Final Project Submission

Please fill out:

- Student name: Lauren Petrillo
- Student pace: Part time
- Scheduled project review date/time:
- Instructor name: Claude Fried
- Blog post URL: https://medium.com/@lauren.petrillo13/how-to-build-your-first-linear-regression-model-3b61f8194cfa

In [256…

```
import pandas as pd
import numpy as np
from pandas import DataFrame, Series
import warnings

import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import plotly.express as px


from scipy import stats
import scipy.stats as stats

import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn import metrics
from sklearn.model_selection import KFold
from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

In [257…

```
data = pd.read_csv('data/kc_house_data.csv')
```

In [258…

```
data.head()
```

Out[258…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vi
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	

5 rows × 21 columns

In [259…

```
data.describe()
```

Out[259…

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floc
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.0000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.4940
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.5396
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.0000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.0000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.5000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.0000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.5000

In [260…

```
data.shape
```

Out[260…

```
(21597, 21)
```

Cleaning/EDA

In [261…

```
data.info()
#need to change sqft_basement and date from objects to ints
#waterfront, view, and yr_renovated have missing values
#look through data to see if any sets need to be dropped
```

```
<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  float64
 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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [262…

```
#detect any missing values
data.isna().any()
```

Out[262…

```
id               False
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront        True
view              True
condition        False
grade            False
sqft_above       False
sqft_basement    False
yr_built         False
yr_renovated      True
zipcode          False
lat              False
long             False
sqft_living15    False
sqft_lot15       False
dtype: bool
```

In [263…

```
data.isna().sum()
```

Out[263…

```
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
```

In [264…

```
#dropped id and view because I didn't think it really affected the data set
data = data.drop(['id'], axis=1)
```

In [265…

```
#replace missing values for waterfront and yr_renovated

fill_waterfront = ['waterfront']
fill_yr_renovated = ['yr_renovated']
fill_view = ['view']
```

```
for replace in fill_waterfront:
    missing = data[replace].mode()[0]
    data[replace].fillna(missing, inplace = True)

for replace in fill_yr_renovated:
    missing = data[replace].mode()[0]
    data[replace].fillna(missing, inplace = True)

for replace in fill_view:
    missing = data[replace].mode()[0]
    data[replace].fillna(missing, inplace = True)
```

In [ ]:

In [266…

```
data.isna().any()
```

Out[266…

```
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
view             False
condition        False
grade            False
sqft_above       False
sqft_basement    False
yr_built         False
yr_renovated     False
zipcode          False
lat              False
long             False
sqft_living15    False
sqft_lot15       False
dtype: bool
```

In [ ]:

In [267…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           21597 non-null  object 
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64  
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64  
 5   sqft_lot       21597 non-null  int64  
 6   floors         21597 non-null  float64
 7   waterfront     21597 non-null  float64
 8   view           21597 non-null  float64
 9   condition      21597 non-null  int64  
 10  grade          21597 non-null  int64  
 11  sqft_above     21597 non-null  int64  
 12  sqft_basement  21597 non-null  object 
 13  yr_built       21597 non-null  int64  
```

```
 14  yr_renovated   21597 non-null  float64
 15  zipcode        21597 non-null  int64
 16  lat            21597 non-null  float64
 17  long           21597 non-null  float64
 18  sqft_living15  21597 non-null  int64
 19  sqft_lot15     21597 non-null  int64
dtypes: float64(8), int64(10), object(2)
memory usage: 3.3+ MB
```

In [268…
```
#split up the month, day, and year from 'date'
data[['month', 'day', 'year']] = data['date'].str.split('/', expand=True)
```

In [269…
```
data['month']
```

Out[269…
```
0        10
1        12
2         2
3        12
4         2
         ..
21592     5
21593     2
21594     6
21595     1
21596    10
Name: month, Length: 21597, dtype: object
```

In [270…
```
#drop the date, day, and year. Only keeping the month
data = data.drop(['date','day', 'year'], axis=1)
```

In [271…
```
#create new feature for month sold
data['month_sold'] = data['month'].sort_values()
```

In [272…
```
data.info()
```

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

In [273…
```
#drop the month since we don't need that anymore
data = data.drop(['month'], axis=1)
```

In [274…
```
#first fill the '?' value with '0.0' and then convert sqft_basement from a string to a 
data['sqft_basement'] = data['sqft_basement'].replace(to_replace = '?', value = 0.0)
data['sqft_basement'] = data['sqft_basement'].astype(str).astype(float)
```

In [275…
```
#convert zipcode into string and month_sold into int
data['zipcode'] = data['zipcode'].astype(int).astype(str)
data['month_sold'] = data['month_sold'].astype(str).astype(int)
```

In [276…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64  
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64  
 4   sqft_lot       21597 non-null  int64  
 5   floors         21597 non-null  float64
 6   waterfront     21597 non-null  float64
 7   view           21597 non-null  float64
 8   condition      21597 non-null  int64  
 9   grade          21597 non-null  int64  
 10  sqft_above     21597 non-null  int64  
 11  sqft_basement  21597 non-null  float64
 12  yr_built       21597 non-null  int64  
 13  yr_renovated   21597 non-null  float64
 14  zipcode        21597 non-null  object 
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64  
 18  sqft_lot15     21597 non-null  int64  
 19  month_sold     21597 non-null  int32  
dtypes: float64(9), int32(1), int64(9), object(1)
memory usage: 3.2+ MB
```

In [277…
```
data['has_basement'] = data['sqft_basement'].astype('bool').astype('str')
```

In [278…
```
data['zipcode'].value_counts()
```

Out[278…
```
98103    602
98038    589
98115    583
98052    574
98117    553
        ... 
98102    104
98010    100
98024     80
98148     57
98039     50
Name: zipcode, Length: 70, dtype: int64
```

In [279…
```
data
```

Out[279…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
0	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3	7
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8
...	...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	0.0	0.0	3	8
21593	400000.0	4	2.50	2310	5813	2.0	0.0	0.0	3	8
21594	402101.0	2	0.75	1020	1350	2.0	0.0	0.0	3	7
21595	400000.0	3	2.50	1600	2388	2.0	0.0	0.0	3	8
21596	325000.0	2	0.75	1020	1076	2.0	0.0	0.0	3	7

21597 rows × 21 columns

Price

In [280…

```
data['price'].describe()
```

Out[280…

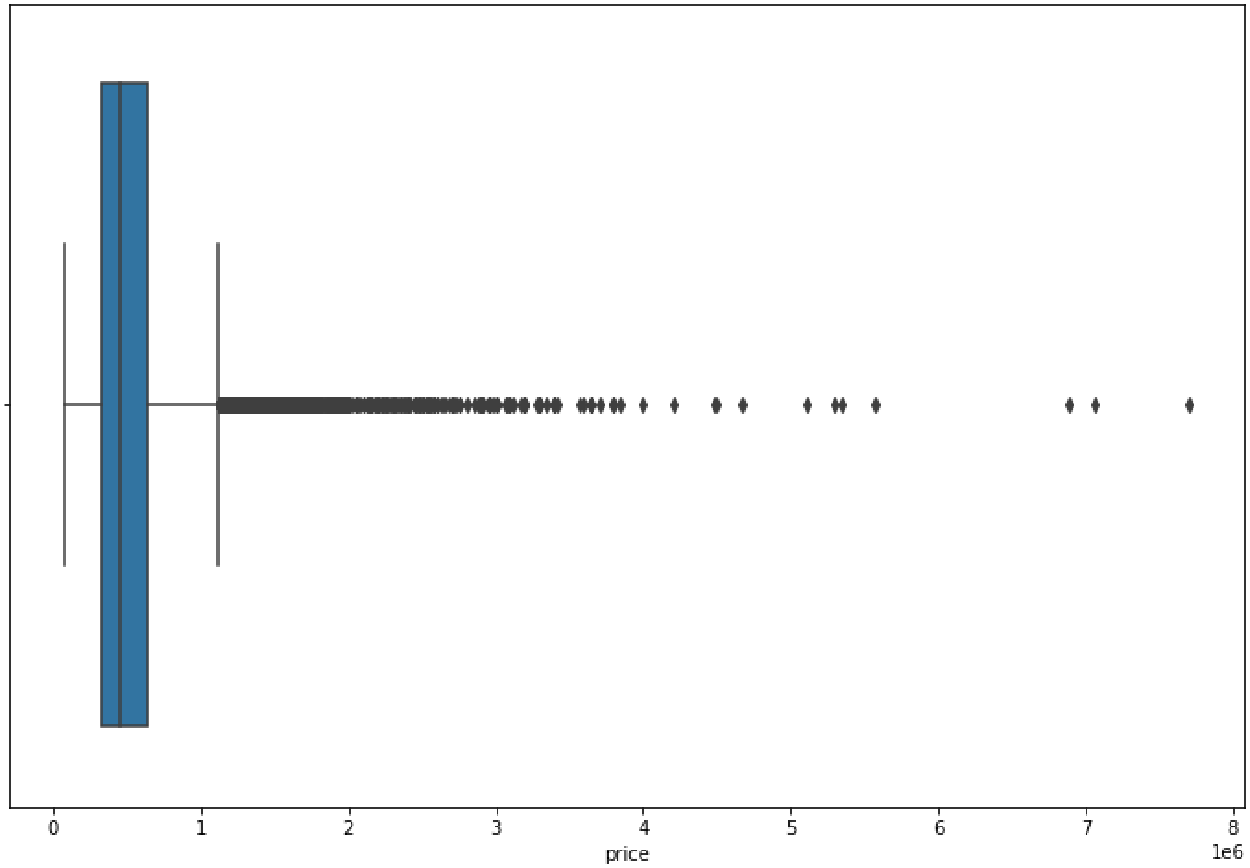
```
count    2.159700e+04
mean     5.402966e+05
std      3.673681e+05
min      7.800000e+04
25%      3.220000e+05
50%      4.500000e+05
75%      6.450000e+05
max      7.700000e+06
Name: price, dtype: float64
```

In [281…

```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='price', data=data, ax=ax)
```

Out[281…

```
<AxesSubplot:xlabel='price'>
```



In [282…
```
#Get rid of outliers
outliers=data[(data['price'])>=7500000].index
data.drop(outliers, inplace=True)
```

