Group 7 Project Submission

```
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# import standard packages

import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
import warnings
warnings.filterwarnings ('ignore')
import matplotlib.pyplot as plt
plt.style.use('ggplot')
from scipy import stats
import statsmodels.api as sm
import statsmodels.graphics as smg
import statsmodels.stats.api as sms
from statsmodels.stats.outliers_influence import
variance_inflation_factor
import datetime as dt

#Loading data set for Analysis
kc = pd.read_csv(r"C:\Users\HP\Documents\Flatiron\Assignments\Phase 2
Project\kc_house_data.csv")

kc.head(5)

           id        date   price  bedrooms  bathrooms  sqft_living
sqft_lot  \
0  7129300520  10/13/2014  221900         3       1.00         1180
5650
1  6414100192   12/9/2014  538000         3       2.25         2570
7242
2  5631500400   2/25/2015  180000         2       1.00          770
10000
3  2487200875   12/9/2014  604000         4       3.00         1960
5000
4  1954400510   2/18/2015  510000         3       2.00         1680
```

```
8080

   floors waterfront  view  ...          grade sqft_above
sqft_basement  \
0     1.0        NaN  NONE  ...      7 Average       1180
0
1     2.0         NO  NONE  ...      7 Average       2170
400
2     1.0         NO  NONE  ...  6 Low Average        770
0
3     1.0         NO  NONE  ...      7 Average       1050
910
4     1.0         NO  NONE  ...         8 Good       1680
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]

#Data understanding and exploration
kc.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  int64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(5), int64(10), object(6)
memory usage: 3.5+ MB
```

```
kc.describe()
```

```
                 id         price      bedrooms     bathrooms
sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000
21597.000000
mean   4.580474e+09  5.402966e+05      3.373200      2.115826
2080.321850
std    2.876736e+09  3.673681e+05      0.926299      0.768984
918.106125
min    1.000102e+06  7.800000e+04      1.000000      0.500000
370.000000
25%    2.123049e+09  3.220000e+05      3.000000      1.750000
1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000
1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000
2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000
13540.000000

           sqft_lot        floors    sqft_above      yr_built
yr_renovated  \
count  2.159700e+04  21597.000000  21597.000000  21597.000000
17755.000000
mean   1.509941e+04      1.494096   1788.596842   1970.999676
83.636778
std    4.141264e+04      0.539683    827.759761     29.375234
399.946414
min    5.200000e+02      1.000000    370.000000   1900.000000
0.000000
25%    5.040000e+03      1.000000   1190.000000   1951.000000
0.000000
50%    7.618000e+03      1.500000   1560.000000   1975.000000
0.000000
75%    1.068500e+04      2.000000   2210.000000   1997.000000
0.000000
max    1.651359e+06      3.500000   9410.000000   2015.000000
```

```
2015.000000

            zipcode           lat          long  sqft_living15
sqft_lot15
count  21597.000000  21597.000000  21597.000000   21597.000000
21597.000000
mean   98077.951845     47.560093   -122.213982    1986.620318
12758.283512
std       53.513072      0.138552      0.140724     685.230472
27274.441950
min    98001.000000     47.155900   -122.519000     399.000000
651.000000
25%    98033.000000     47.471100   -122.328000    1490.000000
5100.000000
50%    98065.000000     47.571800   -122.231000    1840.000000
7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000
10083.000000
max    98199.000000     47.777600   -121.315000    6210.000000
871200.000000

#changing the selling date to  and updating the column name to yr_sold
kc['date']=pd.to_datetime(kc['date'])
kc['date'] = kc['date'].dt.year

kc.rename (columns={'date': 'yr_sold'}, inplace=True)

kc['yr_sold']= kc['yr_sold'].astype(int)

kc.head(5)

           id  yr_sold   price  bedrooms  bathrooms  sqft_living
sqft_lot  \
0  7129300520     2014  221900         3       1.00         1180
5650
1  6414100192     2014  538000         3       2.25         2570
7242
2  5631500400     2015  180000         2       1.00          770
10000
3  2487200875     2014  604000         4       3.00         1960
5000
4  1954400510     2015  510000         3       2.00         1680
8080

   floors waterfront  view  ...          grade sqft_above
sqft_basement  \
0     1.0        NaN  NONE  ...      7 Average       1180
0
1     2.0         NO  NONE  ...      7 Average       2170
400
2     1.0         NO  NONE  ...  6 Low Average        770
```

```
0
3      1.0          NO  NONE  ...       7 Average       1050
910
4      1.0          NO  NONE  ...          8 Good       1680
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]
```

```
kc.isna().sum()
```

```
id                  0
yr_sold             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
```

```
#Filling missing values in the 'view' and 'waterfront' columns
kc['waterfront'].fillna('NO', inplace=True)
kc['view'].fillna('NONE', inplace=True)
kc.isna().sum()
```

```
id                  0
yr_sold             0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront          0
view                0
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
```

```
#Counting the occurences of unique values in 'yr_revovated'
kc['yr_renovated'].value_counts()
```

```
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

```
kc['yr_renovated'].fillna(0.0, inplace=True)
```

```
kc['yr_renovated'].astype(int)
```

```
0           0
1        1991
2           0
3           0
4           0
         ...
21592       0
```

```
21593       0
21594       0
21595       0
21596       0
Name: yr_renovated, Length: 21597, dtype: int32
```

```
kc.isna().sum()
```

```
id               0
yr_sold          0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

```
yr_renovated = kc['yr_renovated']
kc['renovated_last_10'] = (yr_renovated >= (kc['yr_sold'] - 10))
kc['renovated_last_10'] = kc['renovated_last_10'].map({True: 'Yes',
False: 'No'})
```

```
kc.head(5)
```

```
           id  yr_sold   price  bedrooms  bathrooms  sqft_living
sqft_lot  \
0  7129300520     2014  221900         3       1.00         1180
5650
1  6414100192     2014  538000         3       2.25         2570
7242
2  5631500400     2015  180000         2       1.00          770
10000
3  2487200875     2014  604000         4       3.00         1960
5000
4  1954400510     2015  510000         3       2.00         1680
8080
```

```
   floors waterfront  view  ... sqft_above sqft_basement  yr_built  \
0     1.0         NO  NONE  ...       1180             0      1955
1     2.0         NO  NONE  ...       2170           400      1951
2     1.0         NO  NONE  ...        770             0      1933
3     1.0         NO  NONE  ...       1050           910      1965
4     1.0         NO  NONE  ...       1680             0      1987

  yr_renovated  zipcode      lat     long  sqft_living15
sqft_lot15  \
0          0.0    98178  47.5112 -122.257           1340        5650

1       1991.0    98125  47.7210 -122.319           1690        7639

2          0.0    98028  47.7379 -122.233           2720        8062

3          0.0    98136  47.5208 -122.393           1360        5000

4          0.0    98074  47.6168 -122.045           1800        7503


   renovated_last_10
0                 No
1                 No
2                 No
3                 No
4                 No

[5 rows x 22 columns]
```

```
kc['Age'] = kc['yr_sold']-kc['yr_built']

kc.head(5)
```

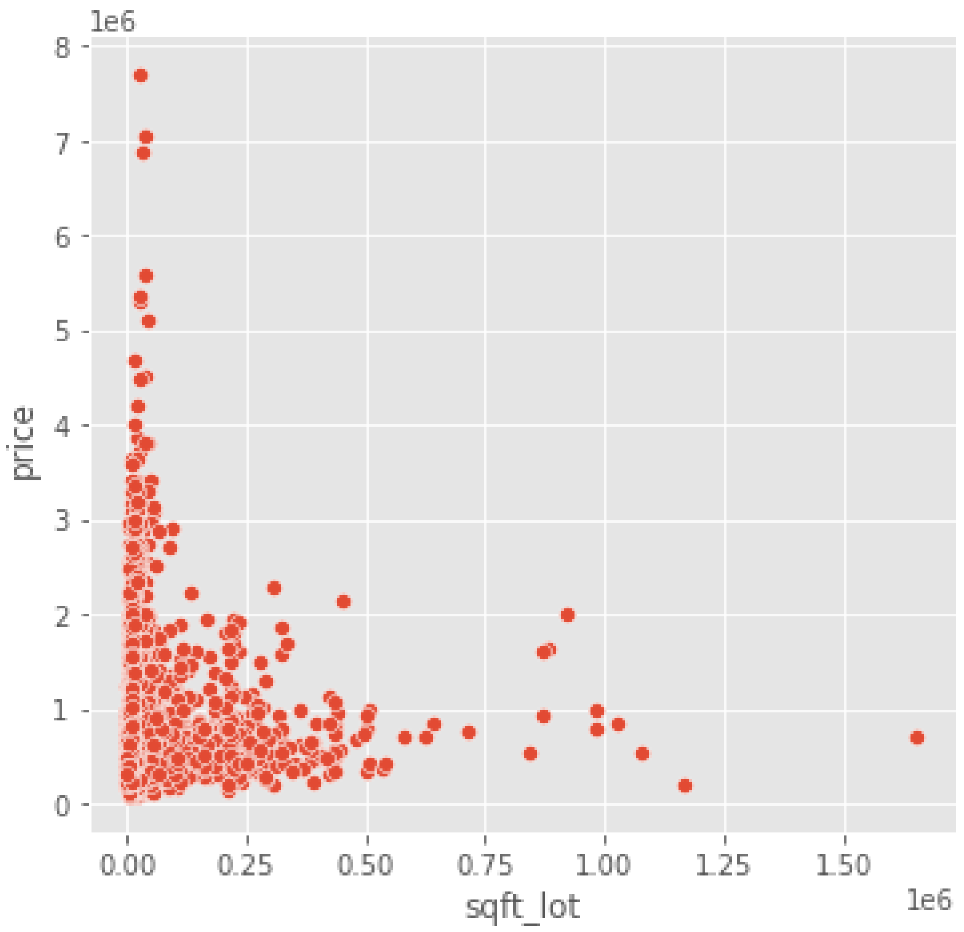
```
           id  yr_sold   price  bedrooms  bathrooms  sqft_living
sqft_lot  \
0  7129300520     2014  221900         3       1.00         1180
5650
1  6414100192     2014  538000         3       2.25         2570
7242
2  5631500400     2015  180000         2       1.00          770
10000
3  2487200875     2014  604000         4       3.00         1960
5000
4  1954400510     2015  510000         3       2.00         1680
8080

   floors waterfront  view  ... sqft_basement yr_built  yr_renovated
zipcode  \
0     1.0         NO  NONE  ...             0     1955           0.0
98178
```

```
1     2.0          NO  NONE  ...            400     1951        1991.0
98125
2     1.0          NO  NONE  ...              0     1933           0.0
98028
3     1.0          NO  NONE  ...            910     1965           0.0
98136
4     1.0          NO  NONE  ...              0     1987           0.0
98074

       lat     long  sqft_living15  sqft_lot15  renovated_last_10  Age

0  47.5112 -122.257           1340        5650                 No   59

1  47.7210 -122.319           1690        7639                 No   63

2  47.7379 -122.233           2720        8062                 No   82

3  47.5208 -122.393           1360        5000                 No   49

4  47.6168 -122.045           1800        7503                 No   28


[5 rows x 23 columns]

#Dropping columns that are not needed
columns_to_drop =
['id','zipcode','lat','long','sqft_living15','sqft_lot15','sqft_baseme
nt','yr_sold','yr_renovated']
kc.drop(columns_to_drop, axis = 1, inplace = True)

#Confirming the new dataframe
kc.head(5)

    price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
waterfront  \
0  221900         3       1.00         1180      5650     1.0
NO
1  538000         3       2.25         2570      7242     2.0
NO
2  180000         2       1.00          770     10000     1.0
NO
3  604000         4       3.00         1960      5000     1.0
NO
4  510000         3       2.00         1680      8080     1.0
NO

   view  condition          grade  sqft_above  yr_built
renovated_last_10  Age
0  NONE    Average      7 Average        1180      1955
No   59
1  NONE    Average      7 Average        2170      1951
```

