

NM DATA ANALYTICS ASSIGNMENT 3 - House Price dataset of India

DONE BY JENSON Y

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 Year
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	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

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	F
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921		0 1:
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909		0 1:
2	6762810998	5	2.75	2910	9480	1.5	0	0	3	8	...	1939		0 1:
3	6762812605	4	2.50	3310	42998	2.0	0	0	3	9	...	2001		0 1:
4	6762812919	3	2.00	2710	4500	1.5	0	0	4	8	...	1929		0 1:

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	F
14615	6762830250	2	1.5	1556	20000	1.0	0	0	4	7	...	1957		0 1:
14616	6762830339	3	2.0	1680	7000	1.5	0	0	4	7	...	1968		0 1:
14617	6762830618	2	1.0	1070	6120	1.0	0	0	3	6	...	1962		0 1:
14618	6762830709	4	1.0	1030	6621	1.0	0	0	4	6	...	1955		0 1:
14619	6762831463	3	1.0	900	4770	1.0	0	0	3	6	...	1969	200	0 1:

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  
Latitude                          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  Latitude          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	condi the
count	1.462000e+04	14620.000000	14620.000000	14620.000000	1.462000e+04	14620.000000	14620.000000	14620.000000	14620.000000
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.

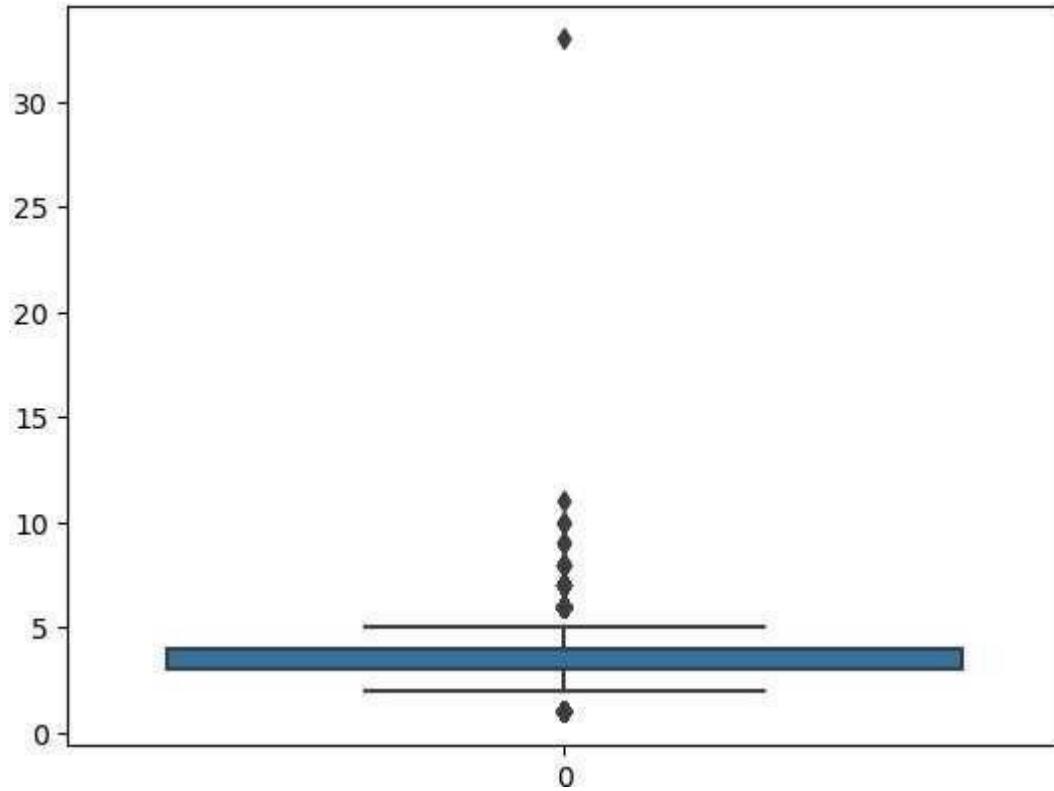
8 rows × 22 columns

UNIVARIATE ANALYSIS

Checking for outliers

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

Out[12]: <AxesSubplot:>



```
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))
```

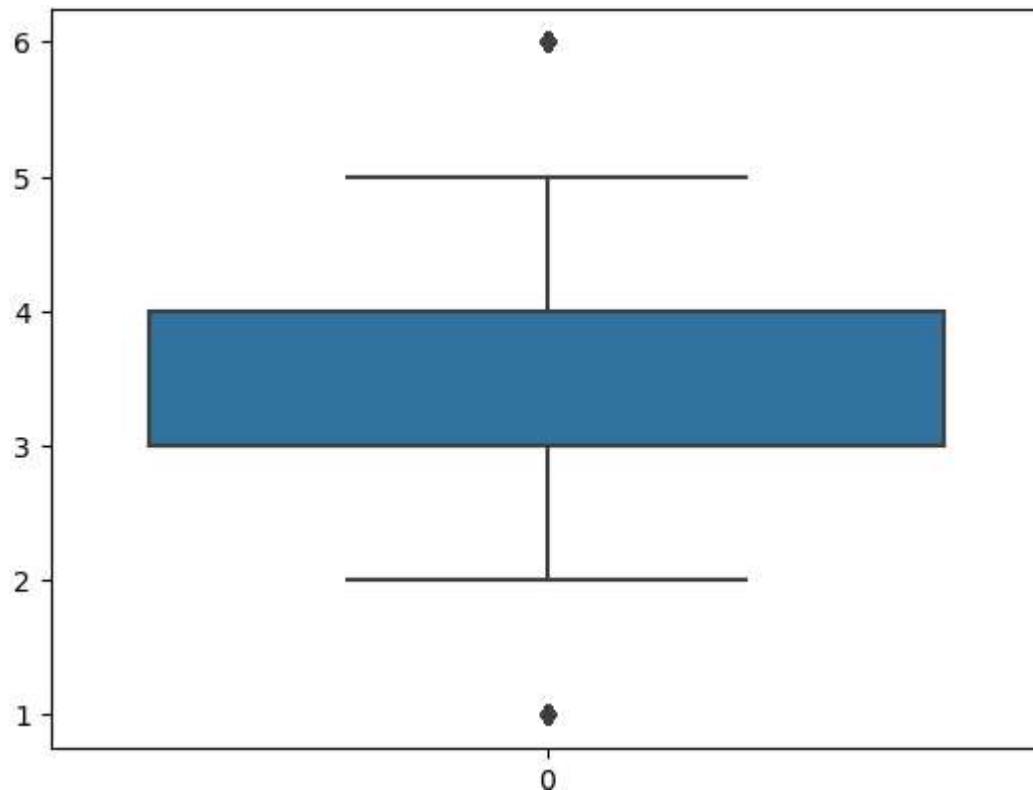
```
(array([], dtype=int64),)
```

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
```

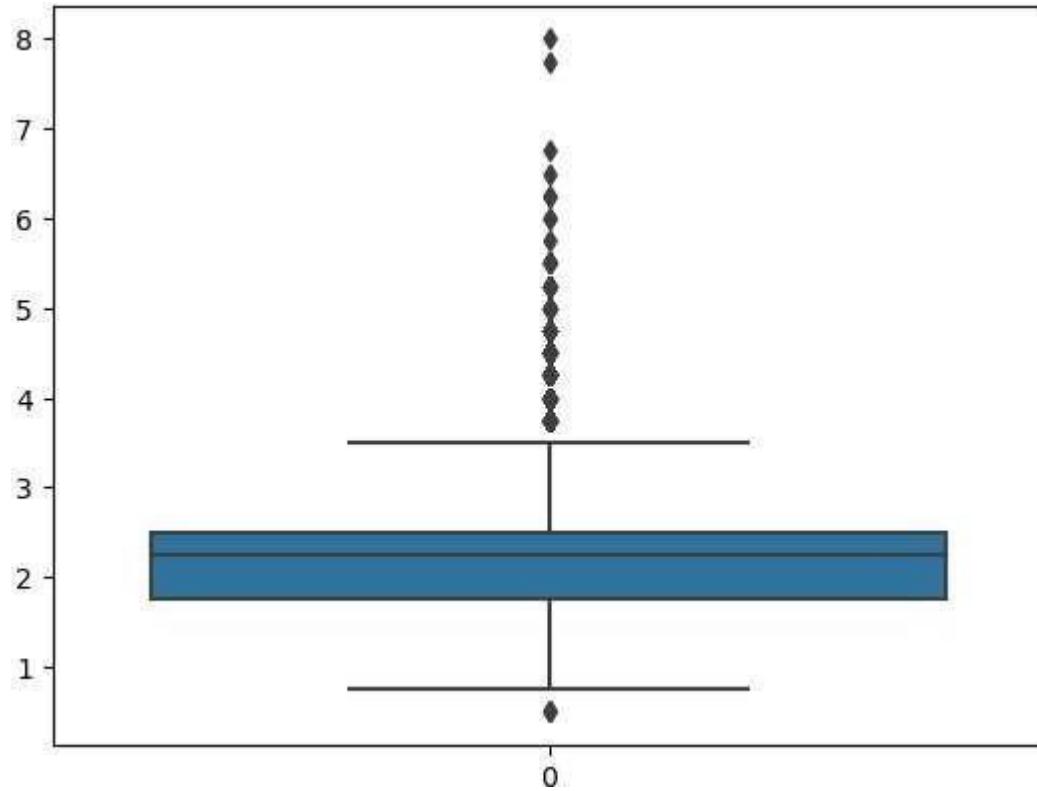

Out[18]:

	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
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	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

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
```