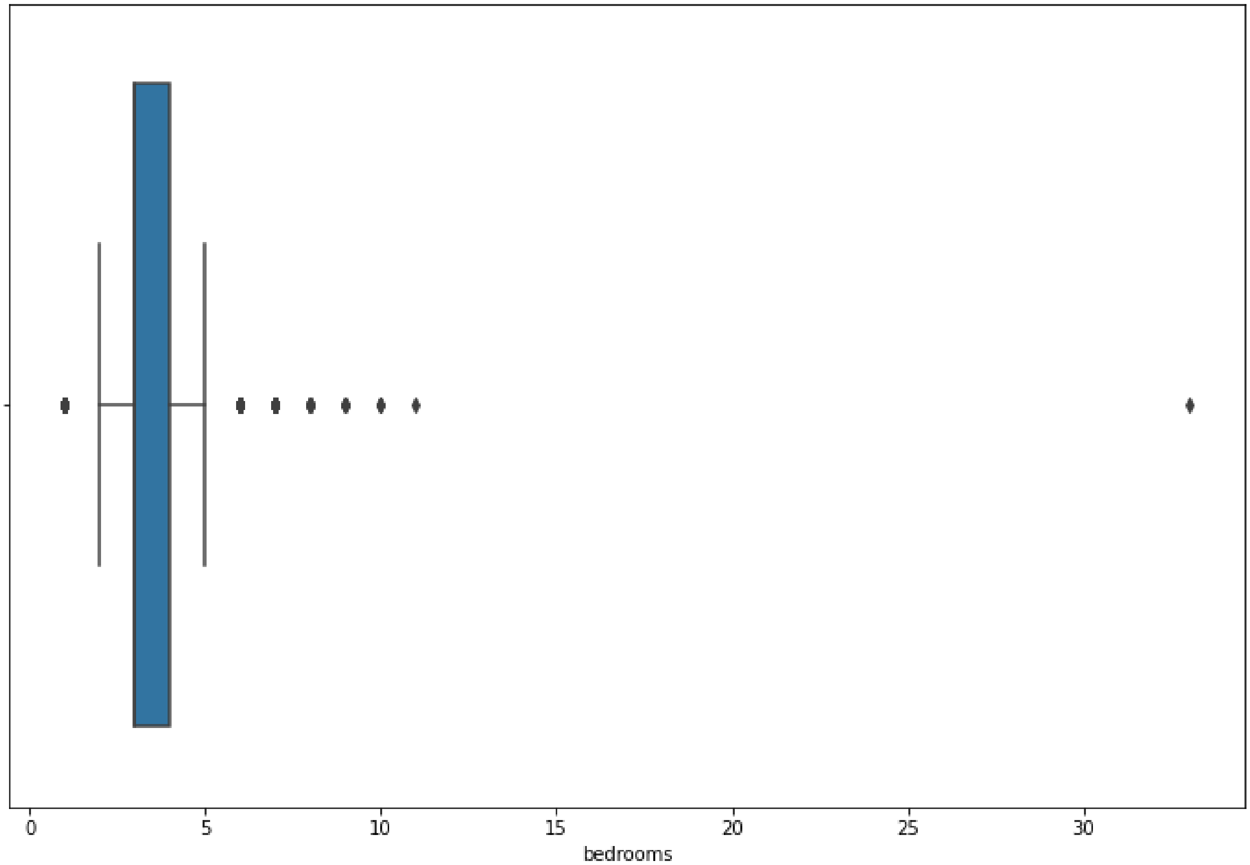
Bedrooms

In [283…
```
#Looking at bedrooms
data['bedrooms'].value_counts()
```

Out[283…
```
3     9824
4     6882
2     2760
5     1601
6      271
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

In [284…
```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='bedrooms', data=data, ax=ax)
```

Out[284…
```
<AxesSubplot:xlabel='bedrooms'>
```



In [285…
```
#drop outliers
data = data.loc[data['bedrooms'] < 15]
```

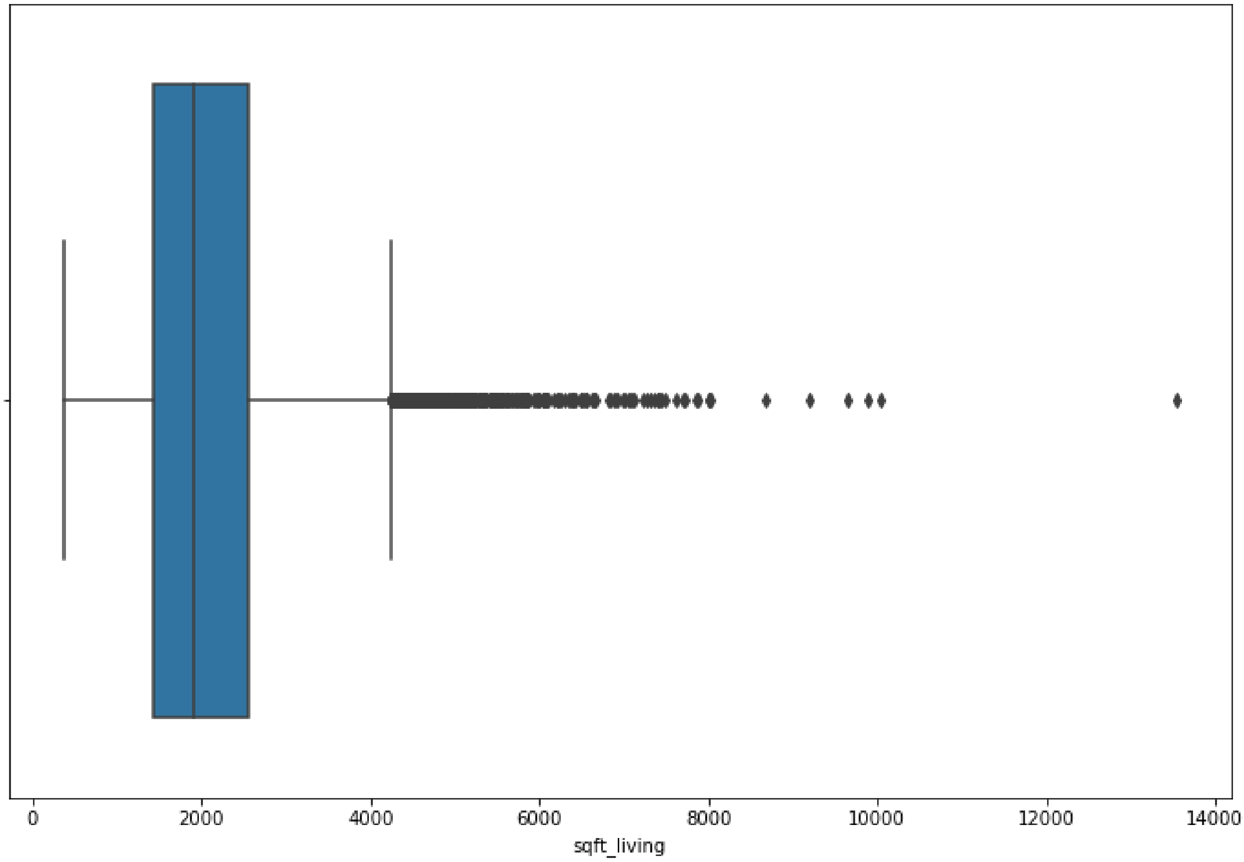
Sqft_living

In [286…
```
#looking at sqft_living column
data['sqft_living'].describe()
```

Out[286…
```
count    21595.000000
mean      2079.881500
std        915.633139
min        370.000000
25%       1430.000000
50%       1910.000000
75%       2550.000000
max      13540.000000
Name: sqft_living, dtype: float64
```

In [287…
```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='sqft_living', data=data, ax=ax)
```

Out[287…
```
<AxesSubplot:xlabel='sqft_living'>
```



In [288…
```
#Get rid of outliers
data = data.loc[data['sqft_living'] < 8000]
```

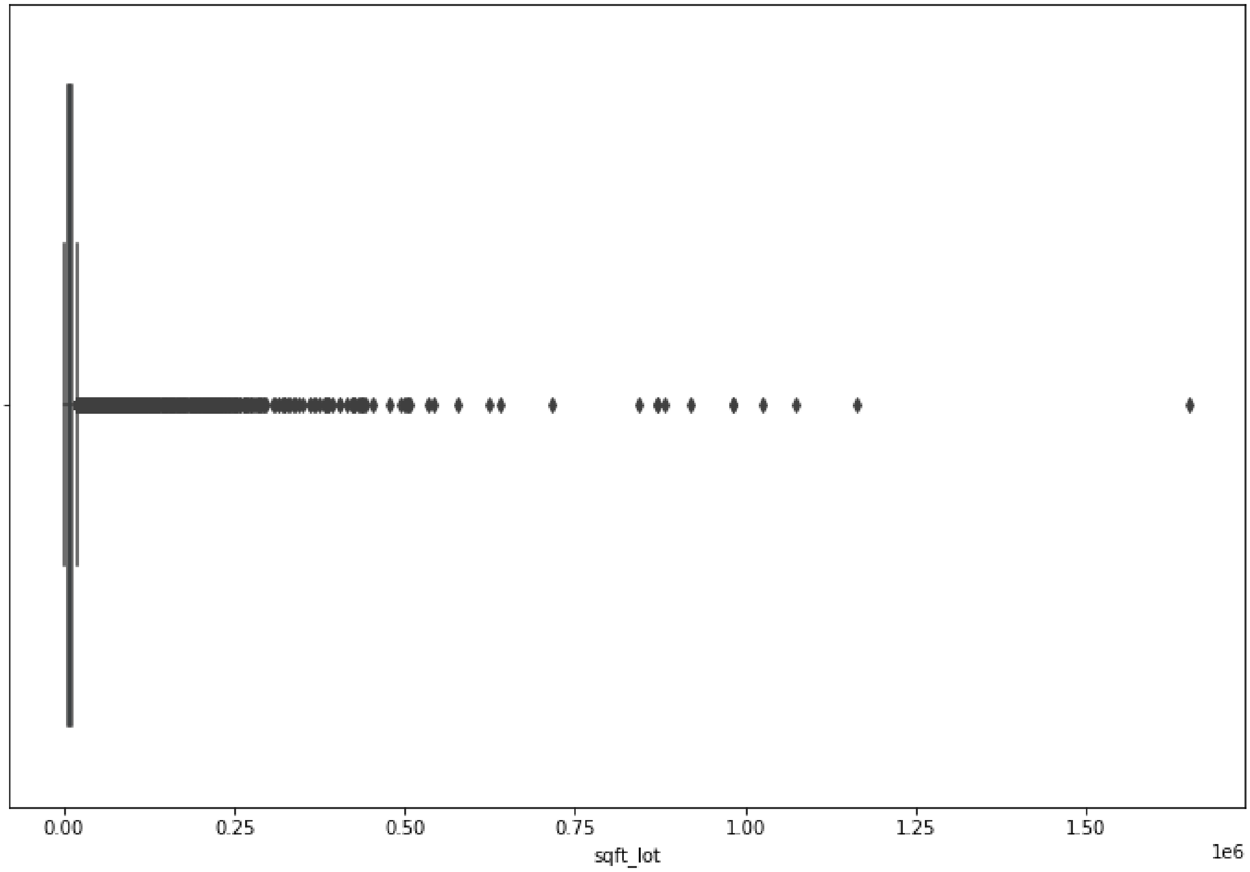
Sqft_lot

In [289…
```
#looking at sqft_lot column
data['sqft_lot'].describe()
```

Out[289…
```
count    2.158600e+04
mean     1.507868e+04
std      4.137255e+04
min      5.200000e+02
25%      5.040000e+03
50%      7.616000e+03
75%      1.066575e+04
max      1.651359e+06
Name: sqft_lot, dtype: float64
```

In [290…
```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='sqft_lot', data=data, ax=ax)
```

Out[290…
```
<AxesSubplot:xlabel='sqft_lot'>
```



In [291...
```
data['sqft_lot'].max()
```

Out[291...
```
1651359
```

In [292...
```
data['sqft_lot'].sort_values()
```

Out[292...
```
15729        520
5821         572
7582         600
3449         609
20588        635
           ...
3945      982998
7762     1024068
7640     1074218
17305    1164794
1717     1651359
Name: sqft_lot, Length: 21586, dtype: int64
```

In [293...
```
#Get rid of outliers
data = data.loc[data['sqft_lot'] < 1000000]
```

Floors

In [294...
```
#Looking at floors column
data['floors'].value_counts()
```

Out[294...
```
1.0    10669
2.0     8227
1.5     1909
3.0      610
2.5      160
```

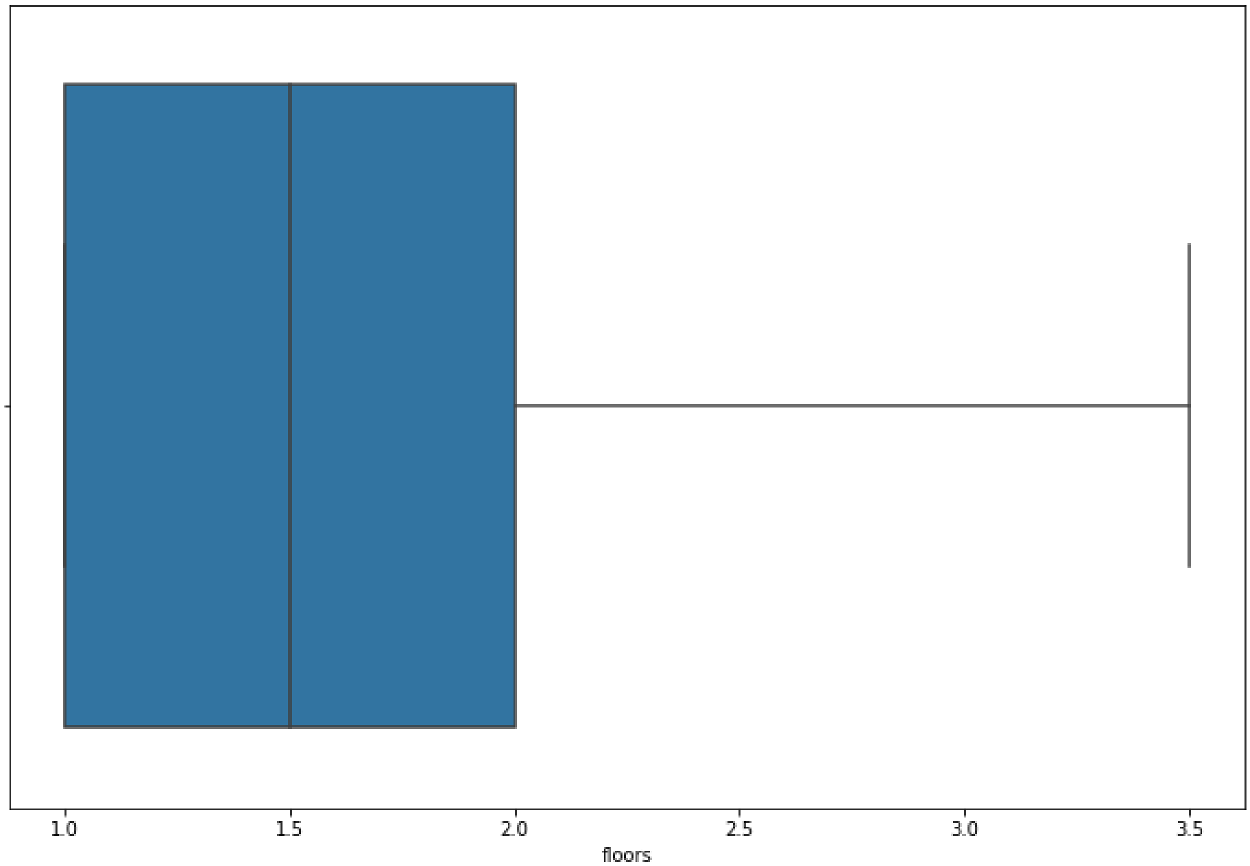
```
3.5        7
Name: floors, dtype: int64
```

In [295…

```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='floors', data=data, ax=ax)
```

Out[295…

```
<AxesSubplot:xlabel='floors'>
```



In [296…

```
data = data.loc[data['floors'] < 2.5]
```

Condition

In [297…

```
#Looking at condition
data['condition'].value_counts()
```

Out[297…

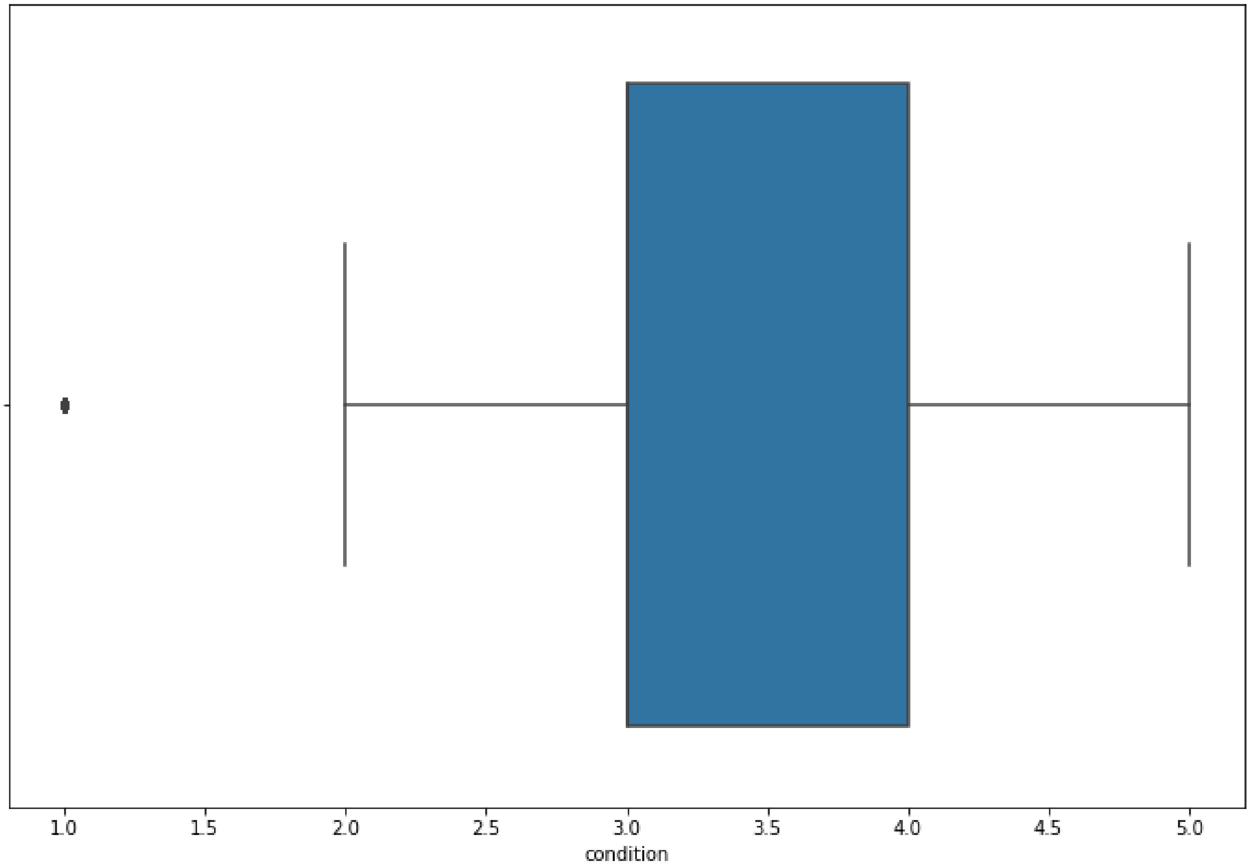
```
3    13308
4     5625
5     1674
2      169
1       29
Name: condition, dtype: int64
```

In [298…

```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='condition', data=data, ax=ax)
```

Out[298…