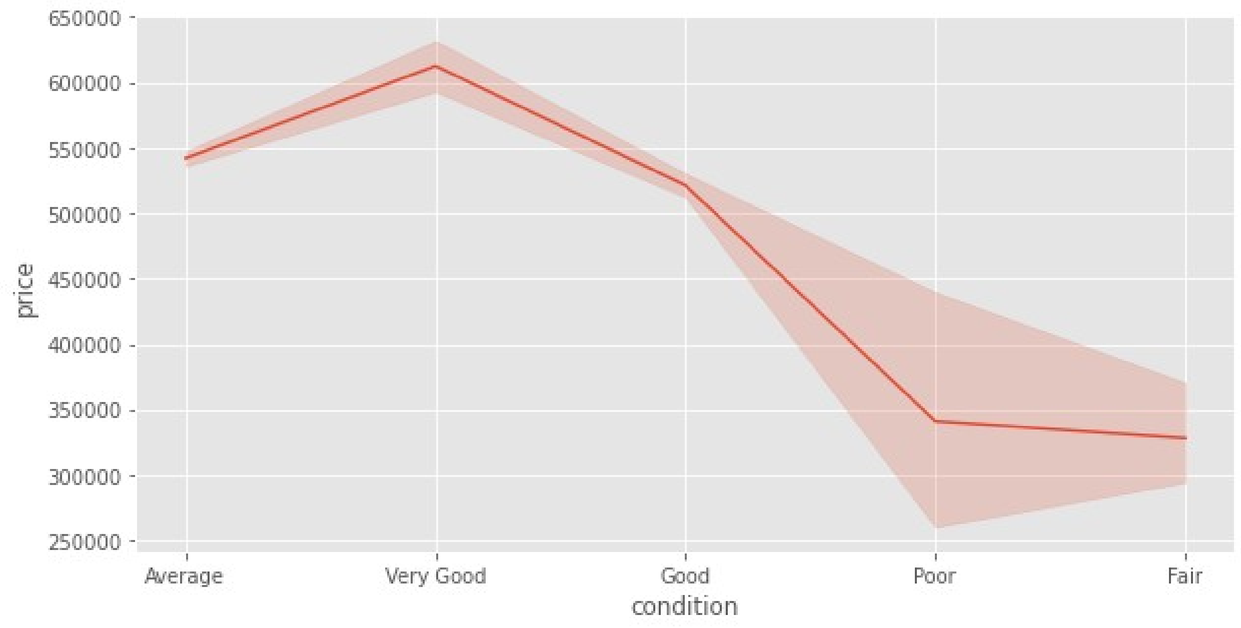
```
No    63
2  NONE    Average  6 Low Average          770       1933
No    82
3  NONE  Very Good       7 Average         1050       1965
No    49
4  NONE    Average          8 Good         1680       1987
No    28
```

Visualizing

```
#Creating a plotting function for ease or resizing in different plots
def resizeplot(l,a):
    plt.figure(figsize=(l,a));

#Creating a plot that will visualize the relationship between price
and sqft_lot
resizeplot(6,4)
sns.relplot(x='sqft_lot',y='price',data=kc,palette='terrain');
plt.show()

<Figure size 432x288 with 0 Axes>
```

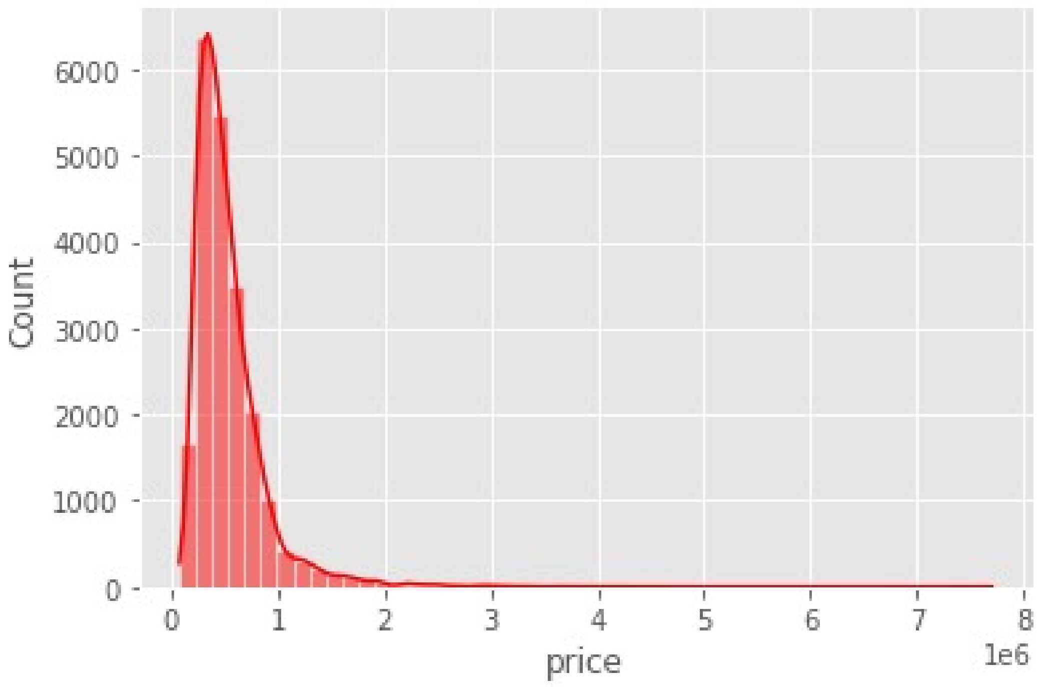


```
#Finding out the occurences of bedroom values
bedrooms_counts = kc['bedrooms'].value_counts()
bedrooms_counts

3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64

#Confirming how the conditon of the house over the year affects the
price
#We can see that if the conditon of the house- is improved then the
price of the house is higher
#Poor conditons leads to lower price
resizeplot(10,5)
sns.lineplot(x='condition',y='price',data=kc,palette='terrain')
plt.show()
```

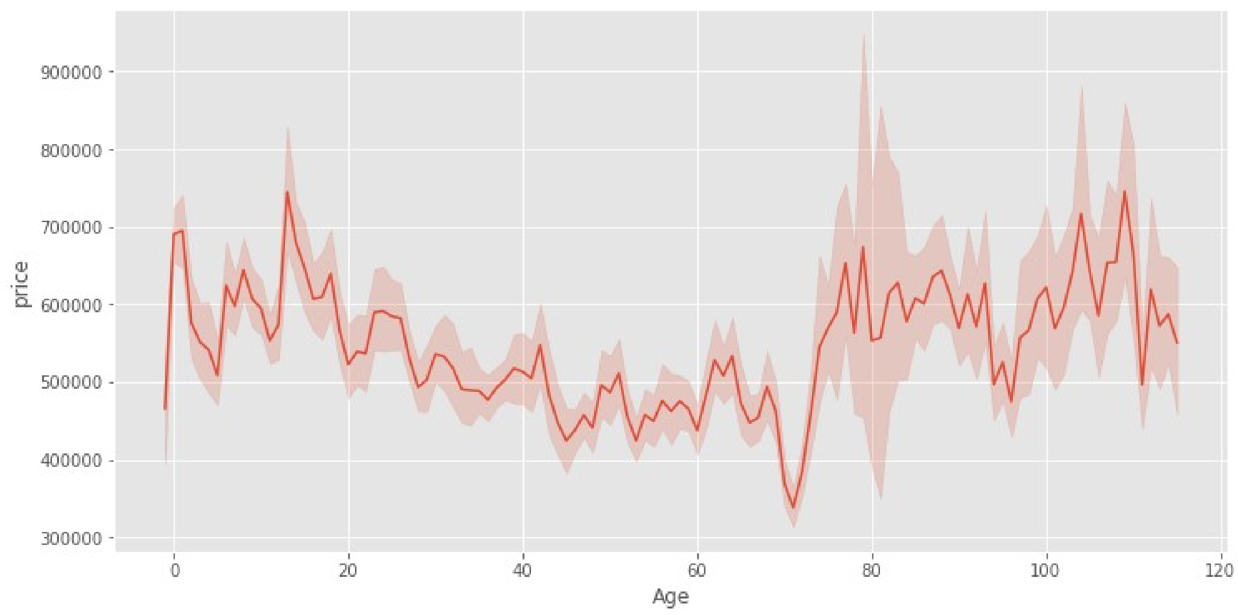


```
#Using histogram to visualize the distribution of the price
#As the count is high then the price increases
```

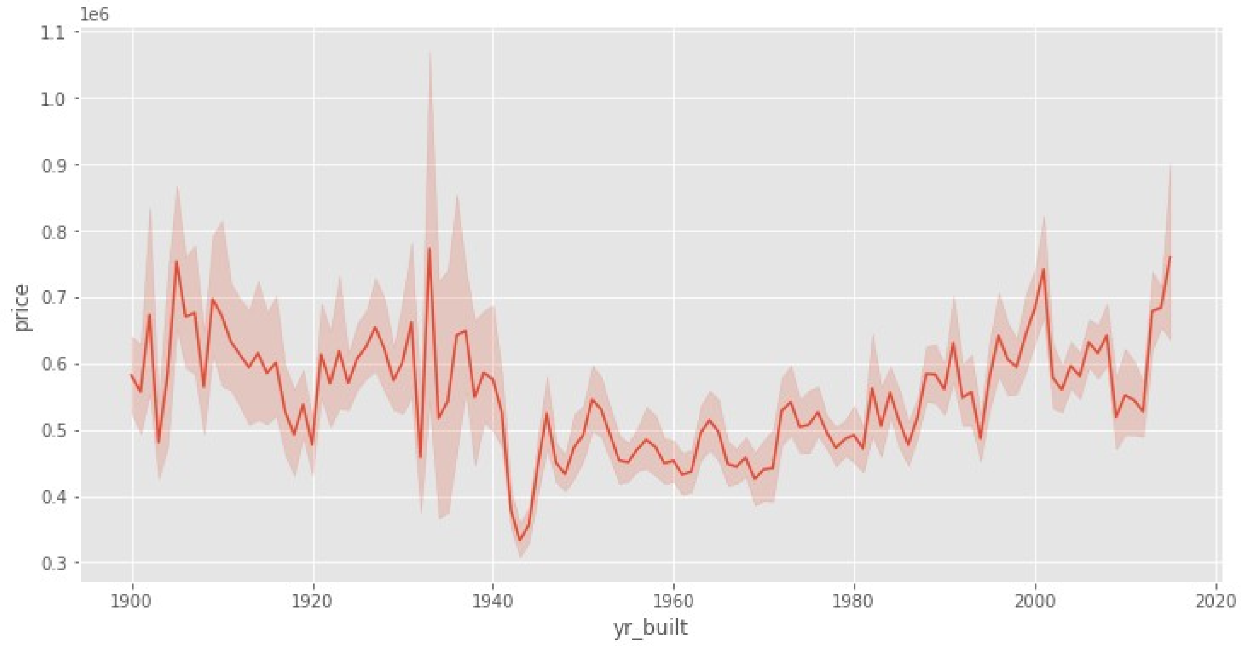
```
resizeplot(6,4)
sns.histplot(kc['price'],kde=True,bins=50, color = 'red');
```



```
#Using linear to analyse price increament over the year
#At the beggingig of the yrs the price is low as the yrs increases
then the price has a higher peak

resizeplot(12,6)
sns.lineplot(x='Age',y='price',data=kc);
```

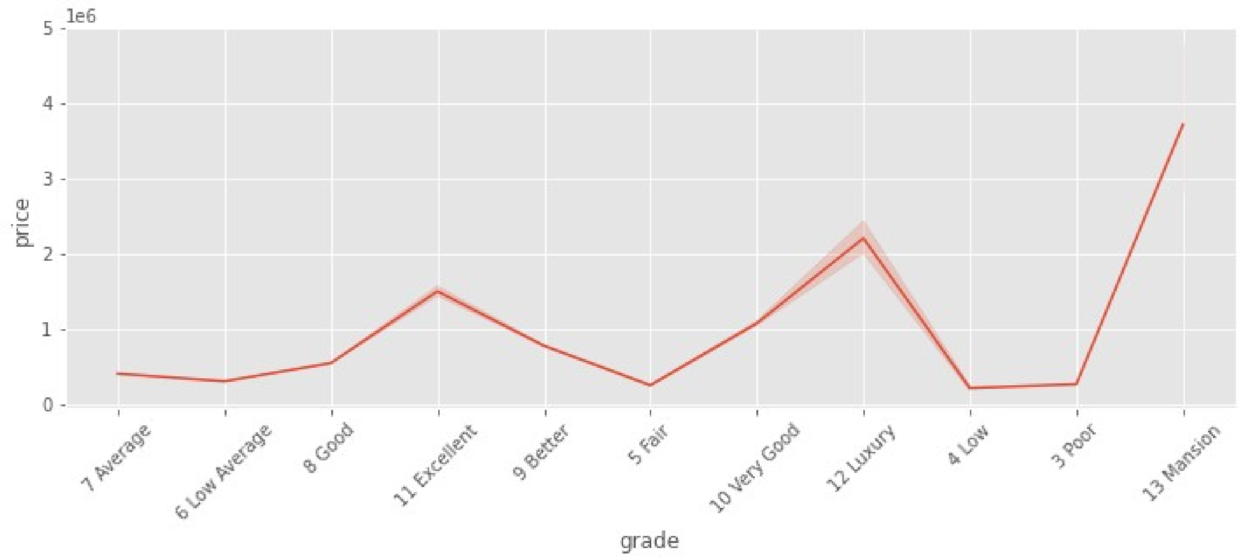


```
#Price trend over the years
#The price from 2000 to 2015 was good meaning the owners of real
estaste were getting good profit
#It seems that the houses had been reinovated

resizeplot(12,6)
sns.lineplot(x='yr_built',y='price',data=kc,palette = 'deep');
```