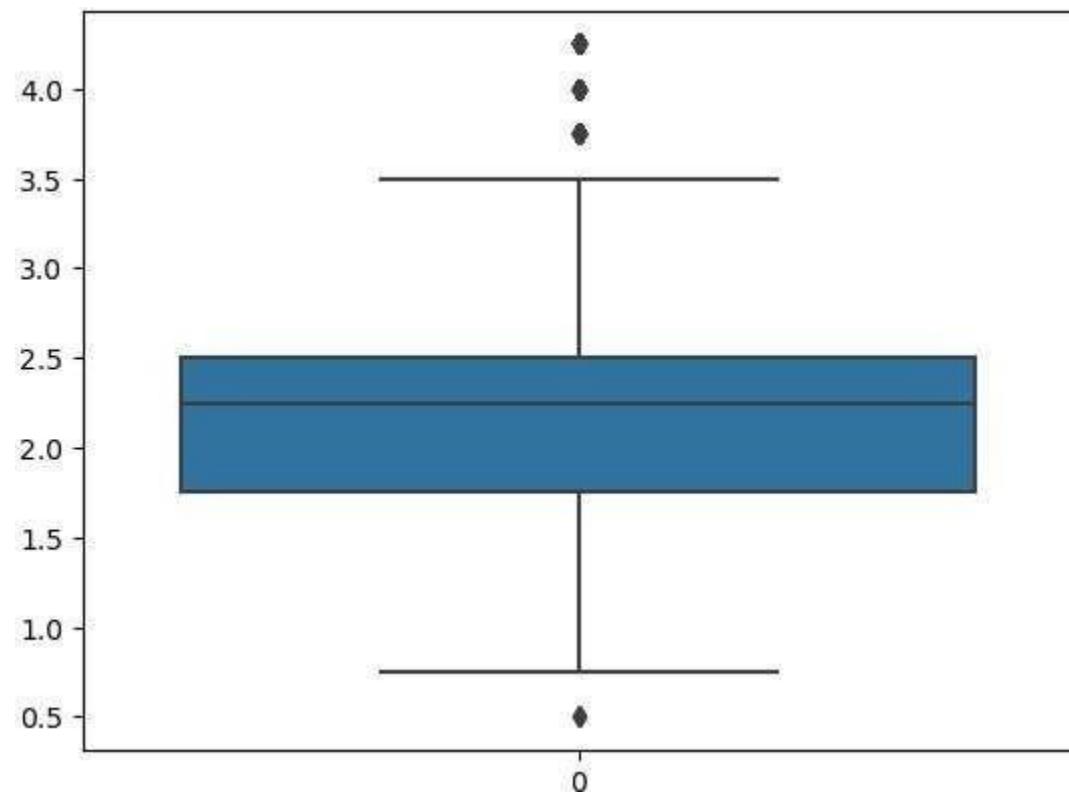
```
In [22]: print(np.where(z<-3))
```

```
(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]:

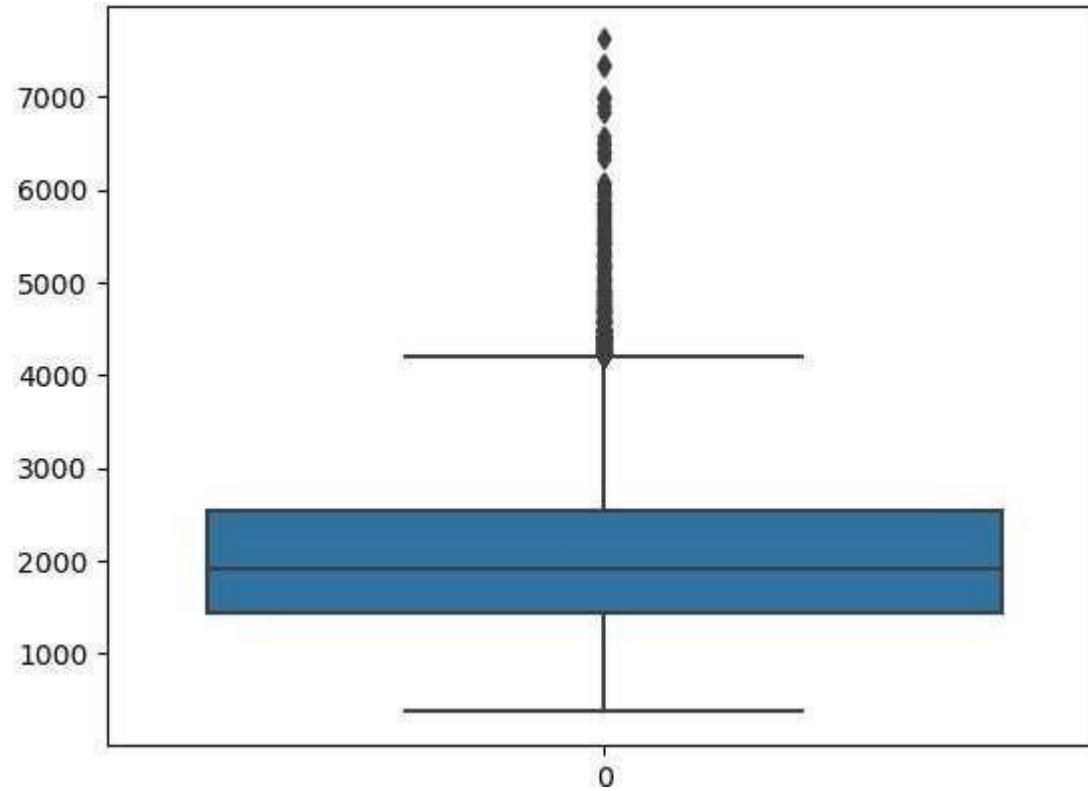
	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	...	Built Year	Renovation Year
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921	
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909	
2	6762810998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

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
```

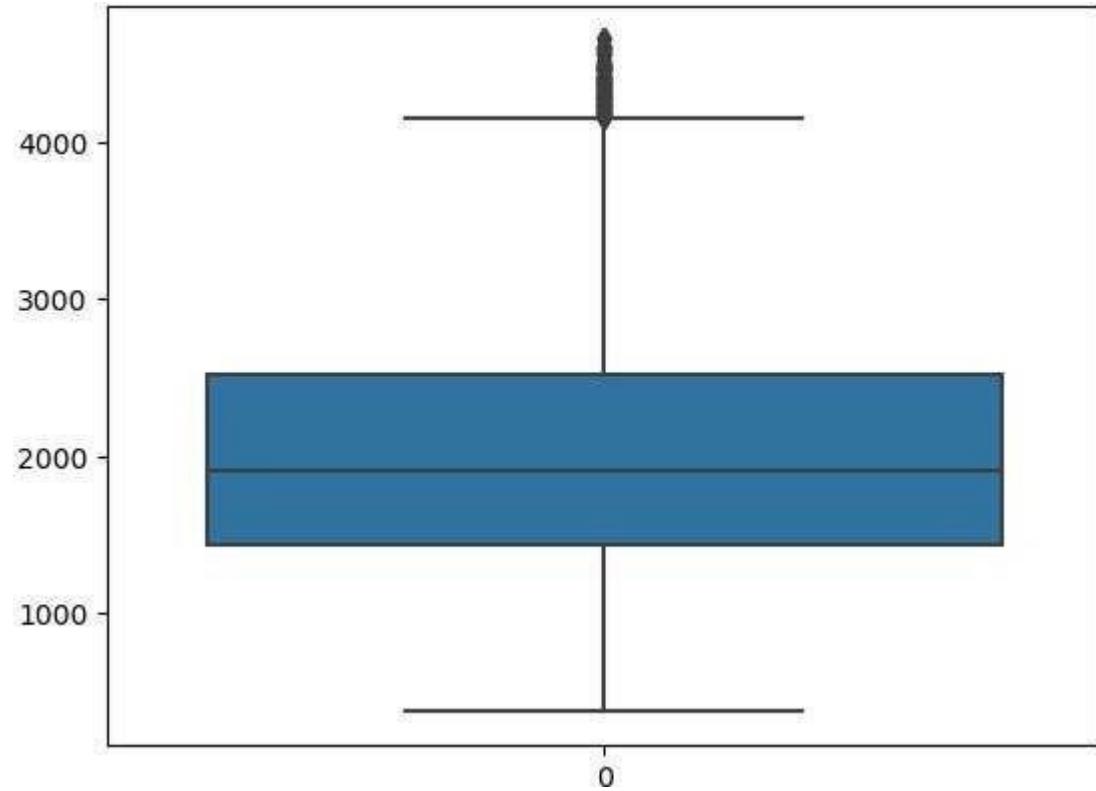
```
In [29]: len(np.where(z<-3)[0])
```

```
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']))
```