```
<AxesSubplot:xlabel='condition'>
```



In [299…
```
data = data.loc[data['condition'] > 2]
```

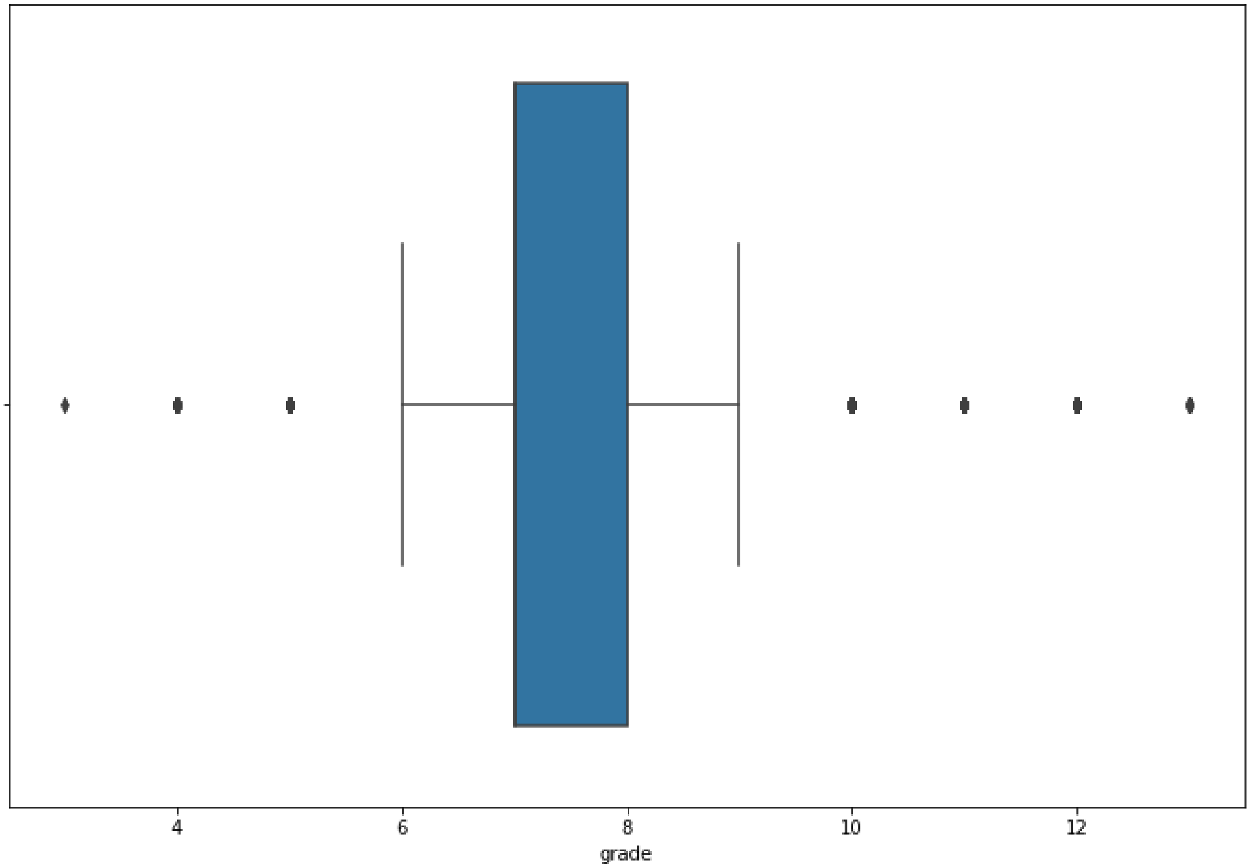
Grade

In [300…
```
#looking at grade
data['grade'].value_counts()
```

Out[300…
```
7     8778
8     5606
9     2485
6     1965
10    1080
11     366
5      218
12      79
4       22
13       7
3        1
Name: grade, dtype: int64
```

In [301…
```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='grade', data=data, ax=ax)
```

Out[301…
```
<AxesSubplot:xlabel='grade'>
```



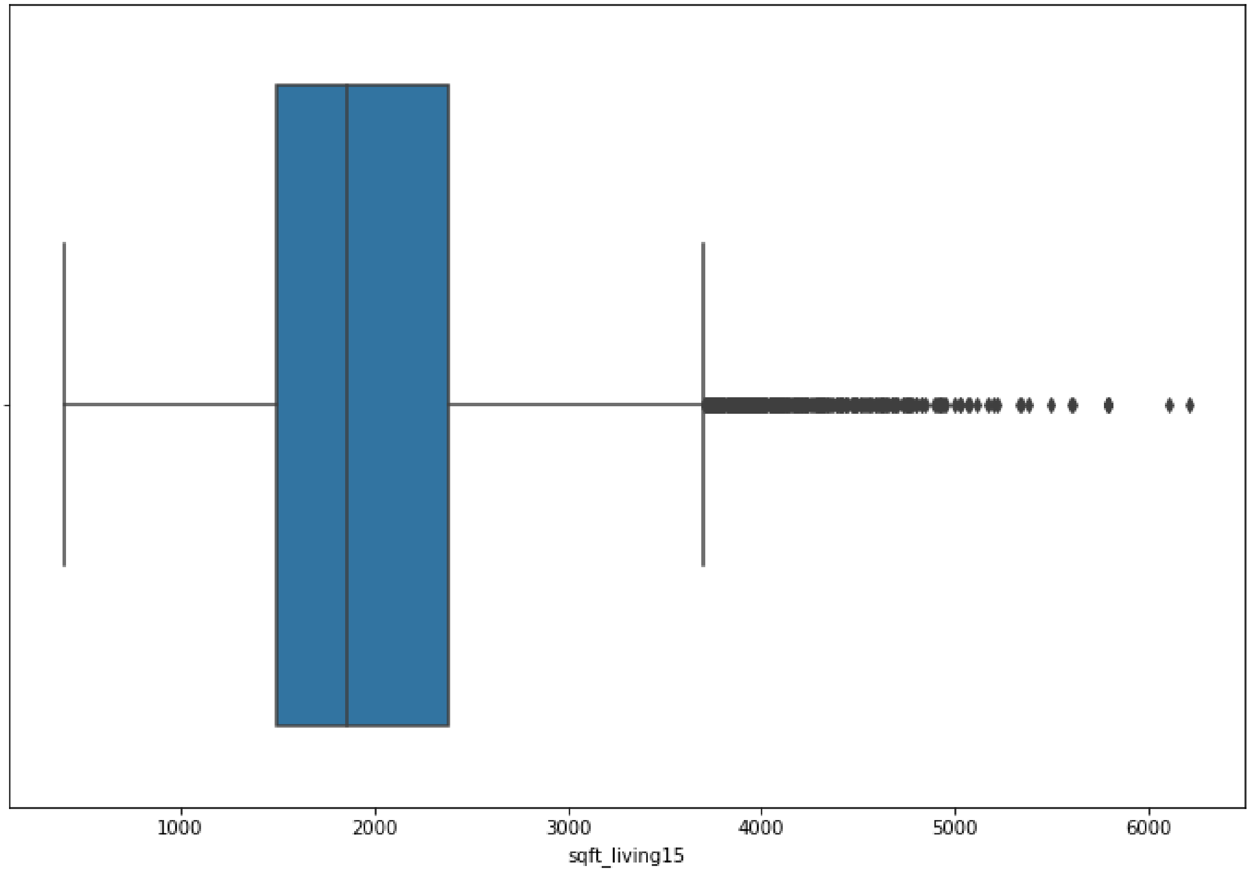
Sqft_living15

In [302...
```
#looking at sqft_living 15
data['sqft_living15'].describe()
```

Out[302...
```
count    20607.000000
mean      1997.899985
std        684.495611
min        399.000000
25%       1500.000000
50%       1860.000000
75%       2380.000000
max       6210.000000
Name: sqft_living15, dtype: float64
```

In [303...
```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='sqft_living15', data=data, ax=ax)
```

Out[303...
```
<AxesSubplot:xlabel='sqft_living15'>
```



In [304...
```
data = data.loc[data['sqft_living15'] < 5000]
```

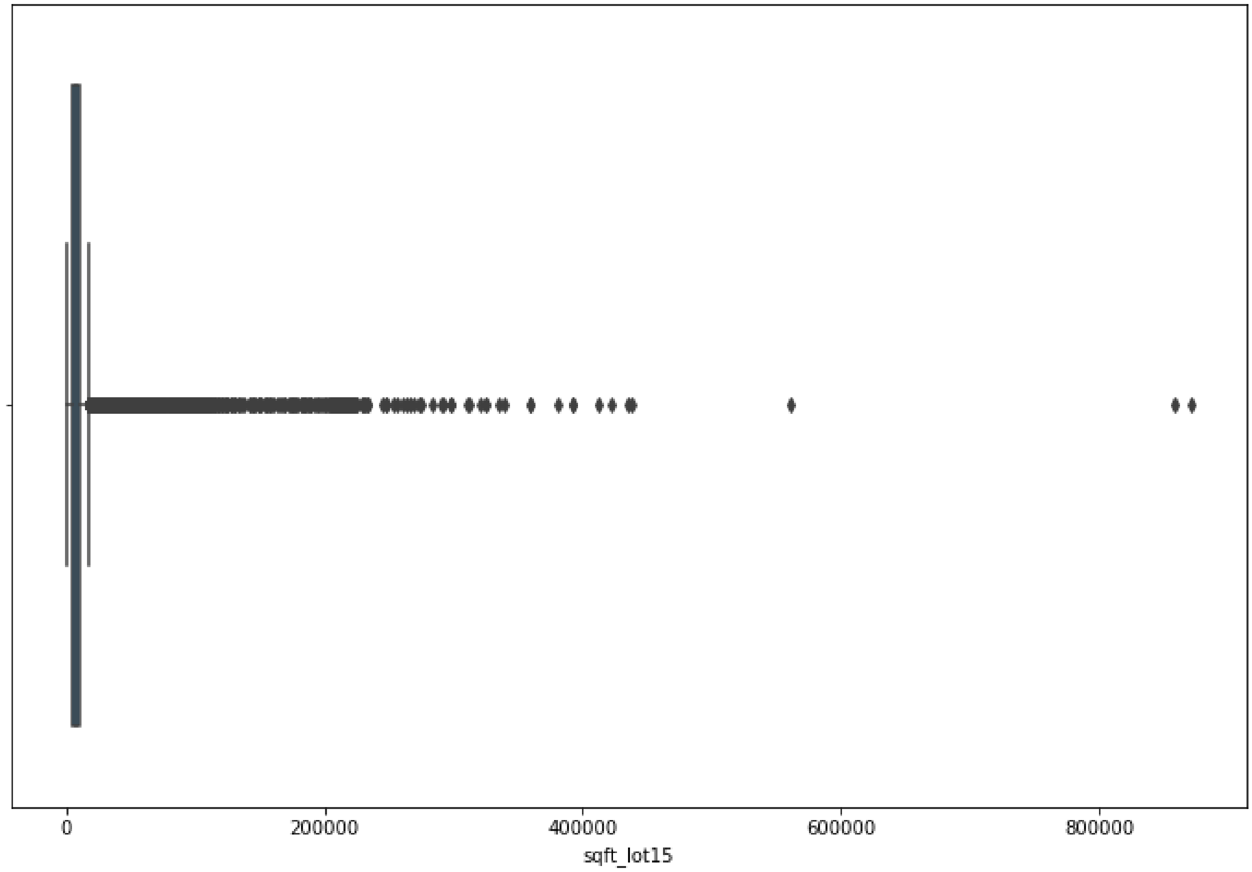
Sqft_lot15

In [305...
```
#looking at sqft_lot 15
data['sqft_lot15'].describe()
```

Out[305...
```
count     20584.000000
mean      12888.522736
std       26948.131256
min         651.000000
25%        5250.000000
50%        7700.000000
75%       10140.250000
max      871200.000000
Name: sqft_lot15, dtype: float64
```

In [306...
```
 fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(x='sqft_lot15', data=data, ax=ax)
```

Out[306... <AxesSubplot:xlabel='sqft_lot15'>



In [307…
```
data = data.loc[data['sqft_lot15'] < 500000]
```

In [308…
```
#Feature Engineering

#create renovated, view, and waterfront to be yes/no
#create new feature for bathrooms per bedroom and price per square foot
data['renovated'] = data['yr_renovated'].astype('bool').astype('int')
data['waterfront'] = data['waterfront'].astype('bool').astype('int')
data['view'] = data['view'].astype('bool').astype('int')
data['bath_per_bed'] = data['bathrooms'] / data['bedrooms']
data['price_per_sqft'] = data['price'] / data['sqft_living']
```

In [309…
```
data['price_per_sqft'].head()
```

Out[309…
```
0    188.050847
1    209.338521
2    233.766234
3    308.163265
4    303.571429
Name: price_per_sqft, dtype: float64
```

In [310…
```
data.columns
```

Out[310…
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'month_sold', 'has_basement',
       'renovated', 'bath_per_bed', 'price_per_sqft'],
      dtype='object')
```

In [311…
```
#dropping yr_renovated and sqft_basement
data = data.drop(['yr_renovated', 'sqft_basement'], axis=1)
```

In [312…

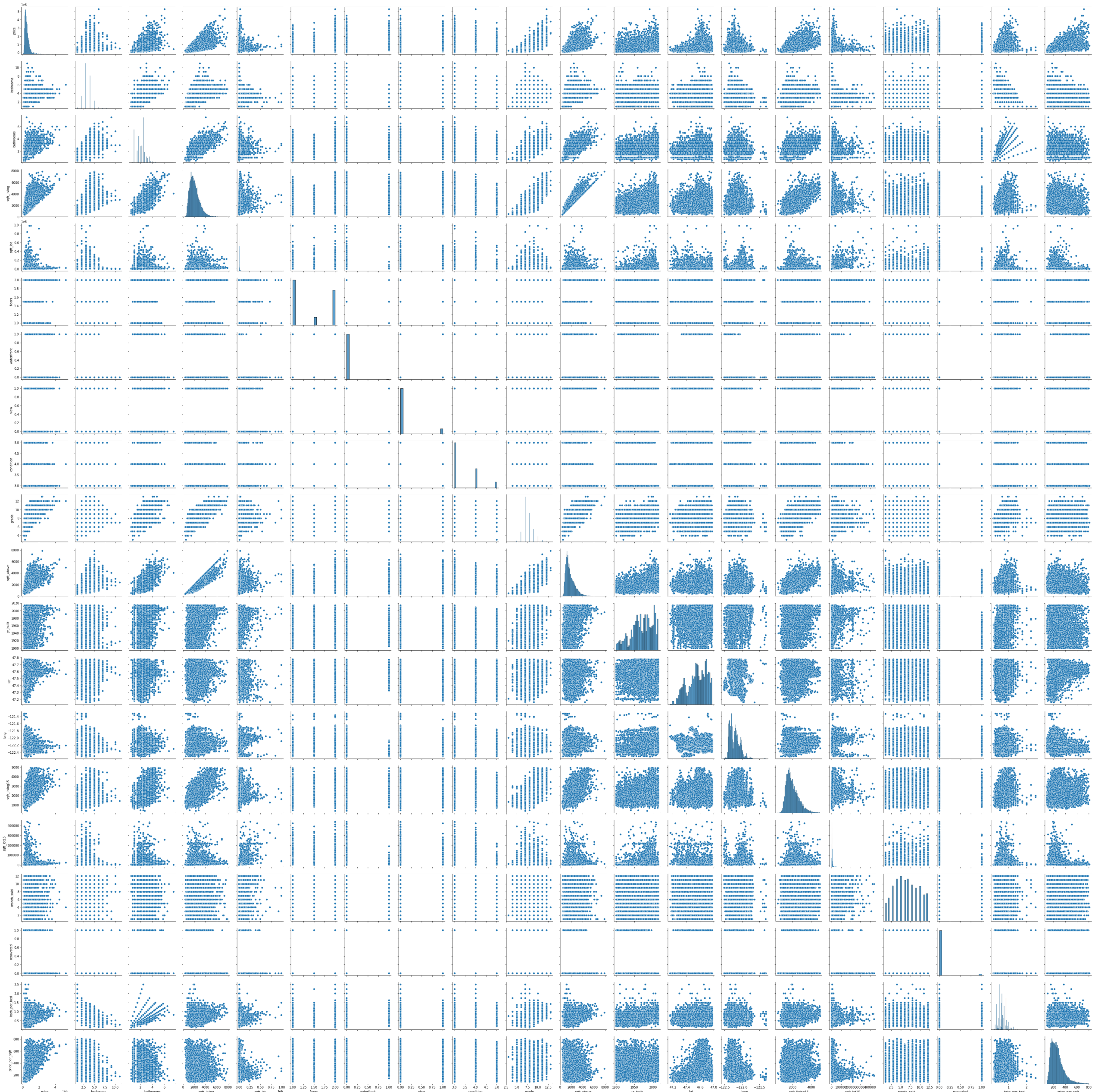
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20581 entries, 0 to 21596
Data columns (total 22 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           20581 non-null  float64
 1   bedrooms        20581 non-null  int64  
 2   bathrooms       20581 non-null  float64
 3   sqft_living     20581 non-null  int64  
 4   sqft_lot        20581 non-null  int64  
 5   floors          20581 non-null  float64
 6   waterfront      20581 non-null  int32  
 7   view            20581 non-null  int32  
 8   condition       20581 non-null  int64  
 9   grade           20581 non-null  int64  
 10  sqft_above      20581 non-null  int64  
 11  yr_built        20581 non-null  int64  
 12  zipcode         20581 non-null  object 
 13  lat             20581 non-null  float64
 14  long            20581 non-null  float64
 15  sqft_living15   20581 non-null  int64  
 16  sqft_lot15      20581 non-null  int64  
 17  month_sold      20581 non-null  int32  
 18  has_basement    20581 non-null  object 
 19  renovated       20581 non-null  int32  
 20  bath_per_bed    20581 non-null  float64
 21  price_per_sqft  20581 non-null  float64
dtypes: float64(7), int32(4), int64(9), object(2)
memory usage: 3.3+ MB
```

Checking Linearity

In [313…