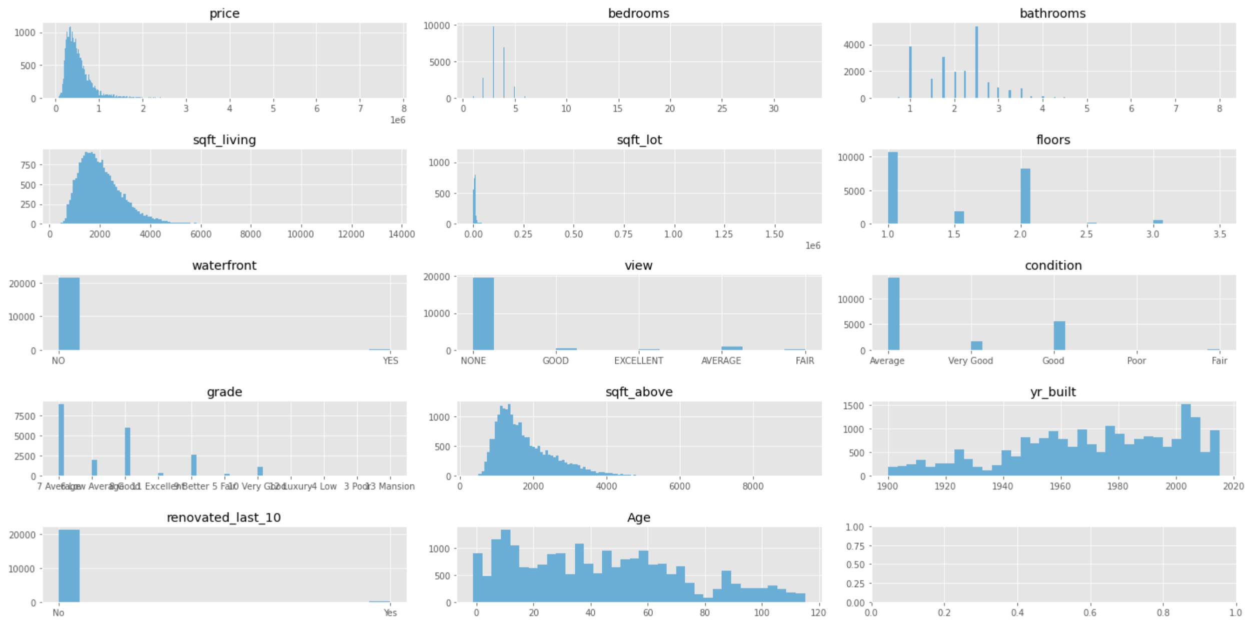
```
#Showing the price changes in relation to unit grade
# poor grade causes the price to decrease and vice versa
```

```python
resizeplot(12,4)# changed the size to give a better view of the grade.
sns.lineplot(x='grade',y='price',data=kc,palette='terrain');
plt.xticks(rotation=45)
plt.show()
```



Categorical Variables

```python
# Plotting histogram for columns within the dataset
#The histogram shows us how different features in each column affect
each other

fig, axes = plt.subplots(nrows=(5), ncols=3, figsize=(20,10))
df_cols = kc.columns

# Using sns color pallets for each plot

color = sns.color_palette("Blues", n_colors=1)[0]

# creation of a function for plotting the hustogram for the given
columns

for col, ax in zip(df_cols, axes.flatten()):
    ax.hist(kc[col].dropna(), bins='auto', color=color )
    ax.set_title(col)


# automatically adjusting subplot params so that the subplot(s) fits
in to the figure area

fig.tight_layout()
```



```
#From the above plots we can see that
floors,waterfront,condition,grade,renovated_last_10,bedrooms,bathrooms
are categorical

#Creating a category of values to work with
categories = ['bedrooms', 'bathrooms', 'floors', 'waterfront', 'view',
'condition', 'grade', 'renovated_last_10']

for cate in categories:

    # getting the  value counts

    counts = kc[cate].value_counts()

    # Isolate offending categories for each variable

    bad_cate = counts[counts < 50].index

    # Isolate indices in the dataset where offending categories are
found

    to_drop = kc[kc[cate].isin(bad_cate)].index
    # Dropping unnecessary data within the category in dataset
    kc.drop(to_drop, inplace=True)

# converting view into binary (binarzing)
#for consistent and easier to compare in the view.
view_dict = {
    'FAIR': 1,
    'AVERAGE': 1,
    'GOOD': 1,
    'EXCELLENT': 1,
    'NONE': 0
}

kc['view'] = kc['view'].map(view_dict)

# Binarizing waterfront
waterfront_dict = {
    'YES': 1,
    'NO': 0
}

kc['waterfront'] = kc['waterfront'].map(waterfront_dict)

# Binarizing renovated_last_10
renovated_dict = {
    'Yes': 1,
    'No': 0
}

kc['renovated_last_10'] = kc['renovated_last_10'].map(renovated_dict)
```

OneHotEncoding

```
#Creating a copy of the dataset so as not to alter the original copy
incase
kc2= kc.copy()
```

Generating dummies

```
#Converting the 3columns: bedrooms,bathrooms,floors to string for
pandas to be able to dumify them
col = ['bedrooms', 'bathrooms', 'floors']
kc[col] =  kc[col].astype(str)

#Checking if the conversion was successful
kc.dtypes

price                     int64
bedrooms                 object
bathrooms                object
sqft_living               int64
sqft_lot                  int64
floors                   object
waterfront                int64
view                      int64
condition                object
grade                    object
sqft_above                int64
yr_built                  int64
```

```
renovated_last_10     int64
Age                   int64
dtype: object
```

```python
# Creating variable from the already cleaned original dataset
kc_binary = kc[['waterfront', 'view', 'renovated_last_10']]
kc_num = kc[['price', 'sqft_living', 'sqft_lot', 'Age']]
kc_cate = kc[['floors', 'bedrooms', 'bathrooms', 'condition',
'grade']]

# Applying one-hot encoding to the categorical features
kc_cate_dummies = pd.get_dummies(kc_cate, dtype=int)

#Creating a list of dummies to be dropped

dummies_to_drop = [
    'floors_1.0',
    'bedrooms_1',
    'bathrooms_0.75',
    'condition_Fair',
    'grade_5 Fair'
    ]
#Dropping the specified dummies

kc_cate_dummies.drop(
    dummies_to_drop,
     axis = 1,
     inplace=True)

#Combining the variable into a single variable
kc = pd.concat([kc_num, kc_binary, kc_cate_dummies], axis=1)

#Confirming if the event was successful
kc.head()
```

```
    price  sqft_living  sqft_lot  Age  waterfront  view
renovated_last_10  \
0  221900         1180      5650   59           0     0
0
1  538000         2570      7242   63           0     0
0
2  180000          770     10000   82           0     0
0
3  604000         1960      5000   49           0     0
0
4  510000         1680      8080   28           0     0
0

   floors_1.5  floors_2.0  floors_2.5  ...  condition_Average
condition_Good  \
0           0           0           0  ...                  1
```

```
0
1           0           1           0  ...                     1
0
2           0           0           0  ...                     1
0
3           0           0           0  ...                     0
0
4           0           0           0  ...                     1
0

   condition_Very Good  grade_10 Very Good  grade_11 Excellent  \
0                    0                   0                   0
1                    0                   0                   0
2                    0                   0                   0
3                    1                   0                   0
4                    0                   0                   0

   grade_12 Luxury  grade_6 Low Average  grade_7 Average  grade_8 Good
\
0                0                    0                1             0

1                0                    0                1             0

2                0                    1                0             0

3                0                    0                1             0

4                0                    0                0             1


   grade_9 Better
0               0
1               0
2               0
3               0
4               0

[5 rows x 40 columns]

#Confirming the columns
kc.columns

Index(['price', 'sqft_living', 'sqft_lot', 'Age', 'waterfront',
'view',
       'renovated_last_10', 'floors_1.5', 'floors_2.0', 'floors_2.5',
       'floors_3.0', 'bedrooms_2', 'bedrooms_3', 'bedrooms_4',
'bedrooms_5',
       'bedrooms_6', 'bathrooms_1.0', 'bathrooms_1.5',
'bathrooms_1.75',
       'bathrooms_2.0', 'bathrooms_2.25', 'bathrooms_2.5',
'bathrooms_2.75',
       'bathrooms_3.0', 'bathrooms_3.25', 'bathrooms_3.5',
'bathrooms_3.75',
       'bathrooms_4.0', 'bathrooms_4.25', 'bathrooms_4.5',
'condition_Average',
       'condition_Good', 'condition_Very Good', 'grade_10 Very Good',
       'grade_11 Excellent', 'grade_12 Luxury', 'grade_6 Low Average',
       'grade_7 Average', 'grade_8 Good', 'grade_9 Better'],
      dtype='object')
```

```
#Setting the columns in an asceding order for easy analysis
grade_columns = [
    'grade_6 Low Average',
    'grade_7 Average',
    'grade_8 Good',
    'grade_9 Better',
    'grade_10 Very Good',
    'grade_11 Excellent',
    'grade_12 Luxury'
]

# Extracting other columns not related to 'grade'

other_columns = [col for col in kc.columns if col not in
grade_columns]

# Reordering columns

reordered_columns = other_columns + grade_columns
kc = kc[reordered_columns]

#Accessing the columns
kc.columns
```

