student

November 7, 2021

0.1 Final Project Submission

Please fill out: * Student name: Huseyin Caglar * Student pace: self paced / part time / full time * Scheduled project review date/time: * Instructor name: * Blog post URL:

0.2 Import Neccesary Libraries and Loading Data

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.express as px
import statsmodels.api as sm
import scipy.stats as stats
from scipy import stats
from statsmodels.formula.api import ols

from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import OneHotEncoder , StandardScaler
from sklearn.preprocessing import OrdinalEncoder
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing
from sklearn.preprocessing import quantile_transform
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
```

[2]:
```
cd data
```

```
C:\Users\AI\Desktop\Flatiron\Phase_2\dsc-phase-2-project\data
```

[3]:
```
ls
```

```
 Volume in drive C has no label.
 Volume Serial Number is A0B5-0BC1

 Directory of C:\Users\AI\Desktop\Flatiron\Phase_2\dsc-phase-2-project\data
```

```
09/26/2021  03:32 PM    <DIR>          .
09/26/2021  03:32 PM    <DIR>          ..
09/16/2021  04:04 PM             1,120 column_names.md
09/16/2021  04:04 PM         2,475,934 kc_house_data.csv
               2 File(s)      2,477,054 bytes
               2 Dir(s)  378,883,657,728 bytes free
```

[4]:
```python
df = pd.read_csv('kc_house_data.csv')
```

[5]:
```python
df.shape
```

[5]:
```
(21597, 21)
```

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

[6]:
```
           id        date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  10/13/2014  221900.0         3       1.00         1180
1  6414100192   12/9/2014  538000.0         3       2.25         2570
2  5631500400   2/25/2015  180000.0         2       1.00          770
3  2487200875   12/9/2014  604000.0         4       3.00         1960
4  1954400510   2/18/2015  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
0      5650     1.0         NaN   0.0  …      7        1180            0.0
1      7242     2.0         0.0   0.0  …      7        2170          400.0
2     10000     1.0         0.0   0.0  …      6         770            0.0
3      5000     1.0         0.0   0.0  …      7        1050          910.0
4      8080     1.0         0.0   0.0  …      8        1680            0.0

  yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0     1955           0.0    98178  47.5112 -122.257           1340        5650
1     1951        1991.0    98125  47.7210 -122.319           1690        7639
2     1933           NaN    98028  47.7379 -122.233           2720        8062
3     1965           0.0    98136  47.5208 -122.393           1360        5000
4     1987           0.0    98074  47.6168 -122.045           1800        7503

[5 rows x 21 columns]
```

0.3 Data Cleaning

[7]:
```python
#Looking for missing values.
df.isna().sum()
```

[7]:
```
id                   0
date                 0
price                0
bedrooms             0
```