```
sns.pairplot(data)
plt.show()
```



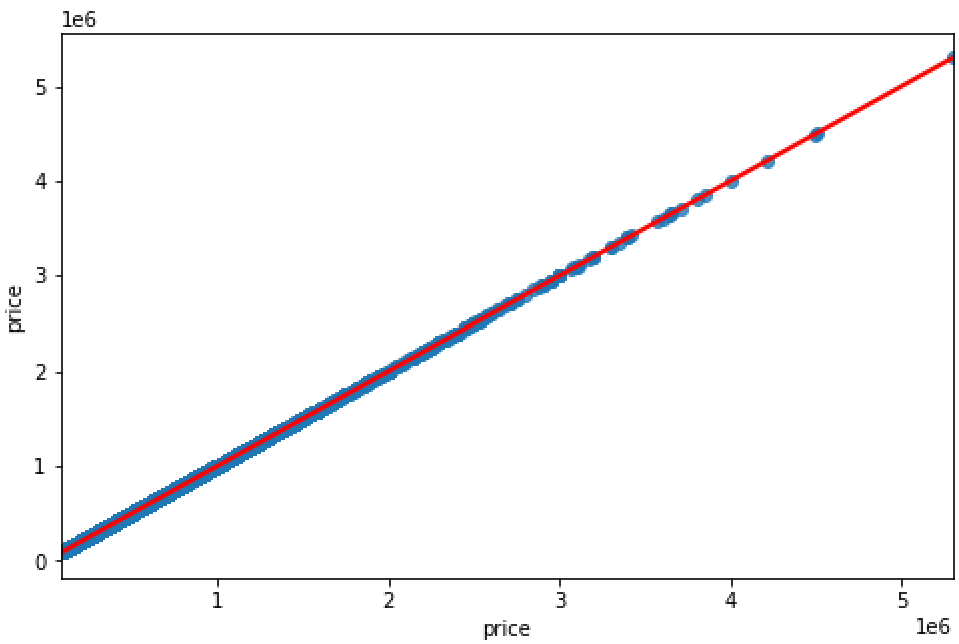
In [314…
```
#make our target!
TARGET = 'price'
X_VALS = [c for c in data.columns if c != TARGET]
TARGET in X_VALS
```
Out[314… False

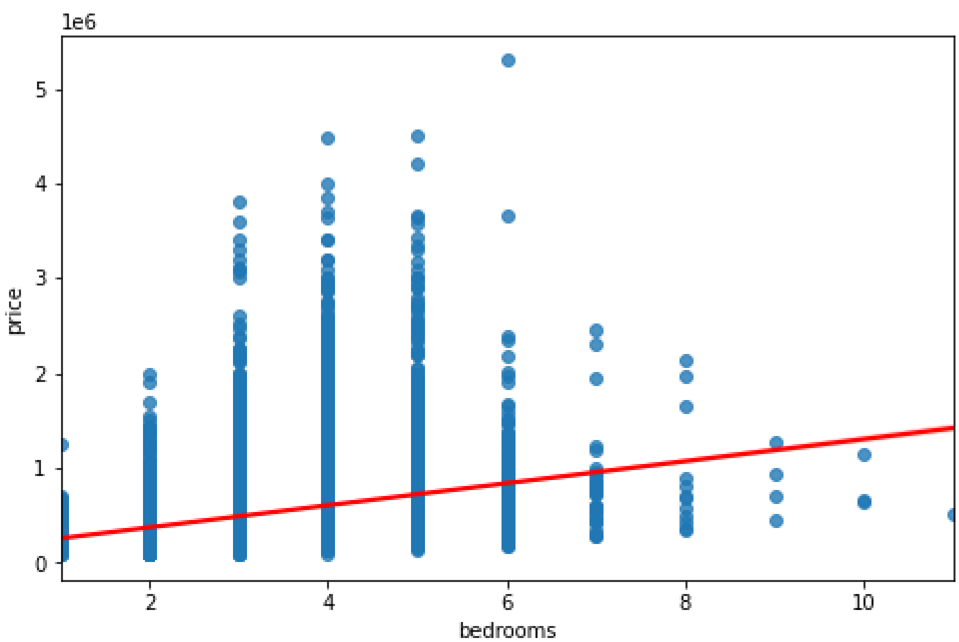
In [315…
```
X_VALS
```
Out[315…
```
['bedrooms',
 'bathrooms',
 'sqft_living',
 'sqft_lot',
 'floors',
 'waterfront',
 'view',
 'condition',
 'grade',
 'sqft_above',
 'yr_built',
```

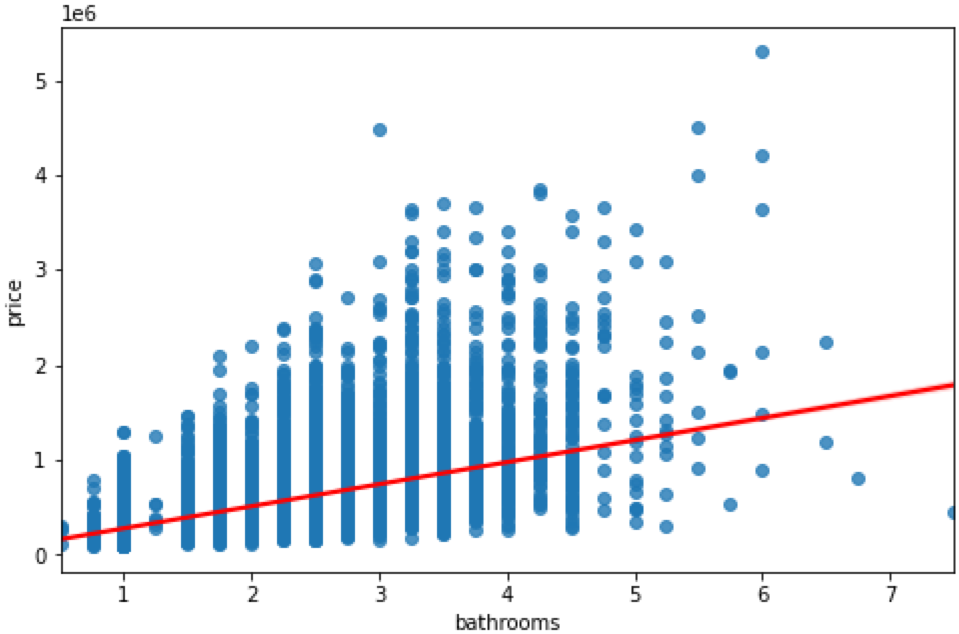
```
 'zipcode',
 'lat',
 'long',
 'sqft_living15',
 'sqft_lot15',
 'month_sold',
 'has_basement',
 'renovated',
 'bath_per_bed',
 'price_per_sqft']
```

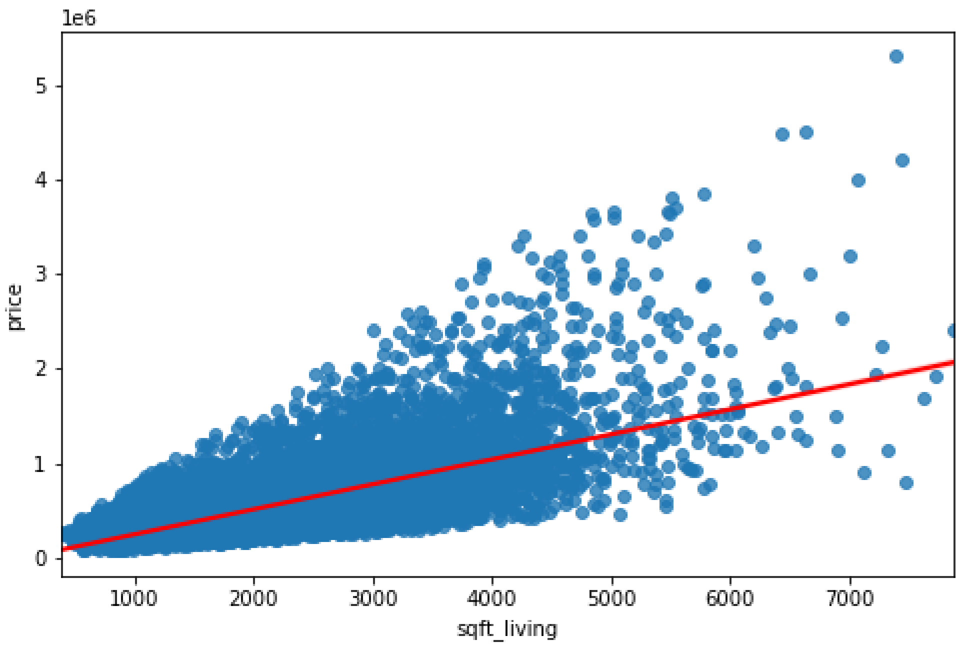
In [316…

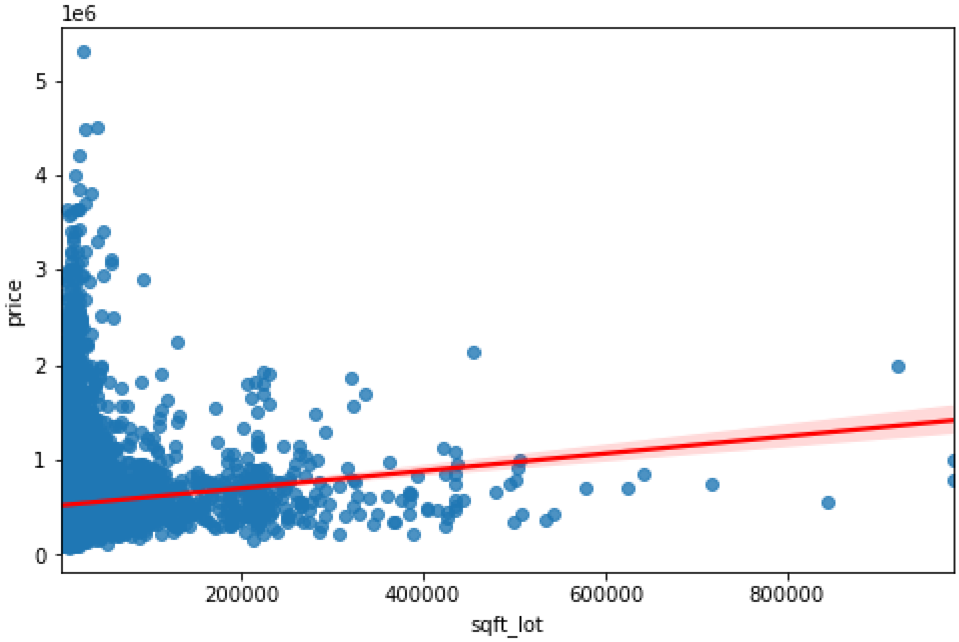
```
#iterate over the continuous data to compare it with the price to see which features
#we want to explore further by using sns.regplot()
for col in data.describe().columns:
    plt.figure(figsize=(8,5))
    sns.regplot(data=data, x=col, y= TARGET, line_kws={'color': 'red'})
```

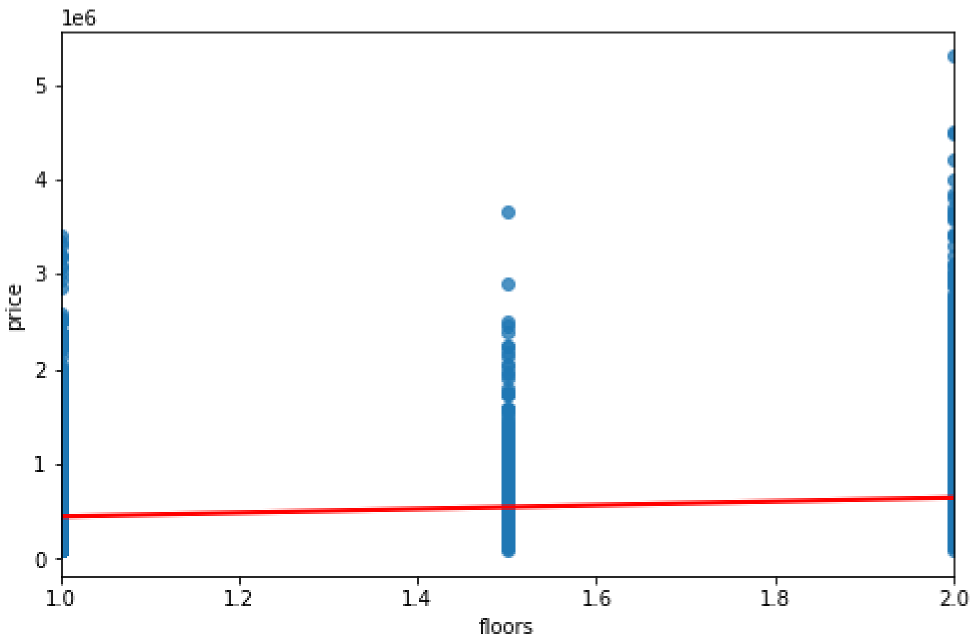


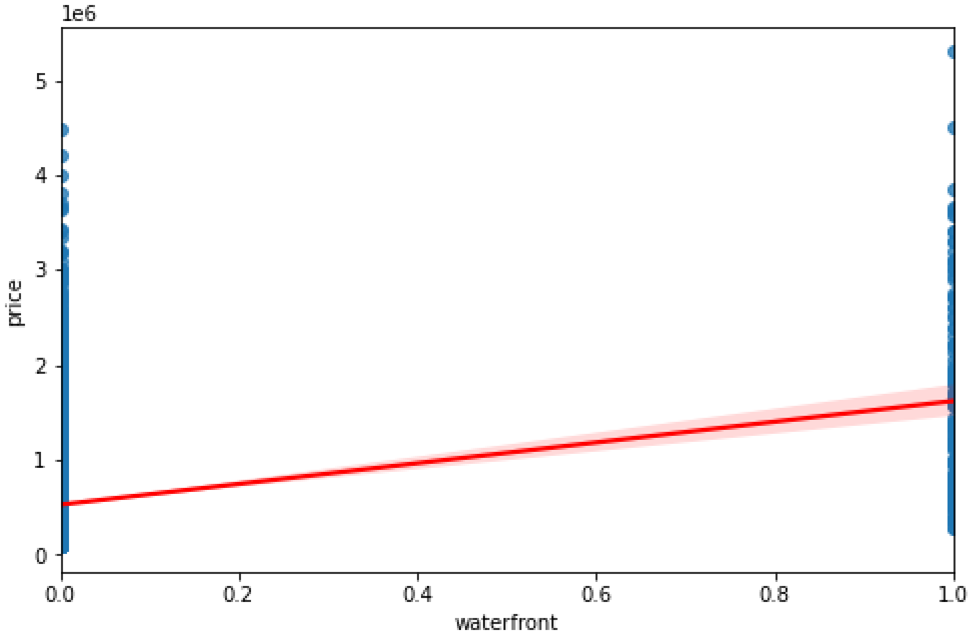


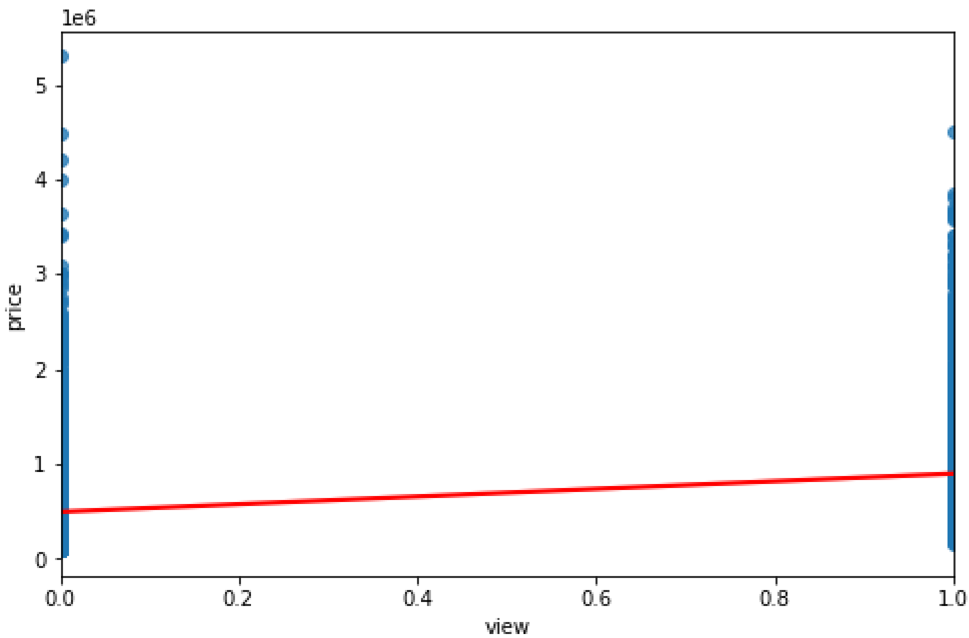

1e6
5
4
3
2
1
0
price
1
2
3
4
5
6
7
bathrooms

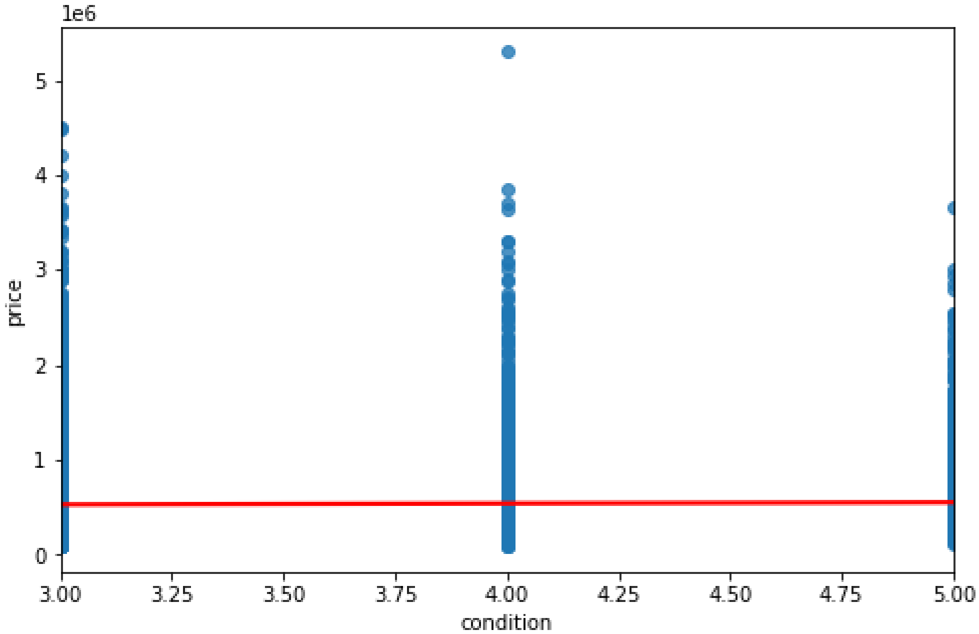

1e6
5
4
3
2
1
0
price
1000
2000
3000
4000
5000
6000
7000
sqft_living