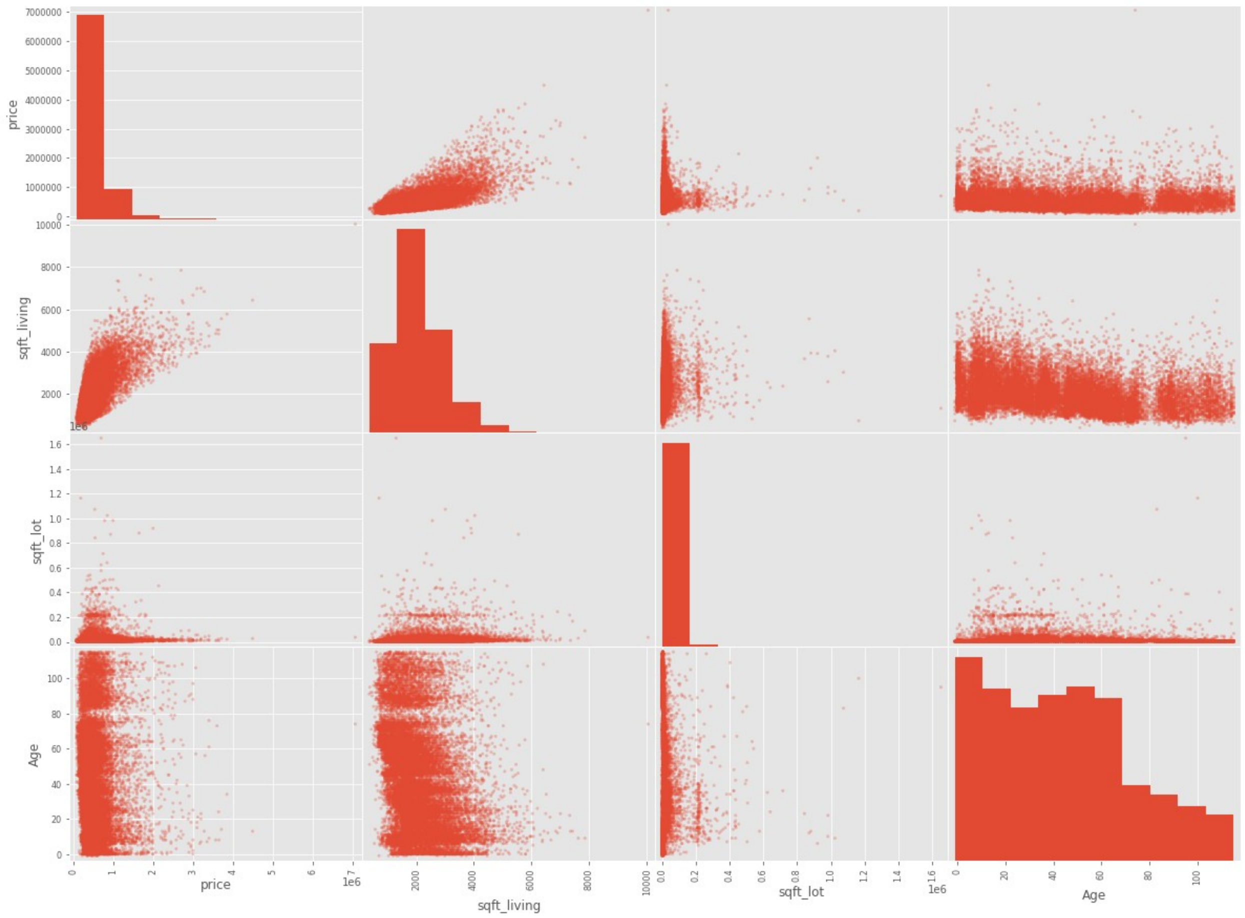
```
Index(['price', 'sqft_living', 'sqft_lot', 'Age', 'waterfront',
'view',
       'renovated_last_10', 'floors_1.5', 'floors_2.0', 'floors_2.5',
       'floors_3.0', 'bedrooms_2', 'bedrooms_3', 'bedrooms_4',
'bedrooms_5',
       'bedrooms_6', 'bathrooms_1.0', 'bathrooms_1.5',
'bathrooms_1.75',
       'bathrooms_2.0', 'bathrooms_2.25', 'bathrooms_2.5',
'bathrooms_2.75',
       'bathrooms_3.0', 'bathrooms_3.25', 'bathrooms_3.5',
'bathrooms_3.75',
       'bathrooms_4.0', 'bathrooms_4.25', 'bathrooms_4.5',
'condition_Average',
       'condition_Good', 'condition_Very Good', 'grade_6 Low Average',
       'grade_7 Average', 'grade_8 Good', 'grade_9 Better',
       'grade_10 Very Good', 'grade_11 Excellent', 'grade_12 Luxury'],
      dtype='object')
```

```
#Accessing the columns and rows
kc.head()

    price  sqft_living  sqft_lot  Age  waterfront  view  
renovated_last_10  \
0  221900         1180      5650   59           0     0  
0  
1  538000         2570      7242   63           0     0  
0  
2  180000          770     10000   82           0     0  
0  
3  604000         1960      5000   49           0     0  
0  
4  510000         1680      8080   28           0     0  
0  

   floors_1.5  floors_2.0  floors_2.5  ...  condition_Average  
condition_Good  \
0           0           0           0  ...                  1  
0  
1           0           1           0  ...                  1  
0  
2           0           0           0  ...                  1  
0  
3           0           0           0  ...                  0  
0  
4           0           0           0  ...                  1  
0  

   condition_Very Good  grade_6 Low Average  grade_7 Average  grade_8 
Good  \
0                    0                    0                1  
0  
1                    0                    0                1  
0  
2                    0                    1                0  
0  
3                    1                    0                1  
0  
4                    0                    0                0  
1  

   grade_9 Better  grade_10 Very Good  grade_11 Excellent  grade_12 
Luxury  
0               0                   0                   0  
0  
1               0                   0                   0  
0  
2               0                   0                   0  
0  
```

```
3                    0                    0                    0
0
4                    0                    0                    0
0

[5 rows x 40 columns]
```

Modeling

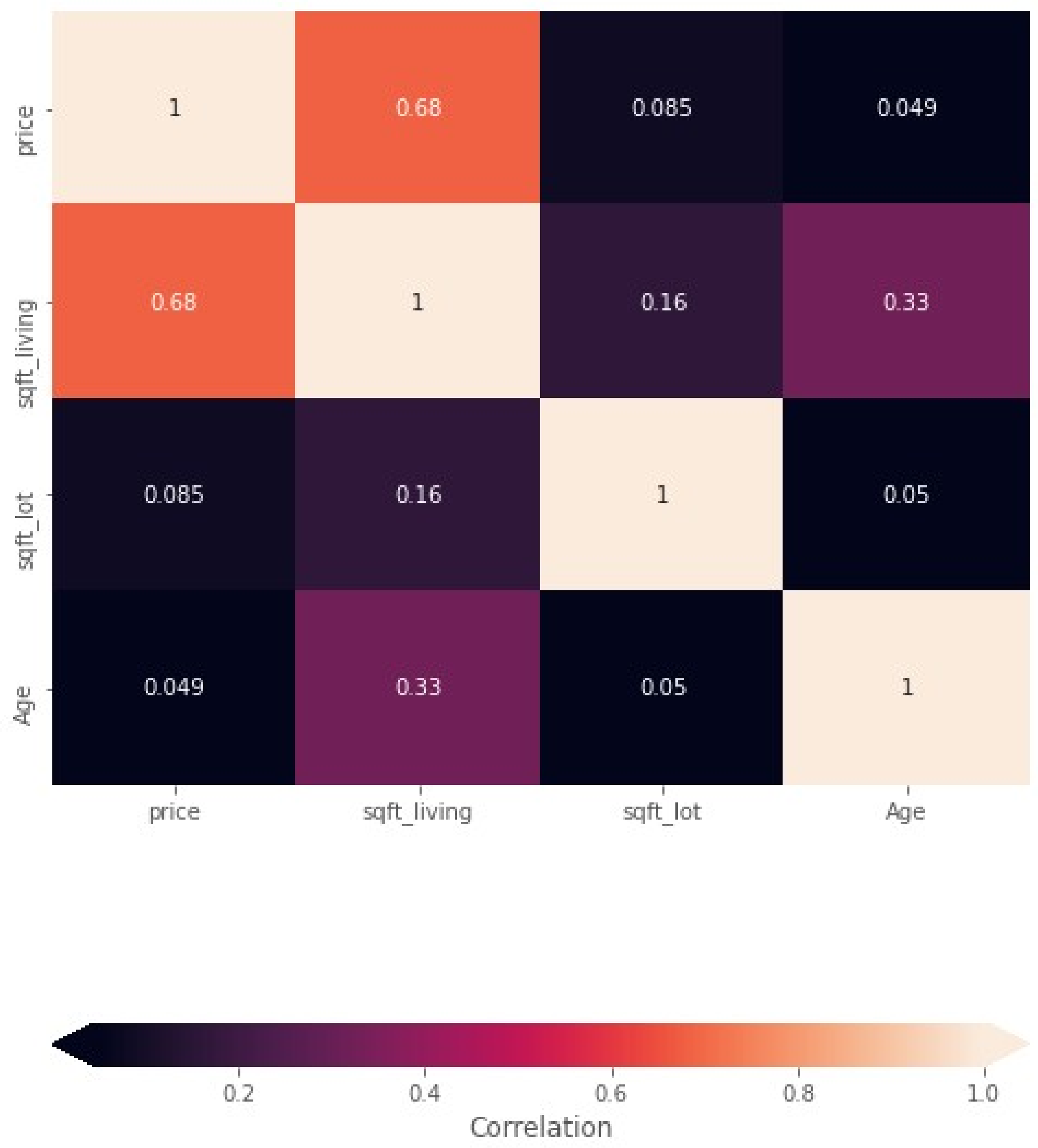
```
#Confirming the linear relationship between variable and price
kc_num.head()

    price  sqft_living  sqft_lot  Age
0  221900         1180      5650   59
1  538000         2570      7242   63
2  180000          770     10000   82
3  604000         1960      5000   49
4  510000         1680      8080   28

#Plotting scatter plot for clear visulaization of different features
pd.plotting.scatter_matrix(kc_num, figsize=(20,15), alpha=.3);
```



```
#Displaying the correlation matrix in responce to  price in descending
order
kc_num.corr()['price'].sort_values(ascending=False)
```

```
price          1.000000
sqft_living    0.682342
sqft_lot       0.084739
Age           -0.048693
Name: price, dtype: float64
```

```
#Ensuring proper visualization using heatmap
#the lighter the color the stronger the correlation

fig, ax = plt.subplots(figsize = (8,10))

sns.heatmap(
    kc_num.corr().abs(),
#     mask=np.triu(np.ones_like(data.corr(), dtype=bool)),
    ax=ax,
    annot=True,
    cbar_kws={"label": "Correlation", "orientation": "horizontal",
"pad": .2, "extend": "both"}
);
```



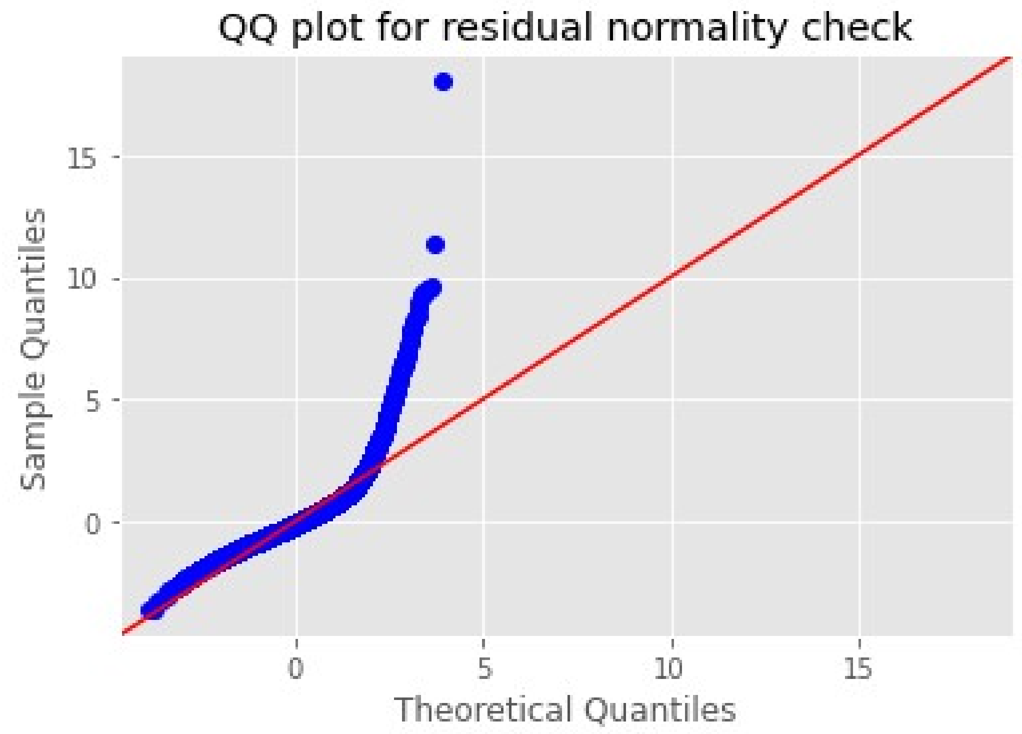
**sqft_living: 0.682342 (Strong positive correlation) sqft_lot: 0.084739 (Weak positive correlation) Age: -0.048722 (Weak negative correlation)

