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)  378,669,268,992 bytes free
```

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

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

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

[6]:
```
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]:
```
#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)
```

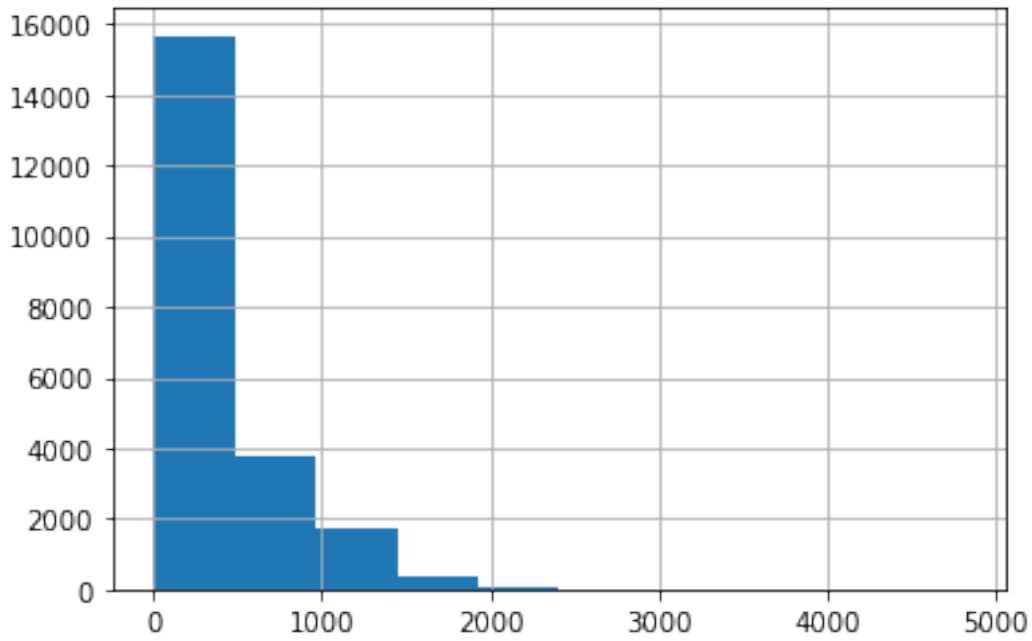
[9]:
```
#Dropping not usual columns.
df.drop(columns=['id','date','zipcode','lat','long'],inplace=True)
```

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

[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	\
0	221900.0	3	1.00	1180	5650	1.0	0.0	
1	538000.0	3	2.25	2570	7242	2.0	0.0	
2	180000.0	2	1.00	770	10000	1.0	0.0	
3	604000.0	4	3.00	1960	5000	1.0	0.0	
4	510000.0	3	2.00	1680	8080	1.0	0.0	

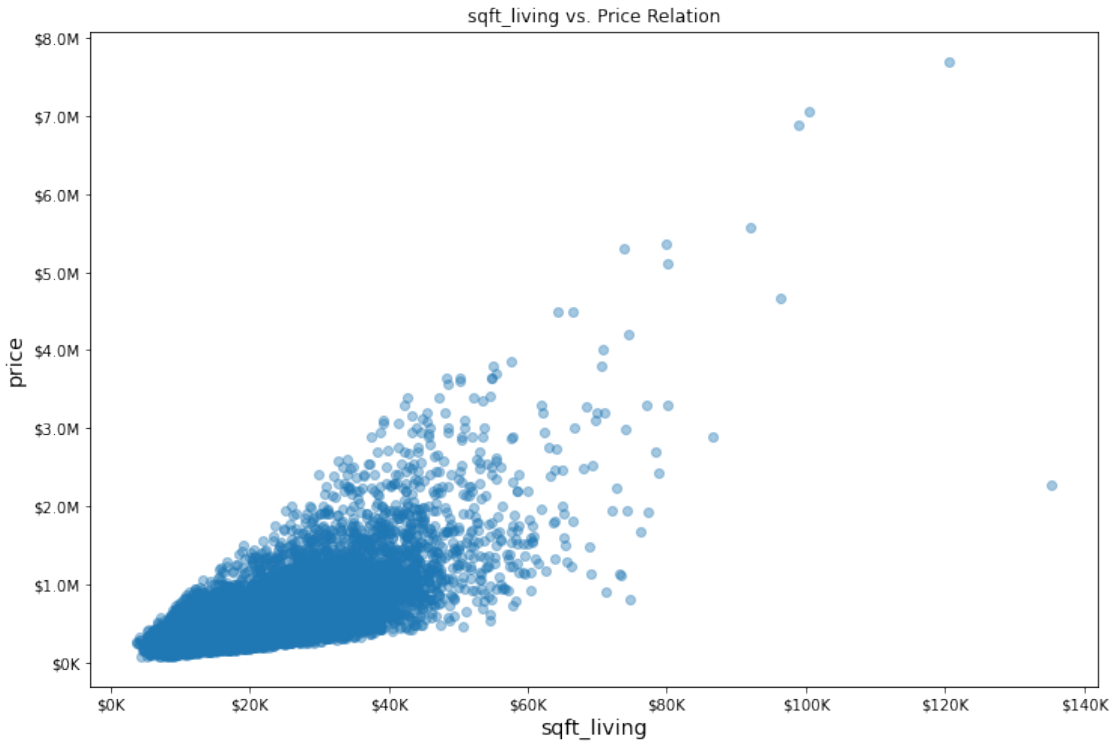
	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	\
0	0.0	3	7	1180	0.0	1955	0.0	
1	0.0	3	7	2170	400.0	1951	1991.0	
2	0.0	3	6	770	0.0	1933	0.0	
3	0.0	5	7	1050	910.0	1965	0.0	
4	0.0	3	8	1680	0.0	1987	0.0	