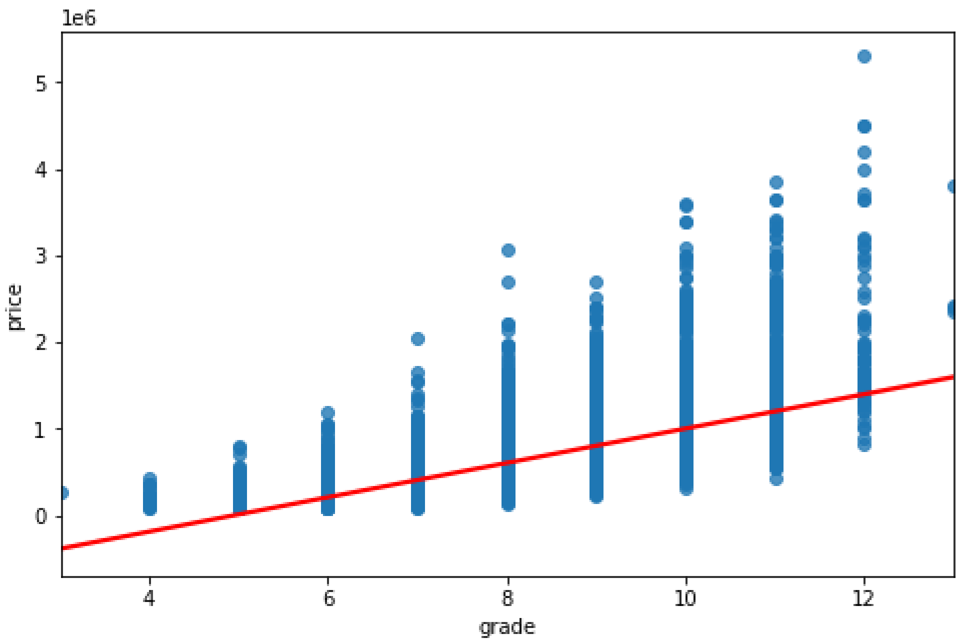

1e6
5
4
3
2
1
0
price
200000
400000
600000
800000
sqft_lot

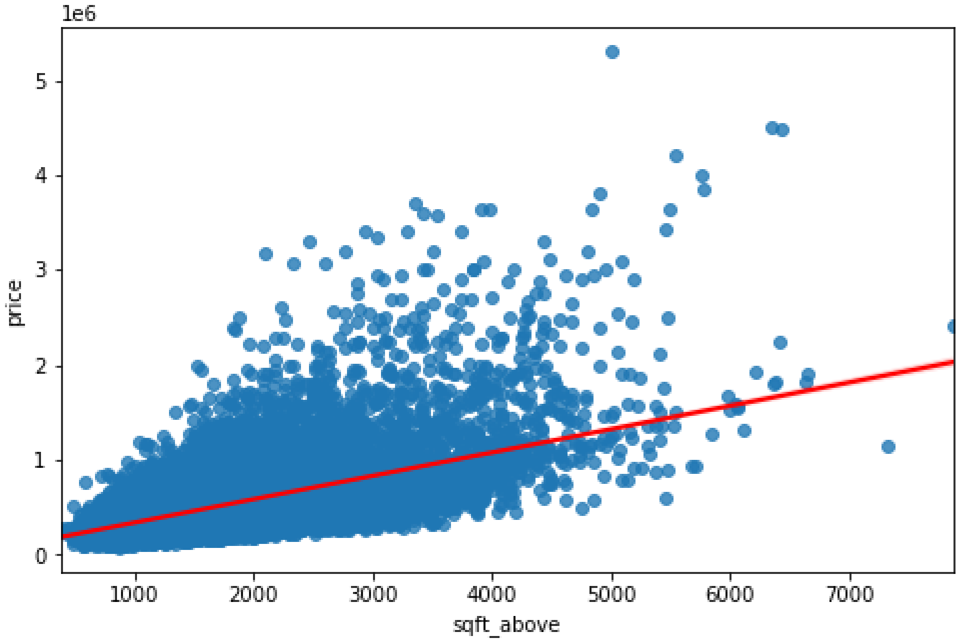

1e6
5
4
3
2
1
0
price
1.0
1.2
1.4
1.6
1.8
2.0
floors

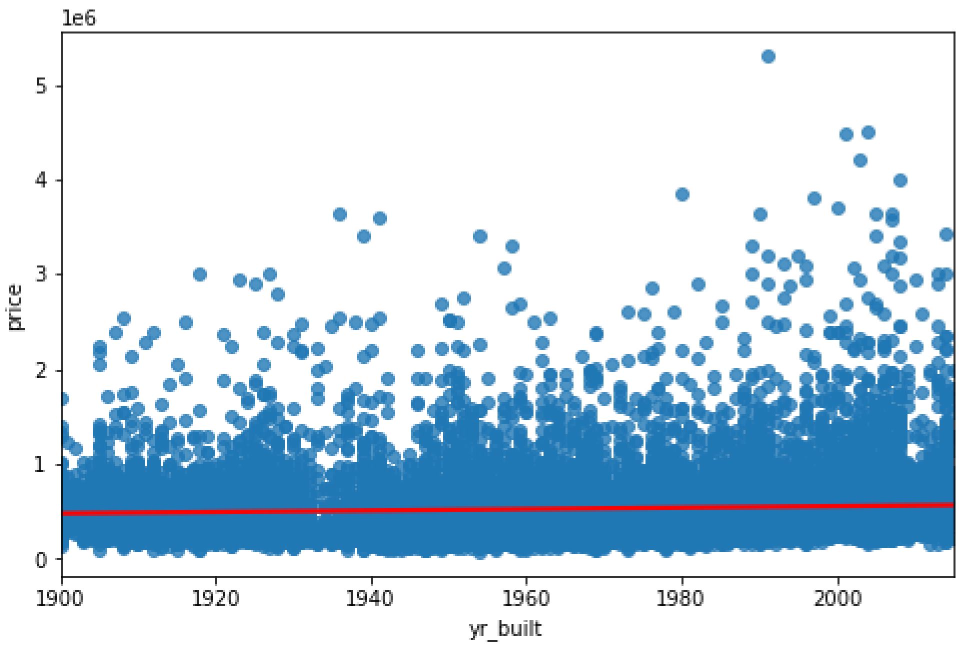

1e6
price
waterfront
0
1
2
3
4
5
0.0
0.2
0.4
0.6
0.8
1.0

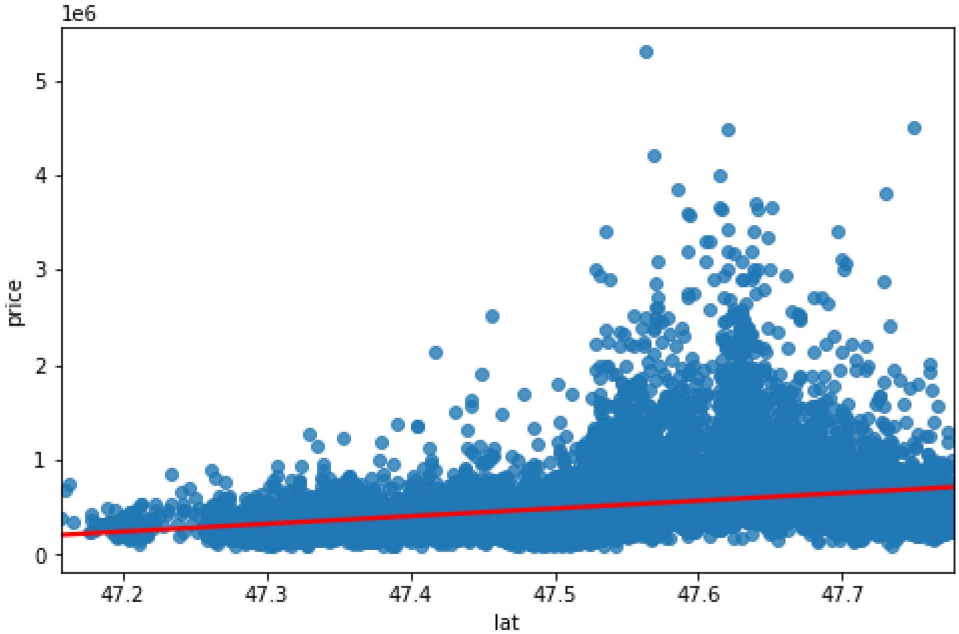

1e6
price
view
0
1
2
3
4
5
0.0
0.2
0.4
0.6
0.8
1.0

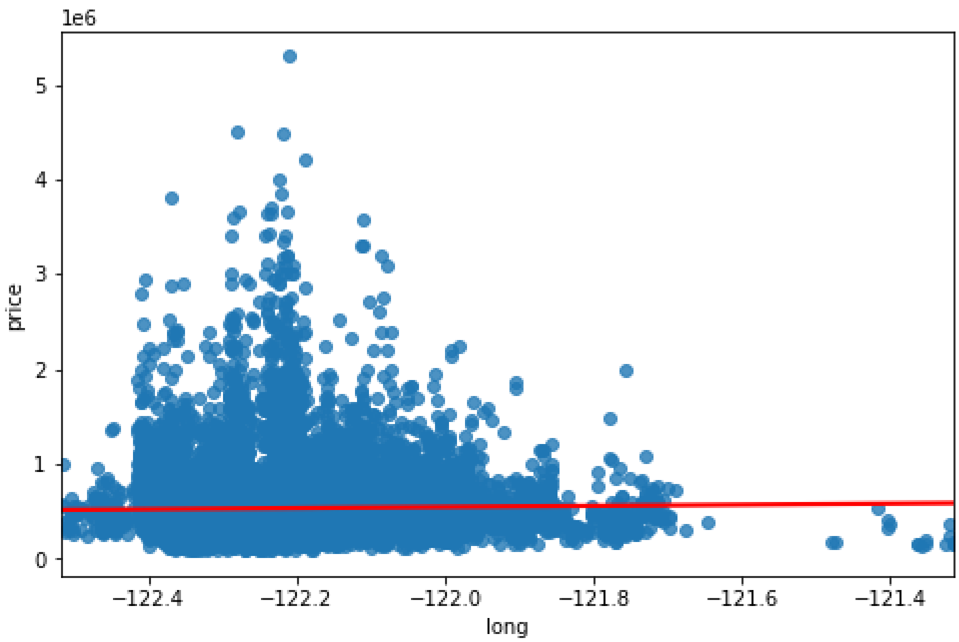

1e6
5
4
3
2
1
0
price
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
condition

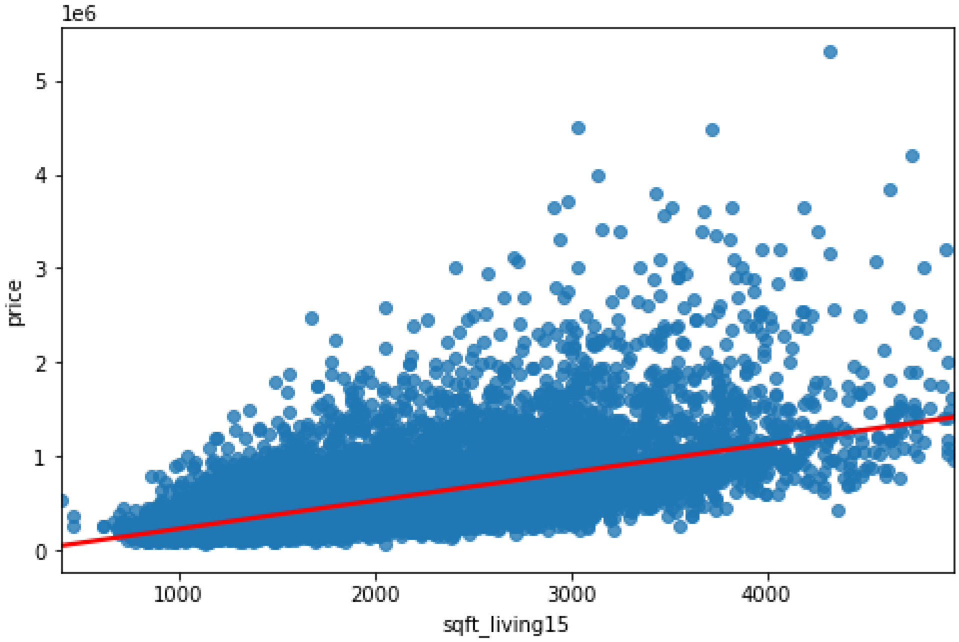

1e6
5
4
3
2
1
0
price
4
6
8
10
12
grade

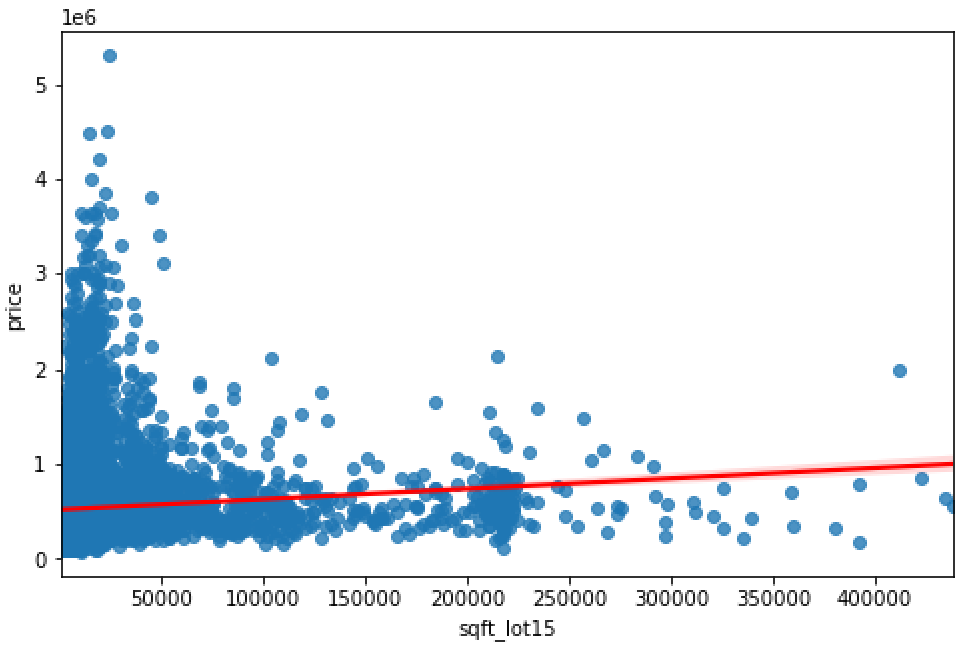

1e6
price
0
1
2
3
4
5
sqft_above
1000
2000
3000
4000
5000
6000
7000

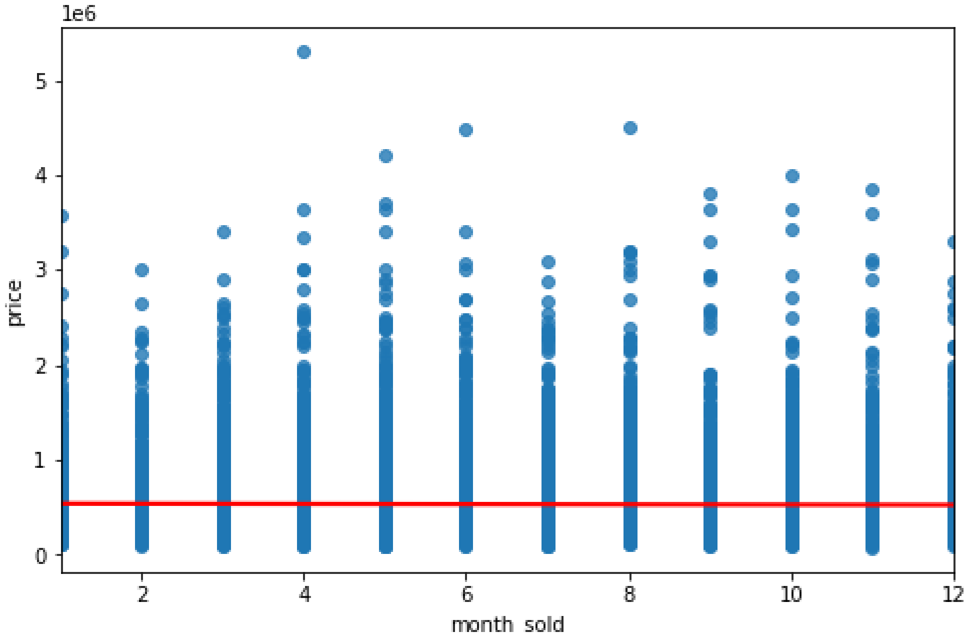

1e6
price
0
1
2
3
4
5
yr_built
1900
1920
1940
1960
1980
2000

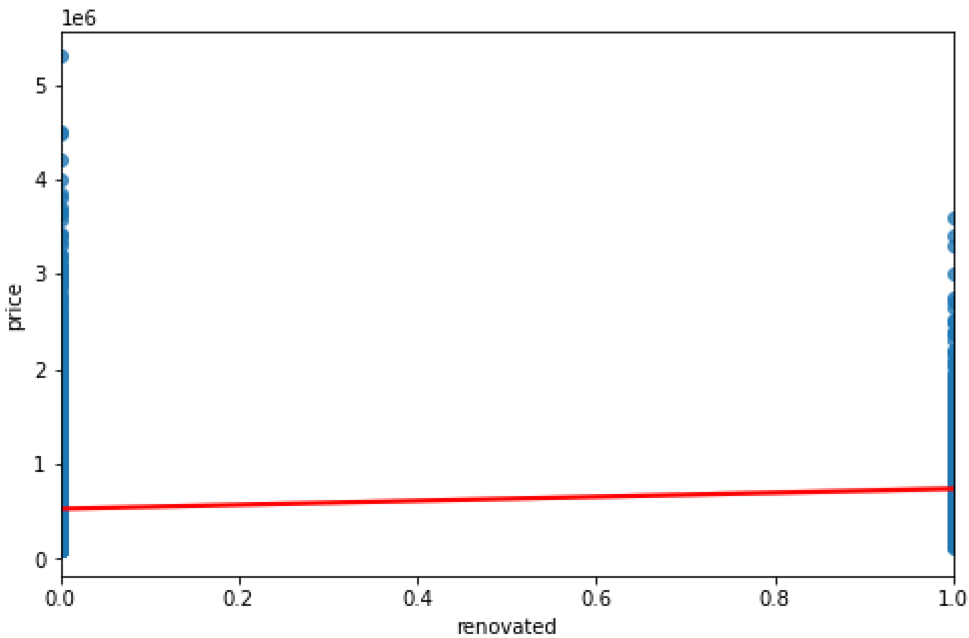

1e6
5
4
3
2
1
0
price
47.2
47.3
47.4
47.5
47.6
47.7
lat

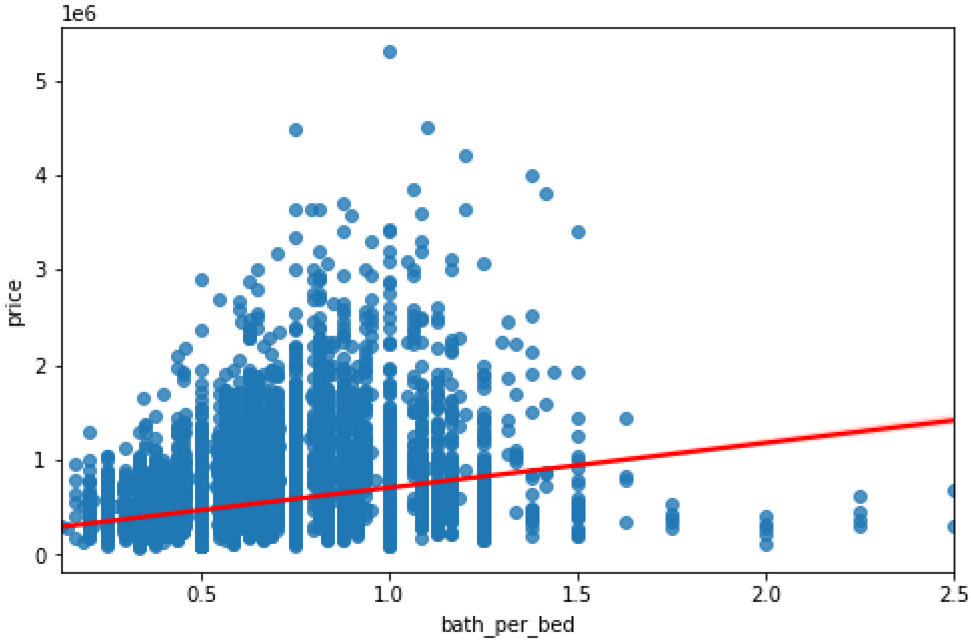

1e6
5
4
3
2
1
0
price
−122.4
−122.2
−122.0
−121.8
−121.6
−121.4
long

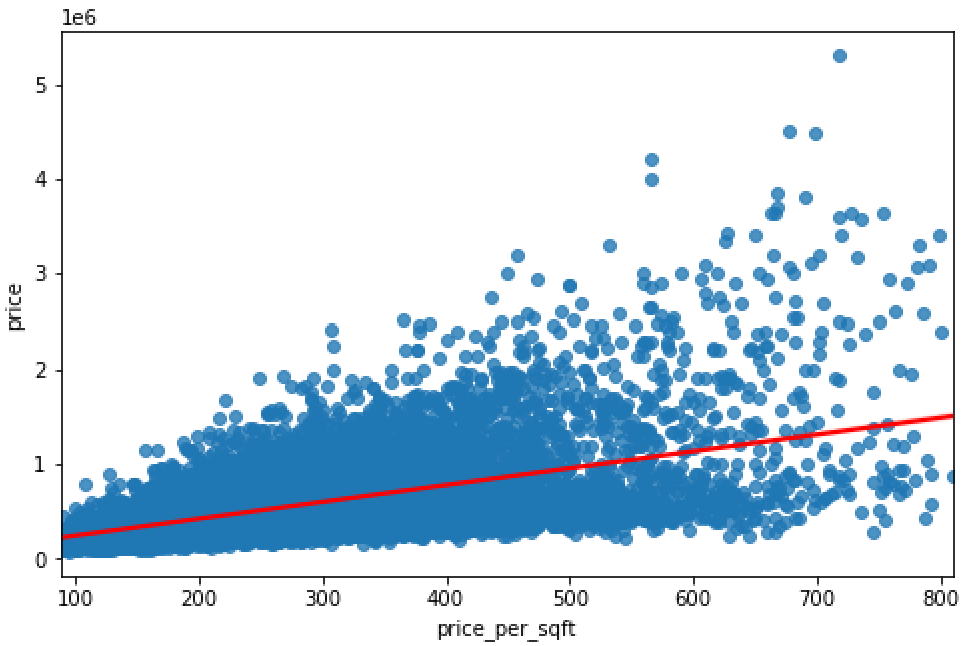

1e6
5
4
3
2
1
0
price
1000
2000
3000
4000
sqft_living15


1e6
5
4
3
2
1
0
price
50000
100000
150000
200000
250000
300000
350000
400000
sqft_lot15


1e6
price
month_sold
0
1
2
3
4
5
2
4
6
8
10
12


1e6
price
renovated
0
1
2
3
4
5
0.0
0.2
0.4
0.6
0.8
1.0





In [317…