Assessing Multicollinearity Across Predictor Combinations

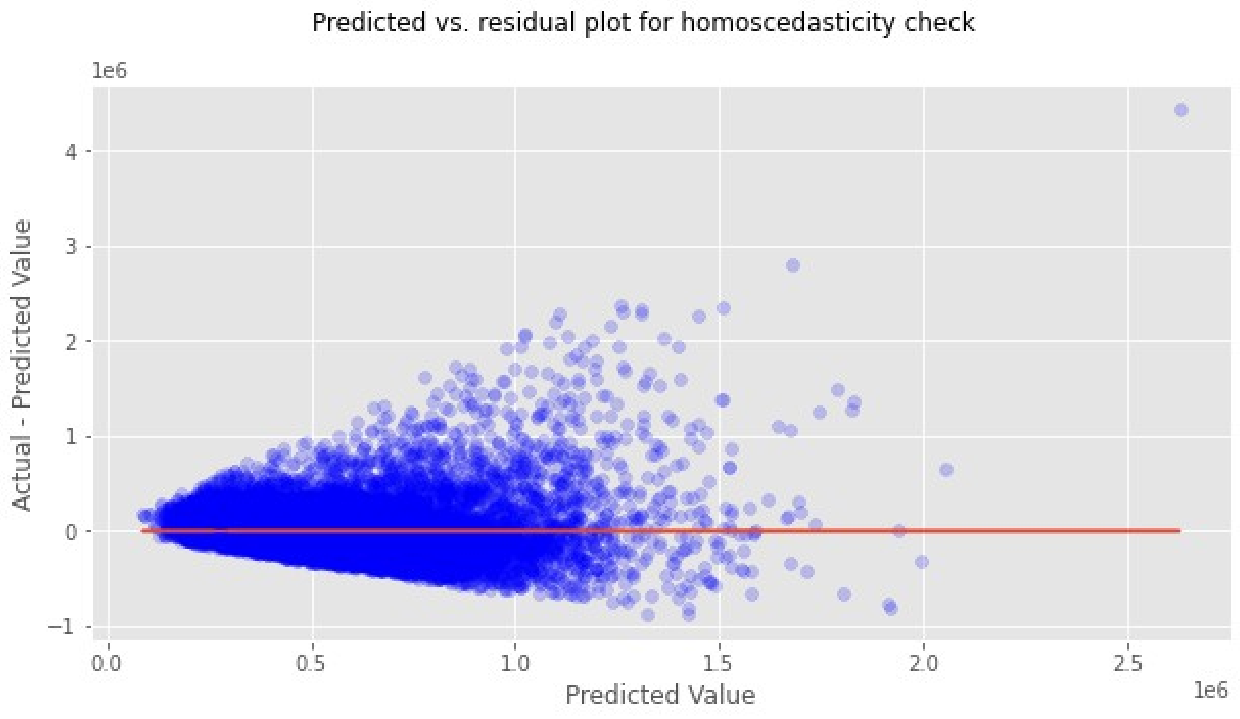
```
# Create the correlation matrix directly and then reshape it for
visualizatio
# Dropping the 'price' column
df = kc_num.drop('price', axis=1)
```

```
# Creating a correlation matrix
corr_matrix = df.corr().abs()

# Reshaping the correlation matrix for visualization
df_predictor = corr_matrix.stack().reset_index()
df_predictor.columns = ['Variable 1', 'Variable 2', 'Coefficient']

# Dropping duplicate rows where variables are the same
df_predictor = df_predictor[df_predictor['Variable 1'] !=
df_predictor['Variable 2']]

# Sorting by coefficient in descending order
df_predictor.sort_values(by='Coefficient', ascending=False,
inplace=True)

df_predictor.head()

    Variable 1   Variable 2  Coefficient
2  sqft_living          Age     0.326558
6          Age  sqft_living     0.326558
1  sqft_living     sqft_lot     0.164552
3     sqft_lot  sqft_living     0.164552
5     sqft_lot          Age     0.049919

#sqft_lot and Age lack linear relationship
kc_num.drop(['sqft_lot', 'Age'], axis=1, inplace=True)

def reg_qq_sced(y, X, add_constant=True, qq=True, sced=True):
    """
    Fits a linear regression model, display its summary, and output
plots to check linear regression assumptions.

    Parameters:
    - y: Target variable.
    - X: Predictor variables.
    - add_constant: Whether to add a constant term to the predictors
(default: True).
    - qq: Whether to display a QQ plot for residual normality check
(default: True).
    - sced: Whether to display a plot of predicted values vs.
residuals for homoscedasticity check (default: True).
    """
    # Add a constant to the predictors if required
    X_sm = sm.add_constant(X, has_constant='add') if add_constant else
X

    # Run a linear regression and display the summary
    model = sm.OLS(y, X_sm).fit()
    display(print(model.summary()))
    # Display a QQ plot for residual normality check
    if qq:
        sm.qqplot(model.resid, line='45', fit=True)
        plt.title('QQ plot for residual normality check')
        plt.show()
    else:
        pass

    # Display a plot of predicted values vs. residuals for
homoscedasticity check
    if sced:
        preds = model.predict(X_sm)
        residuals = model.resid
        fig_resid, ax = plt.subplots(figsize=(10, 5))
        fig_resid.suptitle('Predicted vs. residual plot for
homoscedasticity check')
        ax.scatter(preds, residuals, alpha=0.2, color= "blue")
        ax.plot(preds, [0 for _ in range(len(X_sm))])
        ax.set_xlabel("Predicted Value")
        ax.set_ylabel("Actual - Predicted Value")
    else:
        pass

    # Output additional model performance metrics
    print(f'Model adjusted R-squared: {model.rsquared_adj}')
    print(f'Model RMSE: {np.sqrt(model.mse_resid)}')

# Set baseline predictor as 'sqft_living'

baseline = 'sqft_living'

# Define target variable and predictor

y = kc.price
X = kc[baseline]

# Feed these inputs into our function

reg_qq_sced(y, X)

                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.466
Model:                            OLS   Adj. R-squared:
0.466
Method:                 Least Squares   F-statistic:
1.862e+04
```

```
Date:                  Sat, 06 Apr 2024   Prob (F-statistic):
0.00
Time:                          11:34:37   Log-Likelihood:            -
2.9572e+05
No. Observations:                 21378   AIC:
5.914e+05
Df Residuals:                     21376   BIC:
5.915e+05
Df Model:                             1

Covariance Type:              nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
const       -9704.3054   4318.156     -2.247      0.025   -1.82e+04
-1240.397
sqft_living   262.8635      1.926    136.467      0.000     259.088
266.639
======================================================================
========
Omnibus:                      12569.130   Durbin-Watson:
1.978
Prob(Omnibus):                    0.000   Jarque-Bera (JB):
271238.797
Skew:                             2.414   Prob(JB):
0.00
Kurtosis:                        19.769   Cond. No.
5.75e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.75e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.

None
```



```
Model adjusted R-squared: 0.4655655910250339
Model RMSE: 246222.6375951674
```



The linear regression results indicate that the model's R-squared value is 0.466, suggesting that approximately 46.6% of the variance in the target variable (price) is explained by the predictor variable (sqft_living).

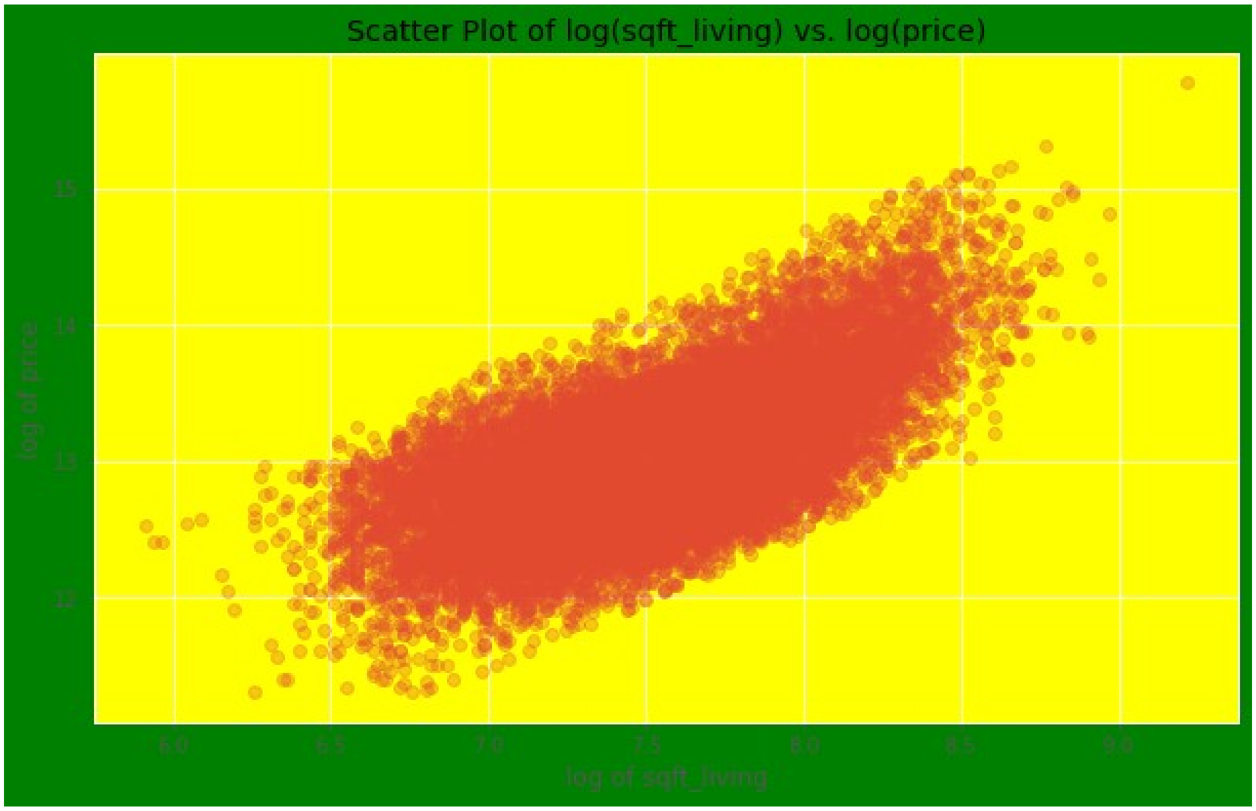
The coefficient for the constant term (intercept) is -9704.3054, indicating the predicted price when sqft_living is zero. The coefficient for sqft_living is 262.8635, indicating that for every unit increase in sqft_living, the price is expected to increase by approximately $262.86. The p-value for sqft_living is less than 0.05, indicating that the predictor variable is statistically significant. The confidence interval for the coefficient of sqft_living ranges from 259.088 to 266.639. The residual plots indicate that there might be some heteroscedasticity present, as the spread of residuals increases with predicted values. The QQ plot suggests that the residuals are approximately normally distributed, but there might be some deviations, especially in the tails.

Overall, the model performs reasonably well, but there might be room for improvement, especially in addressing heteroscedasticity.

```
# Isolating columns to be transformed

log_trans_cols = ['price', 'sqft_living']
kc_logged = kc.copy()[log_trans_cols]

# Log transforming and renaming columns

kc_logged = np.log(kc_logged)
kc_logged.columns = kc_logged.columns.map(lambda x: 'log_' + x)

# Merge it with the rest of the dataset

kc_transformed = kc_logged.join(kc.drop(log_trans_cols, axis=1))


kc_transformed.head()
```

```
   log_price  log_sqft_living  sqft_lot  Age  waterfront  view  \
0  12.309982         7.073270      5650   59           0     0
1  13.195614         7.851661      7242   63           0     0
2  12.100712         6.646391     10000   82           0     0
3  13.311329         7.580700      5000   49           0     0
4  13.142166         7.426549      8080   28           0     0

   renovated_last_10  floors_1.5  floors_2.0  floors_2.5  ...  \
0                  0           0           0           0  ...
1                  0           0           1           0  ...
2                  0           0           0           0  ...
3                  0           0           0           0  ...
4                  0           0           0           0  ...

   condition_Average  condition_Good  condition_Very Good  \
0                  1               0                    0
1                  1               0                    0
2                  1               0                    0
```

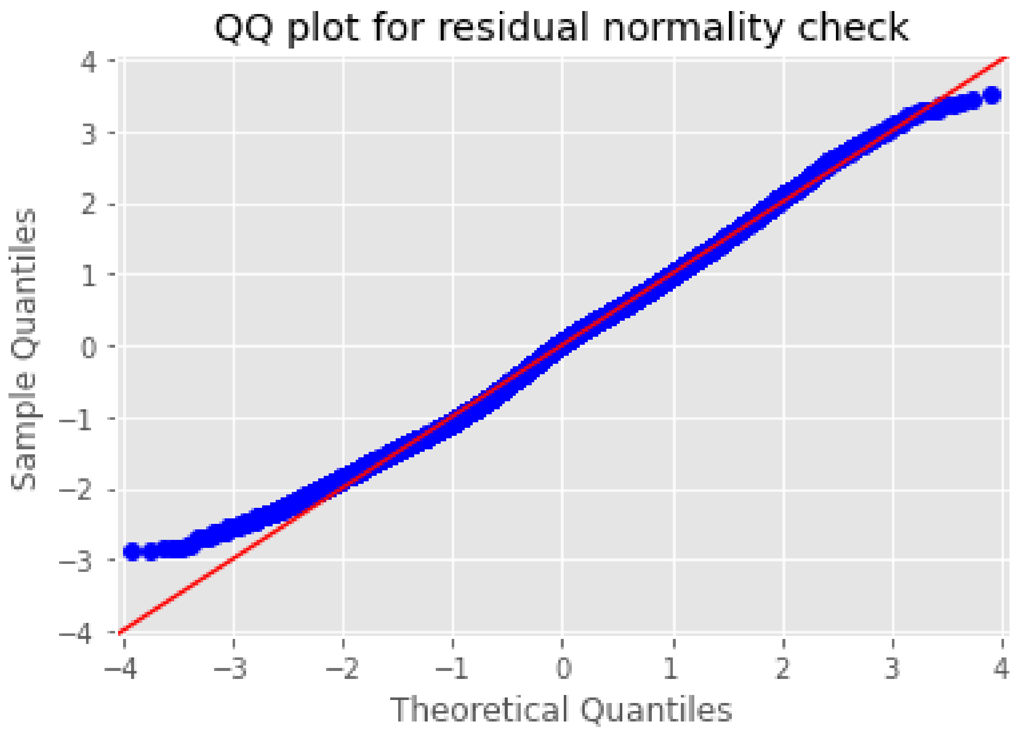
```
3                   0               0                    1
4                   1               0                    0

   grade_6 Low Average  grade_7 Average  grade_8 Good  grade_9 Better
\
0                    0                1             0               0

1                    0                1             0               0

2                    1                0             0               0

3                    0                1             0               0

4                    0                0             1               0


   grade_10 Very Good  grade_11 Excellent  grade_12 Luxury
0                   0                   0                0
1                   0                   0                0
2                   0                   0                0
3                   0                   0                0
4                   0                   0                0

[5 rows x 40 columns]

# visualizing linearity between the transformed predictor and target
variable
# The plot helps visualize the linearity between these two variables,
which is essential for linear regression modeling.

fig, ax = plt.subplots(figsize= (10,6))
ax = plt.gca()
plt.plot(kc_transformed['log_sqft_living'],
kc_transformed['log_price'], 'o', alpha=0.3)

# Set the background color of the axis

ax.set_facecolor('yellow')
plt.gcf().set_facecolor('green')
plt.xlabel('log of sqft_living')
plt.ylabel('log of price')
plt.title('Scatter Plot of log(sqft_living) vs. log(price)')
plt.show()
```