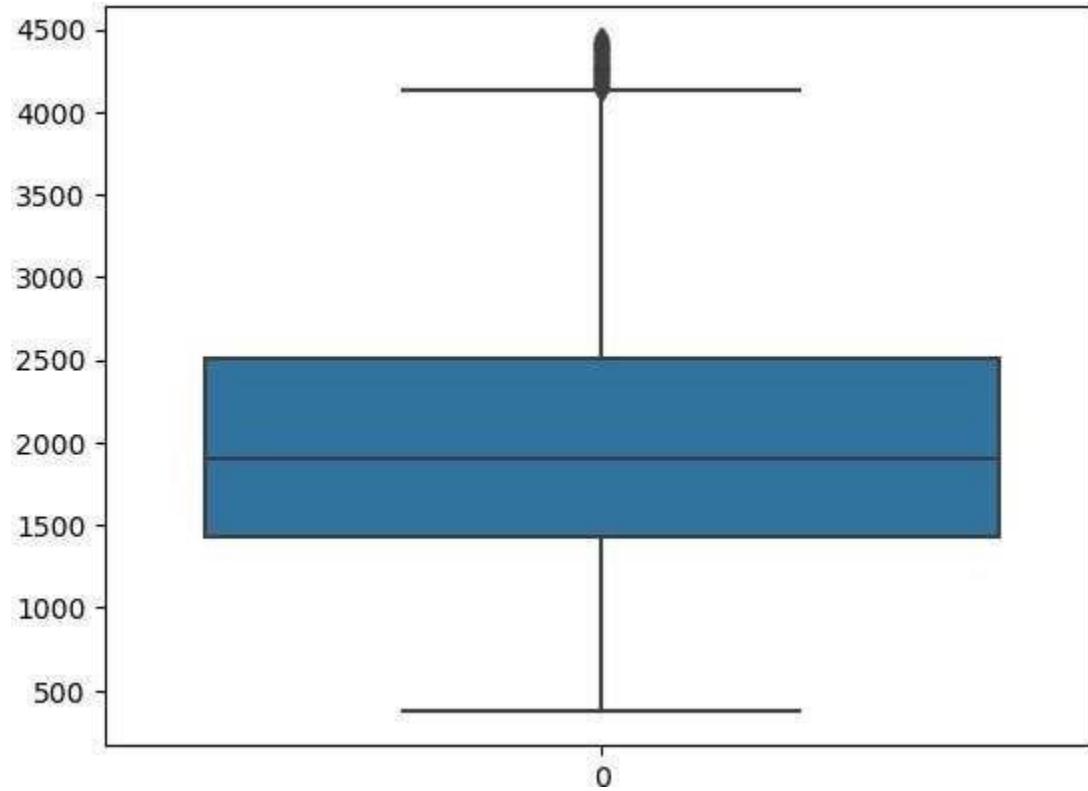
```
In [33]: len(np.where(z>3)[0])
```

```
Out[33]: 67
```

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

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

```
Out[35]: <AxesSubplot:>
```



In [36]: df1

Out[36]:

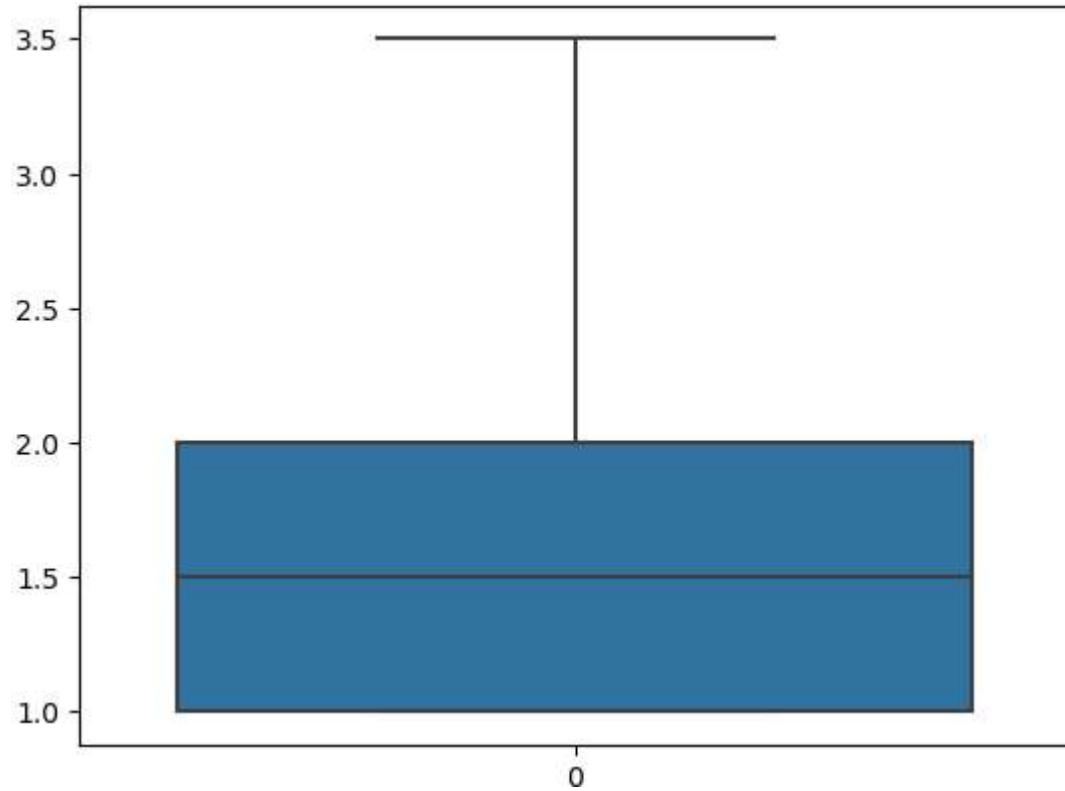
	id	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	... Built Year	Renovation Year
0	6762810145	5	2.50	3650	9050	2.0	0	4	5	10	...	1921
1	6762810635	4	2.50	2920	4000	1.5	0	0	5	8	...	1909
2	6762810998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