```
pd.DataFrame(data.corr()['price']).sort_values(by='price',ascending=False)
```

Out[317…

	price
price	1.000000
sqft_living	0.682820
grade	0.669107
sqft_living15	0.591377
sqft_above	0.579985
price_per_sqft	0.567296
bathrooms	0.513478
view	0.347539

	price
lat	0.330478
bedrooms	0.305270
bath_per_bed	0.286156
floors	0.276330
waterfront	0.255650
renovated	0.113310
sqft_lot	0.097213
sqft_lot15	0.081282
yr_built	0.064430
long	0.024396
condition	0.021642
month_sold	-0.011530

Multicollinearity

In [318...

```
#Identifying multicollinearity
features = data.drop(['price'], axis=1)
target=data['price']
features.head(10)
```

Out[318...

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above
0	3	1.00	1180	5650	1.0	0	0	3	7	1180
1	3	2.25	2570	7242	2.0	0	0	3	7	2170
2	2	1.00	770	10000	1.0	0	0	3	6	770
3	4	3.00	1960	5000	1.0	0	0	5	7	1050
4	3	2.00	1680	8080	1.0	0	0	3	8	1680
5	4	4.50	5420	101930	1.0	0	0	3	11	3890
6	3	2.25	1715	6819	2.0	0	0	3	7	1715
7	3	1.50	1060	9711	1.0	0	0	3	7	1060
8	3	1.00	1780	7470	1.0	0	0	3	7	1050
9	3	2.50	1890	6560	2.0	0	0	3	7	1890

10 rows × 21 columns

In [319...

```
#Select only significant correlations greater than 0.75
abs(features.corr()) > 0.75
```

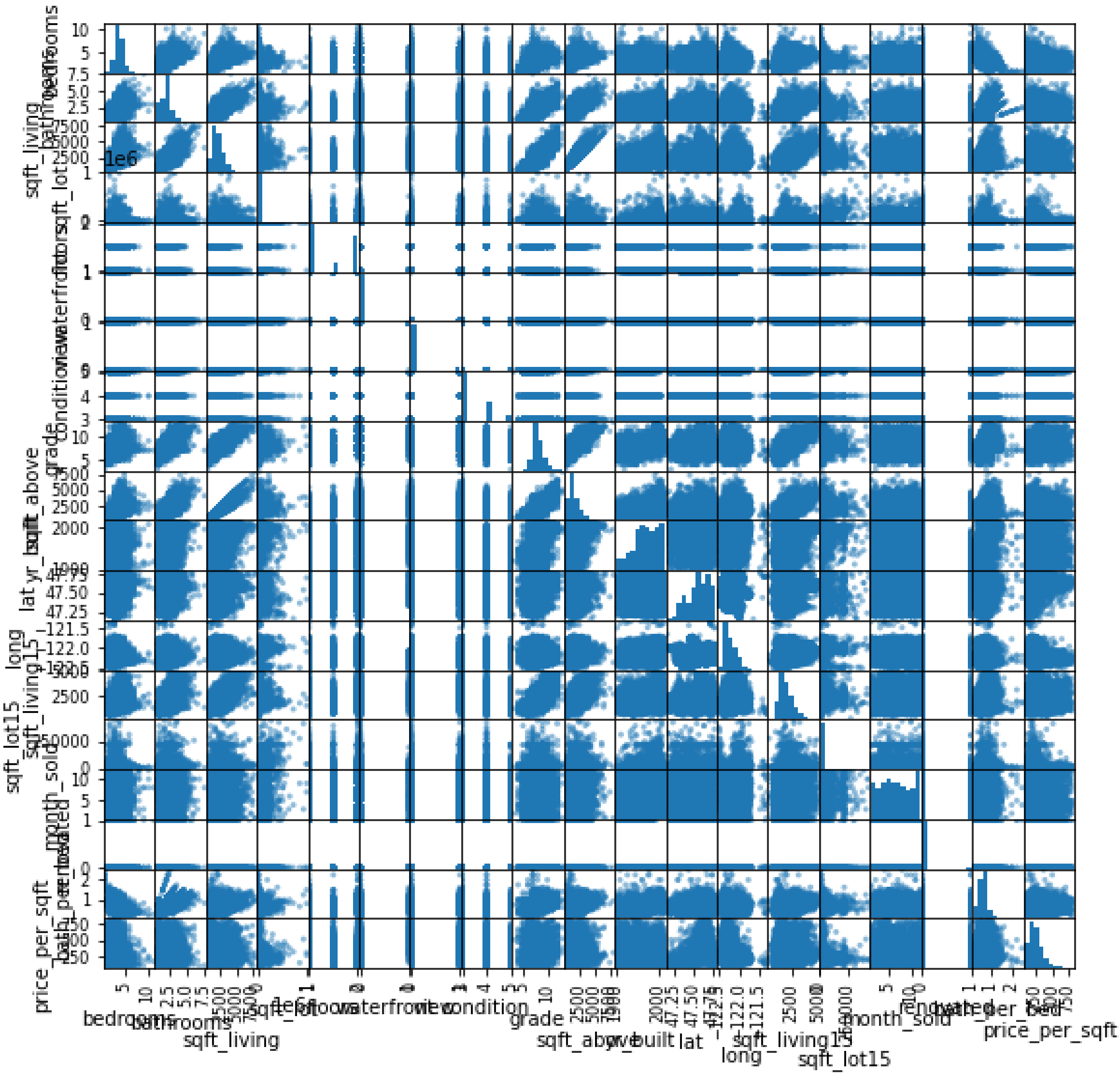
Out[319...

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
bedrooms	True	False	False	False	False	False	False	False	False
bathrooms	False	True	True	False	False	False	False	False	False
sqft_living	False	True	True	False	False	False	False	False	True
sqft_lot	False	False	False	True	False	False	False	False	False
floors	False	False	False	False	True	False	False	False	False
waterfront	False	False	False	False	False	True	False	False	False
view	False	False	False	False	False	False	True	False	False
condition	False	False	False	False	False	False	False	True	False
grade	False	False	True	False	False	False	False	False	True
sqft_above	False	False	True	False	False	False	False	False	True
yr_built	False	False	False	False	False	False	False	False	False
lat	False	False	False	False	False	False	False	False	False
long	False	False	False	False	False	False	False	False	False
sqft_living15	False	False	True	False	False	False	False	False	False
sqft_lot15	False	False	False	False	False	False	False	False	False
month_sold	False	False	False	False	False	False	False	False	False
renovated	False	False	False	False	False	False	False	False	False
bath_per_bed	False	False	False	False	False	False	False	False	False
price_per_sqft	False	False	False	False	False	False	False	False	False

In [320…

```
pd.plotting.scatter_matrix(features,figsize  = [9, 9]);
plt.show()
```



In [321…

```
features.corr()
```

Out[321…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
bedrooms	1.000000	0.532675	0.589761	0.029826	0.246161	-0.006664	0.071618	-0.003750
bathrooms	0.532675	1.000000	0.762974	0.096192	0.532967	0.057809	0.162686	-0.149393
sqft_living	0.589761	0.762974	1.000000	0.181702	0.436330	0.090341	0.251082	-0.093846
sqft_lot	0.029826	0.096192	0.181702	1.000000	0.020515	0.026513	0.063783	-0.007128
floors	0.246161	0.532967	0.436330	0.020515	1.000000	0.019239	0.009121	-0.279252
waterfront	-0.006664	0.057809	0.090341	0.026513	0.019239	1.000000	0.244657	0.022794
view	0.071618	0.162686	0.251082	0.063783	0.009121	0.244657	1.000000	0.045272
condition	-0.003750	-0.149393	-0.093846	-0.007128	-0.279252	0.022794	0.045272	1.000000
grade	0.362056	0.658988	0.767562	0.129389	0.482159	0.076062	0.223943	-0.177408
sqft_above	0.483466	0.683946	0.867945	0.195071	0.614839	0.058973	0.129405	-0.193626
yr_built	0.191494	0.521343	0.362014	0.075862	0.478848	-0.027452	-0.067127	-0.379508

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
lat	-0.004576	0.011276	0.060756	-0.084040	-0.015678	-0.014211	0.011127	-0.007783
long	0.129212	0.245378	0.241529	0.232720	0.230955	-0.044718	-0.096083	-0.130452
sqft_living15	0.395243	0.580559	0.757038	0.154372	0.376182	0.078969	0.262787	-0.124562
sqft_lot15	0.026994	0.086456	0.175196	0.748766	0.015574	0.034416	0.054641	-0.001270
month_sold	-0.000297	0.007300	0.011498	0.007817	0.013971	0.009992	-0.005525	0.020180
renovated	0.011084	0.042295	0.039470	0.007105	0.011992	0.074107	0.081728	-0.062125
bath_per_bed	-0.230506	0.655101	0.330709	0.078173	0.395540	0.073837	0.115775	-0.159969
price_per_sqft	-0.220444	-0.118007	-0.112095	-0.036609	-0.063077	0.183267	0.195708	0.114729

In [322…

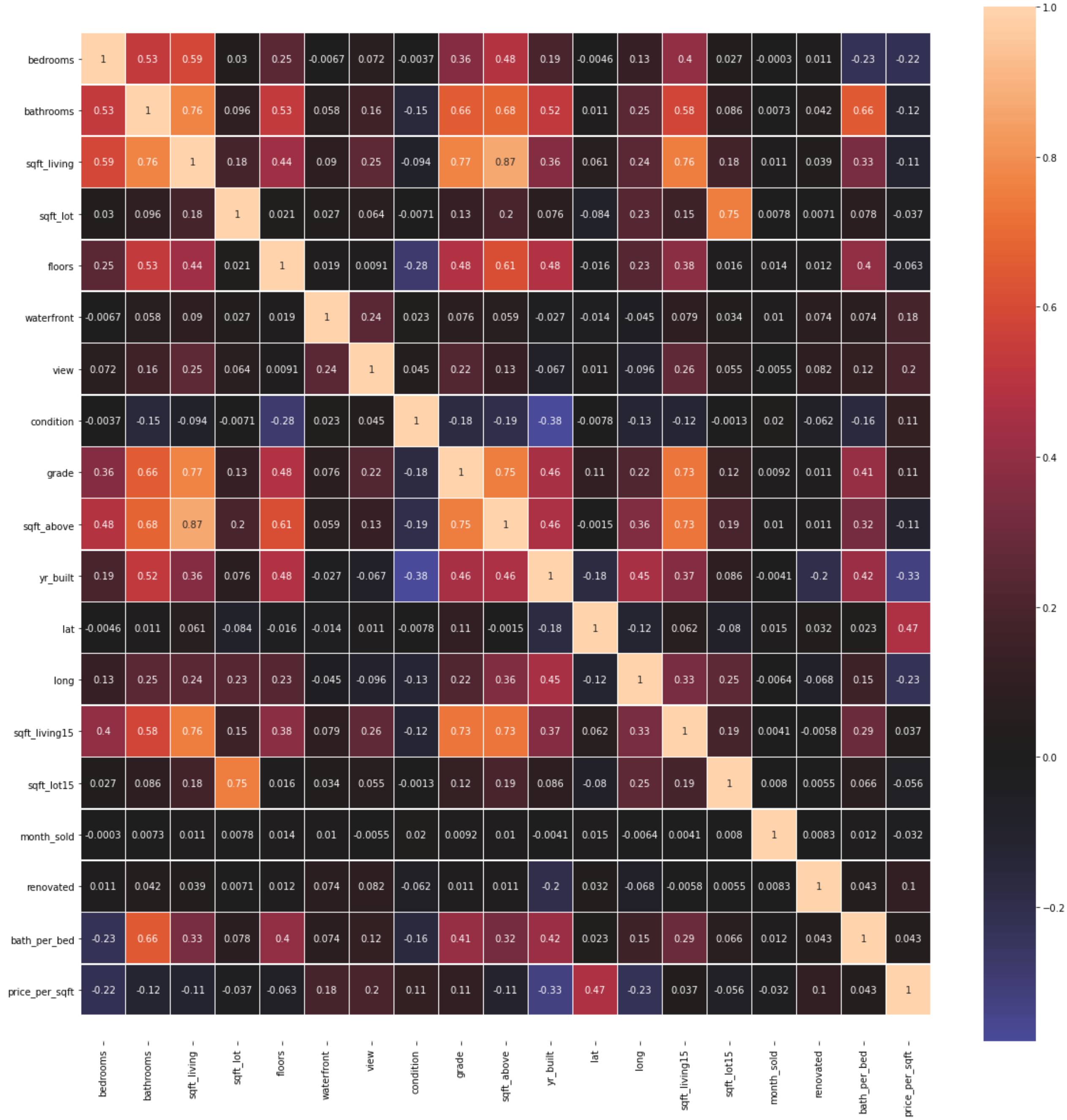
```
#inlude stack and zip to create a more robust solution that will return
#the variable pairs from the correlation matrix that have correlations over .75, but le
df = features.corr().abs().stack().reset_index().sort_values(0, ascending=False)