```
bathrooms            0
sqft_living          0
sqft_lot             0
floors               0
waterfront        2376
view                63
condition            0
grade                0
sqft_above           0
sqft_basement        0
yr_built             0
yr_renovated      3842
zipcode              0
lat                  0
long                 0
sqft_living15        0
sqft_lot15           0
dtype: int64
```

[8]:
```
#Filling missing values.
df['yr_renovated']= df['yr_renovated'].fillna(0)
df['view'] = df['view'].fillna(0.0)
df['waterfront'] = df['waterfront'].fillna(0.0)
```

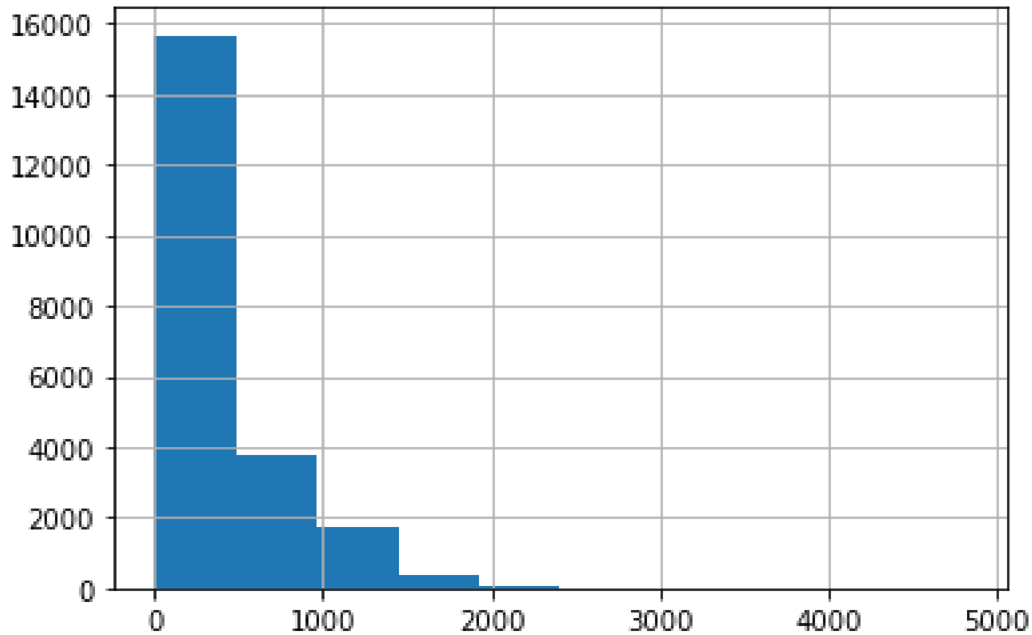
[9]:
```
#Dropping not usual columns.
df.drop(columns=['id','date','zipcode','lat','long'],inplace=True)
```

[10]:
```
#Cleaning sqft_basement column.
df.sqft_basement = df.sqft_basement.replace('?',0.0)
```

[11]:
```
df.sqft_basement = df.sqft_basement.astype(float)
```

[12]:
```
df.sqft_basement.hist()
```

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



