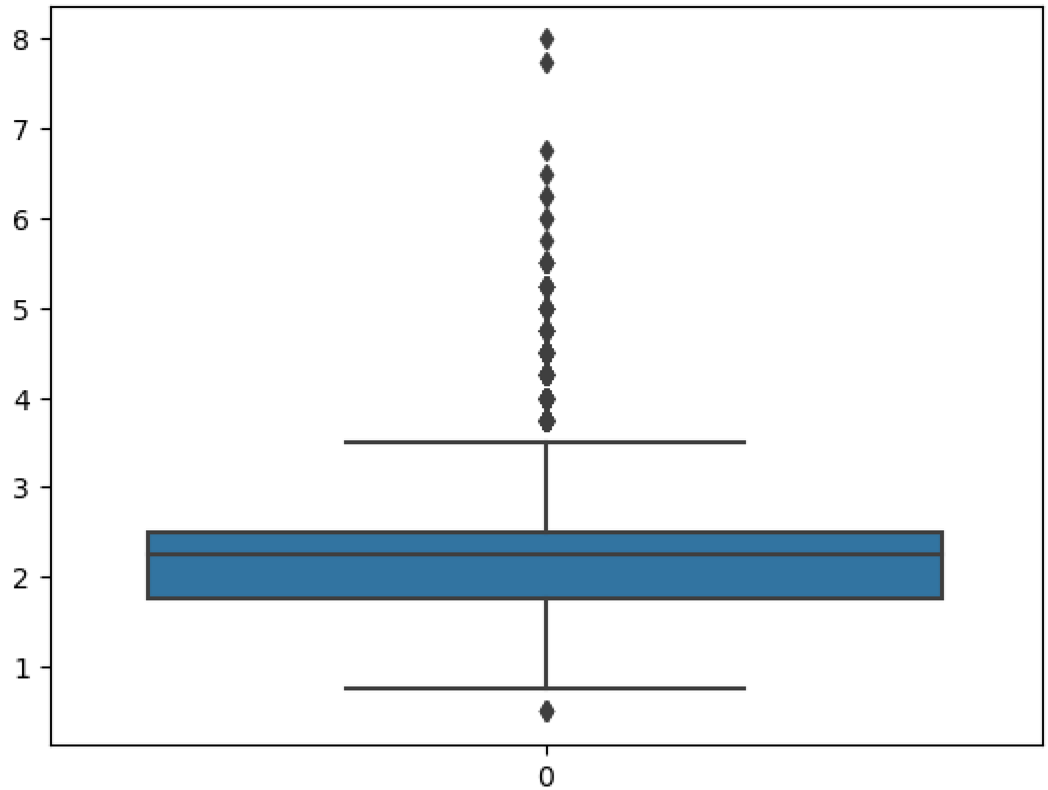
14571 rows × 22 columns

In [19]:

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

Out[19]:

```
<AxesSubplot:>
```



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

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

Out[21]: 124

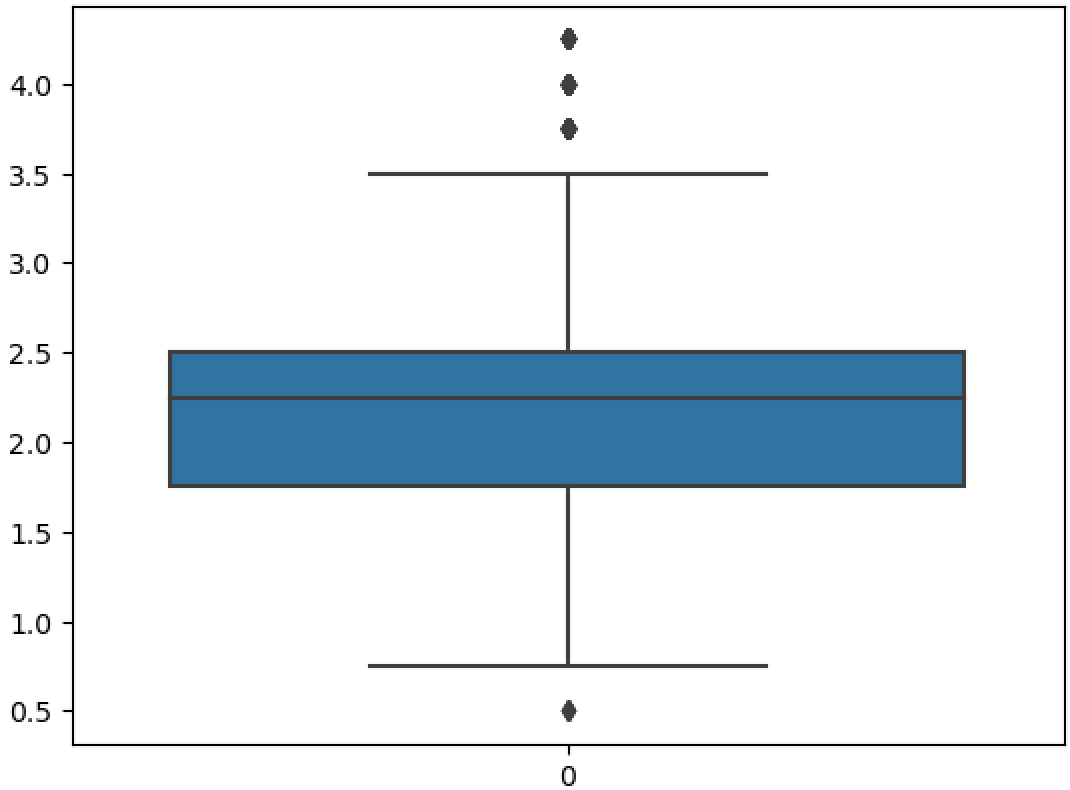
In [22]:
```
print(np.where(z<-3))
```

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

In [23]:
```
df1=df1[(z< 3)]
```

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

Out[24]: <AxesSubplot:>



In [25]:
```
df1
```

Out[25]:

	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	Postal Code	Lat
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	0	122003	52
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	0	122004	52
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

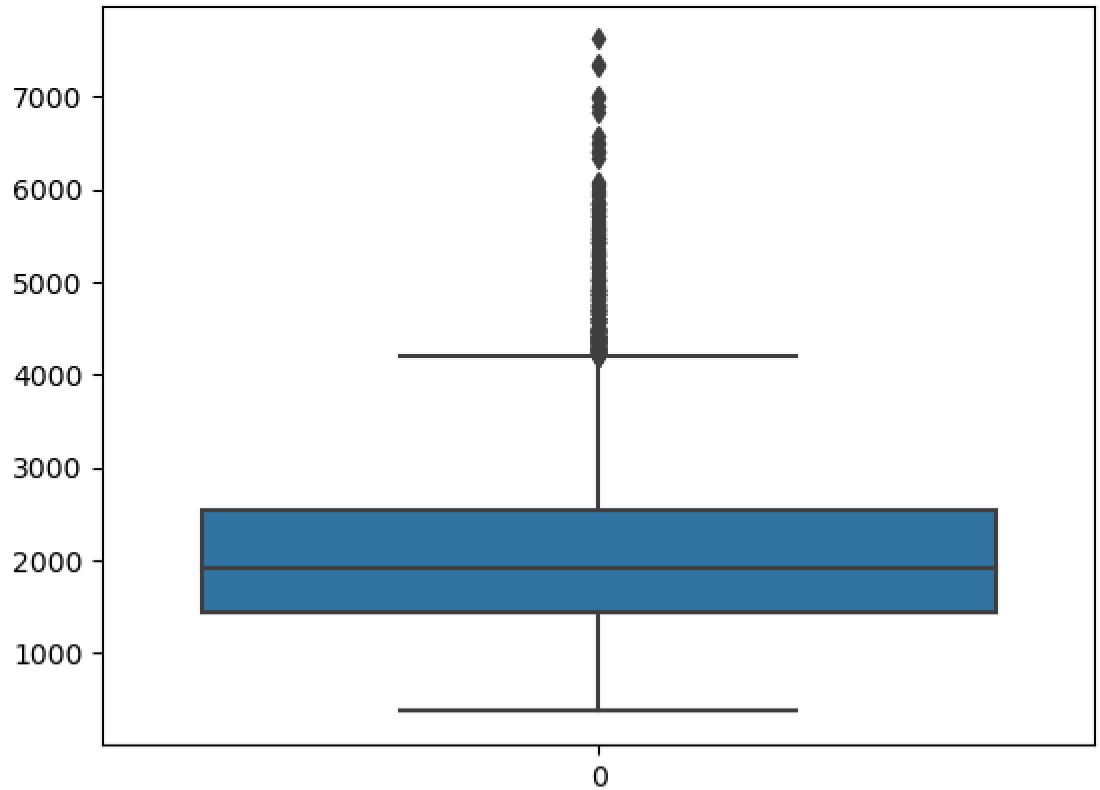
14447 rows × 22 columns

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

In [26]:

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

Out[26]: <AxesSubplot:>



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

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

Out[28]: 136

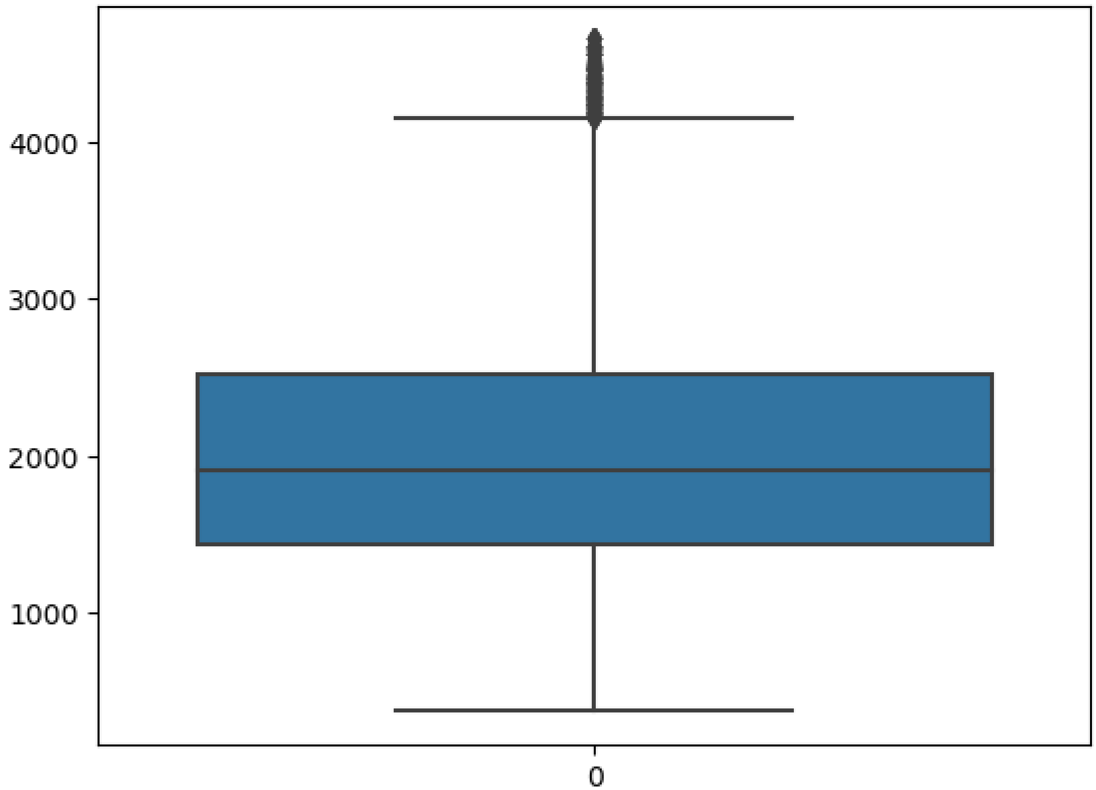
In [29]:
```
len(np.where(z<-3)[0])
```

Out[29]: 0

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

In [31]:
```
sns.boxplot(df1['living area'])
```

Out[31]: <AxesSubplot:>



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

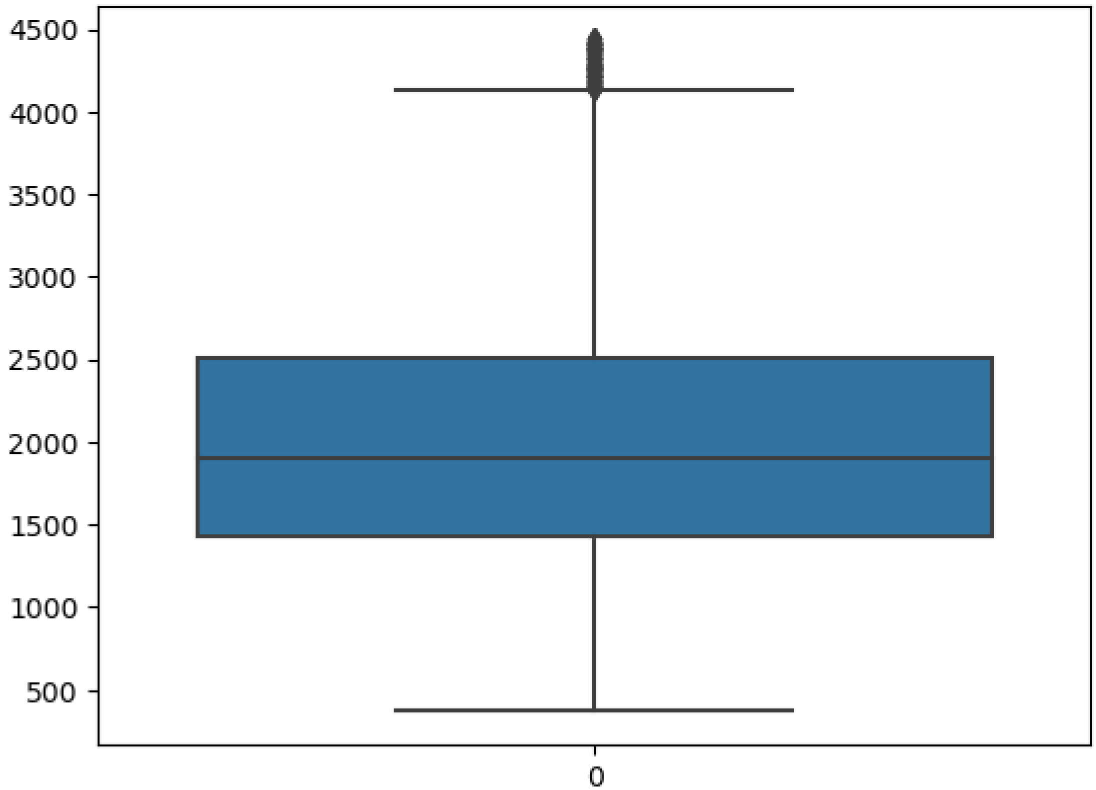
In [33]:
```
len(np.where(z>3)[0])
```

Out[33]: 67

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

In [35]:
```
sns.boxplot(df1['living area'])
```

Out[35]: <AxesSubplot:>



In [36]:
```
df1
```

Out[36]:

	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	Postal Code	Lat
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	0	122003	52
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	0	122004	52
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

14244 rows × 22 columns

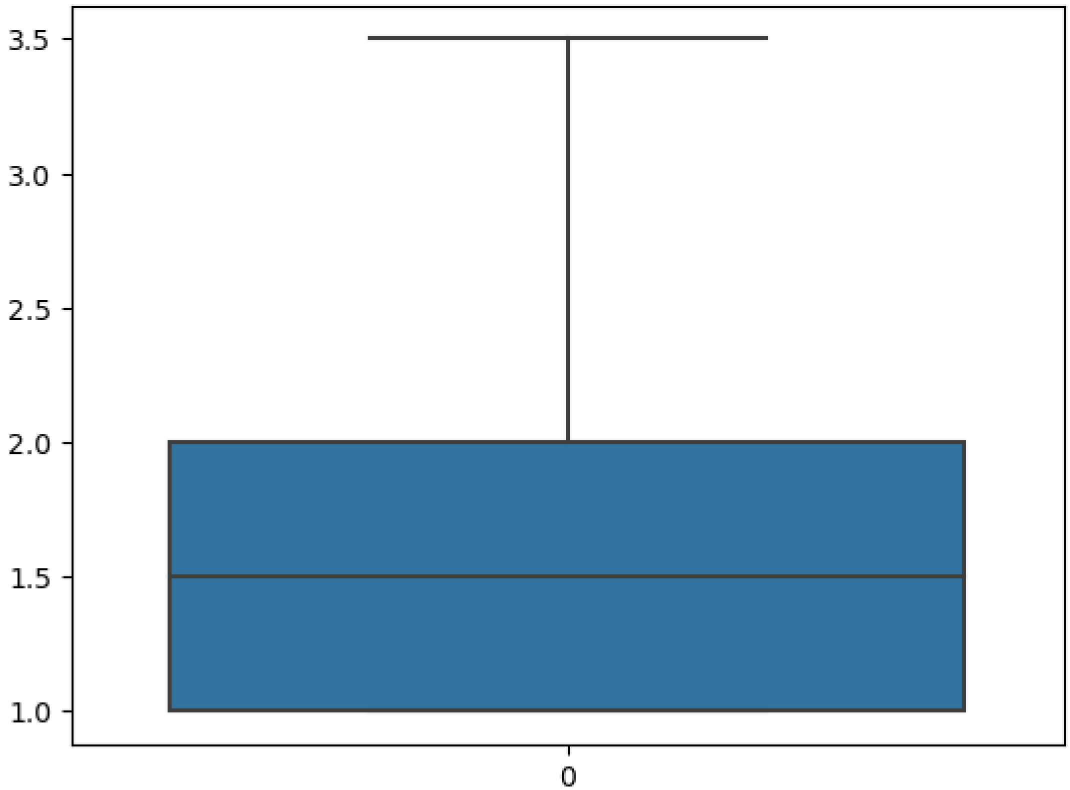
There are 205 outliers in living as proved from the boxplot and the fact that there are observations whose z-score is beyond 3

In [37]:

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

Out[37]:

```
<AxesSubplot:>
```



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

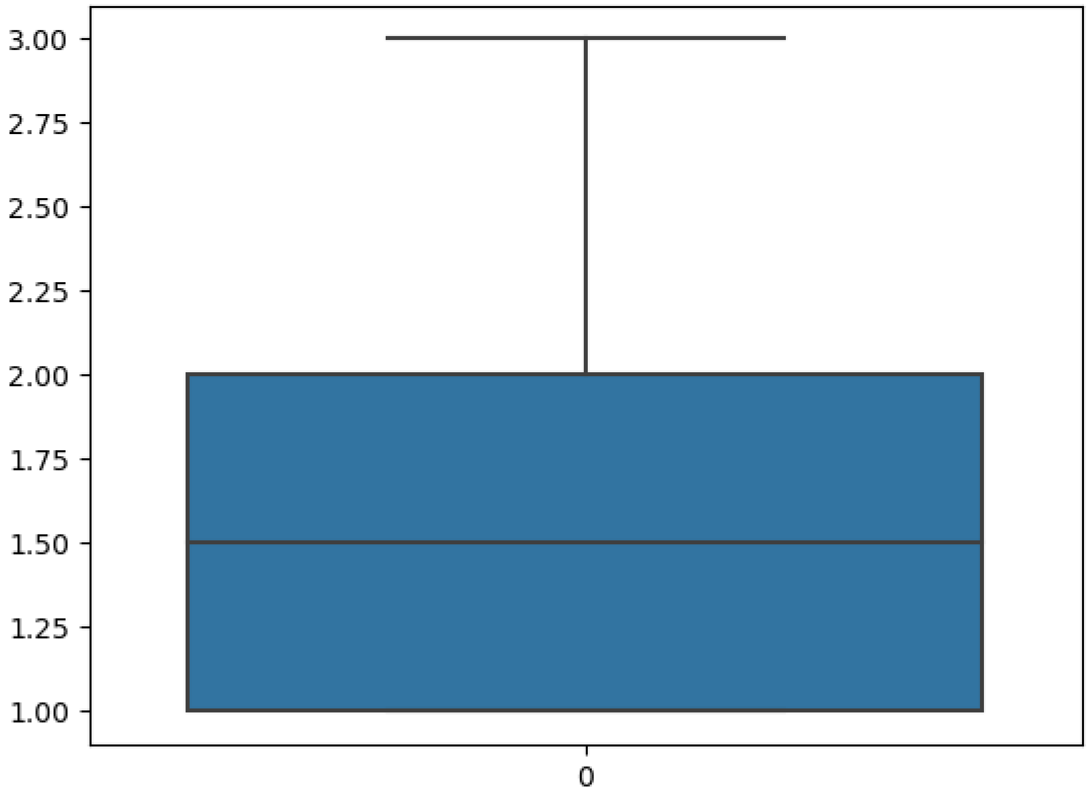
In [39]:
```
len(np.where(z>3)[0])
```

Out[39]: 3

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

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

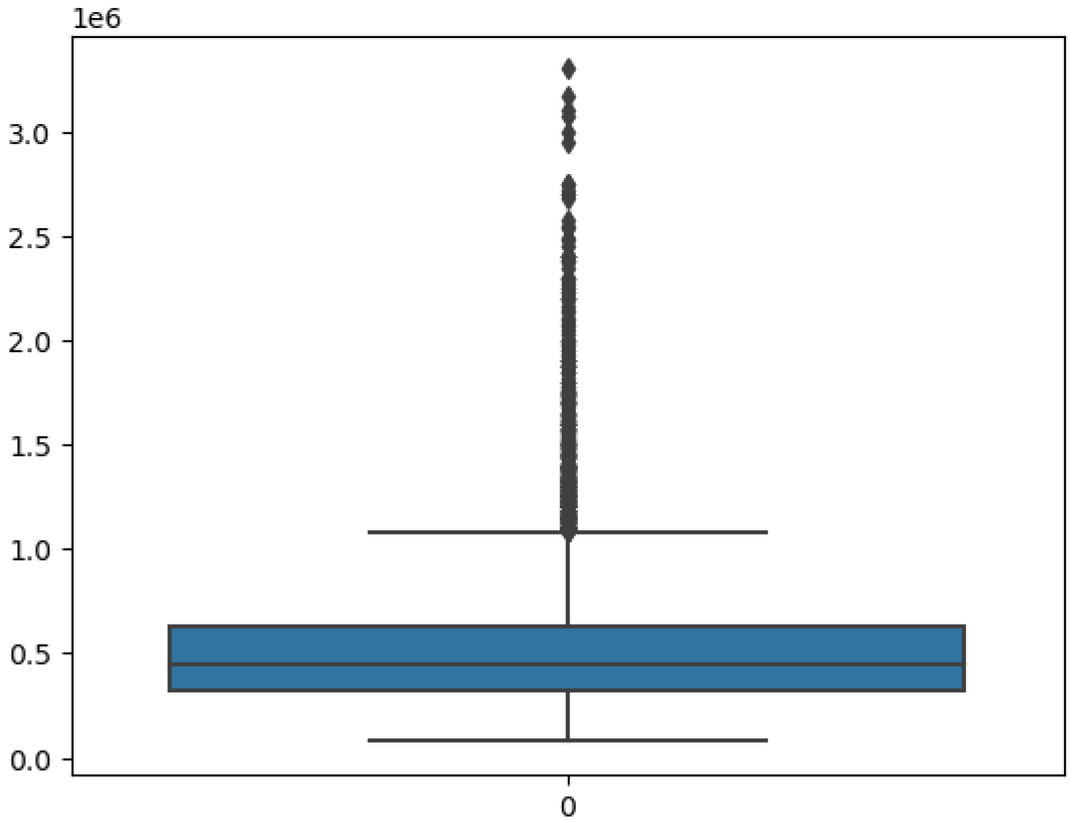
Out[41]: <AxesSubplot:>



There are 3 outliers in number of floors

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

Out[42]: <AxesSubplot:>



In [43]:
```
z=np.abs(stats.zscore(df1['Price']))
```

In [44]:
```
len(np.where(z>3)[0])
```

Out[44]: 259

In [45]:
```
df1=df1[(z<3)]
```

In [46]:
```
df1
```

Out[46]:

	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	Postal Code	Latt
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939	0	122004	52
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001	0	122005	52
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929	0	122006	52
5	6762813105	3	2.50	2600	4750	1.0	0	0	4	9	...	1951	0	122007	52
6	6762813157	5	3.25	3660	11995	2.0	0	2	3	10	...	2006	0	122008	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	1957	0	122066	52
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	1968	0	122072	52
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	1962	0	122056	52
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	1955	0	122042	52
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	1969	2009	122018	52

13982 rows × 22 columns

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

In [48]:
```
df1
```

Out[48]:

	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	...	Area of the basement	Built Year	Postal Code	Lattit
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	0	1939	122004	52.8
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	0	2001	122005	52.9
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	830	1929	122006	52.9
5	6762813105	3	2.50	2600	4750	1.0	0	0	4	9	...	900	1951	122007	52.9
6	6762813157	5	3.25	3660	11995	2.0	0	2	3	10	...	0	2006	122008	52.7
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14615	6762830250	2	1.50	1556	20000	1.0	0	0	4	7	...	0	1957	122066	52.6
14616	6762830339	3	2.00	1680	7000	1.5	0	0	4	7	...	0	1968	122072	52.5
14617	6762830618	2	1.00	1070	6120	1.0	0	0	3	6	...	0	1962	122056	52.7
14618	6762830709	4	1.00	1030	6621	1.0	0	0	4	6	...	0	1955	122042	52.7
14619	6762831463	3	1.00	900	4770	1.0	0	0	3	6	...	0	1969	122018	52.5

13982 rows × 21 columns

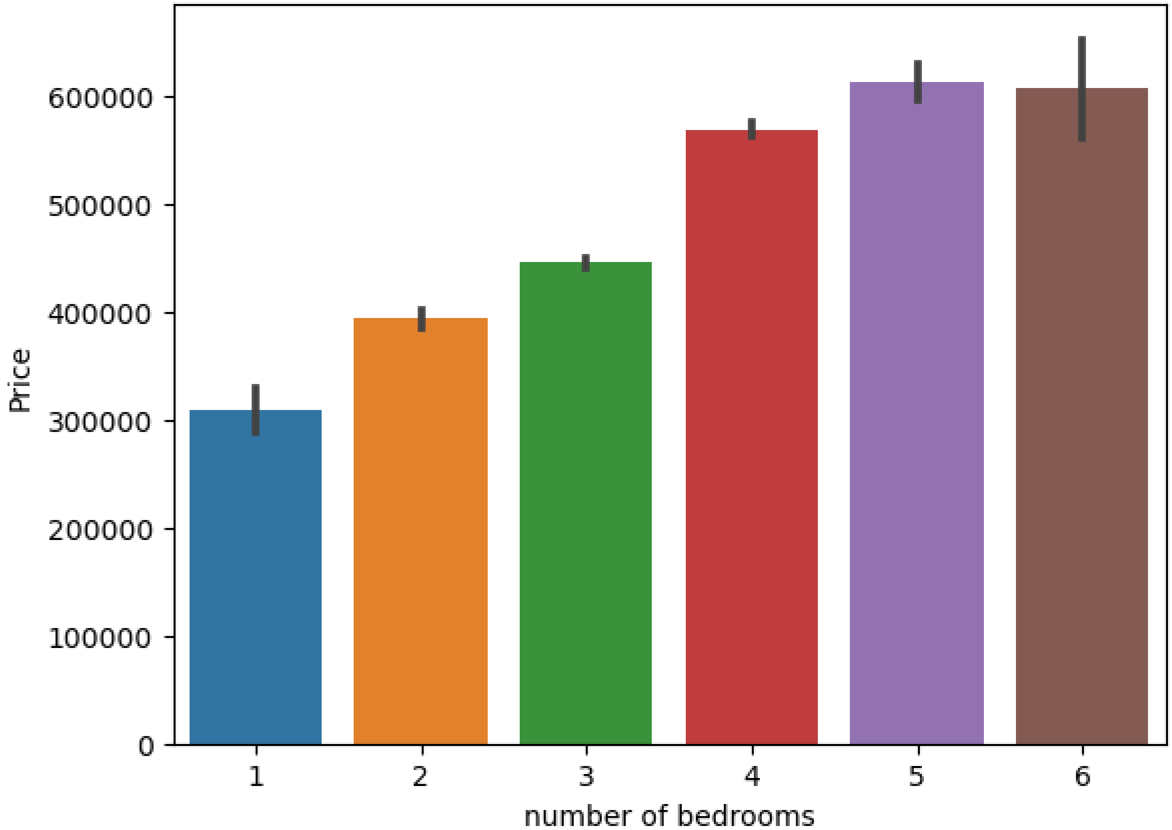
The column Renovation year have been removed. This is because most of the Renovation Year are 0 and proves to be of no use to the model

In [49]:

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

Out[49]:

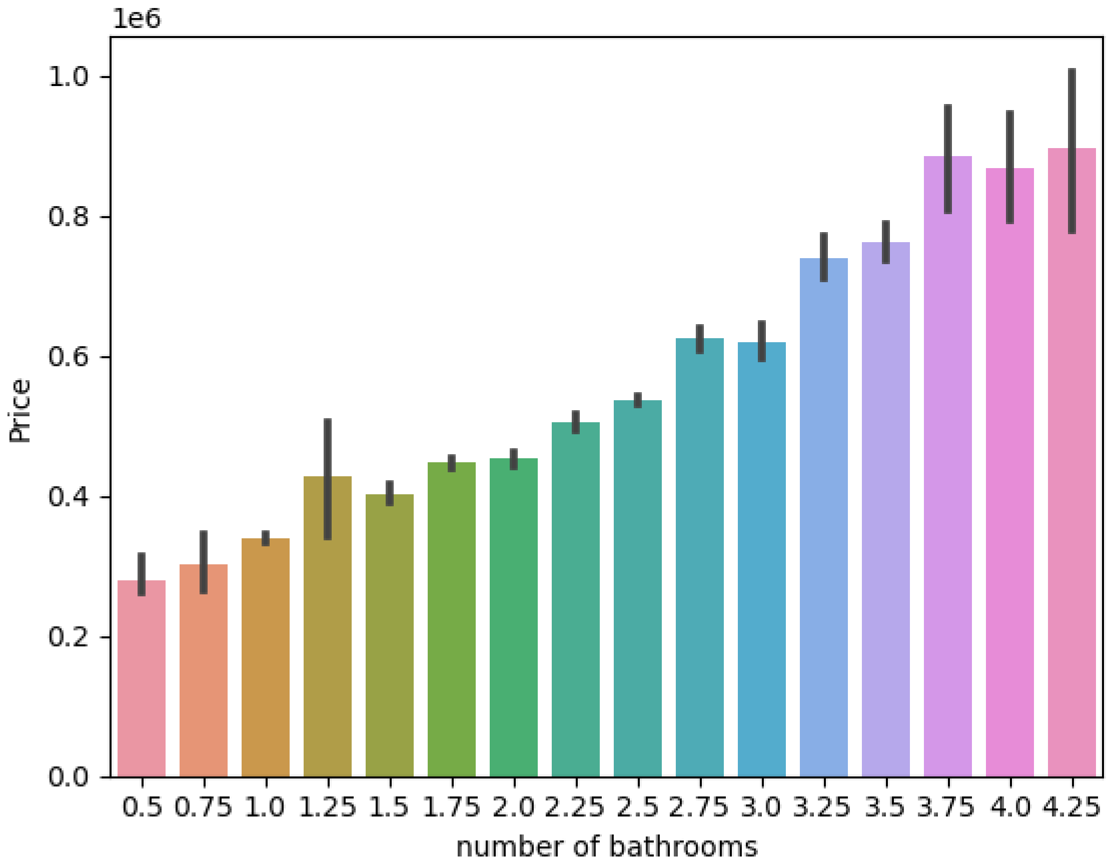
```
<AxesSubplot:xlabel='number of bedrooms', ylabel='Price'>
```



Clear indication of Price increasing with number of bedrooms

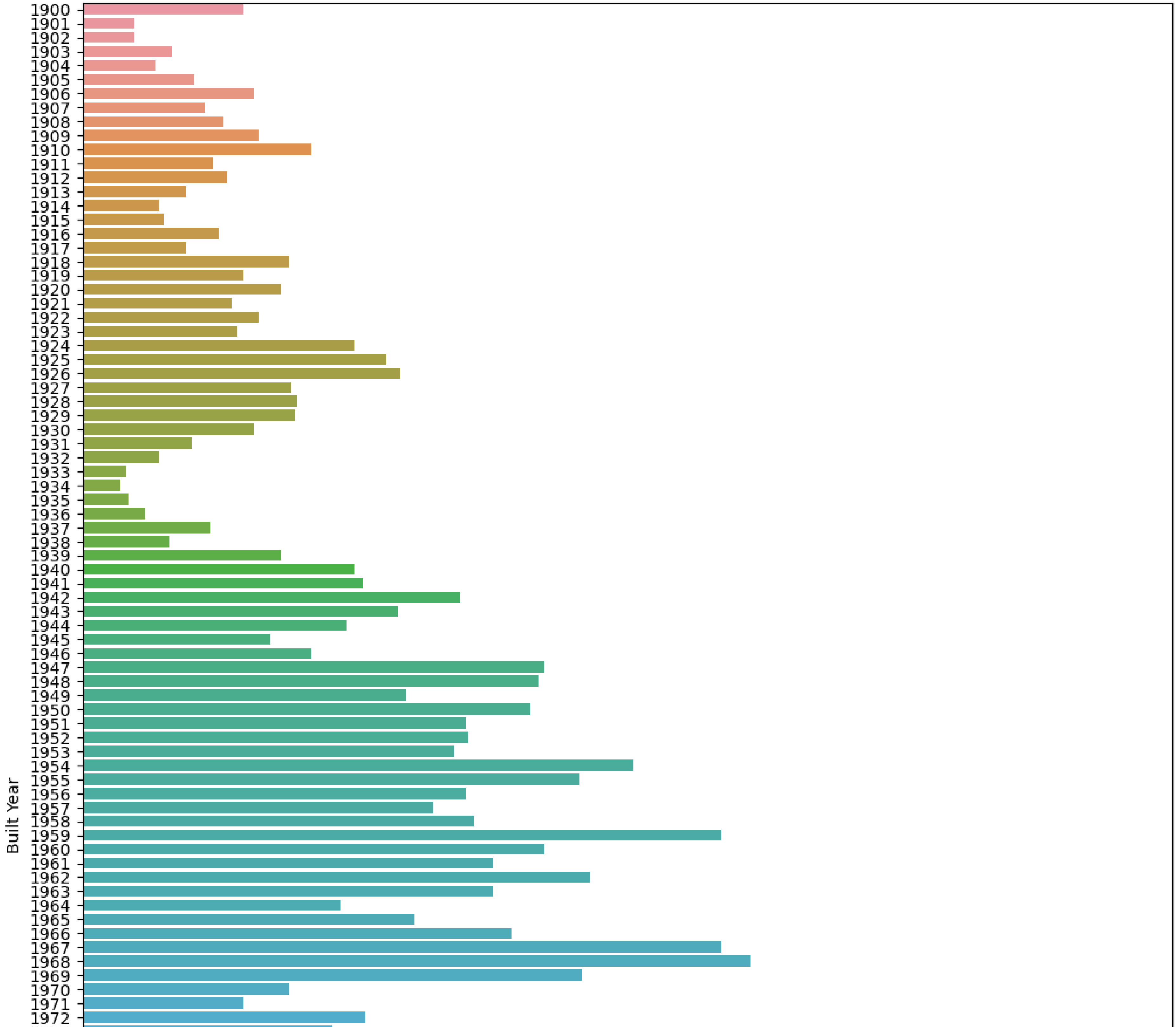
In [50]:
```
sns.barplot(data=df1,x='number of bathrooms',y='Price')
```