# zip the variable name columns (Which were only named level_0 and level_1 by default)
df['pairs'] = list(zip(df.level_0, df.level_1))

# set index to pairs
df.set_index(['pairs'], inplace = True)

#drop level columns
df.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
df.columns = ['cc']

#drop duplicates
df.drop_duplicates(inplace=True)

df[(df.cc>.75) & (df.cc<1)]
```

Out[322…

	cc
pairs	
(sqft_above, sqft_living)	0.867945
(sqft_living, grade)	0.767562
(sqft_living, bathrooms)	0.762974
(sqft_living15, sqft_living)	0.757038
(sqft_above, grade)	0.754693

In [323…

```
#Heat map
plt.figure(figsize=(20, 20))
ax = sns.heatmap(features.corr(), center=0, linewidths=.5, annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.show()
```



Log Transformation

In [324…

```
#separate into continuous and categorical columns
continuous = ['sqft_living', 'sqft_living15', 'sqft_lot', 'sqft_lot15',
              'price', 'price_per_sqft', 'bath_per_bed']

categoricals = ['waterfront', 'floors', 'condition', 'grade','renovated', 'view',
             'zipcode', 'bedrooms', 'bathrooms', 'has_basement', 'month_sold']
```

In [ ]:

```
```

In [325…

```
#Transformation non-normal features
#take out sqft_basement,yr_renovated, these two features after log and normalization ar
#or infinity values I tried diffrent normalization methods and still same result.
```

```
kc_cont = data[continuous]

#log features
log_names = [f'{column}_log' for column in kc_cont.columns]

kc_log = np.log(kc_cont)
kc_log.columns = log_names



# normalize (subract mean and divide by std)

def normalize(feature):
    return (feature - feature.mean()) / feature.std()

kc_log_norm =kc_log.apply(normalize)
```

In [ ]:

OHE

In [326…

```
#Categorial features
#data['waterfront'] = data['waterfront'].astype('category')
#data['floors'] = data['floors'].astype('category')
#data['condition'] = data['condition'].astype('category')
#data['grade'] = data['grade'].astype('category')
#data['renovated'] = data['renovated'].astype('category')
#data['view'] = data['view'].astype('category')
#data['zipcode']=data['zipcode'].astype('category')
#data['bedrooms']=data['bedrooms'].astype('category')
#data['bathrooms']=data['bathrooms'].astype('category')
#data['has_basement']=data['has_basement'].astype('category')
#data['month_sold']=data['month_sold'].astype('category')

#df_dummy = pd.get_dummies(data[categoricals], prefix=categoricals, drop_first=True)
```

In [327…

```
#Combine categorial and continuous features
#preprocessed = pd.concat([kc_log_norm, data[categoricals]], axis=1)
#preprocessed.head()
```

In [ ]:

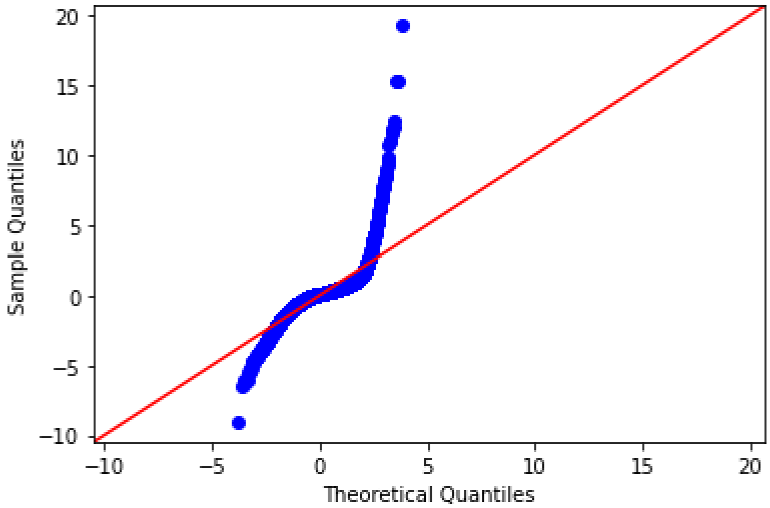
Checking Multiple Linear Regression

In [328…

```
#X = preprocessed.drop('price_log', axis=1)
#y = preprocessed['price_log']
#X_int = sm.add_constant(X)
#model = sm.OLS(y,X_int).fit()
#model.summary()
```

In [329…

```
sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True);
```



Use original cleaned data to build a new model

In [330…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20581 entries, 0 to 21596
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          20581 non-null  float64
 1   bedrooms       20581 non-null  int64  
 2   bathrooms      20581 non-null  float64
 3   sqft_living    20581 non-null  int64  
 4   sqft_lot       20581 non-null  int64  
 5   floors         20581 non-null  float64
 6   waterfront     20581 non-null  int32  
 7   view           20581 non-null  int32  
 8   condition      20581 non-null  int64  
 9   grade          20581 non-null  int64  
 10  sqft_above     20581 non-null  int64  
 11  yr_built       20581 non-null  int64  
 12  zipcode        20581 non-null  object 
 13  lat            20581 non-null  float64
 14  long           20581 non-null  float64
 15  sqft_living15  20581 non-null  int64  
 16  sqft_lot15     20581 non-null  int64  
 17  month_sold     20581 non-null  int32  
 18  has_basement   20581 non-null  object 
 19  renovated      20581 non-null  int32  
 20  bath_per_bed   20581 non-null  float64
 21  price_per_sqft  20581 non-null  float64
dtypes: float64(7), int32(4), int64(9), object(2)
memory usage: 3.3+ MB
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Train-Test Split

Do the train test split to model only the training data.

In [331…

```
y = data[TARGET]
X = data.drop(columns=[TARGET])
X
```

Out[331…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_abo
0	3	1.00	1180	5650	1.0	0	0	3	7	1
1	3	2.25	2570	7242	2.0	0	0	3	7	2
2	2	1.00	770	10000	1.0	0	0	3	6	
3	4	3.00	1960	5000	1.0	0	0	5	7	10
4	3	2.00	1680	8080	1.0	0	0	3	8	10
...	...	...	...	...	...	...	...	...	...	
21591	3	2.50	1310	1294	2.0	0	0	3	8	1
21593	4	2.50	2310	5813	2.0	0	0	3	8	2
21594	2	0.75	1020	1350	2.0	0	0	3	7	10
21595	3	2.50	1600	2388	2.0	0	0	3	8	10
21596	2	0.75	1020	1076	2.0	0	0	3	7	10

20581 rows × 21 columns

In [332…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=2021)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[332…

```
((15435, 21), (5146, 21), (15435,), (5146,))
```

In [333…

```
NUM_COLS = X_train.select_dtypes('number').columns
CAT_COLS = X_train.select_dtypes('object').columns
CAT_COLS
```

Out[333…

```
Index(['zipcode', 'has_basement'], dtype='object')
```

In [ ]:

In [ ]:

In [334…

```
X_train.reset_index(drop=True, inplace=True)
X_test.reset_index(drop=True, inplace=True)
y_train.reset_index(drop=True, inplace=True)
y_test.reset_index(drop=True, inplace=True)
```

In [ ]:

In [335…
```
# OHE
ohe = OneHotEncoder(drop='first', sparse=False)
X_train_ohe = ohe.fit_transform(X_train[CAT_COLS])
X_test_ohe = ohe.transform(X_test[CAT_COLS])

X_train_ohe = pd.DataFrame(X_train_ohe, columns=ohe.get_feature_names(CAT_COLS))
X_test_ohe = pd.DataFrame(X_test_ohe, columns=ohe.get_feature_names(CAT_COLS))

X_train_ohe.columns = [c.lower() for c in X_train_ohe]
X_test_ohe.columns = [c.lower() for c in X_test_ohe]
```

In [336…
```
X_train_ohe.head()
```

Out[336…

	zipcode_98002	zipcode_98003	zipcode_98004	zipcode_98005	zipcode_98006	zipcode_98007	zipcod
0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 70 columns

In [337…
```
X_train_raw = pd.concat([X_train[NUM_COLS],
                         X_train_ohe],
                        axis=1)
X_test_raw = pd.concat([X_test[NUM_COLS],
                        X_test_ohe],
                       axis=1)
```

In [338…
```
# Scaling data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train[NUM_COLS])
X_test_scaled = scaler.transform(X_test[NUM_COLS])

X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train[NUM_COLS].columns)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test[NUM_COLS].columns)
```

In [339…
```
X_train_scaled.shape, X_test_scaled.shape
```

Out[339…
```
((15435, 19), (5146, 19))
```

In [340…
```
X_train_scaled = pd.concat([X_train_scaled,
                            X_train_ohe],
                           axis=1)
X_test_scaled = pd.concat([X_test_scaled,
                           X_test_ohe],
                          axis=1)
```

In [341…
```
X_train_raw
```

Out[341…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_abo
0	3	2.00	3040	41072	1.0	0	0	4	8	1
1	3	1.75	1550	8134	1.0	0	0	4	7	1
2	4	2.75	3040	13559	2.0	0	0	3	11	3
3	4	3.50	4460	16953	1.0	0	0	3	9	2
4	3	2.50	3110	6000	1.0	0	1	3	8	1
...	...	...	...	...	...	...	...	...	...	
15430	3	1.50	2260	5300	1.0	0	0	3	7	1
15431	4	2.50	1914	3272	2.0	0	0	3	8	1
15432	3	1.75	2040	6000	1.0	0	0	5	7	1
15433	2	1.00	590	8717	1.0	0	0	3	6	
15434	3	2.50	3410	41022	2.0	0	0	3	11	3

15435 rows × 89 columns

In [342…

```
X_train_scaled
```

Out[342…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gr
0	-0.424306	-0.137586	1.090109	0.746540	-0.934757	-0.082363	-0.327847	0.879066	0.316
1	-0.424306	-0.467805	-0.596445	-0.187985	-0.934757	-0.082363	-0.327847	0.879066	-0.552
2	0.689686	0.853071	1.090109	-0.034065	1.180162	-0.082363	-0.327847	-0.687541	2.922
3	0.689686	1.843729	2.697429	0.062230	-0.934757	-0.082363	-0.327847	-0.687541	1.184
4	-0.424306	0.522852	1.169343	-0.248531	-0.934757	-0.082363	3.050203	-0.687541	0.316
...	...	...	...	...	...	...	...	...	
15430	-0.424306	-0.798024	0.207215	-0.268391	-0.934757	-0.082363	-0.327847	-0.687541	-0.552
15431	0.689686	0.522852	-0.184428	-0.325930	1.180162	-0.082363	-0.327847	-0.687541	0.316
15432	-0.424306	-0.467805	-0.041807	-0.248531	-0.934757	-0.082363	-0.327847	2.445672	-0.552
15433	-1.538298	-1.458462	-1.683084	-0.171444	-0.934757	-0.082363	-0.327847	-0.687541	-1.420
15434	-0.424306	0.522852	1.508917	0.745121	1.180162	-0.082363	-0.327847	-0.687541	2.922

15435 rows × 89 columns

In [343…

```
def create_vif_dct(dataframe, const_col_name='const'):
    """

    Definition:
    Returns a list with each object in the list being the name of a column and it's var

    Args:
```

```
    df = selected dataframe in number format

    dummy checking


    """

    if const_col_name not in dataframe.columns:
        dataframe = sm.add_constant(dataframe)

    # Dummy-checking.
    df = dataframe.select_dtypes('number')
    if df.shape != dataframe.shape:
        warnings.warn('\n\nThere are non-numerical columns trying to be passed!\nThese
    if df.isna().sum().any():
        raise ValueError('There may not be any missing values in the dataframe!')

    # Creating VIF Dictionary.
    vif_dct = {}

    # Loop through each row and set the variable name to the VIF.
    for i in range(len(df.columns)):
        vif = variance_inflation_factor(df.values, i)
        v = df.columns[i]
        vif_dct[v] = vif