[13]:
```
# Turning sqft_basement column to binary.
df.sqft_basement[df.sqft_basement!=0]=1
```

```
<ipython-input-13-543a2f2e22e8>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.sqft_basement[df.sqft_basement!=0]=1
```

0.4 Checking For Multicollinearity

[14]:
```
x = df.drop('price',axis=1)
```

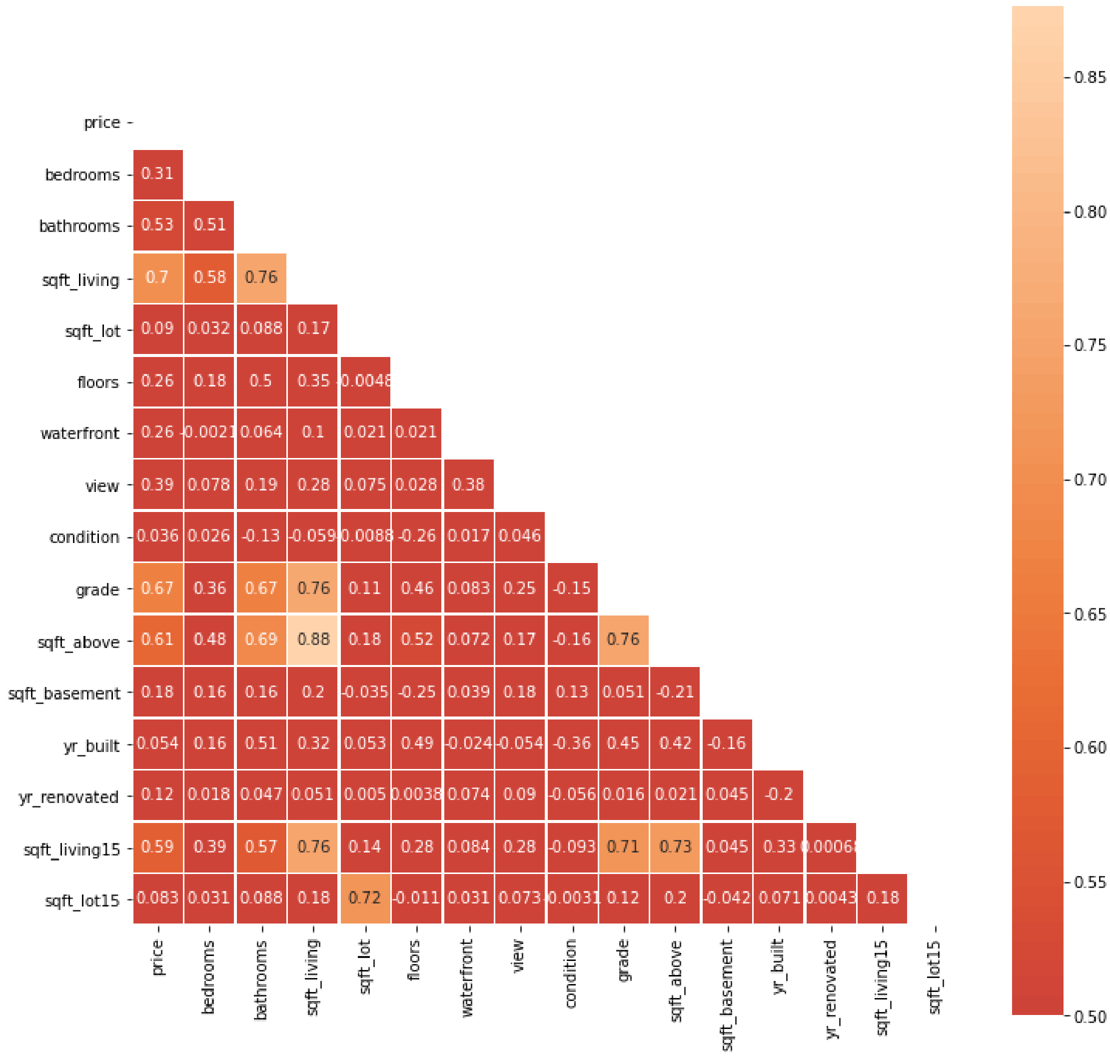
[15]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(x.values, i) for i in range(x.
↪shape[1])]

vif["features"] = x.columns

print(vif)
```

```
    VIF Factor       features
0    23.278227       bedrooms
1    25.361054      bathrooms
2    99.157874    sqft_living
```

```
3     2.362706       sqft_lot
4    16.477404         floors
5     1.185197     waterfront
6     1.483257           view
7    30.190016      condition
8   141.995085          grade
9    89.100513     sqft_above
10    5.155684  sqft_basement
11  128.138178       yr_built
12    1.053819   yr_renovated
13   26.433164  sqft_living15
14    2.574779     sqft_lot15
```