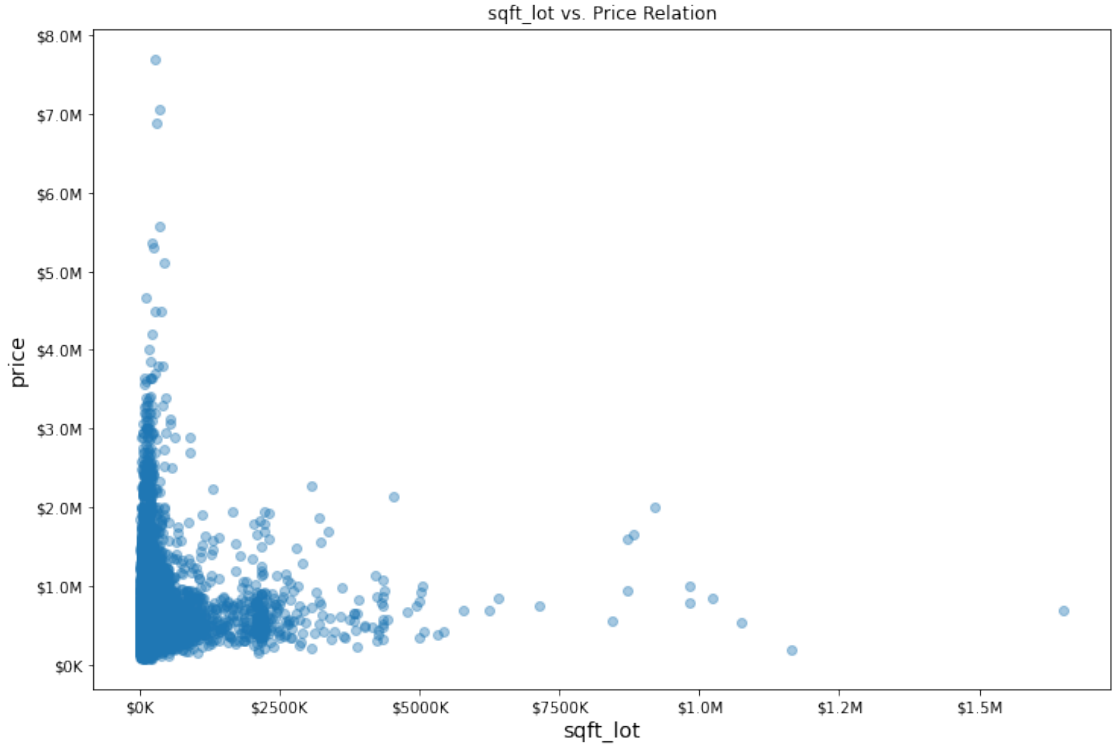
	sqft_living15	sqft_lot15
0	1340	5650
1	1690	7639
2	2720	8062
3	1360	5000
4	1800	7503