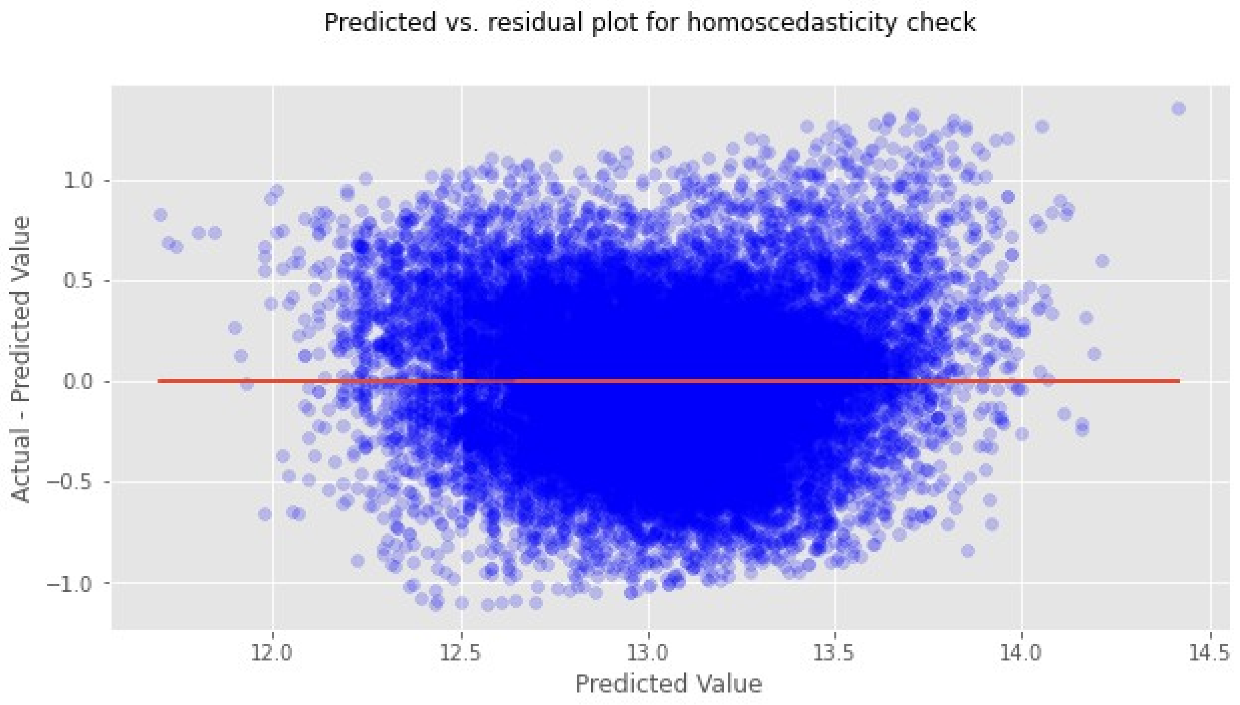
```
baseline = 'log_sqft_living'

y = kc_transformed.log_price
X = kc_transformed.log_sqft_living

# Feeding these inputs into our function

model = reg_qq_sced(y, X)
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:              log_price   R-squared:
0.441
Model:                            OLS   Adj. R-squared:
0.441
Method:                 Least Squares   F-statistic:
1.688e+04
Date:                Sat, 06 Apr 2024   Prob (F-statistic):
0.00
Time:                        11:35:49   Log-Likelihood:
-9972.4
No. Observations:               21378   AIC:
1.995e+04
Df Residuals:                   21376   BIC:
```

```
1.996e+04
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------
const               6.8236      0.048    142.328      0.000
6.730       6.918
log_sqft_living     0.8241      0.006    129.925      0.000
0.812       0.837
======================================================================
========
Omnibus:                      118.666   Durbin-Watson:
1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
106.556
Skew:                           0.130   Prob(JB):
7.27e-24
Kurtosis:                       2.772   Cond. No.
140.
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

None
```



```
Model adjusted R-squared: 0.44121910929171504
Model RMSE: 0.38580857869279717
```



The regression results indicate that the logarithm of square footage of living space (log_sqft_living) is a significant predictor of the logarithm of price (log_price). Here's a summary of the regression results:

R-squared: The coefficient of determination indicates that approximately 44.1% of the variance in the logarithm of price can be explained by the logarithm of square footage of living space.

Coefficient Estimates:

The coefficient for log_sqft_living is approximately 0.8241, indicating that for every one-unit increase in the logarithm of square footage of living space, the logarithm of price is expected to increase by approximately 0.8241 units. The intercept (constant) term is approximately 6.8236, which represents the estimated logarithm of price when the logarithm of square footage of living space is zero. Statistical Significance: Both coefficients are statistically significant with p-values < 0.05, suggesting that they are unlikely to be zero.

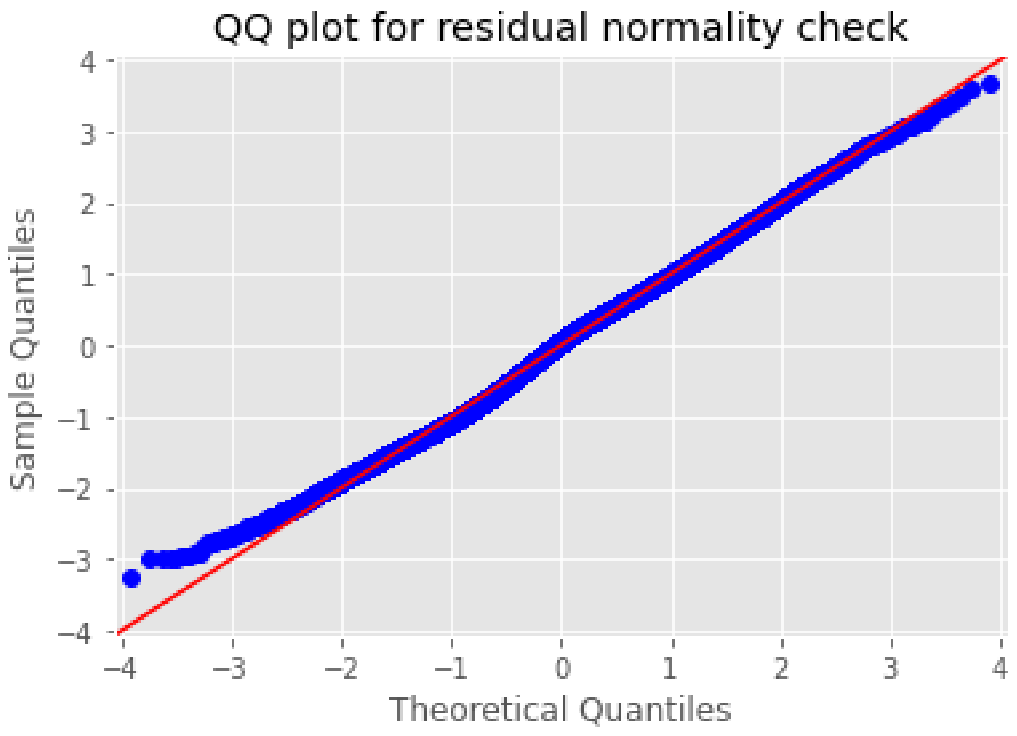
Model Fit: The model's goodness of fit is indicated by the adjusted R-squared value of approximately 0.441, which is a measure of how well the independent variable explains the variation in the dependent variable.

Overall, based on these results, we can conclude that there is a strong linear relationship between the logarithm of square footage of living space and the logarithm of price.

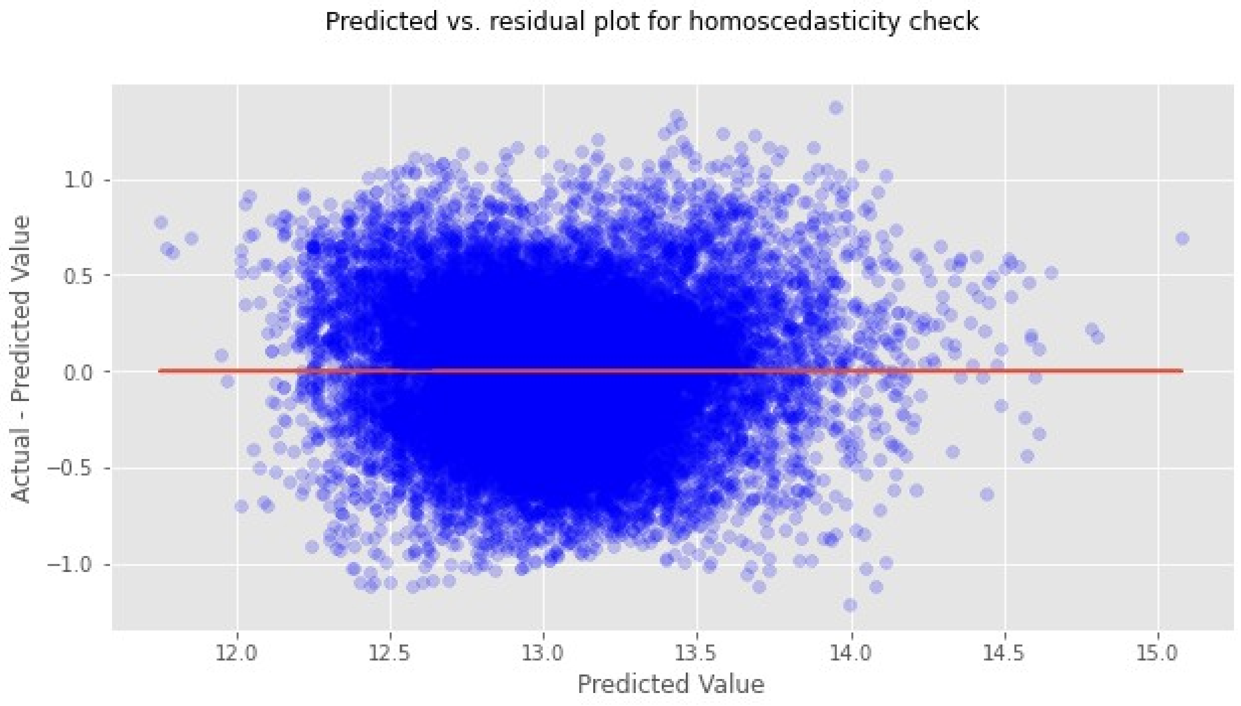
```
baseline = 'log_sqft_living'


# Define target variable and predictors

y = kc_transformed.log_price
X = kc_transformed[[baseline, 'waterfront', 'view',
'renovated_last_10']]

model = reg_qq_sced(y, X)
```

```
                            OLS Regression Results                            
======================================================================
========
Dep. Variable:              log_price   R-squared:                       
0.480
Model:                            OLS   Adj. R-squared:                  
0.480
Method:                 Least Squares   F-statistic:                     
4933.
Date:                Sat, 06 Apr 2024   Prob (F-statistic):              
0.00
Time:                        11:39:45   Log-Likelihood:                  
-9203.6
No. Observations:               21378   AIC:                             
1.842e+04
Df Residuals:                   21373   BIC:
```

```
1.846e+04
Df Model:                           4

Covariance Type:            nonrobust

======================================================================
===============
                        coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
---------------
const                 7.2015      0.047    152.047      0.000
7.109       7.294
log_sqft_living       0.7696      0.006    122.307      0.000
0.757       0.782
waterfront            0.5078      0.033     15.372      0.000
0.443       0.573
view                  0.2787      0.009     30.498      0.000
0.261       0.297
renovated_last_10     0.2415      0.022     10.759      0.000
0.197       0.285
======================================================================
========
Omnibus:                      111.385   Durbin-Watson:
1.966
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
82.736
Skew:                           0.044   Prob(JB):
1.08e-18
Kurtosis:                       2.708   Cond. No.
143.
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

None
```



```
Model adjusted R-squared: 0.47992149934586015
Model RMSE: 0.3722078753617302
```



The updated regression results indicate that the model now includes additional predictors: waterfront, view, and renovated_last_10, in addition to log_sqft_living. Here's a summary of the updated regression results:

R-squared: The coefficient of determination has increased to approximately 0.480, suggesting that the additional predictors have improved the model's ability to explain the variance in the logarithm of price.