[16]:

```
plt.figure(figsize=(12,12))
corr = df.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

sns.heatmap(corr, mask=mask ,annot=True, center=0, vmin=.5, square=True,␣
 ↪linewidth=.5)
plt.show()
```



[17]:
```
#Dropping most multicollinearity columns.
df.drop(columns=['sqft_above','grade','bathrooms'],inplace=True)
```

[18]:
```
#Binning yr_built.
df.yr_built.describe()

built_bins=[1900,1930,1960,1990,2020]
labels=['1900_1930', '1930_1960','1960_1990','1990_2020']
bins_built= pd.cut(df['yr_built'], built_bins , labels=labels )
bins_built = bins_built.cat.as_unordered()
df.yr_built=bins_built
```

[19]:
```
#Cleaning columns for one hot coding.
df=df.round({'floors': 0})
```

```python
df.floors=df.floors.astype(int)
df.waterfront=df.waterfront.astype(int)
df.view=df.view.astype(int)

cat_list=['yr_built','condition','waterfront','floors','view',␣
↪'bedrooms','sqft_basement']
```

[20]:
```python
df_cat=pd.DataFrame()
for i in cat_list:
    df_cat[i]=df[i].astype('category')
```

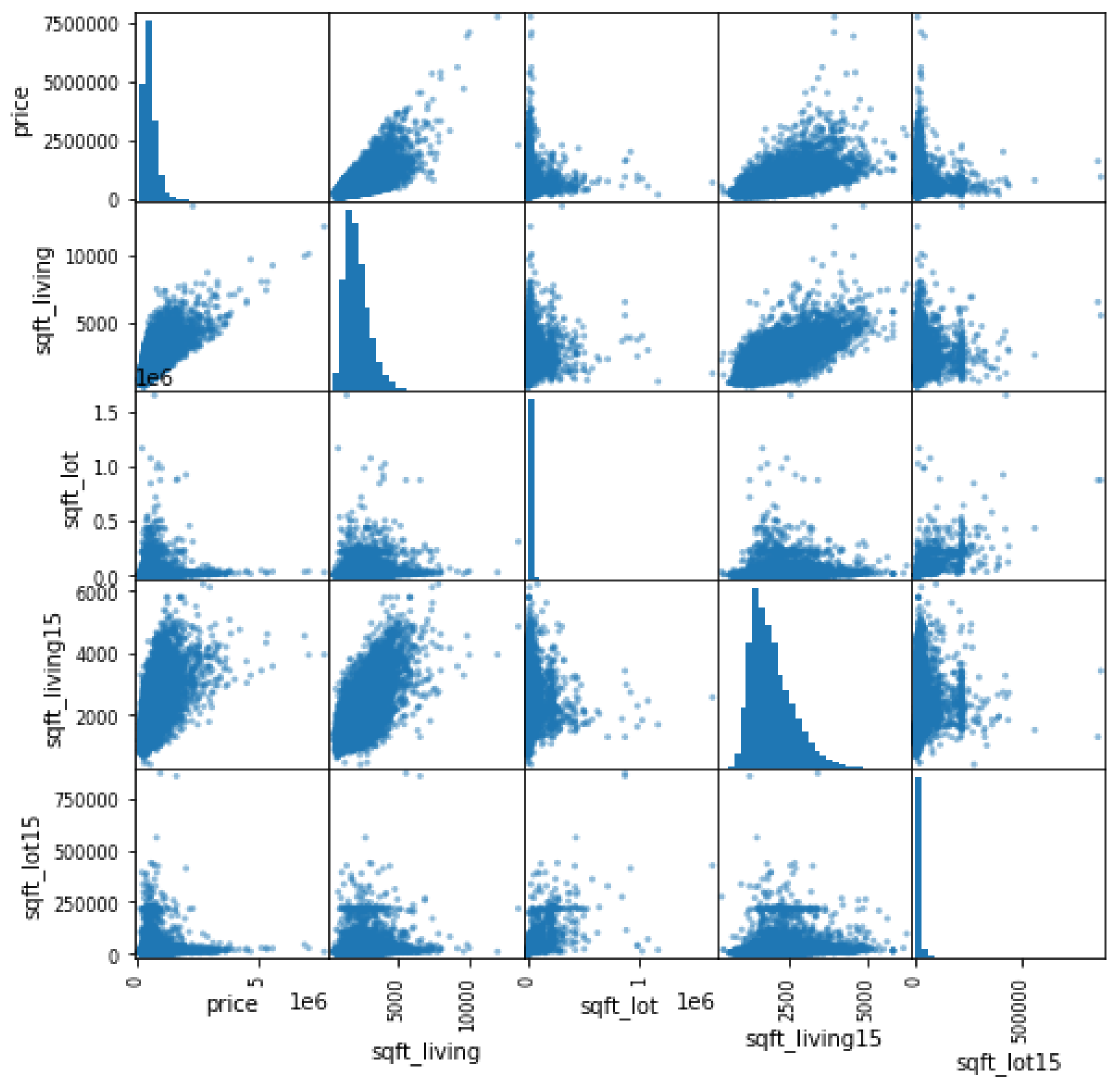
[21]:
```python
for i in cat_list:
    dummies=pd.get_dummies(df_cat[i],prefix=i, drop_first=True)
    df_cat=df_cat.join(dummies)
    df_cat.drop([i], axis=1, inplace=True)
```

[22]:
```python
df_cat.head()
```

[22]:
```
   yr_built_1930_1960  yr_built_1960_1990  yr_built_1990_2020  condition_2  \
0                   1                   0                   0            0
1                   1                   0                   0            0
2                   1                   0                   0            0
3                   0                   1                   0            0
4                   0                   1                   0            0

   condition_3  condition_4  condition_5  waterfront_1  floors_2  floors_3  \
0            1            0            0             0         0         0
1            1            0            0             0         1         0
2            1            0            0             0         0         0
3            0            0            1             0         0         0
4            1            0            0             0         0         0

   …  bedrooms_4  bedrooms_5  bedrooms_6  bedrooms_7  bedrooms_8  \
0  …           0           0           0           0           0
1  …           0           0           0           0           0
2  …           0           0           0           0           0
3  …           1           0           0           0           0
4  …           0           0           0           0           0

   bedrooms_9  bedrooms_10  bedrooms_11  bedrooms_33  sqft_basement_1.0
0           0            0            0            0                  0
1           0            0            0            0                  1
2           0            0            0            0                  0
3           0            0            0            0                  1
4           0            0            0            0                  0

[5 rows x 27 columns]
```