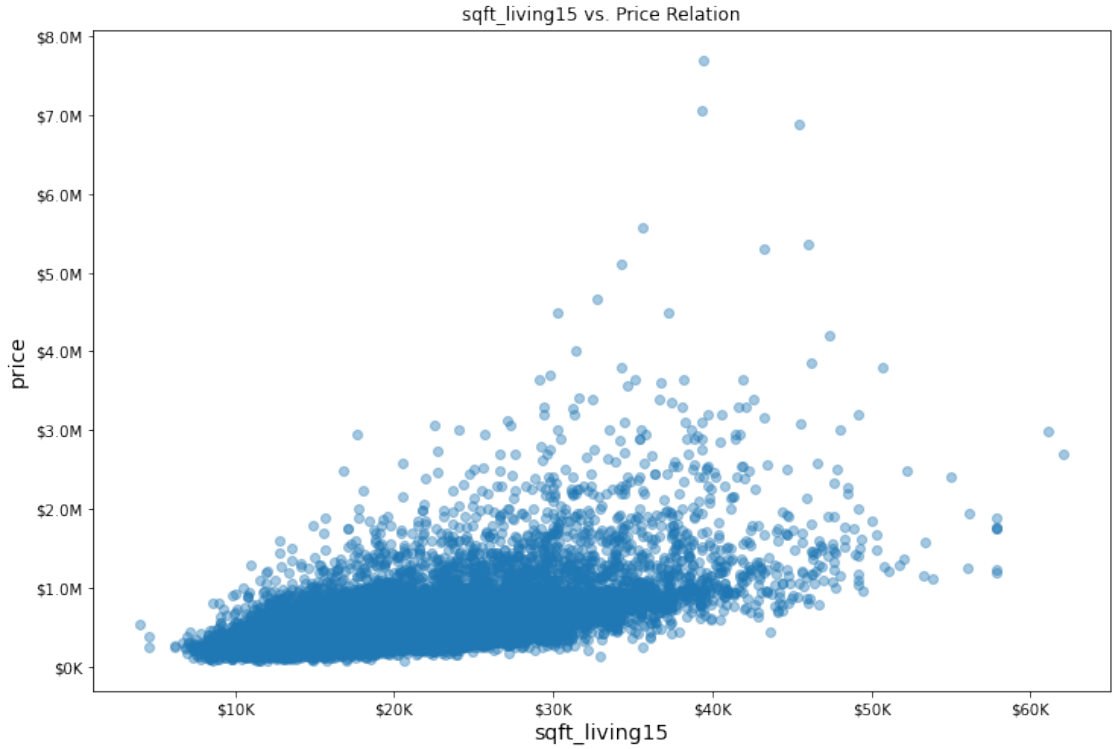
[14]:
```
#Creating function to fix scientific notations.
def currency(x, pos):
    """The two args are the value and tick position"""
```

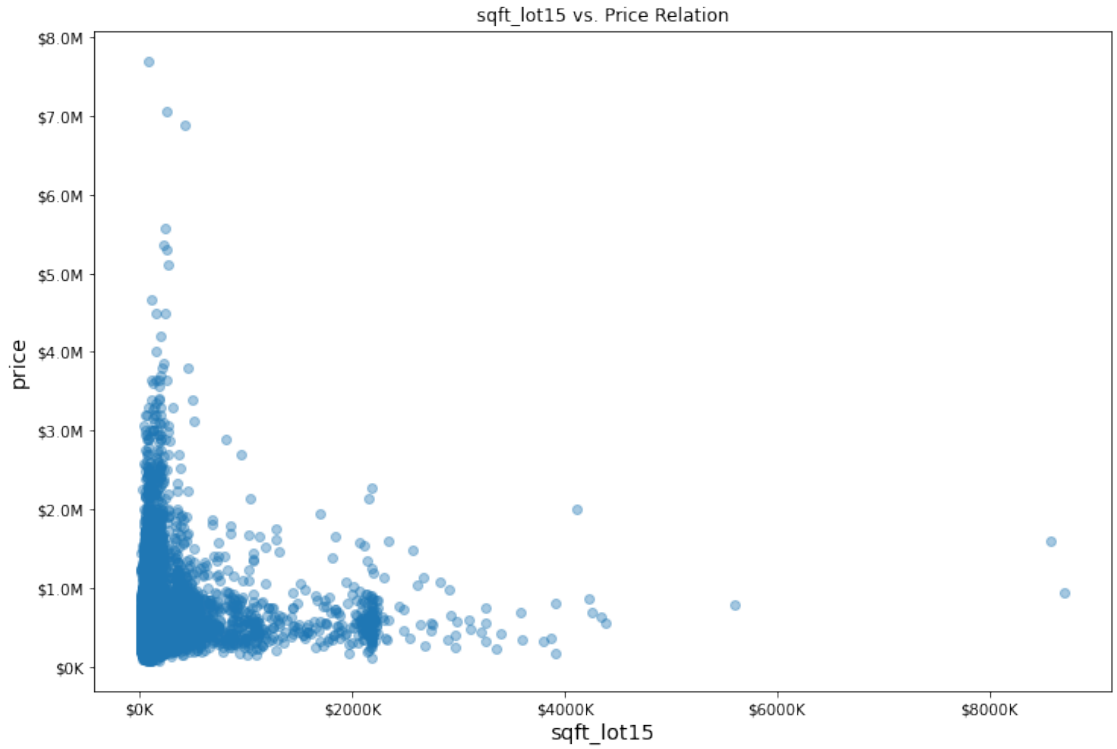
```
    if x >= 1e10:
        s = '${:1.1f}B'.format(x*1e-10)
    elif x >= 1e6:
        s = '${:1.1f}M'.format(x*1e-6)
    else:
        s = '${:1.0f}K'.format(x*1e-2)
    return s
```