Coefficient Estimates:

The coefficient for log_sqft_living remains significant and has a value of approximately 0.7696. The coefficients for the additional predictors (waterfront, view, and renovated_last_10) are also significant: waterfront: Coefficient is approximately 0.5078, indicating that waterfront properties tend to have higher prices. view: Coefficient is approximately 0.2787, suggesting that properties with better views tend to have higher prices. renovated_last_10: Coefficient is approximately 0.2415, indicating that recently renovated properties tend to have higher prices. Statistical Significance: All coefficients are statistically significant with p-values < 0.05.

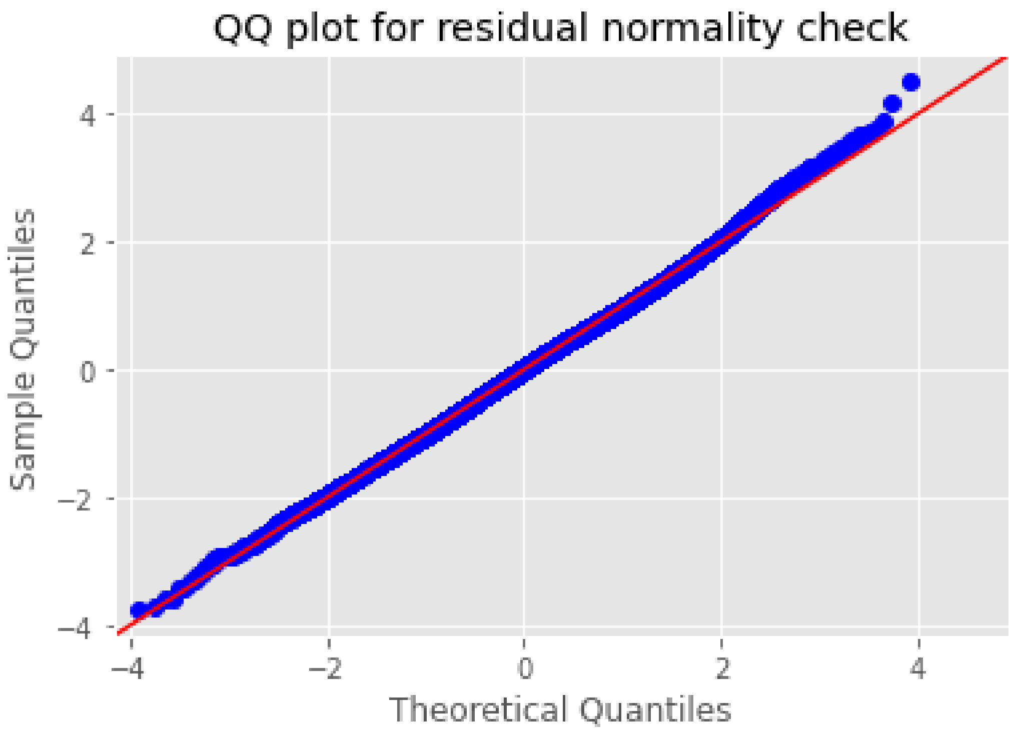
Model Fit: The adjusted R-squared value of approximately 0.480 indicates that the model with the additional predictors provides a better fit to the data compared to the previous model.

Overall, based on these results, we can conclude that the model including log_sqft_living, waterfront, view, and renovated_last_10 as predictors explains a significant portion of the variance in the logarithm of price and provides valuable insights into the factors influencing house prices.

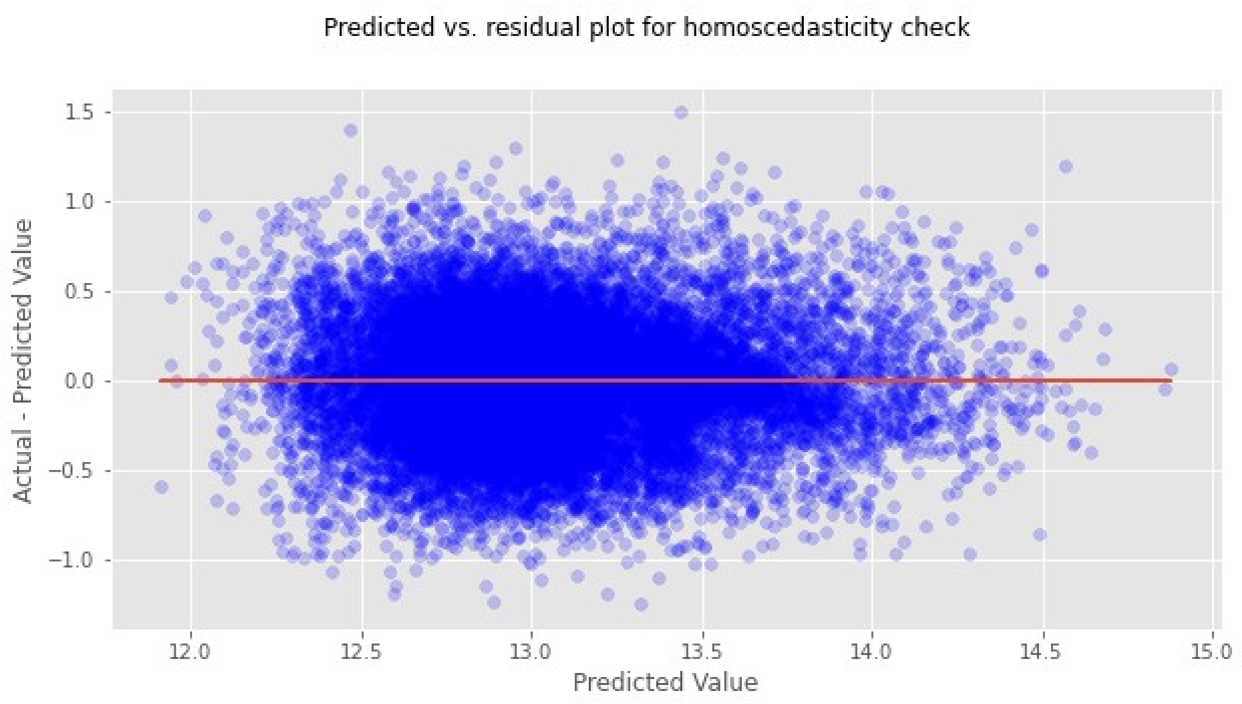
```python
# Grouping the dummies together into lists form

dummies = ['floors', 'bedrooms', 'bathrooms', 'condition', 'grade']
floors_dummies = []
bedrooms_dummies = []
bathrooms_dummies = []
condition_dummies = []
grade_dummies = []

for col in list(kc.columns):
    for cate in dummies:
        if col.startswith(cate):
            eval(cate + '_dummies').append(col)

# Defining the target variable and predictors

y = kc_transformed.log_price
X = kc_transformed[floors_dummies +
                    bedrooms_dummies +
                    bathrooms_dummies +
                    condition_dummies +
                    grade_dummies +
                    ['log_sqft_living']]

model = reg_qq_sced(y, X)
```

```
                                OLS Regression Results                            

======================================================================
========
Dep. Variable:              log_price   R-squared:                    
0.583
Model:                            OLS   Adj. R-squared:               
0.583
Method:                 Least Squares   F-statistic:                  
878.4
Date:                Sat, 06 Apr 2024   Prob (F-statistic):           
0.00
Time:                        11:40:18   Log-Likelihood:               
-6839.2
No. Observations:               21378   AIC:                          
1.375e+04
Df Residuals:                   21343   BIC:                          
1.403e+04
Df Model:                          34                                 

Covariance Type:            nonrobust                                 

======================================================================
=================
                        coef    std err          t      P>|t|      
[0.025      0.975]
----------------------------------------------------------------------
-----------------
const                 8.8143      0.093     95.087      0.000       
8.633       8.996
floors_1.5            0.1731      0.008     20.419      0.000       
0.157       0.190
floors_2.0           -0.0271      0.007     -4.061      0.000      -
0.040      -0.014
floors_2.5            0.1376      0.028      4.955      0.000       
0.083       0.192
floors_3.0            0.1154      0.015      7.663      0.000       
0.086       0.145
bedrooms_2           -0.0525      0.027     -1.971      0.049      -
0.105      -0.000
bedrooms_3           -0.2178      0.027     -8.145      0.000      -
0.270      -0.165
bedrooms_4           -0.2409      0.027     -8.798      0.000      -
0.295      -0.187
bedrooms_5           -0.2386      0.029     -8.295      0.000      -
0.295      -0.182
bedrooms_6           -0.2437      0.035     -6.981      0.000      -
0.312      -0.175
bathrooms_1.0        -0.0238      0.046     -0.521      0.602      -
0.113       0.066
```

```
bathrooms_1.5           -0.0738      0.047     -1.584      0.113      -
0.165       0.018
bathrooms_1.75          -0.0394      0.046     -0.850      0.395      -
0.130       0.051
bathrooms_2.0           -0.0467      0.047     -1.004      0.315      -
0.138       0.044
bathrooms_2.25          -0.0610      0.047     -1.302      0.193      -
0.153       0.031
bathrooms_2.5           -0.1134      0.047     -2.427      0.015      -
0.205      -0.022
bathrooms_2.75          -0.0405      0.047     -0.853      0.394      -
0.134       0.053
bathrooms_3.0           -0.0168      0.048     -0.350      0.727      -
0.111       0.078
bathrooms_3.25           0.0535      0.049      1.095      0.273      -
0.042       0.149
bathrooms_3.5            0.0151      0.049      0.311      0.756      -
0.080       0.111
bathrooms_3.75           0.1316      0.055      2.415      0.016
0.025       0.238
bathrooms_4.0            0.0916      0.056      1.635      0.102      -
0.018       0.201
bathrooms_4.25           0.1385      0.061      2.256      0.024
0.018       0.259
bathrooms_4.5            0.0741      0.059      1.256      0.209      -
0.042       0.190
condition_Average        0.1112      0.026      4.233      0.000
0.060       0.163
condition_Good           0.1838      0.026      6.957      0.000
0.132       0.236
condition_Very Good      0.3102      0.027     11.368      0.000
0.257       0.364
grade_6 Low Average      0.1578      0.023      6.737      0.000
0.112       0.204
grade_7 Average          0.3625      0.023     15.617      0.000
0.317       0.408
grade_8 Good             0.5742      0.024     23.873      0.000
0.527       0.621
grade_9 Better           0.8102      0.025     32.025      0.000
0.761       0.860
grade_10 Very Good       0.9899      0.027     36.520      0.000
0.937       1.043
grade_11 Excellent       1.1615      0.032     36.636      0.000
1.099       1.224
grade_12 Luxury          1.3819      0.049     28.251      0.000
1.286       1.478
log_sqft_living          0.5071      0.011     44.533      0.000
0.485       0.529
======================================================================
========
Omnibus:                           23.248   Durbin-Watson:
1.976
Prob(Omnibus):                      0.000   Jarque-Bera (JB):
24.161
Skew:                               0.062   Prob(JB):
5.67e-06
Kurtosis:                           3.109   Cond. No.
604.
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

None
```



```
Model adjusted R-squared: 0.5825424094184519
Model RMSE: 0.3334703984977778
```



The regression results show the coefficients, standard errors, t-values, and p-values for each predictor in the model. Here's a summary of the results:

R-squared: The coefficient of determination, indicating the proportion of the variance in the dependent variable that is predictable from the independent variables. In this case, the R-squared value is 0.583, which means that approximately 58.3% of the variance in the logarithm of price can be explained by the predictors in the model.