0.5 Standardization

[23]:
```
#Using quantile transformation to fix skewness and scaling them.
df_cont=df.loc[:
 ↪,['price','sqft_living','sqft_lot','sqft_living15','sqft_lot15']]
#g = sns.pairplot(df_cont)


pd.plotting.scatter_matrix(df_cont,hist_kwds={'bins':30},figsize=(8,8))
plt.show()
```

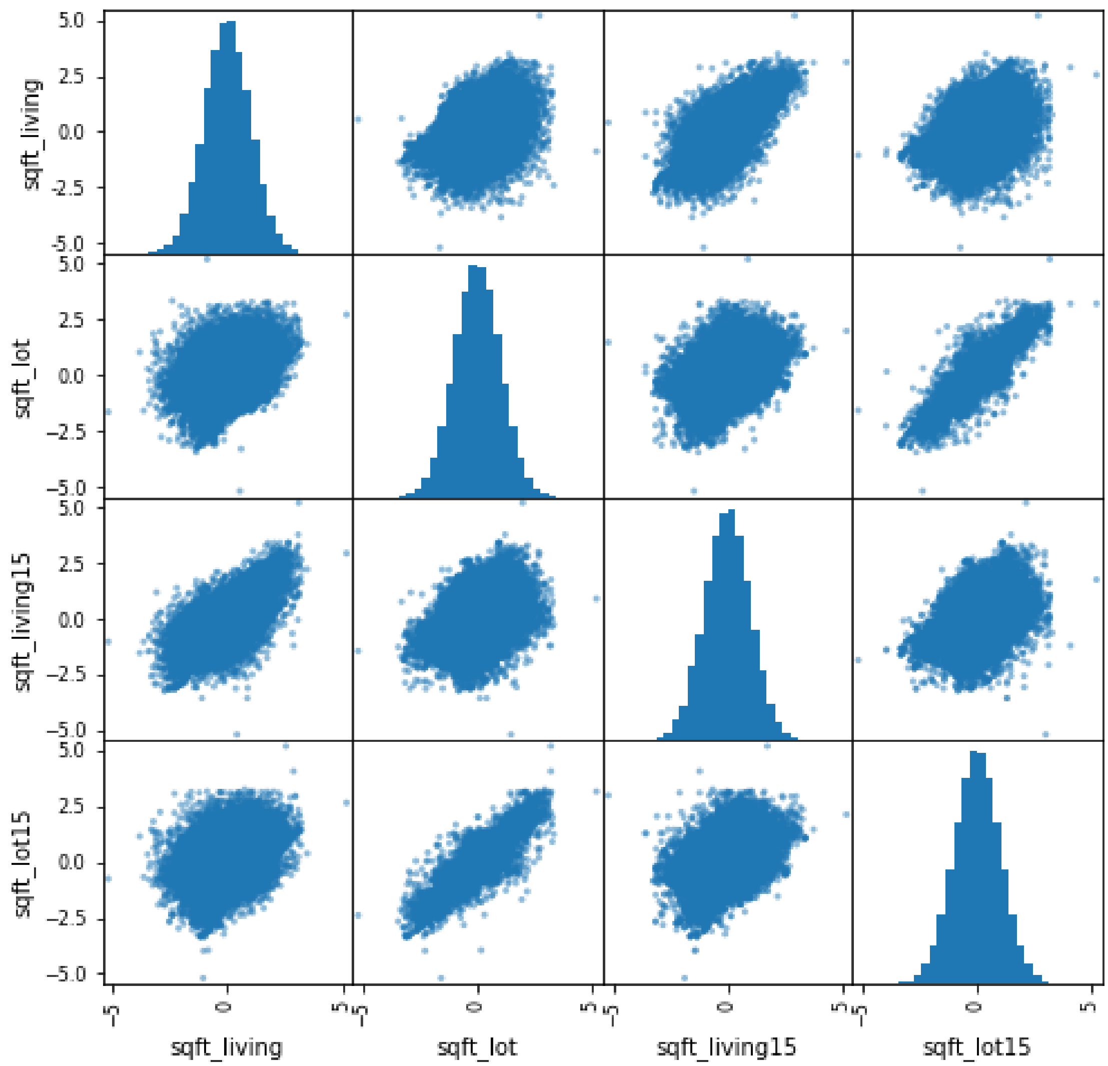


[24]:
```
#Standardizing.
standart = quantile_transform(df_cont[['sqft_living',
                                       'sqft_lot',
```

```
                                    'sqft_living15',
                                    'sqft_lot15']],
                            output_distribution = 'normal'
                             )

cont_std = pd.DataFrame(standart)
cont_std.columns=['sqft_living',
                  'sqft_lot',
                  'sqft_living15',
                  'sqft_lot15']
```

[25]:

```
pd.plotting.scatter_matrix(cont_std,hist_kwds={'bins':30},figsize=(8,8))
plt.show()
```



[26]:
```
# Features now normally distributed.
```

[27]:
```
#ss = StandardScaler()
#scaled = ss.fit_transform(cont_std)
#scaled = pd.DataFrame(scaled)
#scaled
```

0.6 Modeling

[32]:
```
df_final=pd.concat([cont_std, df_cat ,df.price], axis=1)
```

[33]:
```
#Looking final missing values before modeling.
df_final.isna().sum()
```

[33]:
```
sqft_living          0
sqft_lot             0
sqft_living15        0
sqft_lot15           0
yr_built_1930_1960   0
yr_built_1960_1990   0
yr_built_1990_2020   0
condition_2          0
condition_3          0
condition_4          0
condition_5          0
waterfront_1         0
floors_2             0
floors_3             0
floors_4             0
view_1               0
view_2               0
view_3               0
view_4               0
bedrooms_2           0
bedrooms_3           0
bedrooms_4           0
bedrooms_5           0
bedrooms_6           0
bedrooms_7           0
bedrooms_8           0
bedrooms_9           0
bedrooms_10          0
bedrooms_11          0
bedrooms_33          0
sqft_basement_1.0    0
price                0
dtype: int64
```

[34]:
```
df_final
```

[34]:
```
       sqft_living  sqft_lot  sqft_living15  sqft_lot15  yr_built_1930_1960  \
0        -1.109378 -0.517790      -1.037937   -0.517790                   1
1         0.694311 -0.115464      -0.247134    0.007616                   1
2        -2.131682  0.562796       1.064091    0.154186                   1
3         0.051460 -0.718462      -0.985610   -0.744694                   0
4        -0.293986  0.128003      -0.062770   -0.040336                   0
…              …         …            …          …                  …
21592    -0.509202 -2.132221      -0.573115   -1.831578                   0
21593     0.436240 -0.475178      -0.012546   -0.165095                   0
21594    -1.428482 -1.837261      -2.043115   -1.644085                   0
21595    -0.406079 -1.515547      -0.862544   -2.068024                   0