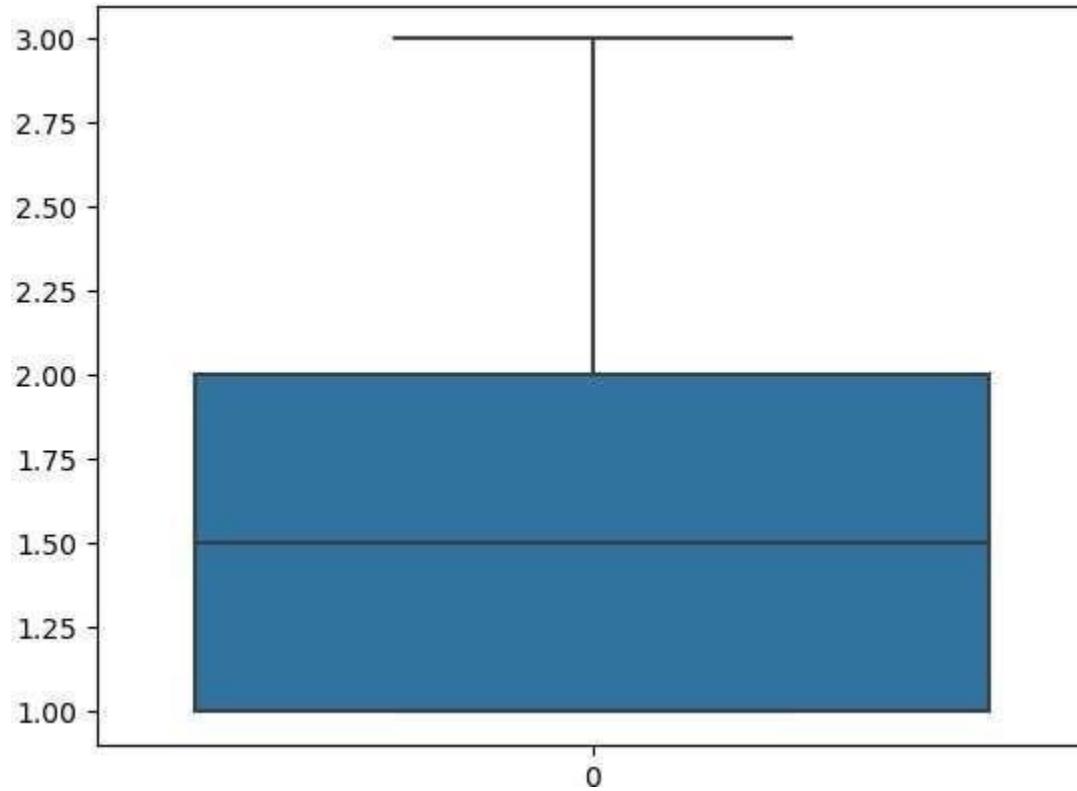
```
In [39]: len(np.where(z>3)[0])
```

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

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

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

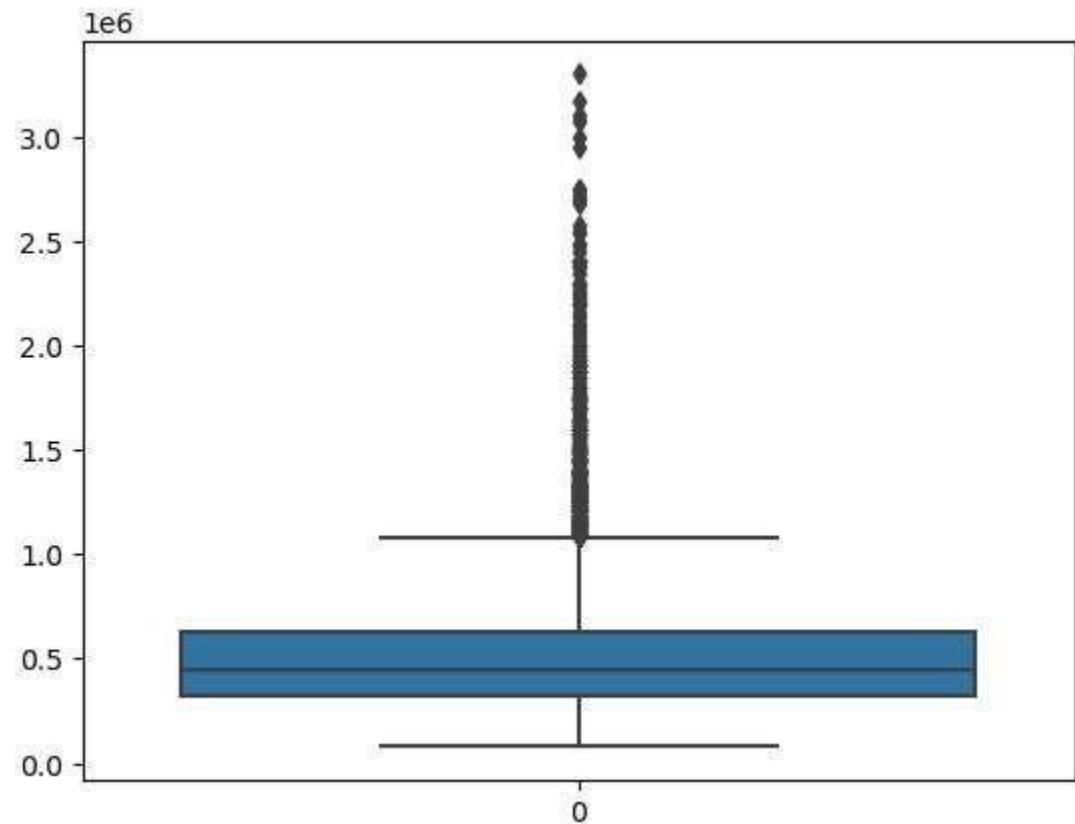
```
Out[41]: <AxesSubplot:>
```



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
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	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

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
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		5	3.25	3660	11995	2.0	0	2	3	10	...	0	2006
...
14615	6762830250		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	6	...	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

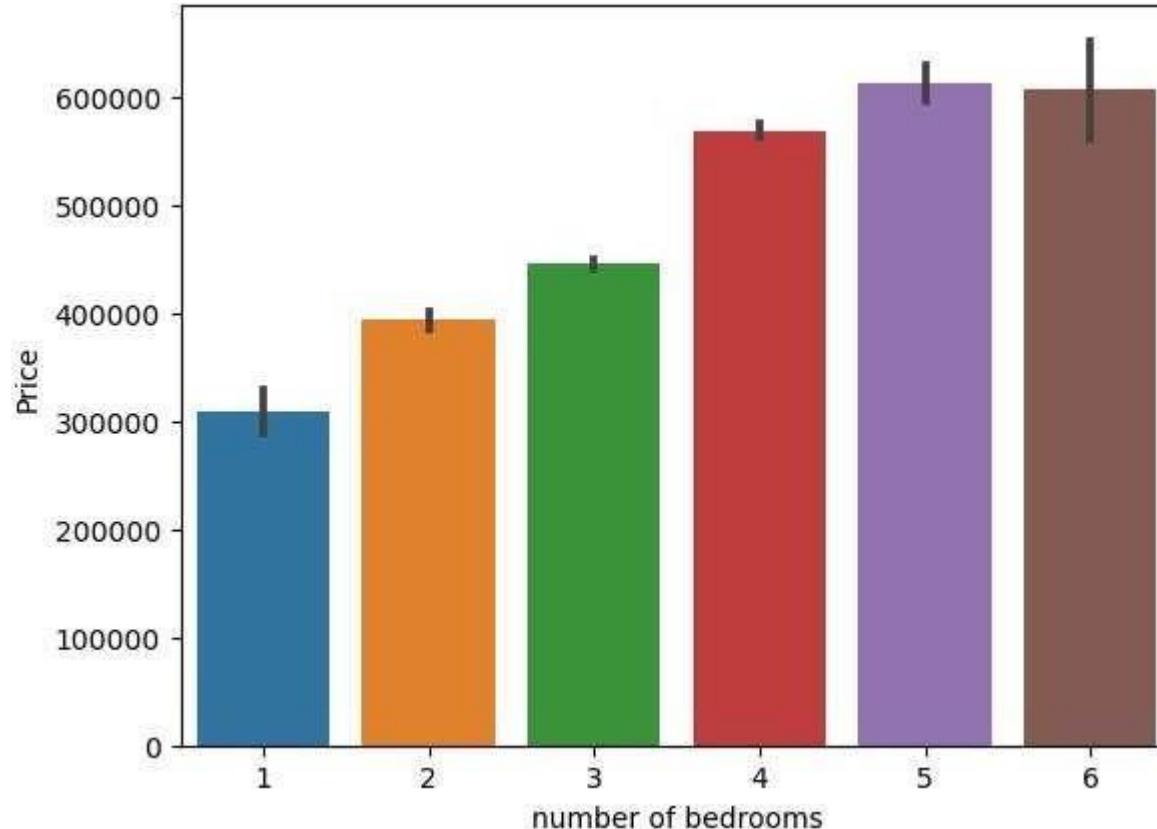
13982 rows × 21 columns

BI - VARIATE ANALYSIS

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')`

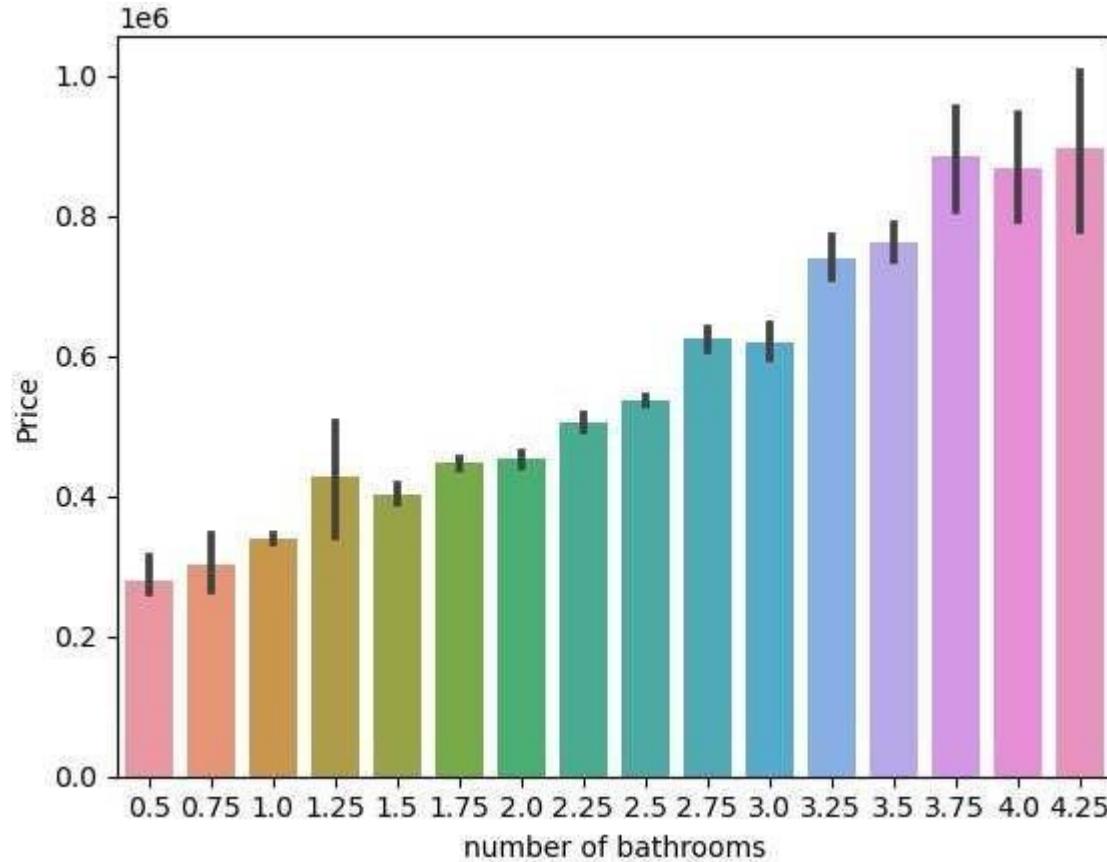
```
Out[49]: <AxesSubplot:xlabel='number of bedrooms', ylabel='Price'>
```