[15]:
```
for column in ['sqft_living', 'sqft_lot', 'sqft_living15', 'sqft_lot15']:
    fig , ax = plt.subplots(figsize=(12,8))
    ax.scatter(df[column], df.price ,alpha=.4)
    ax.set_xlabel(column, fontsize=14)
    ax.set_ylabel('price',fontsize=14)
    ax.set_title(f'{column} vs. Price Relation')
    ax.yaxis.set_major_formatter(currency)
    ax.xaxis.set_major_formatter(currency)
    plt.show()
```




sqft_lot vs. Price Relation
price
$8.0M
$7.0M
$6.0M
$5.0M
$4.0M
$3.0M
$2.0M
$1.0M
$0K
$0K
$2500K
$5000K
$7500K
$1.0M
$1.2M
$1.5M
sqft_lot


sqft_living15 vs. Price Relation
price
$8.0M
$7.0M
$6.0M
$5.0M
$4.0M
$3.0M
$2.0M
$1.0M
$0K
$10K
$20K
$30K
$40K
$50K
$60K
sqft_living15



[16]:
```
# Turning sqft_basement column to binary.
df.sqft_basement[df.sqft_basement!=0]=1
```

```
<ipython-input-16-543a2f2e22e8>: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

[17]:
```
x = df.drop('price',axis=1)
```

[18]:
```
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)
```

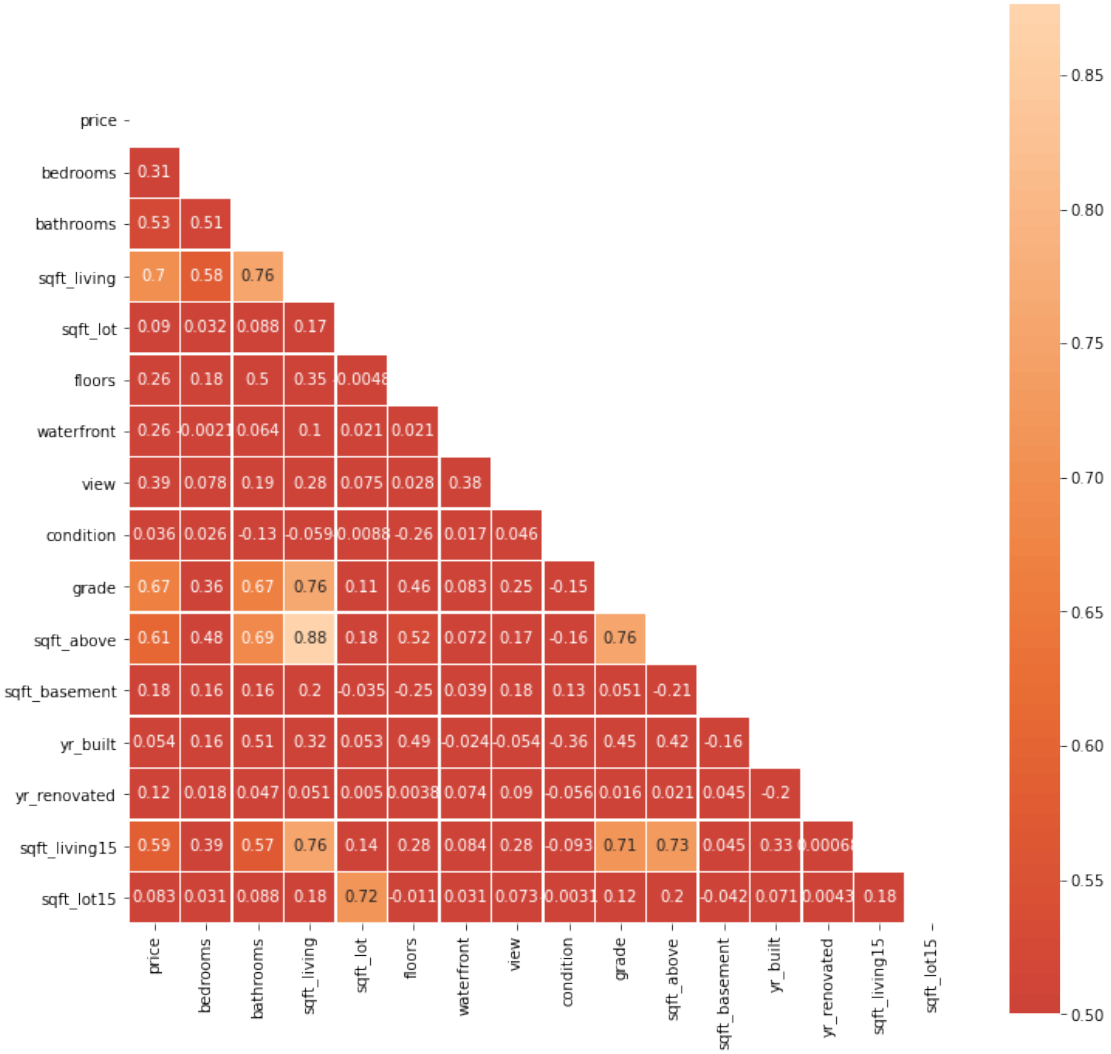
```
    VIF Factor       features
0    23.278227       bedrooms
```