21596    -1.428482 -2.220813      -2.043115   -1.954804                   0

       yr_built_1960_1990  yr_built_1990_2020  condition_2  condition_3  \
0                       0                   0            0            1
1                       0                   0            0            1
2                       0                   0            0            1
3                       1                   0            0            0
4                       1                   0            0            1
…                     …                   …            …            …
21592                   0                   1            0            1
21593                   0                   1            0            1
21594                   0                   1            0            1
21595                   0                   1            0            1
21596                   0                   1            0            1

       condition_4  …  bedrooms_5  bedrooms_6  bedrooms_7  bedrooms_8  \
0                0  …           0           0           0           0
1                0  …           0           0           0           0
2                0  …           0           0           0           0
3                0  …           0           0           0           0
4                0  …           0           0           0           0
…              …  …         …           …           …           …
21592            0  …           0           0           0           0
21593            0  …           0           0           0           0
21594            0  …           0           0           0           0
21595            0  …           0           0           0           0
21596            0  …           0           0           0           0

       bedrooms_9  bedrooms_10  bedrooms_11  bedrooms_33  sqft_basement_1.0  \
0               0            0            0            0                  0
1               0            0            0            0                  1
2               0            0            0            0                  0
3               0            0            0            0                  1
4               0            0            0            0                  0
```

```
…           …          …          …          …             …
21592           0          0          0          0                  0
21593           0          0          0          0                  0
21594           0          0          0          0                  0
21595           0          0          0          0                  0
21596           0          0          0          0                  0

          price
0      221900.0
1      538000.0
2      180000.0
3      604000.0
4      510000.0
…           …
21592  360000.0
21593  400000.0
21594  402101.0
21595  400000.0
21596  325000.0

[21597 rows x 32 columns]
```