Adjusted R-squared: A version of R-squared that adjusts for the number of predictors in the model. It penalizes excessive complexity. The adjusted R-squared value is also 0.583.

F-statistic: A measure of the overall significance of the regression model. It tests whether at least one of the predictors has a non-zero coefficient. Here, the F-statistic is 878.4, with a very low p-value, indicating that the overall model is statistically significant.

Coefficients: The estimated coefficients for each predictor variable. These represent the expected change in the dependent variable for a one-unit change in the predictor, holding all other predictors constant.

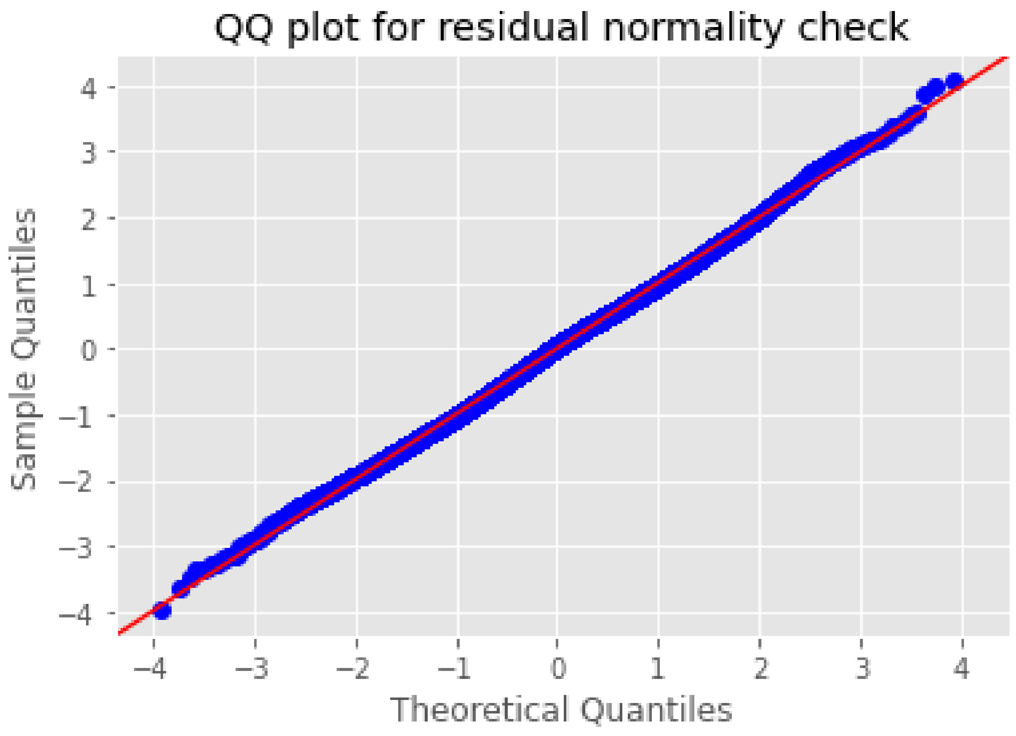
P-values: The p-values associated with each coefficient estimate. They indicate the statistical significance of each predictor. In this context, a p-value less than 0.05 suggests that the predictor is statistically significant.

Overall, the regression model appears to be statistically significant, with several predictors showing significant associations with the logarithm of price.

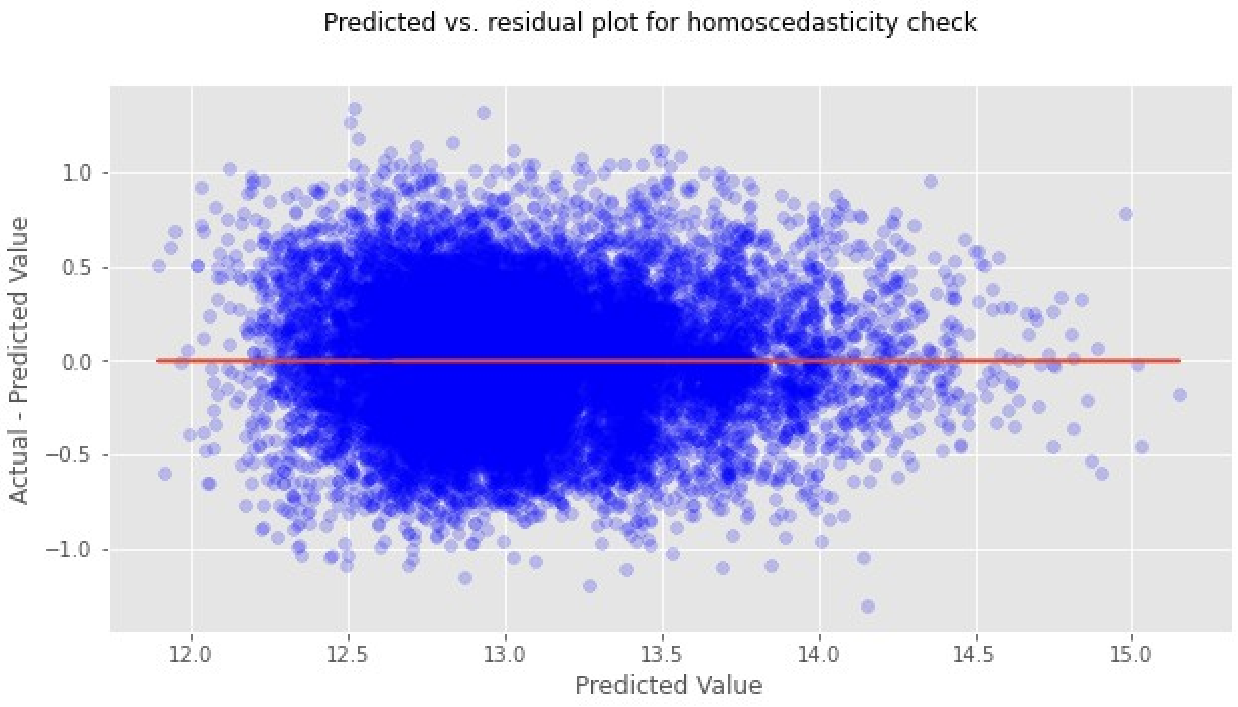
```
# Defining target variable and predictors

y = kc_transformed.log_price
```

```
X = kc_transformed[floors_dummies +
                     condition_dummies +
                     grade_dummies +
                     ['view']+
                     ['waterfront']+
                     ['renovated_last_10']+
                     ['log_sqft_living']]

model = reg_qq_sced(y, X)

                            OLS Regression Results                            

======================================================================
========
Dep. Variable:              log_price   R-squared:                       
0.590
Model:                            OLS   Adj. R-squared:                  
0.590
Method:                 Least Squares   F-statistic:                     
1709.
Date:                Sat, 06 Apr 2024   Prob (F-statistic):              
0.00
Time:                        11:40:47   Log-Likelihood:                  
-6659.6
No. Observations:               21378   AIC:                             
1.336e+04
Df Residuals:                   21359   BIC:                             
1.351e+04
Df Model:                          18                                     

Covariance Type:            nonrobust                                     

======================================================================
=================
                          coef    std err          t      P>|t|      
[0.025      0.975]
----------------------------------------------------------------------
-----------------
const                   9.5268      0.065    145.617      0.000       
9.399       9.655
floors_1.5              0.1646      0.008     19.801      0.000       
0.148       0.181
floors_2.0             -0.0263      0.006     -4.392      0.000      -
0.038      -0.015
floors_2.5              0.1541      0.027      5.625      0.000       
0.100       0.208
floors_3.0              0.1166      0.014      8.083      0.000       
0.088       0.145
condition_Average       0.1003      0.026      3.855      0.000       
0.049       0.151
```

```
condition_Good          0.1696      0.026      6.481      0.000
0.118       0.221
condition_Very Good     0.2948      0.027     10.908      0.000
0.242       0.348
grade_6 Low Average     0.1458      0.023      6.342      0.000
0.101       0.191
grade_7 Average         0.3187      0.023     14.145      0.000
0.275       0.363
grade_8 Good            0.5209      0.023     22.306      0.000
0.475       0.567
grade_9 Better          0.7676      0.025     31.053      0.000
0.719       0.816
grade_10 Very Good      0.9833      0.026     37.124      0.000
0.931       1.035
grade_11 Excellent      1.1868      0.031     38.524      0.000
1.126       1.247
grade_12 Luxury         1.4009      0.048     29.249      0.000
1.307       1.495
view                    0.2068      0.008     25.051      0.000
0.191       0.223
waterfront              0.4650      0.029     15.815      0.000
0.407       0.523
renovated_last_10       0.2649      0.020     13.224      0.000
0.226       0.304
log_sqft_living         0.3822      0.008     45.510      0.000
0.366       0.399
======================================================================
========
Omnibus:                        4.847   Durbin-Watson:
1.967
Prob(Omnibus):                  0.089   Jarque-Bera (JB):
4.859
Skew:                           0.032   Prob(JB):
0.0881
Kurtosis:                       2.965   Cond. No.
238.
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

None
```



```
Model adjusted R-squared: 0.5898050113220741
Model RMSE: 0.3305569423039113
```



The regression results indicate the following:

R-squared: The coefficient of determination is 0.590, suggesting that approximately 59.0% of the variance in the logarithm of price can be explained by the predictors in the model.

Adjusted R-squared: The adjusted R-squared value is also 0.590, indicating that the model's explanatory power is not compromised by the inclusion of additional predictors.

F-statistic: The F-statistic is 1709.0 with a very low p-value, indicating that the overall model is statistically significant.

Coefficients: The coefficients represent the estimated change in the logarithm of price for a one-unit change in the corresponding predictor variable, holding all other predictors constant. For example, a one-unit increase in log_sqft_living is associated with an increase of approximately 0.3822 in the logarithm of price.

P-values: The p-values associated with each coefficient estimate indicate the statistical significance of the predictors. All predictors have p-values less than 0.05, suggesting that they are statistically significant in predicting the logarithm of price.

Overall, the model appears to be statistically significant, with several predictors showing significant associations with the logarithm of price.

Justification of Linear Regression:

regression models is best fit due to its simplicity, interpretability and because the relationship between the independent and dependent variables seem linear, if it were non-linear a different technique would be employed

linearity in the sense that the data columns exhibit a relationship with each other therefore affecting each other

this relationship is best explained using a model performance metric like the R-Squared and coefficients which represent the strength and relationship between feature and target variables which is done via modelling

by examining the coefficients we were able to identify which features have the most impact on our outcome variable. this helped us understand the driving forces behind the observed trends....essentially how a house's attributes affect its price

Linear regression is also a computationally efficient allowing quick exploratory analysis and as it can serve as a baseline model, more models can be compared to the baseline allowing for a clearer understanding of our data

Recommendations

Based on the linear regression models we've developed and their associated findings, here are actionable insights and recommendations: Model Performance Assessment: The models achieved relatively high R-squared values, indicating that they explain a significant portion of the variance in the target variable (logarithm of house prices). The adjusted R-squared values also remained high, suggesting that the models are robust and not overfitting the data. Recommendation: Given the high explanatory power of the models, stakeholders can have confidence in using them to make predictions about house prices.

Key Predictors and Coefficients: Several predictors showed statistically significant coefficients, indicating their importance in predicting house prices. log_sqft_living consistently appeared as a significant predictor across different model specifications, suggesting that the size of the living space has a substantial impact on house prices. Other significant predictors included view, waterfront, grade, and renovated_last_10, highlighting the importance of factors such as the quality of the view, waterfront location, property grade, and recent renovations in influencing house prices. Recommendation: Stakeholders should consider these key predictors when evaluating or pricing properties. Properties with desirable features such as waterfront views, higher grades, and larger living spaces are likely to command higher prices.

Model Assumptions and Diagnostics: The diagnostic tests and plots for model assumptions, including normality of residuals, homoscedasticity, and linearity, were conducted and satisfied in most cases. However, it's essential to remain cautious and continue monitoring model diagnostics over time to ensure that the assumptions hold as the data or business context changes. Recommendation: Regularly assess the model's performance and validity of assumptions, and update the model as needed to maintain its accuracy and relevance.

Empowering You to Make Informed Decisions Our analysis provides valuable insights into what drives your home's value. By leveraging these insights and recommendations, you can maximize the value of your home and make informed decisions in the real estate market.