    return vif_dct
```

In [344…

```
model = sm.OLS(y_train, X_train_scaled).fit()
model.summary()
```

Out[344…

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.970
Model:	OLS	**Adj. R-squared (uncentered):**	0.970
Method:	Least Squares	**F-statistic:**	5528.
Date:	Sun, 24 Oct 2021	**Prob (F-statistic):**	0.00
Time:	23:07:45	**Log-Likelihood:**	-2.0112e+05
No. Observations:	15435	**AIC:**	4.024e+05
Df Residuals:	15346	**BIC:**	4.031e+05
Df Model:	89		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bedrooms	-1.409e+04	2587.866	-5.444	0.000	-1.92e+04	-9014.917
bathrooms	2.712e+04	3550.462	7.639	0.000	2.02e+04	3.41e+04
sqft_living	2.104e+05	3607.863	58.331	0.000	2.03e+05	2.18e+05
sqft_lot	-2778.2649	1340.877	-2.072	0.038	-5406.542	-149.988
floors	-5984.4317	1399.750	-4.275	0.000	-8728.108	-3240.756
waterfront	2.81e+04	994.389	28.263	0.000	2.62e+04	3.01e+04

view	9194.9283	1053.589	8.727	0.000	7129.768	1.13e+04
condition	6286.5903	1038.745	6.052	0.000	4250.527	8322.654
grade	3.12e+04	1757.462	17.755	0.000	2.78e+04	3.46e+04
sqft_above	1.81e+04	3525.884	5.132	0.000	1.12e+04	2.5e+04
yr_built	-2375.3243	1552.812	-1.530	0.126	-5419.019	668.371
lat	-2.266e+05	3540.425	-63.994	0.000	-2.34e+05	-2.2e+05
long	-3.692e+04	4975.898	-7.421	0.000	-4.67e+04	-2.72e+04
sqft_living15	-1.207e+04	1632.823	-7.392	0.000	-1.53e+04	-8868.967
sqft_lot15	-281.5090	1366.896	-0.206	0.837	-2960.788	2397.769
month_sold	-938.9786	896.274	-1.048	0.295	-2695.781	817.824
renovated	3815.9350	951.893	4.009	0.000	1950.111	5681.759
bath_per_bed	-1.563e+04	2883.419	-5.422	0.000	-2.13e+04	-9982.360
price_per_sqft	1.949e+05	1674.407	116.389	0.000	1.92e+05	1.98e+05
zipcode_98002	1.604e+05	1.09e+04	14.709	0.000	1.39e+05	1.82e+05
zipcode_98003	1.008e+05	9563.759	10.535	0.000	8.2e+04	1.19e+05
zipcode_98004	7.977e+05	8238.341	96.822	0.000	7.82e+05	8.14e+05
zipcode_98005	6.37e+05	1.04e+04	61.024	0.000	6.16e+05	6.57e+05
zipcode_98006	5.679e+05	6594.231	86.115	0.000	5.55e+05	5.81e+05
zipcode_98007	6.332e+05	1.07e+04	58.981	0.000	6.12e+05	6.54e+05
zipcode_98008	6.461e+05	8521.797	75.817	0.000	6.29e+05	6.63e+05
zipcode_98010	2.039e+05	1.59e+04	12.793	0.000	1.73e+05	2.35e+05
zipcode_98011	8.326e+05	1.07e+04	77.538	0.000	8.12e+05	8.54e+05
zipcode_98014	8.196e+05	1.79e+04	45.852	0.000	7.85e+05	8.55e+05
zipcode_98019	8.798e+05	1.34e+04	65.564	0.000	8.54e+05	9.06e+05
zipcode_98022	8370.8278	1.52e+04	0.550	0.582	-2.15e+04	3.82e+04
zipcode_98023	6.175e+04	9209.330	6.705	0.000	4.37e+04	7.98e+04
zipcode_98024	6.126e+05	1.87e+04	32.811	0.000	5.76e+05	6.49e+05
zipcode_98027	4.888e+05	9153.657	53.404	0.000	4.71e+05	5.07e+05
zipcode_98028	8.268e+05	9503.423	87.005	0.000	8.08e+05	8.45e+05
zipcode_98029	5.854e+05	1.03e+04	56.651	0.000	5.65e+05	6.06e+05
zipcode_98030	2.223e+05	9419.239	23.596	0.000	2.04e+05	2.41e+05
zipcode_98031	2.769e+05	8817.238	31.402	0.000	2.6e+05	2.94e+05
zipcode_98032	2.254e+05	1.22e+04	18.533	0.000	2.02e+05	2.49e+05
zipcode_98033	7.588e+05	7196.436	105.435	0.000	7.45e+05	7.73e+05
zipcode_98034	8e+05	7118.473	112.382	0.000	7.86e+05	8.14e+05

zipcode_98038	2.58e+05	1.02e+04	25.402	0.000	2.38e+05	2.78e+05
zipcode_98039	1.061e+06	1.86e+04	57.166	0.000	1.02e+06	1.1e+06
zipcode_98040	6.465e+05	8150.106	79.319	0.000	6.3e+05	6.62e+05
zipcode_98042	2.323e+05	8452.933	27.481	0.000	2.16e+05	2.49e+05
zipcode_98045	4.978e+05	1.88e+04	26.465	0.000	4.61e+05	5.35e+05
zipcode_98052	7.476e+05	6912.582	108.157	0.000	7.34e+05	7.61e+05
zipcode_98053	7.721e+05	9486.176	81.397	0.000	7.54e+05	7.91e+05
zipcode_98055	3.769e+05	8321.496	45.290	0.000	3.61e+05	3.93e+05
zipcode_98056	4.45e+05	6707.240	66.352	0.000	4.32e+05	4.58e+05
zipcode_98058	3.426e+05	7300.074	46.925	0.000	3.28e+05	3.57e+05
zipcode_98059	4.191e+05	7038.018	59.544	0.000	4.05e+05	4.33e+05
zipcode_98065	5.437e+05	1.46e+04	37.120	0.000	5.15e+05	5.72e+05
zipcode_98070	1.167e+05	1.6e+04	7.318	0.000	8.55e+04	1.48e+05
zipcode_98072	8.486e+05	9754.571	86.991	0.000	8.29e+05	8.68e+05
zipcode_98074	6.589e+05	8484.503	77.653	0.000	6.42e+05	6.75e+05
zipcode_98075	6.007e+05	9870.457	60.863	0.000	5.81e+05	6.2e+05
zipcode_98077	8.417e+05	1.12e+04	74.974	0.000	8.2e+05	8.64e+05
zipcode_98092	8.503e+04	9678.097	8.786	0.000	6.61e+04	1.04e+05
zipcode_98102	6.084e+05	1.57e+04	38.673	0.000	5.78e+05	6.39e+05
zipcode_98103	6.52e+05	9188.864	70.957	0.000	6.34e+05	6.7e+05
zipcode_98105	7.171e+05	1.02e+04	70.594	0.000	6.97e+05	7.37e+05
zipcode_98106	4.598e+05	8816.068	52.158	0.000	4.43e+05	4.77e+05
zipcode_98107	6.241e+05	1.16e+04	53.725	0.000	6.01e+05	6.47e+05
zipcode_98108	4.883e+05	1.03e+04	47.610	0.000	4.68e+05	5.08e+05
zipcode_98109	6.166e+05	1.44e+04	42.721	0.000	5.88e+05	6.45e+05
zipcode_98112	7.208e+05	9835.683	73.288	0.000	7.02e+05	7.4e+05
zipcode_98115	6.941e+05	7794.347	89.056	0.000	6.79e+05	7.09e+05
zipcode_98116	4.75e+05	1.01e+04	47.104	0.000	4.55e+05	4.95e+05
zipcode_98117	6.506e+05	9647.497	67.441	0.000	6.32e+05	6.7e+05
zipcode_98118	4.833e+05	6505.390	74.289	0.000	4.71e+05	4.96e+05
zipcode_98119	6.241e+05	1.26e+04	49.395	0.000	5.99e+05	6.49e+05
zipcode_98122	5.697e+05	9233.357	61.699	0.000	5.52e+05	5.88e+05
zipcode_98125	7.451e+05	8959.313	83.161	0.000	7.28e+05	7.63e+05
zipcode_98126	4.433e+05	9300.956	47.663	0.000	4.25e+05	4.62e+05
zipcode_98133	7.781e+05	9643.834	80.687	0.000	7.59e+05	7.97e+05

zipcode_98136	4.146e+05	1.06e+04	39.136	0.000	3.94e+05	4.35e+05
zipcode_98144	5.566e+05	8154.771	68.260	0.000	5.41e+05	5.73e+05
zipcode_98146	4.19e+05	9308.766	45.012	0.000	4.01e+05	4.37e+05
zipcode_98148	3.254e+05	1.71e+04	18.981	0.000	2.92e+05	3.59e+05
zipcode_98155	8.201e+05	9249.660	88.661	0.000	8.02e+05	8.38e+05
zipcode_98166	2.916e+05	9622.979	30.301	0.000	2.73e+05	3.1e+05
zipcode_98168	4.377e+05	8883.698	49.274	0.000	4.2e+05	4.55e+05
zipcode_98177	7.876e+05	1.15e+04	68.586	0.000	7.65e+05	8.1e+05
zipcode_98178	4.279e+05	8501.333	50.338	0.000	4.11e+05	4.45e+05
zipcode_98188	3.393e+05	1.16e+04	29.162	0.000	3.16e+05	3.62e+05
zipcode_98198	2.229e+05	9351.066	23.836	0.000	2.05e+05	2.41e+05
zipcode_98199	6.288e+05	1.08e+04	58.371	0.000	6.08e+05	6.5e+05
has_basement_true	2.073e+04	3367.254	6.156	0.000	1.41e+04	2.73e+04

Omnibus:	8980.276	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	669725.912
Skew:	1.980	**Prob(JB):**	0.00
Kurtosis:	35.026	**Cond. No.**	124.

Notes:
[1] R^2 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.

In [345…

```
for data in [X_train_scaled, X_train_raw, X_test_scaled, X_test_raw]:
    if ('floors', 'sqft_lot15', 'month_sold', 'zipcode_98022',
        'zipcode_98023', 'zipcode_98070')in data.columns:
        data.drop('floors', 'sqft_lot15', 'month_sold', 'zipcode_98022',
        'zipcode_98023', 'zipcode_98070', axis=1, inplace=True)
```

In [346…

```
X_train_raw.columns
```

Out[346…

```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above', 'yr_built',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'month_sold', 'renovated',
       'bath_per_bed', 'price_per_sqft', 'zipcode_98002', 'zipcode_98003',
       'zipcode_98004', 'zipcode_98005', 'zipcode_98006', 'zipcode_98007',
       'zipcode_98008', 'zipcode_98010', 'zipcode_98011', 'zipcode_98014',
       'zipcode_98019', 'zipcode_98022', 'zipcode_98023', 'zipcode_98024',
       'zipcode_98027', 'zipcode_98028', 'zipcode_98029', 'zipcode_98030',
       'zipcode_98031', 'zipcode_98032', 'zipcode_98033', 'zipcode_98034',
       'zipcode_98038', 'zipcode_98039', 'zipcode_98040', 'zipcode_98042',
       'zipcode_98045', 'zipcode_98052', 'zipcode_98053', 'zipcode_98055',
       'zipcode_98056', 'zipcode_98058', 'zipcode_98059', 'zipcode_98065',
       'zipcode_98070', 'zipcode_98072', 'zipcode_98074', 'zipcode_98075',
       'zipcode_98077', 'zipcode_98092', 'zipcode_98102', 'zipcode_98103',
```

```
       'zipcode_98105', 'zipcode_98106', 'zipcode_98107', 'zipcode_98108',
       'zipcode_98109', 'zipcode_98112', 'zipcode_98115', 'zipcode_98116',
       'zipcode_98117', 'zipcode_98118', 'zipcode_98119', 'zipcode_98122',
       'zipcode_98125', 'zipcode_98126', 'zipcode_98133', 'zipcode_98136',
       'zipcode_98144', 'zipcode_98146', 'zipcode_98148', 'zipcode_98155',
       'zipcode_98166', 'zipcode_98168', 'zipcode_98177', 'zipcode_98178',
       'zipcode_98188', 'zipcode_98198', 'zipcode_98199', 'has_basement_true'],
      dtype='object')
```

In [347…

```
model = sm.OLS(y_train, X_train_scaled).fit()

# https://stackoverflow.com/a/52976810
results_as_html = model.summary().tables[1].as_html()
results = pd.read_html(results_as_html, header=0, index_col=0)[0]
results = results.sort_values('coef', ascending=False)
```

In [352…

```
results.head(50)
```

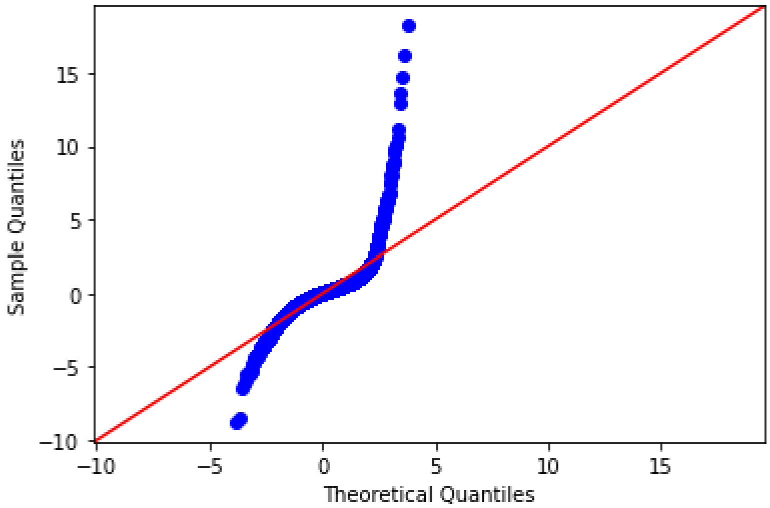
Out[352…

	coef	std err	t	P>|t|	[0.025	0.975]
zipcode_98039	1061000.0	18600.000	57.166	0.0	1020000.0	1100000.0
zipcode_98019	879800.0	13400.000	65.564	0.0	854000.0	906000.0
zipcode_98072	848600.0	9754.571	86.991	0.0	829000.0	868000.0
zipcode_98077	841700.0	11200.000	74.974	0.0	820000.0	864000.0
zipcode_98011	832600.0	10700.000	77.538	0.0	812000.0	854000.0
zipcode_98028	826800.0	9503.423	87.005	0.0	808000.0	845000.0
zipcode_98155	820100.0	9249.660	88.661	0.0	802000.0	838000.0
zipcode_98014	819600.0	17900.000	45.852	0.0	785000.0	855000.0
zipcode_98034	800000.0	7118.473	112.382	0.0	786000.0	814000.0
zipcode_98004	797700.0	8238.341	96.822	0.0	782000.0	814000.0
zipcode_98177	787600.0	11500.000	68.586	0.0	765000.0	810000.0
zipcode_98133	778100.0	9643.834	80.687	0.0	759000.0	797000.0
zipcode_98053	772100.0	9486.176	81.397	0.0	754000.0	791000.0
zipcode_98033	758800.0	7196.436	105.435	0.0	745000.0	773000.0
zipcode_98052	747600.0	6912.582	108.157	0.0	734000.0	761000.0
zipcode_98125	745100.0	8959.313	83.161	0.0	728000.0	763000.0
zipcode_98112	720800.0	9835.683	73.288	0.0	702000.0	740000.0
zipcode_98105	717100.0	10200.000	70.594	0.0	697000.0	737000.0
zipcode_98115	694100.0	7794.347	89.056	0.0	679000.0	709000.0
zipcode_98074	658900.0	8484.503	77.653	0.0	642000.0	675000.0
zipcode_98103	652000.0	9188.864	70.957	0.0	634000.0	670000.0
zipcode_98117	650600.0	9647.497	67.441	0.0	632000.0	670000.0
zipcode_98040	646500.0	8150.106	79.319	0.0	630000.0	662000.0

	coef	std err	t	P>|t|	[0.025	0.975]
zipcode_98008	646100.0	8521.797	75.817	0.0	629000.0	663000.0
zipcode_98005	637000.0	10400.000	61.024	0.0	616000.0	657000.0
zipcode_98007	633200.0	10700.000	58.981	0.0	612000.0	654000.0
zipcode_98199	628800.0	10800.000	58.371	0.0	608000.0	650000.0
zipcode_98107	624100.0	11600.000	53.725	0.0	601000.0	647000.0
zipcode_98119	624100.0	12600.000	49.395	0.0	599000.0	649000.0
zipcode_98109	616600.0	14400.000	42.721	0.0	588000.0	645000.0
zipcode_98024	612600.0	18700.000	32.811	0.0	576000.0	649000.0
zipcode_98102	608400.0	15700.000	38.673	0.0	578000.0	639000.0
zipcode_98075	600700.0	9870.457	60.863	0.0	581000.0	620000.0
zipcode_98029	585400.0	10300.000	56.651	0.0	565000.0	606000.0
zipcode_98122	569700.0	9233.357	61.699	0.0	552000.0	588000.0
zipcode_98006	567900.0	6594.231	86.115	0.0	555000.0	581000.0
zipcode_98144	556600.0	8154.771	68.260	0.0	541000.0	573000.0
zipcode_98065	543700.0	14600.000	37.120	0.0	515000.0	572000.0
zipcode_98045	497800.0	18800.000	26.465	0.0	461000.0	535000.0
zipcode_98027	488800.0	9153.657	53.404	0.0	471000.0	507000.0
zipcode_98108	488300.0	10300.000	47.610	0.0	468000.0	508000.0
zipcode_98118	483300.0	6505.390	74.289	0.0	471000.0	496000.0
zipcode_98116	475000.0	10100.000	47.104	0.0	455000.0	495000.0
zipcode_98106	459800.0	8816.068	52.158	0.0	443000.0	477000.0
zipcode_98056	445000.0	6707.240	66.352	0.0	432000.0	458000.0
zipcode_98126	443300.0	9300.956	47.663	0.0	425000.0	462000.0
zipcode_98168	437700.0	8883.698	49.274	0.0	420000.0	455000.0
zipcode_98178	427900.0	8501.333	50.338	0.0	411000.0	445000.0
zipcode_98059	419100.0	7038.018	59.544	0.0	405000.0	433000.0
zipcode_98146	419000.0	9308.766	45.012	0.0	401000.0	437000.0

In [349…
```
resids = model.resid
```

In [350…
```
sm.graphics.qqplot(resids, stats.norm, line='45', fit=True);
```



In [351…

```
create_vif_dct(X_train_scaled)
```

Out[351…

```
{'const': 273.3193734764532,
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 'sqft_lot': 2.268210929145194,
 'floors': 2.476779628948699,
 'waterfront': 1.2472653294814657,
 'view': 1.4001779470433515,
 'condition': 1.3614459772294658,
 'grade': 3.895945779929304,
 'sqft_above': 15.76398125252129,
 'yr_built': 3.0447337672069503,
 'lat': 64.72830504713296,
 'long': 32.659402000928296,
 'sqft_living15': 3.3640747318462902,
 'sqft_lot15': 2.356767583839578,
 'month_sold': 1.013353065751807,
 'renovated': 1.1431891284989697,
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 'price_per_sqft': 3.5595380387054774,
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 'zipcode_98039': 2.1126898682061444,
```

```
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 'zipcode_98052': 16.17377567481279,
 'zipcode_98053': 13.013500970067897,
 'zipcode_98055': 2.781232638502755,
 'zipcode_98056': 4.979171875413932,
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 'has_basement_true': 3.4277577119456195}
```

Conclusion

The most important features in relation to the price of a house in Kings County are square footage, location, and grade of the house

Recommendations

1. If you are selling your house or increase the value of it, try and increase the square footage of the house (whether it's adding an addition to the property)
2. If you are buying a house, do your research on the area. Houses tend to be higher in price in certain zipcodes and lower in others. There might be certain qualities in neighborhoods that are more appealing to live in than others.

3. If you are selling, improve the quality of your house by investing in upgrades. Grade has proven to be a huge factor correlating with the price

Future Work

1. Gather data from different school districts in KC to see if there is a relationship with prices of a house and the quality of schools.
2. Get before/after stats on renovated houses to see the frequency houses are being renovated and if it has an affect on prices

```
In [ ]:
```