0.7 Train Test Split

[35]:
```python
y = df_final['price']
X= df_final.drop('price',axis=1)
```

[36]:
```python
X_train , X_test , y_train , y_test = train_test_split(X,y,random_state = 200)
X_train.shape , X_test.shape , y_train.shape , y_test.shape
```

[36]:
```
((16197, 31), (5400, 31), (16197,), (5400,))
```

[37]:
```python
model = sm.OLS(y_train, X_train).fit()
model.summary()
```

[37]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:                  price   R-squared (uncentered):
0.846
Model:                            OLS   Adj. R-squared (uncentered):
0.846
Method:                 Least Squares   F-statistic:
2866.
Date:                Sun, 07 Nov 2021   Prob (F-statistic):
```

```
0.00
Time:                        11:14:01   Log-Likelihood:
-2.2468e+05
No. Observations:               16197   AIC:
4.494e+05
Df Residuals:                   16166   BIC:
4.497e+05
Df Model:                          31
Covariance Type:            nonrobust
================================================================================
======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
sqft_living         1.941e+05   4156.881     46.689      0.000    1.86e+05
2.02e+05
sqft_lot           -1.189e+04   5447.142     -2.183      0.029   -2.26e+04
-1216.538
sqft_living15       7.906e+04   3232.187     24.461      0.000    7.27e+04
8.54e+04
sqft_lot15         -7700.0396   5379.862     -1.431      0.152   -1.82e+04
2845.086
yr_built_1930_1960 -7.218e+04   7690.198     -9.386      0.000   -8.73e+04
-5.71e+04
yr_built_1960_1990 -1.783e+05   7635.611    -23.347      0.000   -1.93e+05
-1.63e+05
yr_built_1990_2020 -1.868e+05   7933.696    -23.544      0.000   -2.02e+05
-1.71e+05
condition_2         6.806e+05   3.08e+04     22.102      0.000     6.2e+05
7.41e+05
condition_3         7.081e+05   2.16e+04     32.709      0.000    6.66e+05
7.51e+05
condition_4         7.225e+05   2.18e+04     33.203      0.000     6.8e+05
7.65e+05
condition_5         7.617e+05   2.25e+04     33.859      0.000    7.18e+05
8.06e+05
waterfront_1         5.52e+05   2.96e+04     18.663      0.000    4.94e+05
6.1e+05
floors_2            2.656e+04   5844.280      4.545      0.000    1.51e+04
3.8e+04
floors_3            1.802e+05   1.42e+04     12.695      0.000    1.52e+05
2.08e+05
floors_4            1.641e+05   1.15e+05      1.428      0.153   -6.12e+04
3.89e+05
view_1               1.58e+05   1.65e+04      9.599      0.000    1.26e+05
1.9e+05
```

```
view_2               1.002e+05   9954.529     10.066      0.000     8.07e+04
1.2e+05
view_3               1.996e+05   1.37e+04     14.583      0.000     1.73e+05
2.26e+05
view_4               3.633e+05   2.06e+04     17.636      0.000     3.23e+05
4.04e+05
bedrooms_2           2.164e+04   2.09e+04      1.035      0.301    -1.94e+04
6.26e+04
bedrooms_3          -8.437e+04   2.09e+04     -4.046      0.000    -1.25e+05
-4.35e+04
bedrooms_4          -1.181e+05   2.15e+04     -5.504      0.000     -1.6e+05
-7.61e+04
bedrooms_5          -8.359e+04   2.28e+04     -3.671      0.000    -1.28e+05
-3.9e+04
bedrooms_6           -3.75e+04   2.88e+04     -1.304      0.192    -9.39e+04
1.89e+04
bedrooms_7          -9.805e+04   5.34e+04     -1.836      0.066    -2.03e+05
6652.955
bedrooms_8          -7.512e+04   8.41e+04     -0.894      0.372     -2.4e+05
8.97e+04
bedrooms_9          -1.861e+05    1.5e+05     -1.242      0.214     -4.8e+05
1.07e+05
bedrooms_10         -1.997e+05    1.5e+05     -1.335      0.182    -4.93e+05
9.36e+04
bedrooms_11         -3.707e+05   2.57e+05     -1.441      0.150    -8.75e+05
1.34e+05
bedrooms_33          9.552e+04   2.57e+05      0.371      0.710    -4.09e+05
6e+05
sqft_basement_1.0     720.6053   5074.422      0.142      0.887    -9225.824
1.07e+04
==============================================================================
Omnibus:                    15721.756   Durbin-Watson:                   1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2416517.545
Skew:                           4.317   Prob(JB):                         0.00
Kurtosis:                      62.213   Cond. No.                         207.
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[38]:
```
#Removing features with a pvalue < 0.05.
columns = model.pvalues[model.pvalues <= 0.05]
columns.index
```

```python
model = sm.OLS(y_train, X_train[columns.index]).fit()
model.summary()
```