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))
sns.countplot(data=df1,y='Built Year')
plt.show()
```


Built Year
1900
1901
1902
1903
1904
1905
1906
1907
1908
1909
1910
1911
1912
1913
1914
1915
1916
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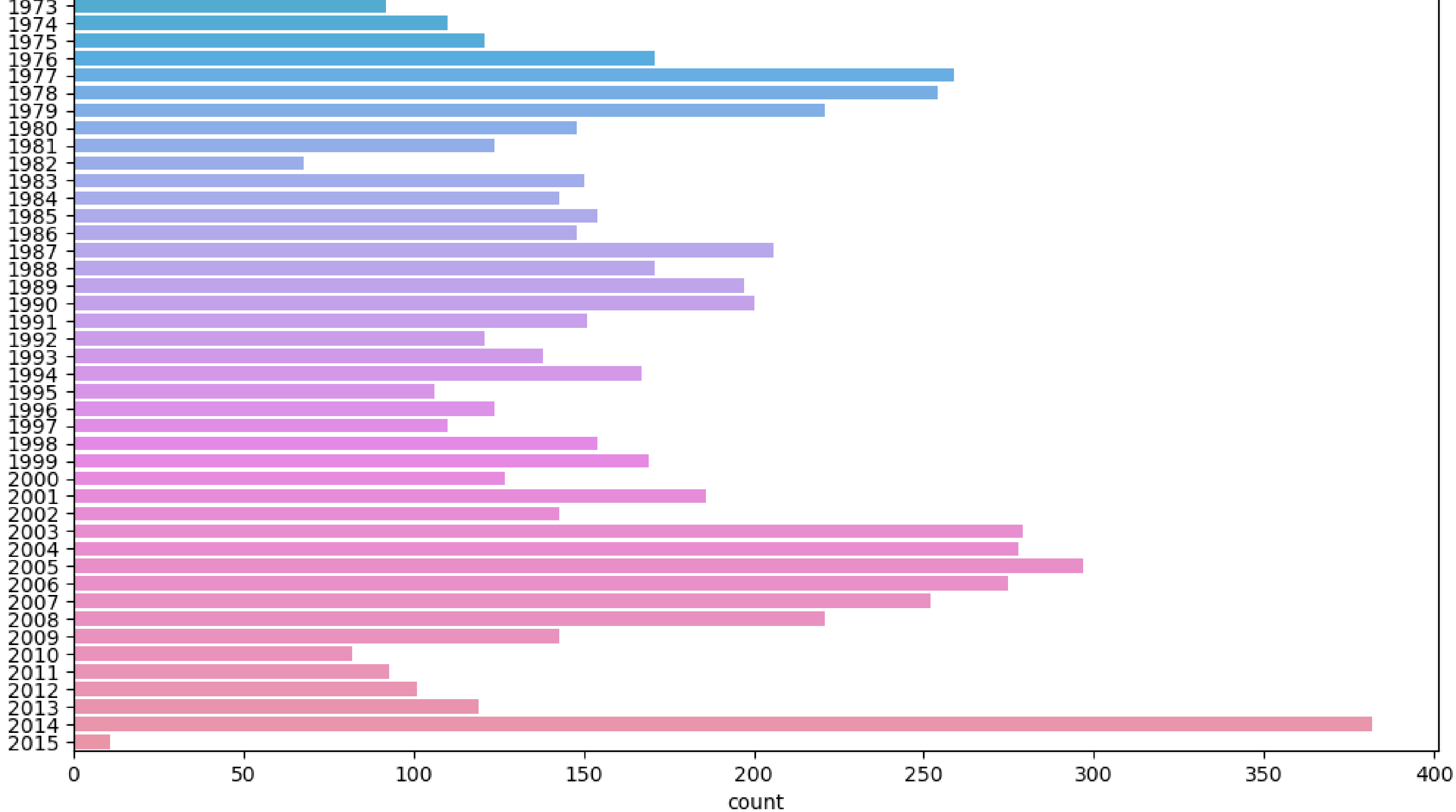
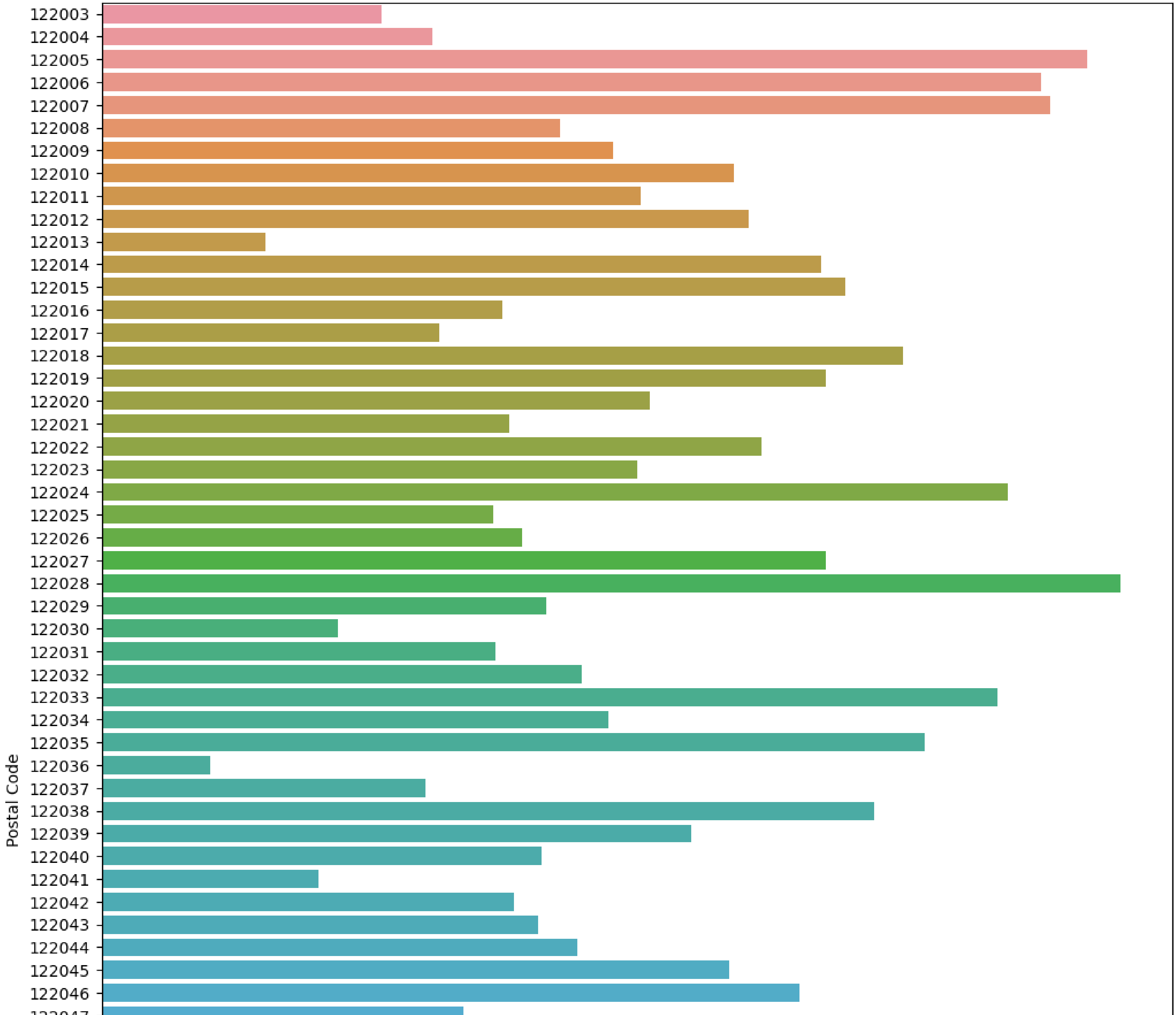
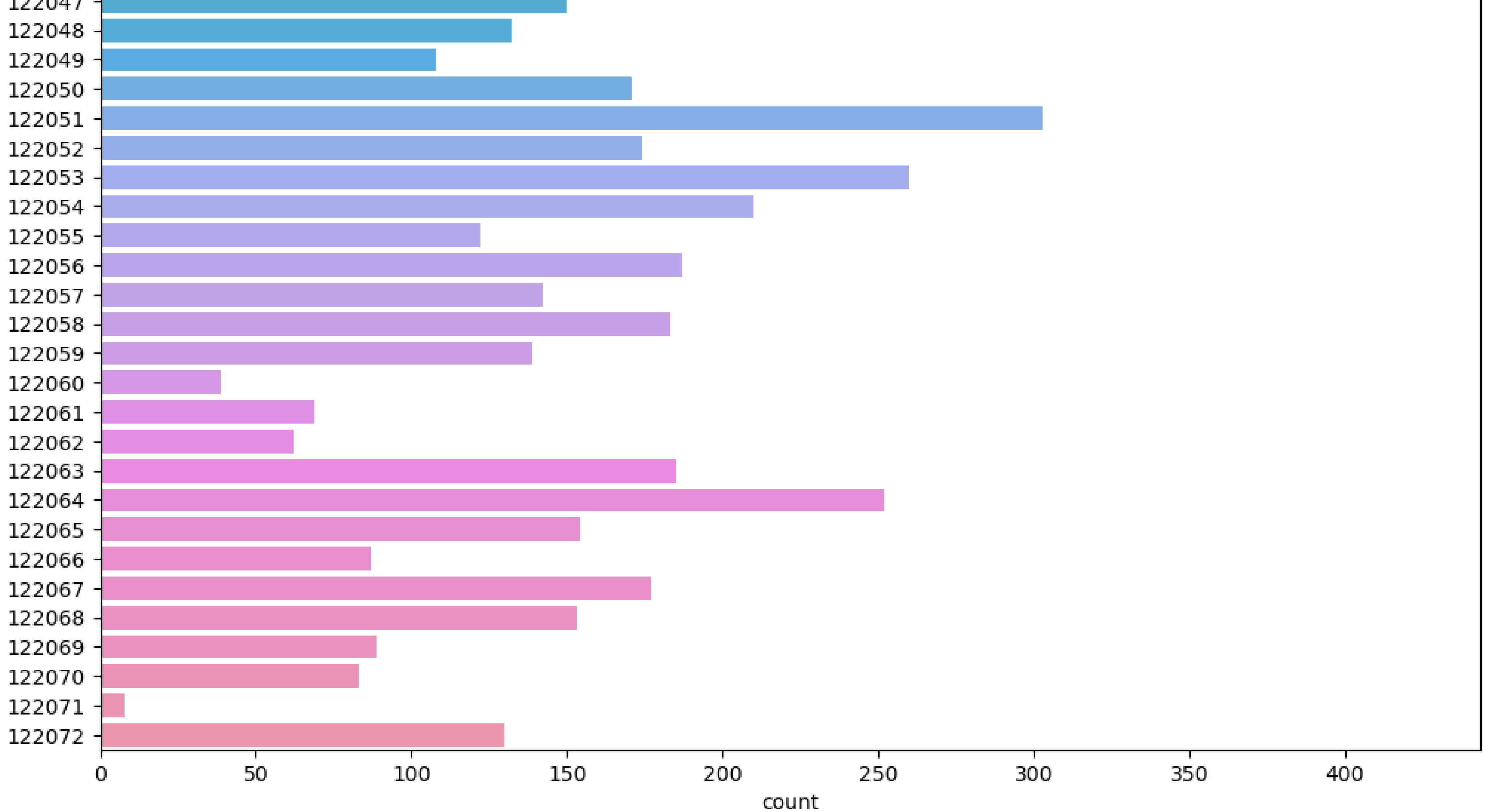
1970
1971
1972



Most of the houses were listed for sale in 2017

In [52]:
```
plt.figure(figsize=(12,18))
sns.countplot(data=df1,y='Postal Code')
plt.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
122046