Clear indication of Price increasing with number of bedrooms

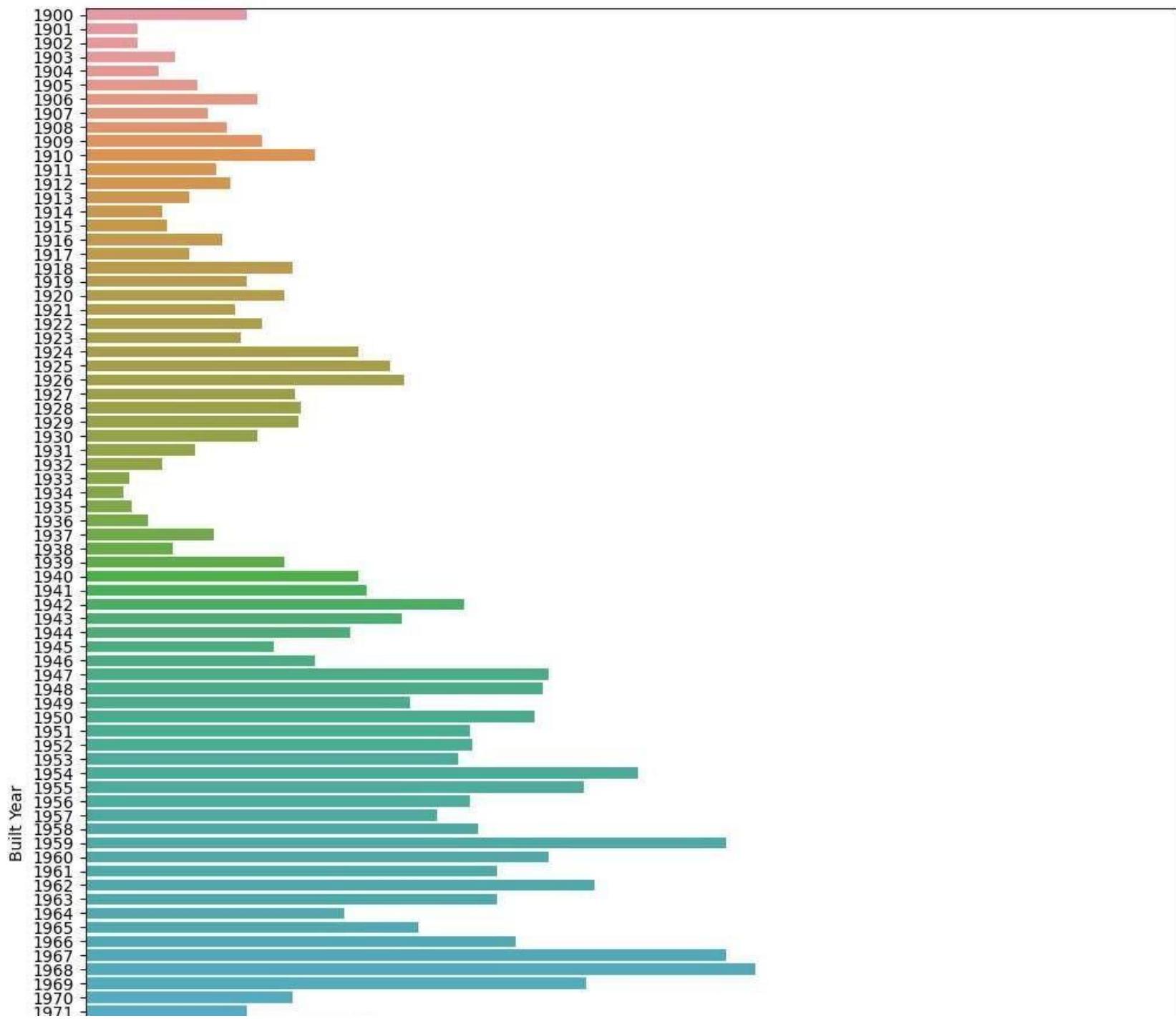
```
In [50]: sns.barplot(data=df1,x='number of bathrooms',y='Price')
```

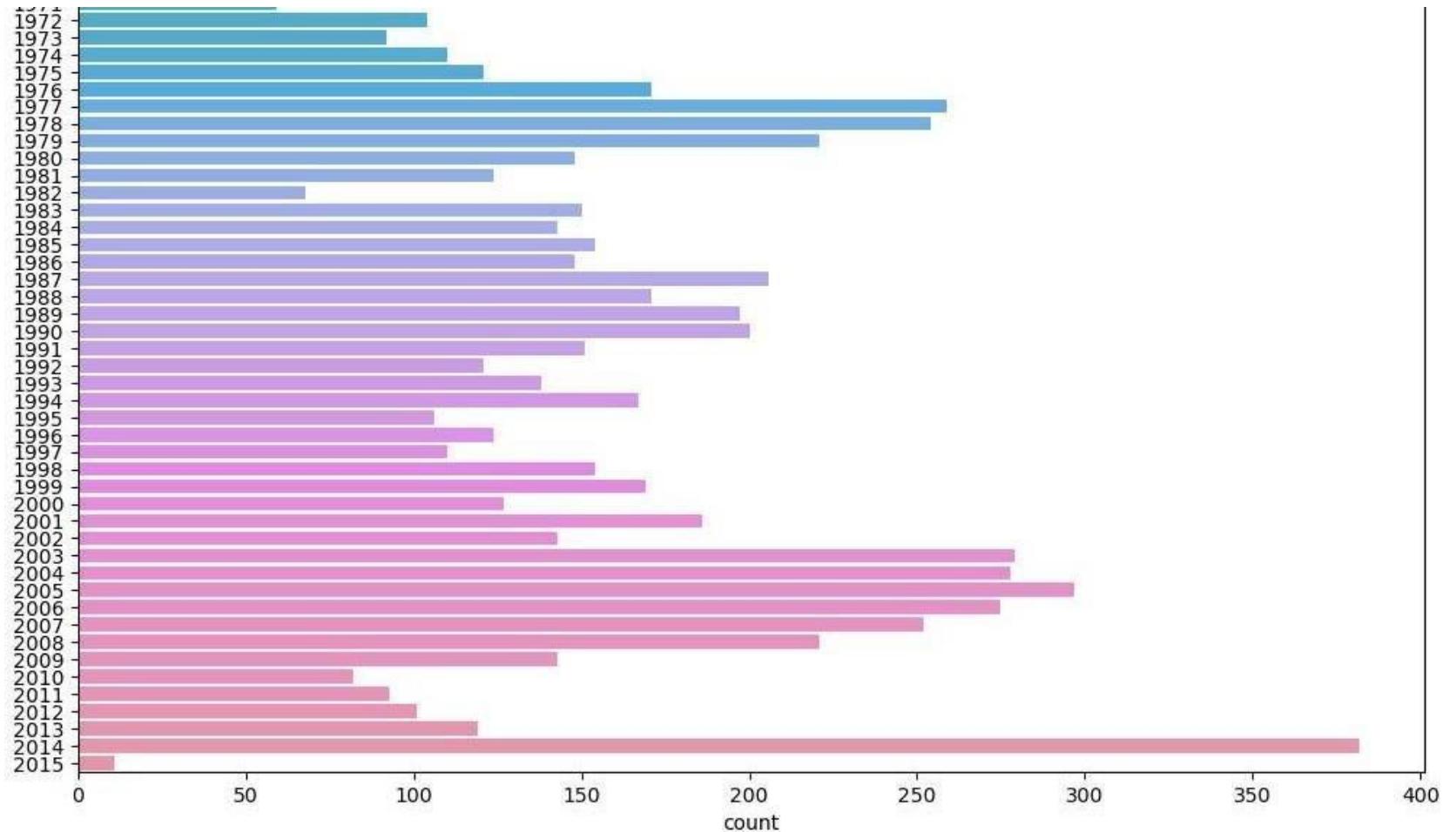
```
Out[50]: <AxesSubplot:xlabel='number of bathrooms', ylabel='Price'>
```