[38]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:                  price   R-squared (uncentered):
0.846
Model:                            OLS   Adj. R-squared (uncentered):
0.846
Method:                 Least Squares   F-statistic:
4437.
Date:                Sun, 07 Nov 2021   Prob (F-statistic):
0.00
Time:                        11:14:04   Log-Likelihood:
-2.2469e+05
No. Observations:               16197   AIC:
4.494e+05
Df Residuals:                   16177   BIC:
4.496e+05
Df Model:                          20
Covariance Type:            nonrobust
================================================================================
======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
sqft_living         1.902e+05   3605.769     52.754      0.000    1.83e+05
1.97e+05
sqft_lot           -1.885e+04   2638.495     -7.144      0.000    -2.4e+04
-1.37e+04
sqft_living15       7.944e+04   3175.713     25.015      0.000    7.32e+04
8.57e+04
yr_built_1930_1960 -7.273e+04   7634.977     -9.526      0.000   -8.77e+04
-5.78e+04
yr_built_1960_1990 -1.799e+05   7546.354    -23.841      0.000   -1.95e+05
-1.65e+05
yr_built_1990_2020 -1.851e+05   7790.451    -23.762      0.000      -2e+05
-1.7e+05
condition_2         6.918e+05   2.36e+04     29.372      0.000    6.46e+05
7.38e+05
condition_3          7.19e+05   8876.465     81.002      0.000    7.02e+05
7.36e+05
condition_4         7.332e+05   8986.730     81.589      0.000    7.16e+05
```

```
7.51e+05
condition_5        7.73e+05   1.05e+04     73.418      0.000    7.52e+05
7.94e+05
waterfront_1      5.534e+05   2.96e+04     18.726      0.000    4.95e+05
6.11e+05
floors_2          2.577e+04   5401.318      4.771      0.000    1.52e+04
3.64e+04
floors_3          1.794e+05   1.39e+04     12.918      0.000    1.52e+05
2.07e+05
view_1            1.591e+05   1.64e+04      9.691      0.000    1.27e+05
1.91e+05
view_2            1.011e+05   9926.868     10.186      0.000    8.17e+04
1.21e+05
view_3            2.012e+05   1.37e+04     14.738      0.000    1.74e+05
2.28e+05
view_4             3.64e+05   2.06e+04     17.683      0.000    3.24e+05
4.04e+05
bedrooms_3        -9.53e+04   6369.181    -14.963      0.000   -1.08e+05
-8.28e+04
bedrooms_4       -1.263e+05   7497.402    -16.845      0.000   -1.41e+05
-1.12e+05
bedrooms_5       -9.014e+04   1.03e+04     -8.720      0.000    -1.1e+05
-6.99e+04
==============================================================================
Omnibus:                    15640.414   Durbin-Watson:                   1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2352228.145
Skew:                           4.285   Prob(JB):                         0.00
Kurtosis:                      61.412   Cond. No.                         23.5
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

0.8 Conclusion

This model %84 percent predict house price.

Findings ; 1. Living size(Square feet) 2. Waterfront effects a lot. 3. Condition is one of most importants. 4. Views effects a lot also.

0.9 Future Work

For future work for this model could be work on location with lat long or zipcode.