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

In [53]:
```
df1[df1['Built Year']==2014]['Lattitude'].mean()
```

Out[53]: 52.77583376963351

In [54]:
```
df1[df1['Built Year']==2014]['Longitude'].mean()
```

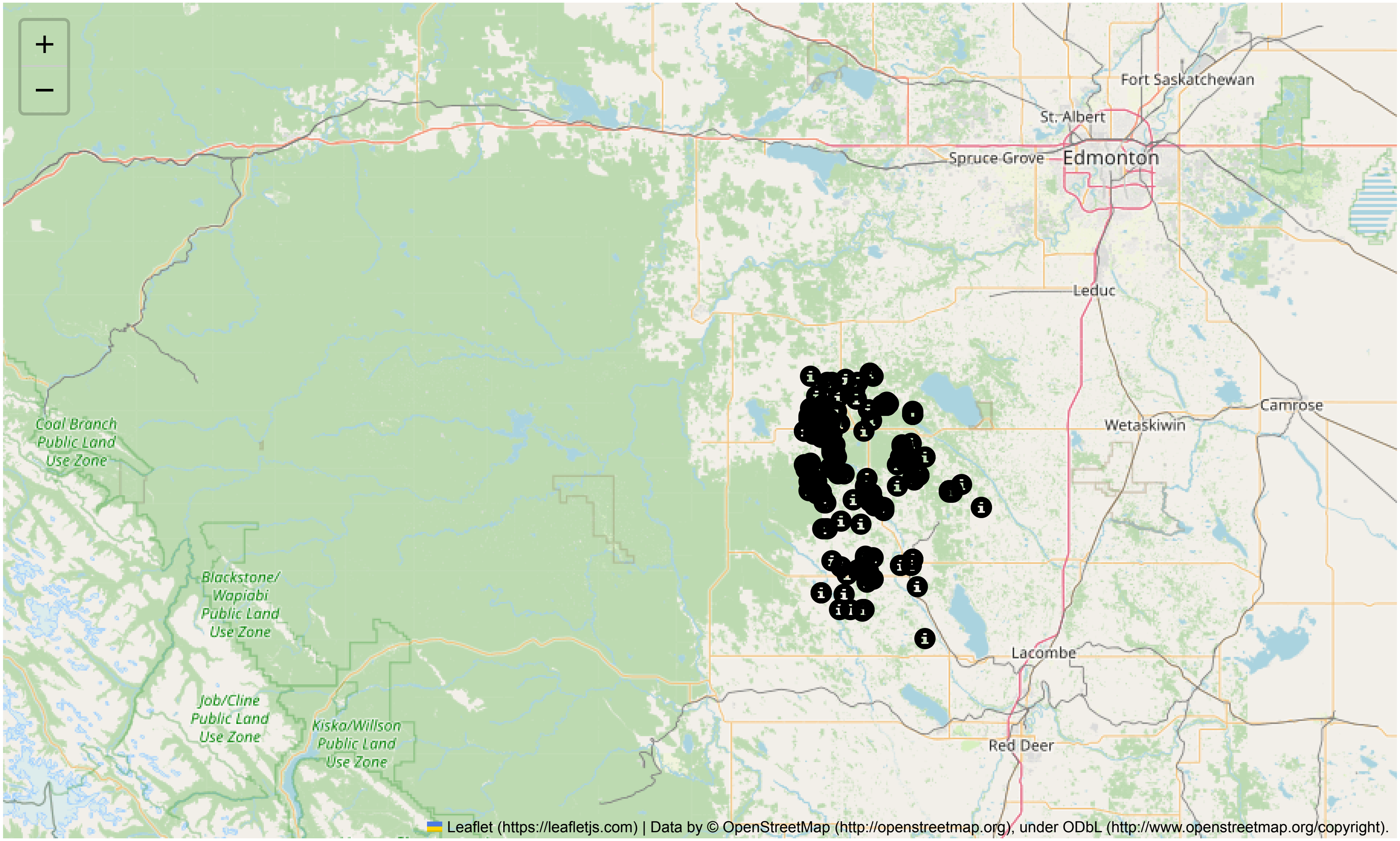
Out[54]: -114.38898952879582

In [55]:
```
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']<=70)].iterrows():
```

```
    folium.Marker([location_info["Lattitude"], location_info["Longitude"]], popup=location_info["Price"],icon=folium.Icon(color='r
m
```

Out[55]:



In [56]:
```
df1[df1['Built Year']>=2014]['Lattitude'].mean()
```

Out[56]: 52.77850305343512

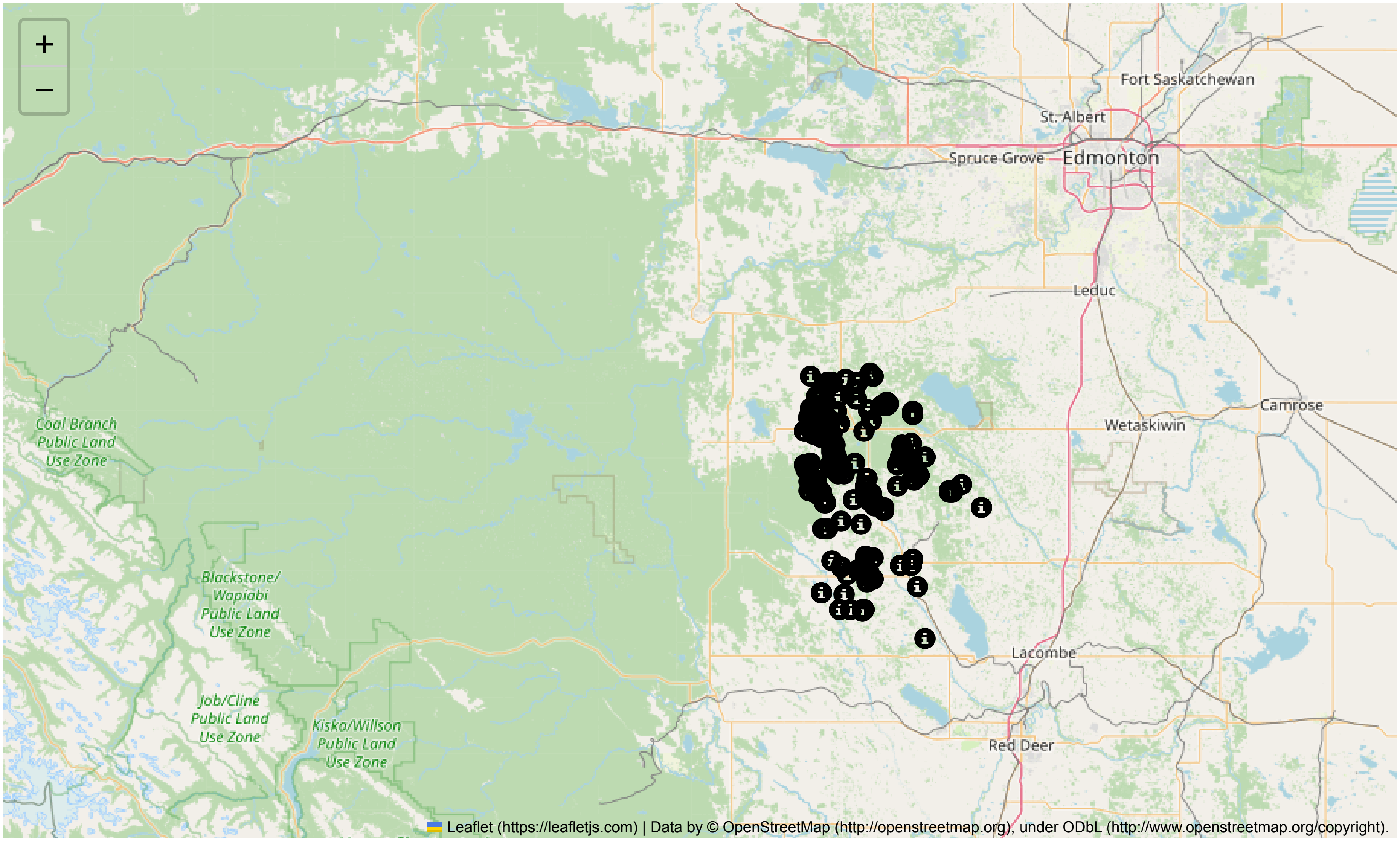
In [57]:
```
df1[df1['Built Year']>=2014]['Longitude'].mean()
```

Out[57]: -114.39186768447837

In [58]:
```
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']<=70)].iterrows():
    folium.Marker([location_info["Lattitude"], location_info["Longitude"]], popup=location_info["Price"],icon=folium.Icon(color='r
m
```

Out[58]:



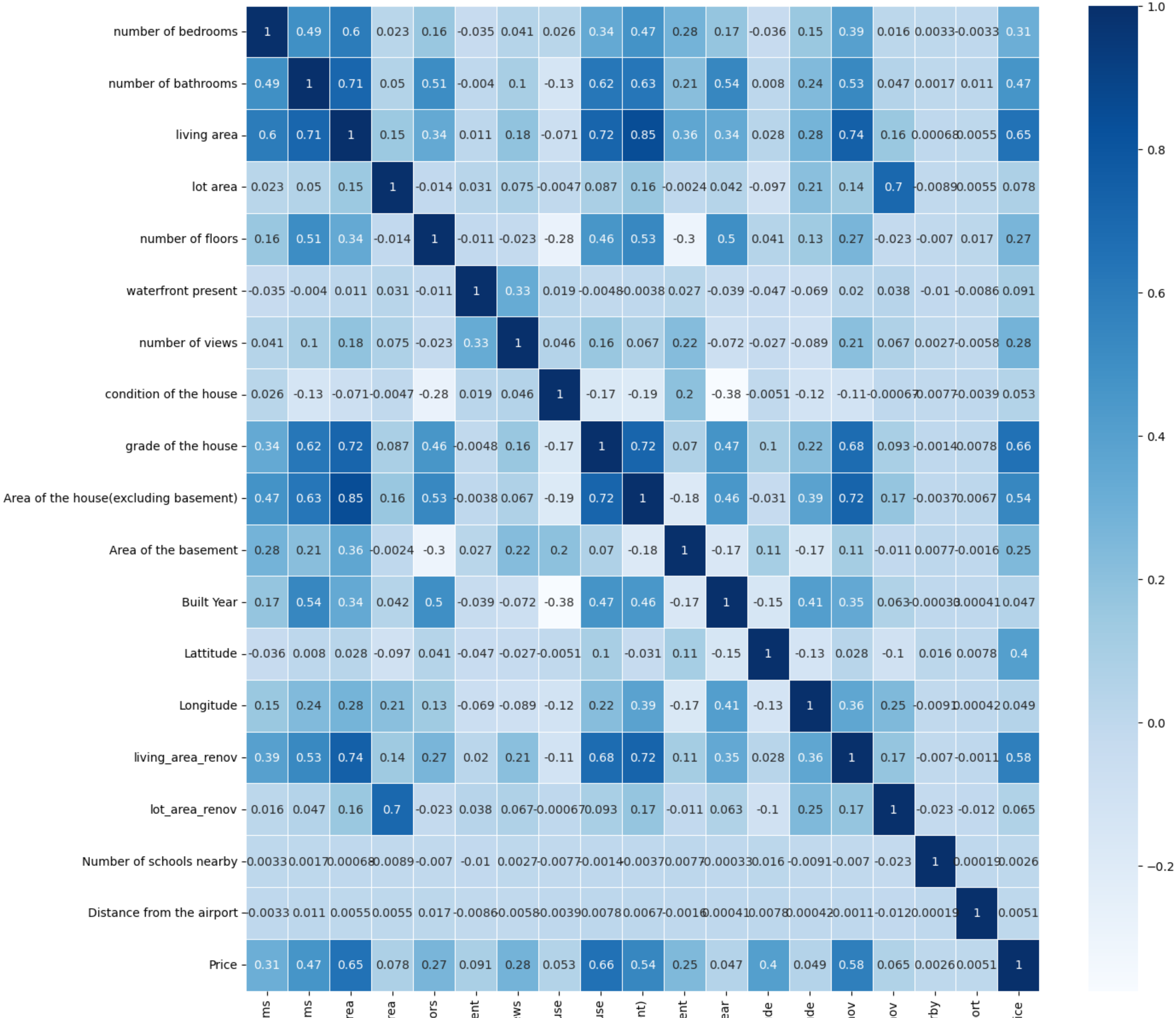
The houses listed for sale in this dataset are located in Alberta, Canada