```
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
```

[19]:
```
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()
```



[20]:
```
#Dropping most multicollinearity columns.
df.drop(columns=['sqft_above','grade','bathrooms'],inplace=True)
```

[21]:
```
#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
```

[26]:
```
#Cleaning columns for one hot coding.
df=df.round({'floors': 0})
```

```
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']
```

[27]:
```
df_cat=pd.DataFrame()
for i in cat_list:
    df_cat[i]=df[i].astype('category')
```

[28]:
```
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)
```

[29]:
```
df_cat.head()
```

[29]:

	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	

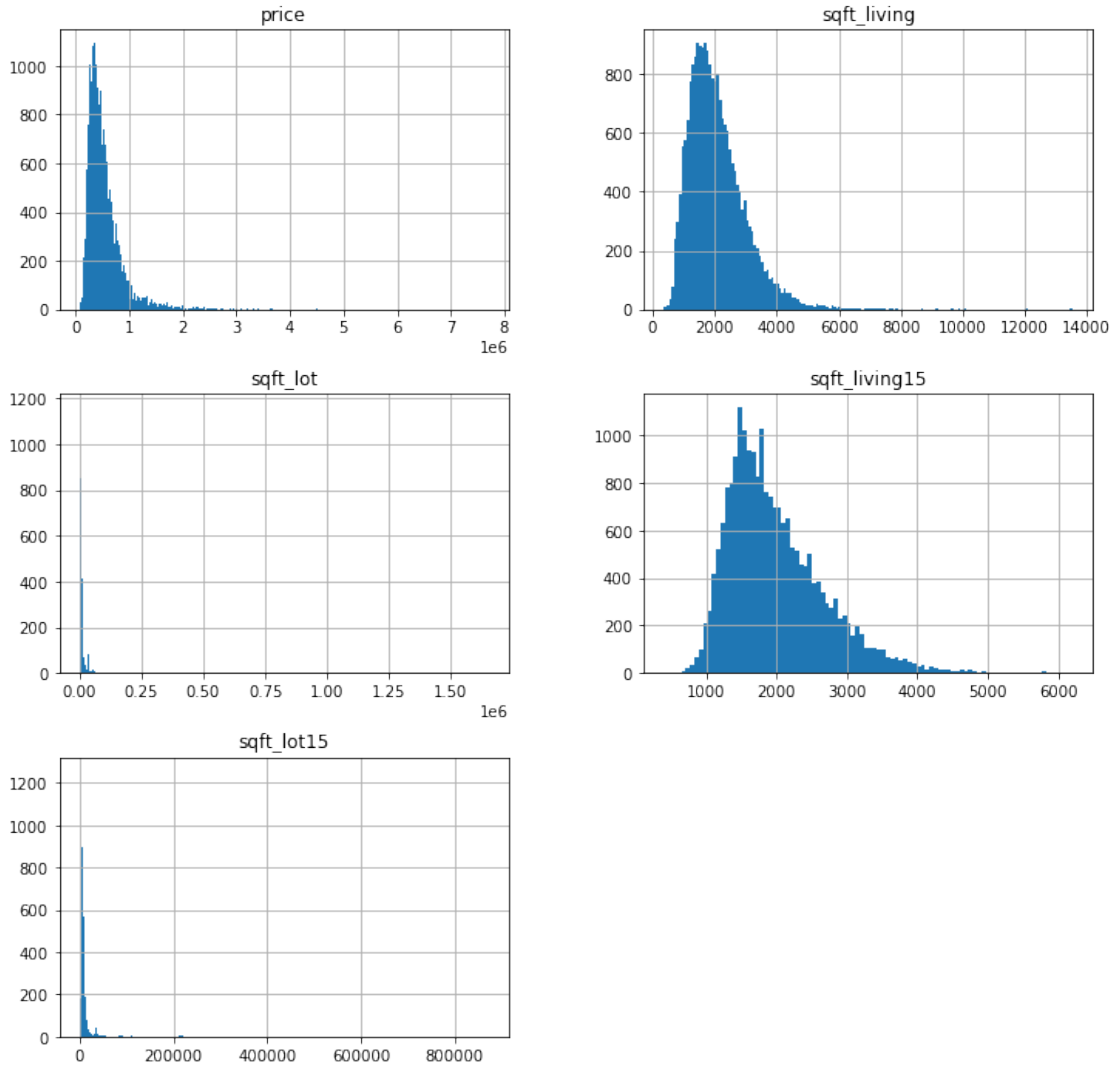
	bedrooms_9	bedrooms_10	bedrooms_11	bedrooms_33	sqft_basement_1.0
0	0	0	0	0	0
1	0	0	0	0	1
2	0	0	0	0	0
3	0	0	0	0	1
4	0	0	0	0	0

[5 rows x 27 columns]

0.5 Standardization

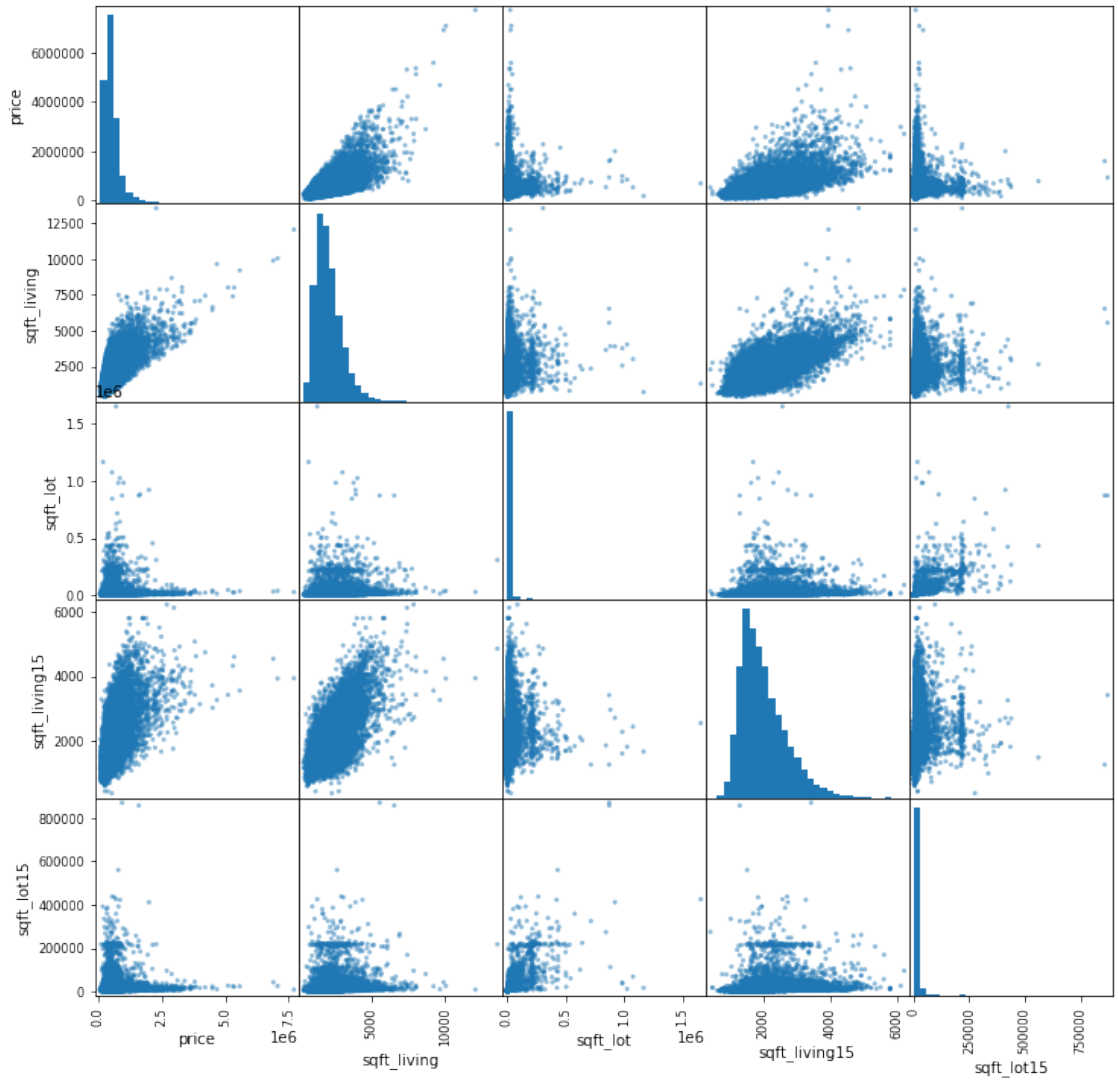
[33]:
```
df_cont.hist(bins='auto',figsize=(12,12))