Clear indication of Price increasing with number of bathrooms

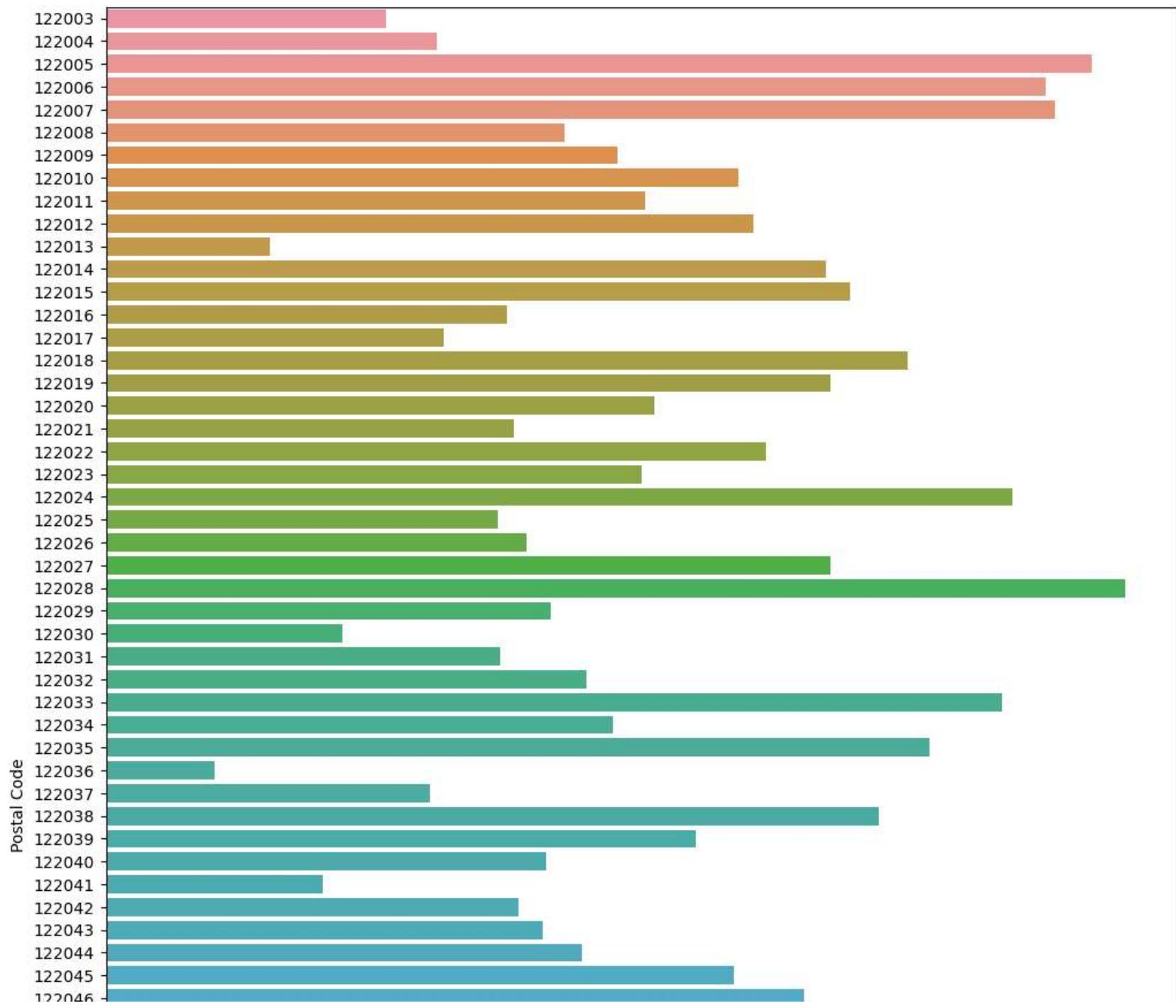
```
In [51]: plt.figure(figsize=(12,18))
sns.countplot(data=df1,y='Built Year')
plt.show()
```

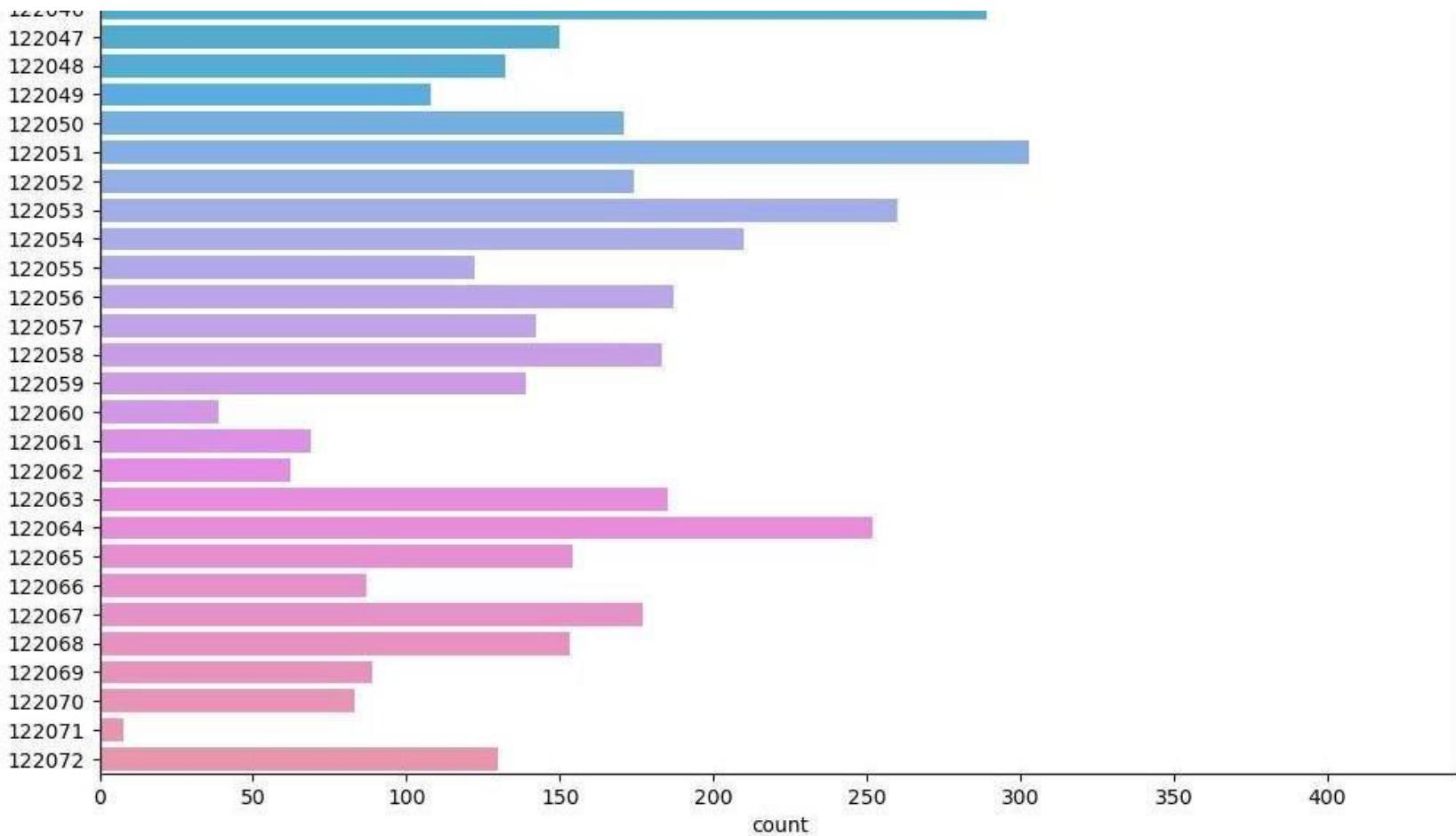




Most of the houses were listed for sale in 2017

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





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

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

```
Out[53]: 52.77583376963351
```