In [59]:
```
df1=df1.drop(['id'],axis=1)
```

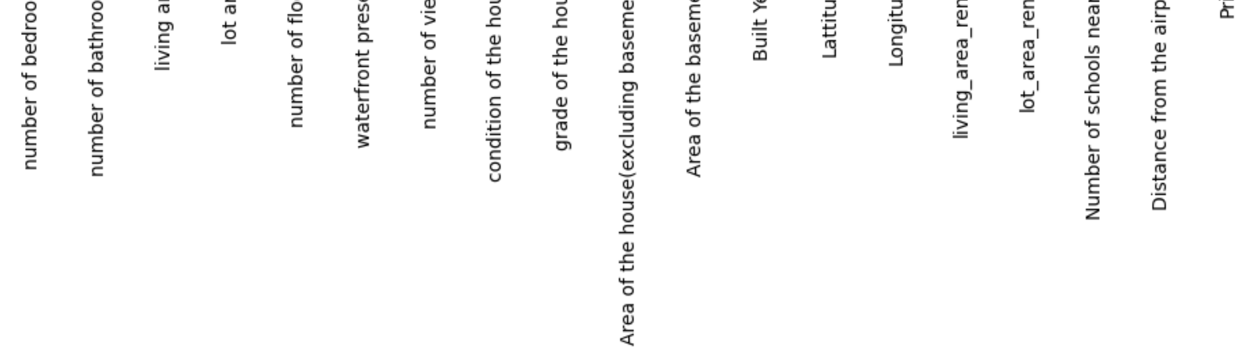
In [60]:
```
df1=df1.drop(['Postal Code'],axis=1)
```

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(df1.corr(),linewidths=0.5,annot=True,cmap='Blues')
plt.show()
```



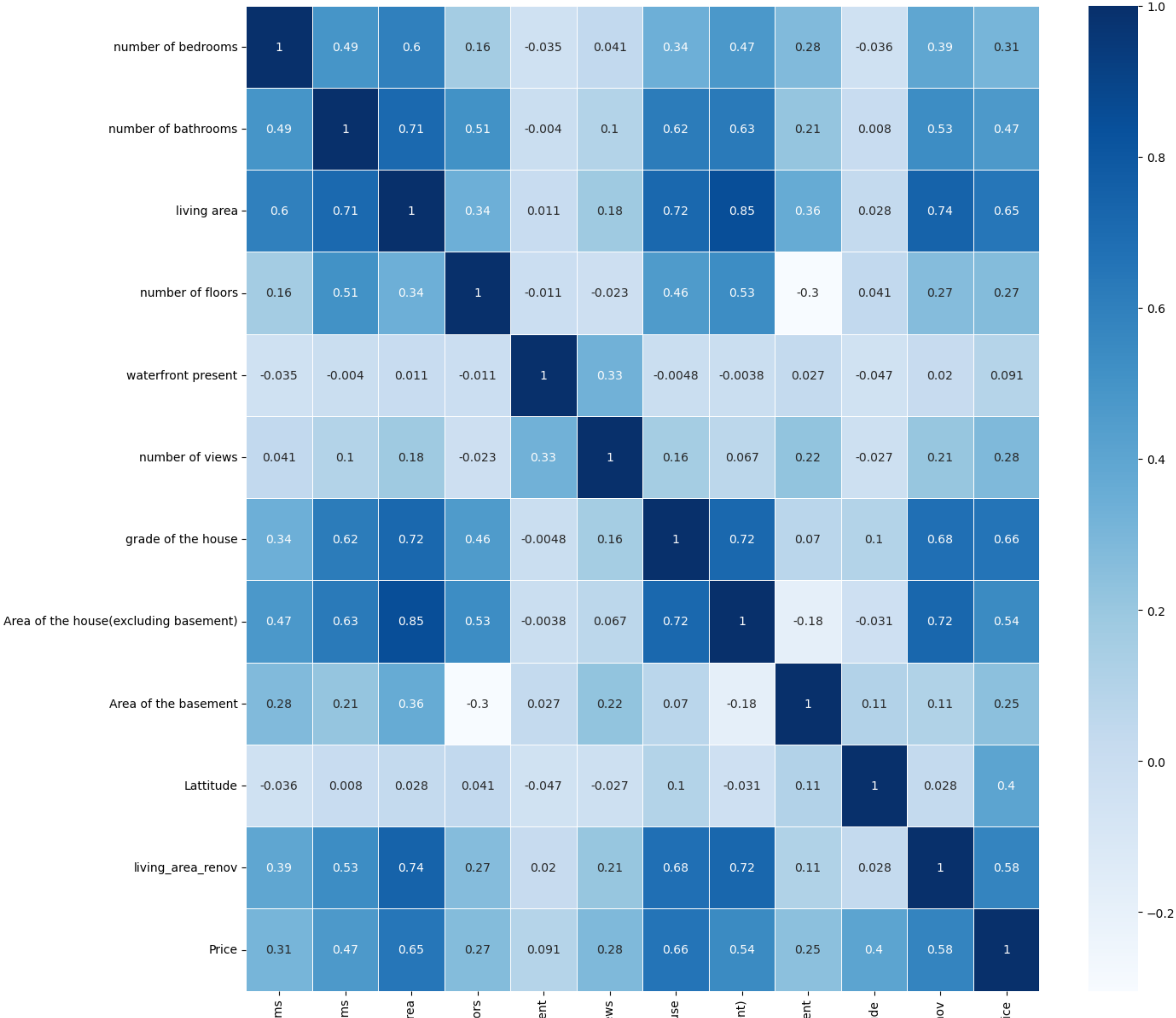
number of bedrooms
number of bathrooms
living area
lot area
number of floors
waterfront present
number of views
condition of the house
grade of the house
Area of the house(excluding basement)
Area of the basement
Built Year
Lattitude
Longitude
living_area_renov
lot_area_renov
Number of schools nearby
Distance from the airport
Price
1 0.49 0.6 0.023 0.16 -0.035 0.041 0.026 0.34 0.47 0.28 0.17 -0.036 0.15 0.39 0.016 0.0033 -0.0033 0.31
0.49 1 0.71 0.05 0.51 -0.004 0.1 -0.13 0.62 0.63 0.21 0.54 0.008 0.24 0.53 0.047 0.0017 0.011 0.47
0.6 0.71 1 0.15 0.34 0.011 0.18 -0.071 0.72 0.85 0.36 0.34 0.028 0.28 0.74 0.16 0.00068 0.0055 0.65
0.023 0.05 0.15 1 -0.014 0.031 0.075 -0.0047 0.087 0.16 -0.0024 0.042 -0.097 0.21 0.14 0.7 -0.0089 0.0055 0.078
0.16 0.51 0.34 -0.014 1 -0.011 -0.023 -0.28 0.46 0.53 -0.3 0.5 0.041 0.13 0.27 -0.023 -0.007 0.017 0.27
-0.035 -0.004 0.011 0.031 -0.011 1 0.33 0.019 -0.0048 -0.0038 0.027 -0.039 -0.047 -0.069 0.02 0.038 -0.01 -0.0086 0.091
0.041 0.1 0.18 0.075 -0.023 0.33 1 0.046 0.16 0.067 0.22 -0.072 -0.027 -0.089 0.21 0.067 0.0027 -0.0058 0.28
0.026 -0.13 -0.071 -0.0047 -0.28 0.019 0.046 1 -0.17 -0.19 0.2 -0.38 -0.0051 -0.12 -0.11 -0.00067 -0.0077 -0.0039 0.053
0.34 0.62 0.72 0.087 0.46 -0.0048 0.16 -0.17 1 0.72 0.07 0.47 0.1 0.22 0.68 0.093 -0.0014 0.0078 0.66
0.47 0.63 0.85 0.16 0.53 -0.0038 0.067 -0.19 0.72 1 -0.18 0.46 -0.031 0.39 0.72 0.17 -0.0037 0.0067 0.54
0.28 0.21 0.36 -0.0024 -0.3 0.027 0.22 0.2 0.07 -0.18 1 -0.17 0.11 -0.17 0.11 -0.011 0.0077 -0.0016 0.25
0.17 0.54 0.34 0.042 0.5 -0.039 -0.072 -0.38 0.47 0.46 -0.17 1 -0.15 0.41 0.35 0.063 -0.00033 0.00041 0.047
-0.036 0.008 0.028 -0.097 0.041 -0.047 -0.027 -0.0051 0.1 -0.031 0.11 -0.15 1 -0.13 0.028 -0.1 0.016 0.0078 0.4
0.15 0.24 0.28 0.21 0.13 -0.069 -0.089 -0.12 0.22 0.39 -0.17 0.41 -0.13 1 0.36 0.25 -0.0091 0.00042 0.049
0.39 0.53 0.74 0.14 0.27 0.02 0.21 -0.11 0.68 0.72 0.11 0.35 0.028 0.36 1 0.17 -0.007 -0.0011 0.58
0.016 0.047 0.16 0.7 -0.023 0.038 0.067 -0.00067 0.093 0.17 -0.011 0.063 -0.1 0.25 0.17 1 -0.023 -0.012 0.065
-0.0033 0.0017 0.00068 -0.0089 -0.007 -0.01 0.0027 -0.0077 -0.0014 -0.0037 0.0077 -0.00033 0.016 -0.0091 -0.007 -0.023 1 0.00019 0.0026
-0.0033 0.011 0.0055 0.0055 0.017 -0.0086 -0.0058 -0.0039 0.0078 0.0067 -0.0016 0.00041 0.0078 0.00042 -0.0011 -0.012 0.00019 1 0.0051
0.31 0.47 0.65 0.078 0.27 0.091 0.28 0.053 0.66 0.54 0.25 0.047 0.4 0.049 0.58 0.065 0.0026 0.0051 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



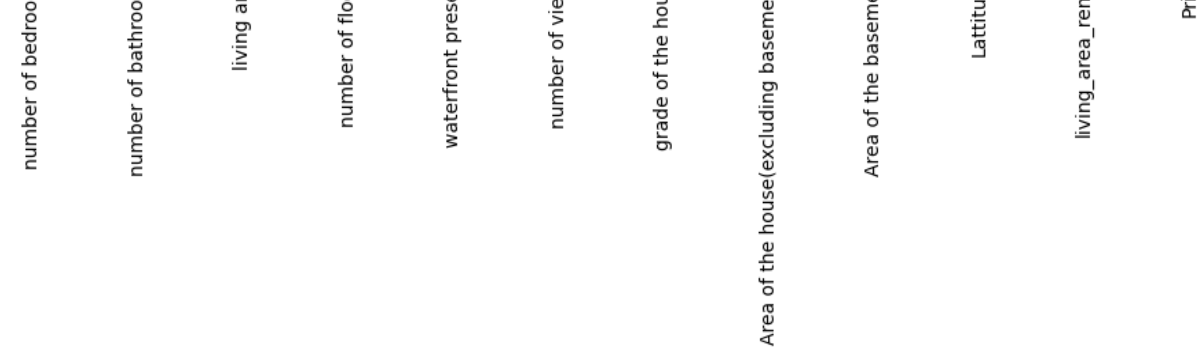
Columns like 'lot area','condition of the house','Built Year','lot_area_renov','Number of schools nearby','Distance from the airport','Longitude' contribute minimal to Price which is the Target variable. Hence it is removed before training

In [62]:
```
df1=df1.drop(['lot area','condition of the house','Built Year','lot_area_renov','Number of schools nearby','Distance from the airp
```

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



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

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

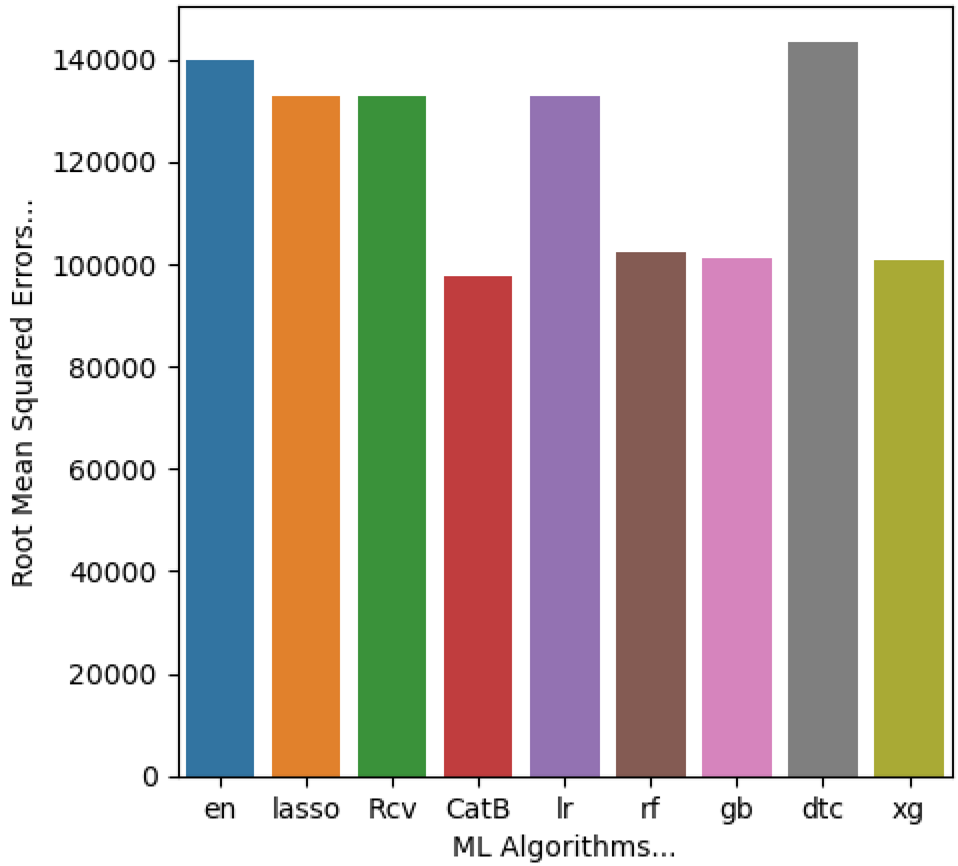
```
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_coordinate_descent.py:648: ConvergenceWarning: Objective did not conve
rge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Du
ality gap: 4.781e+12, tolerance: 5.929e+10
  coef_, l1_reg, l2_reg, X, y, max_iter, tol, rng, random, positive
Learning rate set to 0.05996
0:      learn: 221490.1496581   total: 61.4ms   remaining: 1m 1s
999:    learn: 77595.2298921    total: 2.85s    remaining: 0us
```

In [75]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
maes=[]
al=[]
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)
plt.show()
```