```

[33]:
```
array([[<AxesSubplot:title={'center':'price'}>,
        <AxesSubplot:title={'center':'sqft_living'}>],
       [<AxesSubplot:title={'center':'sqft_lot'}>,
        <AxesSubplot:title={'center':'sqft_living15'}>],
       [<AxesSubplot:title={'center':'sqft_lot15'}>, <AxesSubplot:>]],
      dtype=object)
```



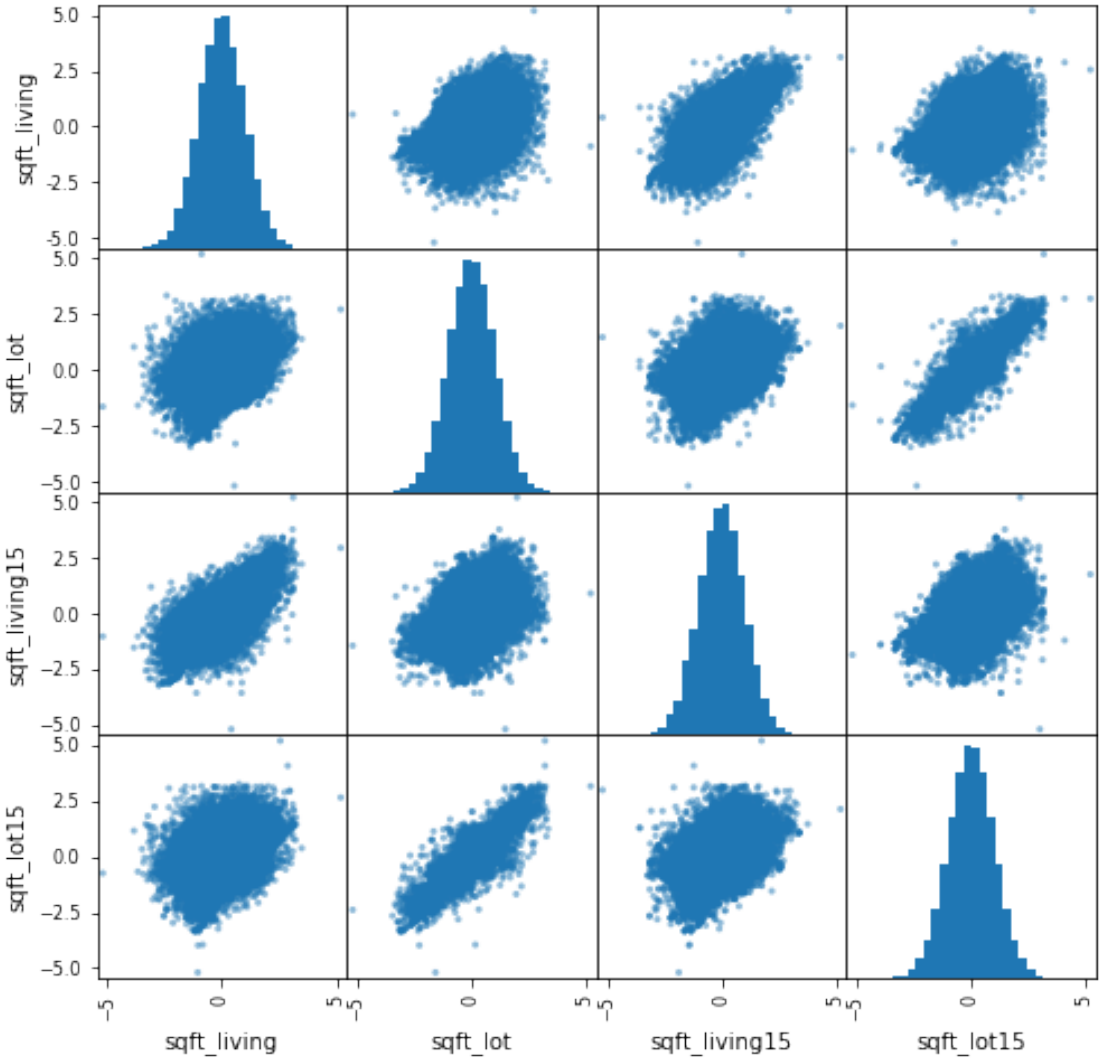
[34]:
```
#Looking for each feature relation with each other.
df_cont=df.loc[:
 ↪,['price','sqft_living','sqft_lot','sqft_living15','sqft_lot15']]
```