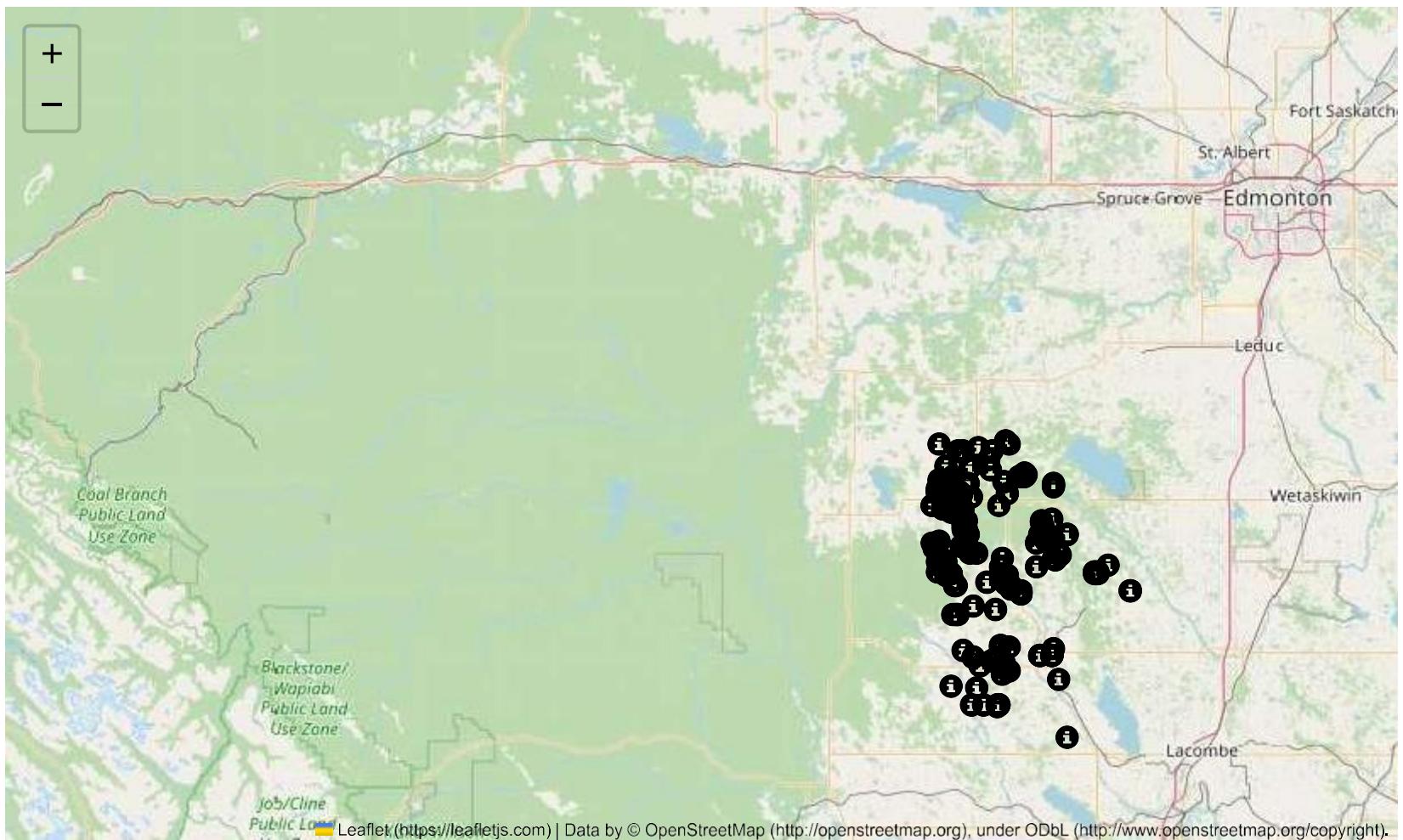
```
In [54]: df1[df1['Built Year']==2014]['Longitude'].mean()
```

```
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["Latitude"], location_info["Longitude"]], popup=location_info["Price"],icon=folium.
```

```
m
```



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

```
Out[56]: 52.77850305343512
```

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

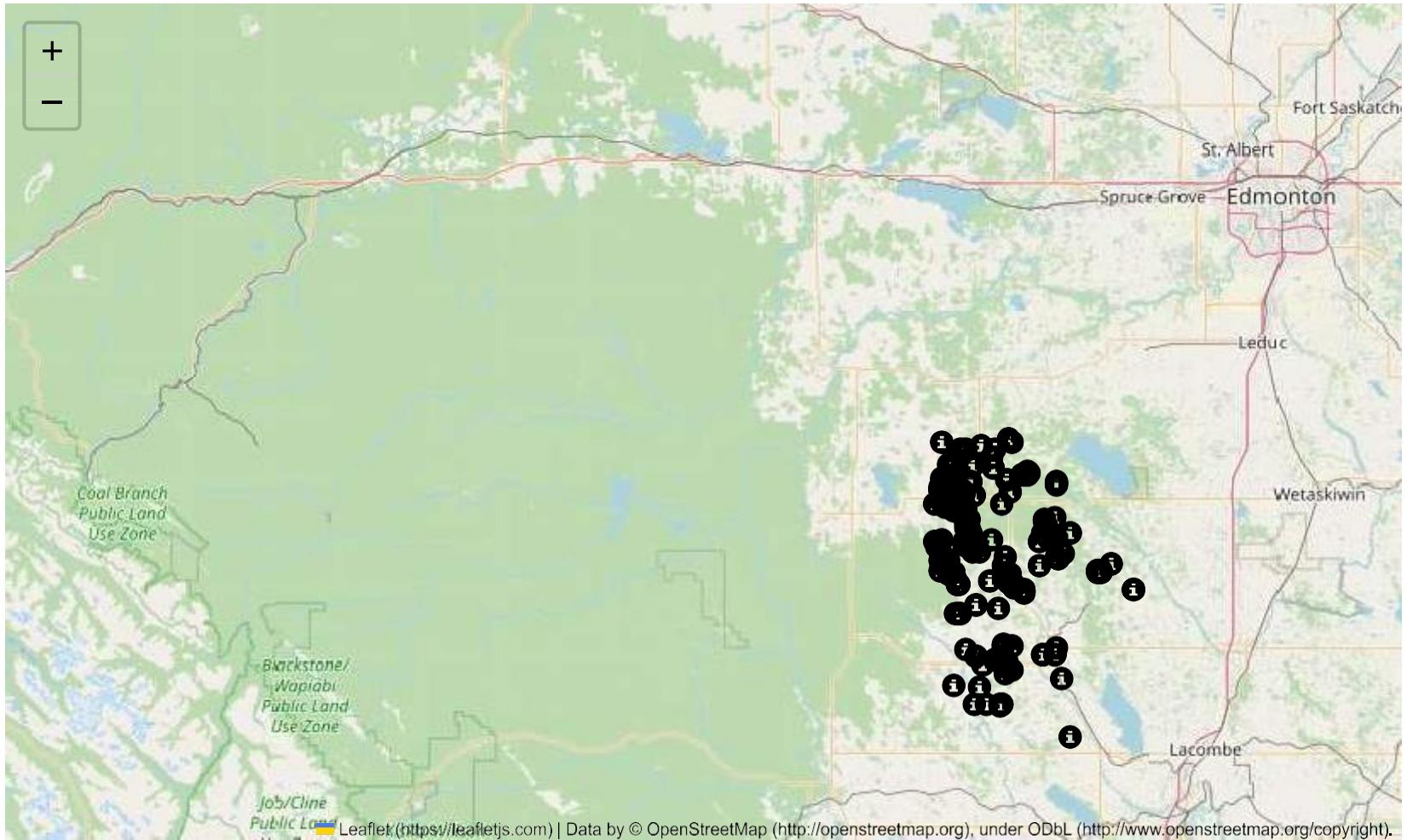
```
Out[57]: -114.39186768447837
```

```
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["Latitude"], location_info["Longitude"]], popup=location_info["Price"], icon=folium.
```

```
m
```

Out[58]:



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

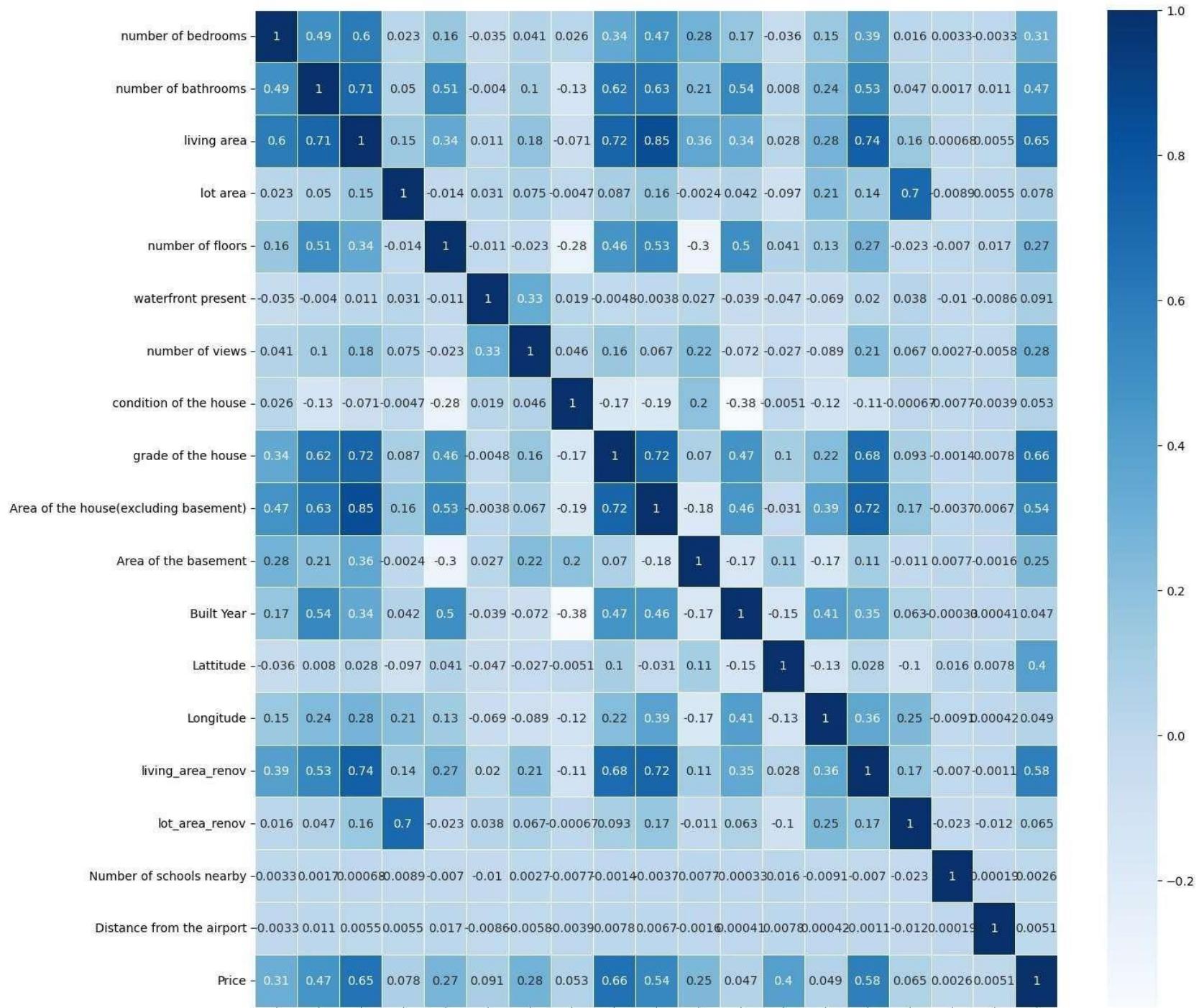
In [59]: `df1=df1.drop(['id'],axis=1)`

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

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

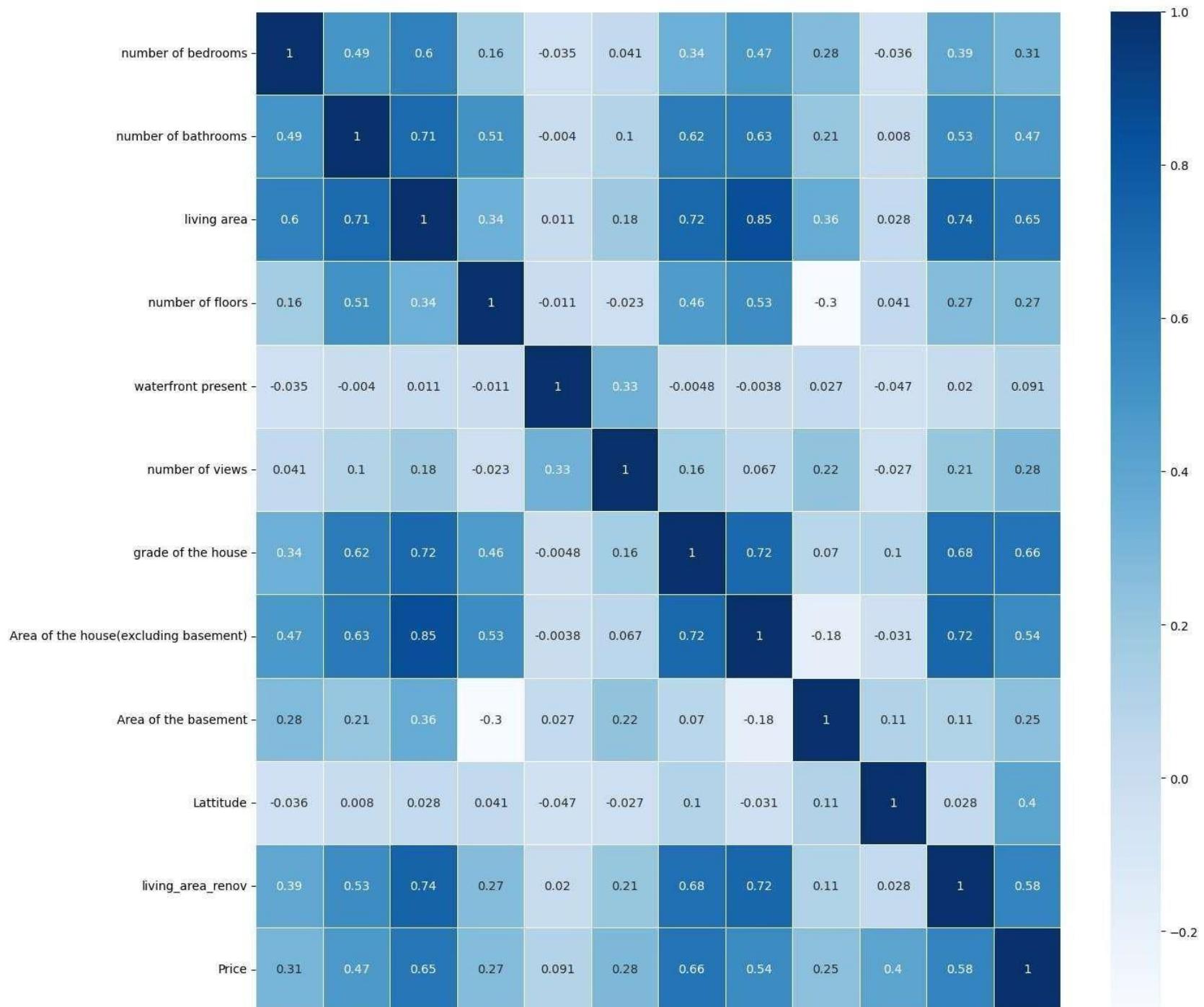


number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	grade of the house	Area of the house(excluding basement)	Area of the basement	Built Year	Latitude	Longitude	living_area_renov	lot_area_renov	Number of schools nearby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

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
```

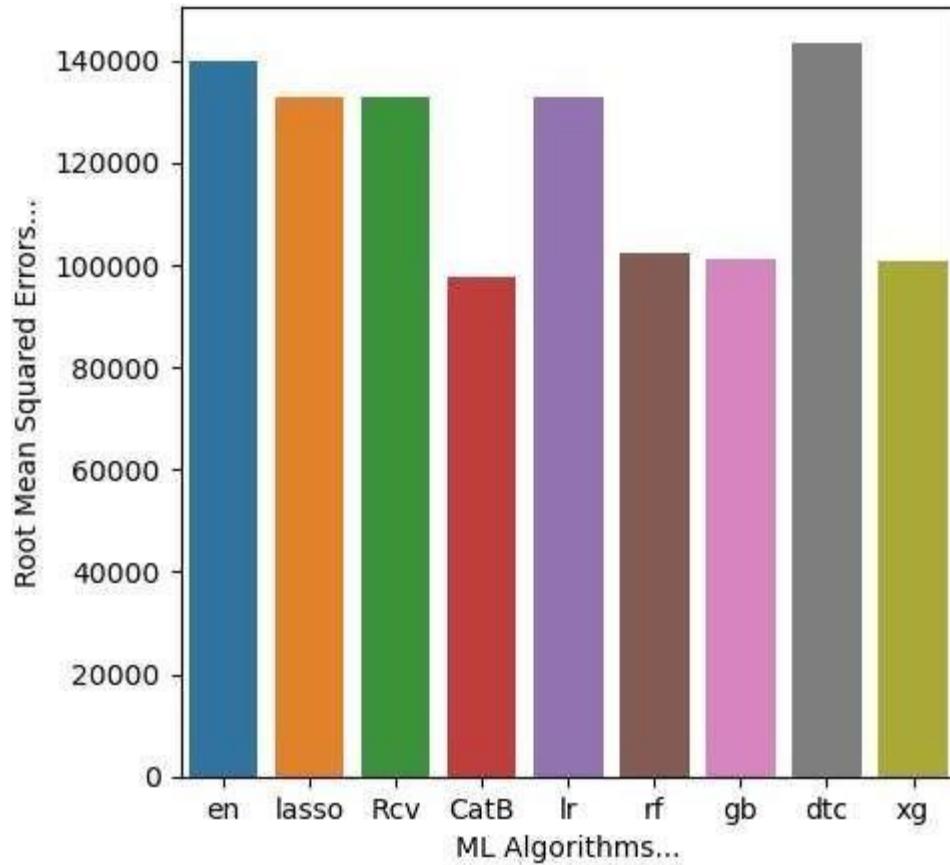
```
/opt/conda/lib/python3.7/site-packages/scikit-learn/_linear_model/_coordinate_descent.py:648: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.781e+12, tolerance: 5.929e+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=[]
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 66637.30790160663
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 [ ]: 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
```

```
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()
```