In [77]:
```
CatB = CatBoostRegressor(verbose=1000,eval_metric='RMSE')
rf = RandomForestRegressor()
gb = GradientBoostingRegressor()
xg = XGBRegressor()
lr=LinearRegression()

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

pipeline = make_pipeline(
    StandardScaler(),
    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
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 0.057883
0:	learn: 222546.8538661	total: 2.94ms	remaining: 2.94s
999:	learn: 75466.5961681	total: 2.51s	remaining: 0us
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 0.057883
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: 2.47ms	remaining: 2.47s
999:	learn: 74522.7989238	total: 2.51s	remaining: 0us
Root Mean Squared Error: 96981.0172
```

In [78]:
```
mean_squared_error(y_test,y_pred)**0.5
```

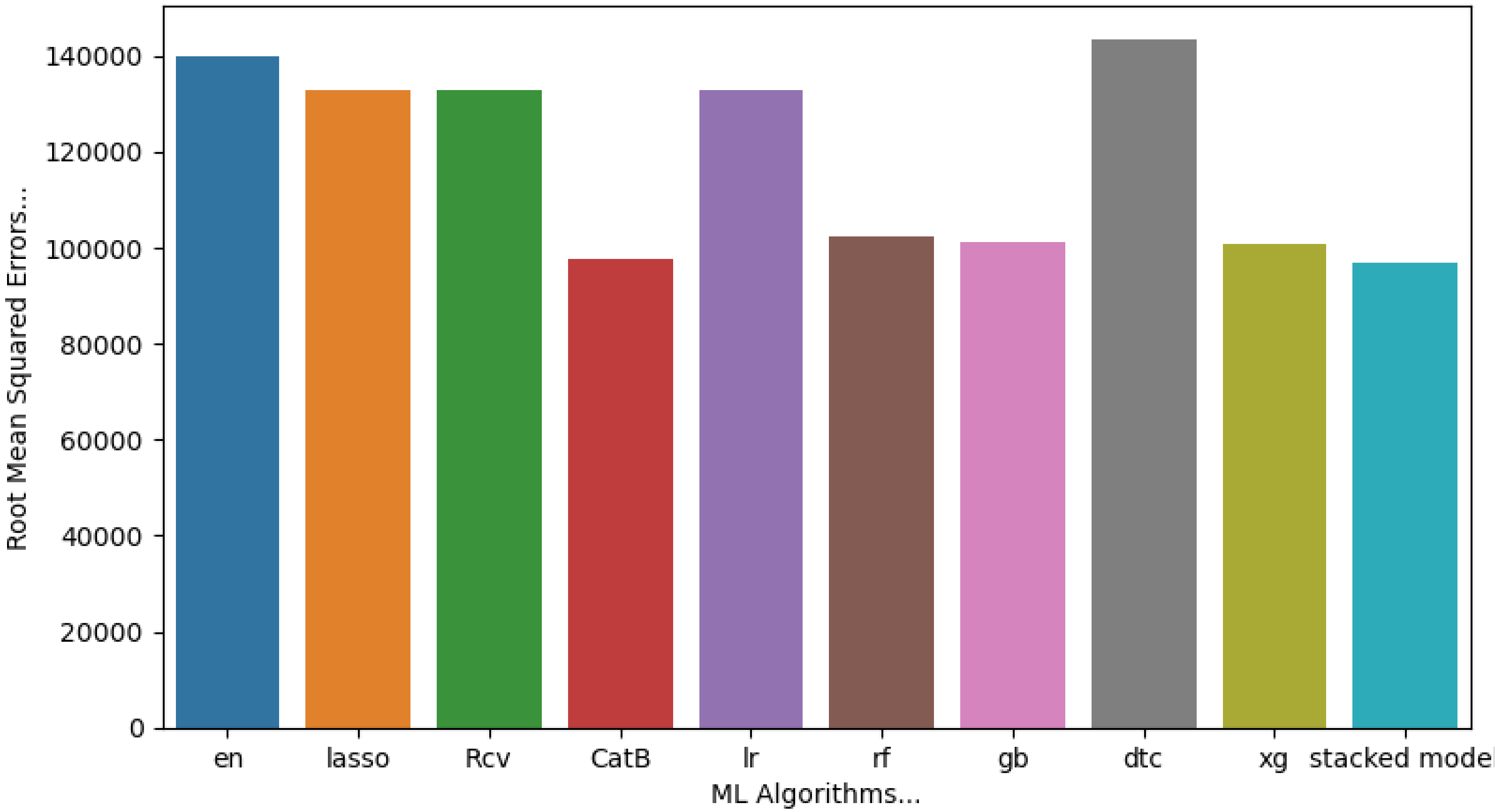
Out[78]:
```
96981.01722371299
```

In [79]:
```
al.append('stacked model')
maes.append(mean_squared_error(y_test,y_pred)**0.5)
```

In [80]:
```
for i in range(10):
    print("The RMSE of",al[i],'is',maes[i])
```

```
The RMSE of en is 140011.53917862213
The RMSE of lasso is 132916.1566456281
The RMSE of Rcv is 132918.333682342
The RMSE of CatB is 97508.34029611414
The RMSE of lr is 132952.7515959945
The RMSE of rf is 102292.3632979867
The RMSE of gb is 101056.41447857216
The RMSE of dtc is 143316.21683052482
The RMSE of xg is 100694.41040458805
The RMSE of stacked model is 96981.01722371299
```

In [81]:
```
plt.figure(figsize=(9,5))
plt.xlabel('ML Algorithms...')
plt.ylabel('Root Mean Squared Errors...')
ax=sns.barplot(x=al,y=maes)
plt.show()
```


Root Mean Squared Errors...
140000
120000
100000
80000
60000
40000
20000
0
en
lasso
Rcv
CatB
lr
rf
gb
dtc
xg
stacked model
ML Algorithms...