```
pd.plotting.scatter_matrix(df_cont,hist_kwds={'bins':30},figsize=(12,12))
plt.show()
```



[35]:
```
#Using quantile transformation to fix skewness and scaling them.
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']
```

[36]:
```
pd.plotting.scatter_matrix(cont_std,hist_kwds={'bins':30},figsize=(8,8))
plt.show()
```



[37]:
```
# Features now normally distributed.
```

[46]:
```
def calculate_residuals(model, features, label):
    """
    Creates predictions on the features with the model and calculates residuals
    """
    predictions = model.predict(features)
    df_results = pd.DataFrame({'Actual': label, 'Predicted': predictions})
    df_results['Residuals'] = abs(df_results['Actual']) -␣
↪abs(df_results['Predicted'])
```

```
    return df_results
```

[45]:
```
#Creating function to visualize homoscedasticity.
def visualize_homoscedasticity(model,features, label):
    df_results = calculate_residuals(model, features, label)

    plt.subplots(figsize=(12, 6))
    ax = plt.subplot(111)  # To remove spines
    plt.scatter(x=df_results.index, y=df_results.Residuals, alpha=0.5)
    plt.plot(np.repeat(0, df_results.index.max()), color='darkorange',␣
 ↪linestyle='--')
    ax.spines['right'].set_visible(False)  # Removing the right spine
    ax.spines['top'].set_visible(False)  # Removing the top spine
    plt.title('Residuals')
    plt.show()
```

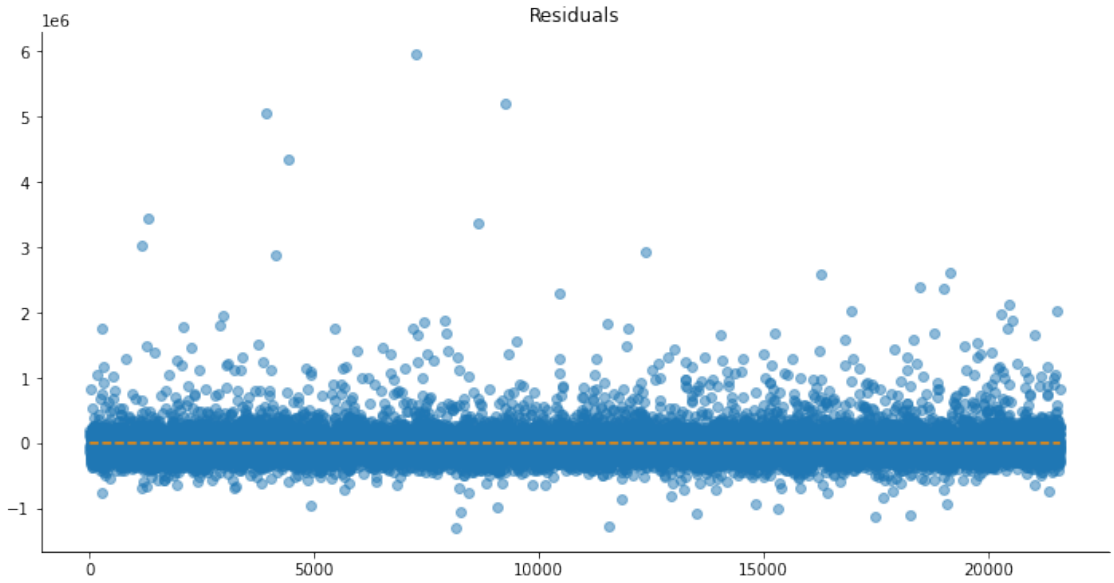
[47]:
```
lin = LinearRegression()
lin.fit(X_train,y_train)
```

[47]:
```
LinearRegression()
```

[48]:
```
lin.score(X_train,y_train)
```

[48]:
```
0.5177498055744425
```

[51]:
```
#Looking for train data homoscedasticity.
visualize_homoscedasticity(lin, X_train, y_train)
```



0.6 Modeling

[38]:
```
df_final=pd.concat([cont_std, df_cat ,df.price], axis=1)
```

[39]:
```
#Looking final missing values before modeling.
df_final.isna().sum()
```

[39]:
```
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
```

0.7 Train Test Split

[40]:
```
y = df_final['price']
X= df_final.drop('price',axis=1)
```

[41]:
```
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
```

[41]:
```
((16197, 31), (5400, 31), (16197,), (5400,))
```

[42]:
```
model = sm.OLS(y_train, X_train).fit()
model.summary()
```

[42]:
```
<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:                         20:17:45   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.
"""
```

[43]:
```
#Removing features with a pvalue < 0.05.
columns = model.pvalues[model.pvalues <= 0.05]
columns.index
model = sm.OLS(y_train, X_train[columns.index]).fit()
model.summary()
```

[43]:
```
<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:                         20:17:45   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.