1 Final Project Submission

Please fill out:

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- Student pace: Full Time
- Scheduled project review date/time:
- Instructor name: Yish Lim
- Blog post URL: https://jhusney1.github.io/why_is_multicollinearity_a_problem_for_linear_regression (https://jhusney1.github.io/why_is_multicollinearity_a_problem_for_linear_regression)

1.1 TABLE OF CONTENTS

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2 INTRODUCTION

2.1 Project goals and methodology

As a real estate agency, our goal is to give recommendations to customers on how to increase the value of their home. This will be done through analyzing the data in the "King County House Sales" dataset and investigating which features are correlated with higher sales prices. Using the OSEMN process, we hope to give suggestions that are meaningful and reliable. The OSEMN framework consists of an iterative process of Obtaining the data, Scrubbing it, Exploring, Modeling, and iNterpreting the data into meaningful suggestions for the client.

2.2 The Data

The king county house sales dataset contains data from houses in the Seattle Washington area sold between the time period May 2014 - May 2015. The following features are contained in this dataset:

- **id** - unique identified for a house
- **dateDate** - house was sold
- **pricePrice** - is prediction target
- **bedroomsNumber** - of Bedrooms/House
- **bathroomsNumber** - of bathrooms/bedrooms
- **sqft_livingsquare** - footage of the home
- **sqft_lotsquare** - footage of the lot
- **floorsTotal** - floors (levels) in house
- **waterfront** - House which has a view to a waterfront
- **view** - Has been viewed
- **condition** - How good the condition is (Overall)
- **grade** - overall grade given to the housing unit, based on King County grading system
- **sqft_above** - square footage of house apart from basement
- **sqft_basement** - square footage of the basement
- **yr_built** - Built Year
- **yr_renovated** - Year when house was renovated
- **zipcode** - zip
- **lat** - Latitude coordinate
- **long** - Longitude coordinate
- **sqft_living15** - The square footage of interior housing living space for the nearest 15 neighbors
- **sqft_lot15** - The square footage of the land lots of the nearest 15 neighbors

3 OBTAIN

In [239]:

```
# import necessary modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import f_regression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score

from scipy import stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols

pd.options.display.max_columns = 100

plt.style.use('seaborn-poster')
plt.rcParams['figure.figsize'] = (20,15)
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

In [123]:
```
# read dataset into df
df = pd.read_csv('kc_house_data.csv')
df.drop(['id'], axis=1, inplace=True)
df.head()
```

Out[123]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	10/13/2014	221900.00000	3	1.00000	1180	5650	1.00000	nan	0.00000
1	12/9/2014	538000.00000	3	2.25000	2570	7242	2.00000	0.00000	0.00000
2	2/25/2015	180000.00000	2	1.00000	770	10000	1.00000	0.00000	0.00000
3	12/9/2014	604000.00000	4	3.00000	1960	5000	1.00000	0.00000	0.00000
4	2/18/2015	510000.00000	3	2.00000	1680	8080	1.00000	0.00000	0.00000

In [124]:
```
df.shape
```

Out[124]: (21597, 20)

In [125]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
floors           21597 non-null float64
waterfront       19221 non-null float64
view             21534 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     17755 non-null float64
zipcode          21597 non-null int64
```

3.1 Observations

- May want to remove date column
- sqft basement should be a float instead of string
- Get rid of null values
- Separate categorical and continuous columns

4 SCRUB

4.0.1 Modify necessary datatypes

In [126]:
```
df_cleaned = df.copy()
df_cleaned.drop(['date'], axis=1, inplace=True)
```

In [127]:
```
df_cleaned.columns
```

Out[127]:
```
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'],
      dtype='object')
```

4.0.2 Check for NULL values

In [128]:
```
df_cleaned.isna().sum()
```

Out[128]:
```
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
```

4.0.3 Deal with null values

In [129]:
```
df_cleaned['waterfront'].head()
```

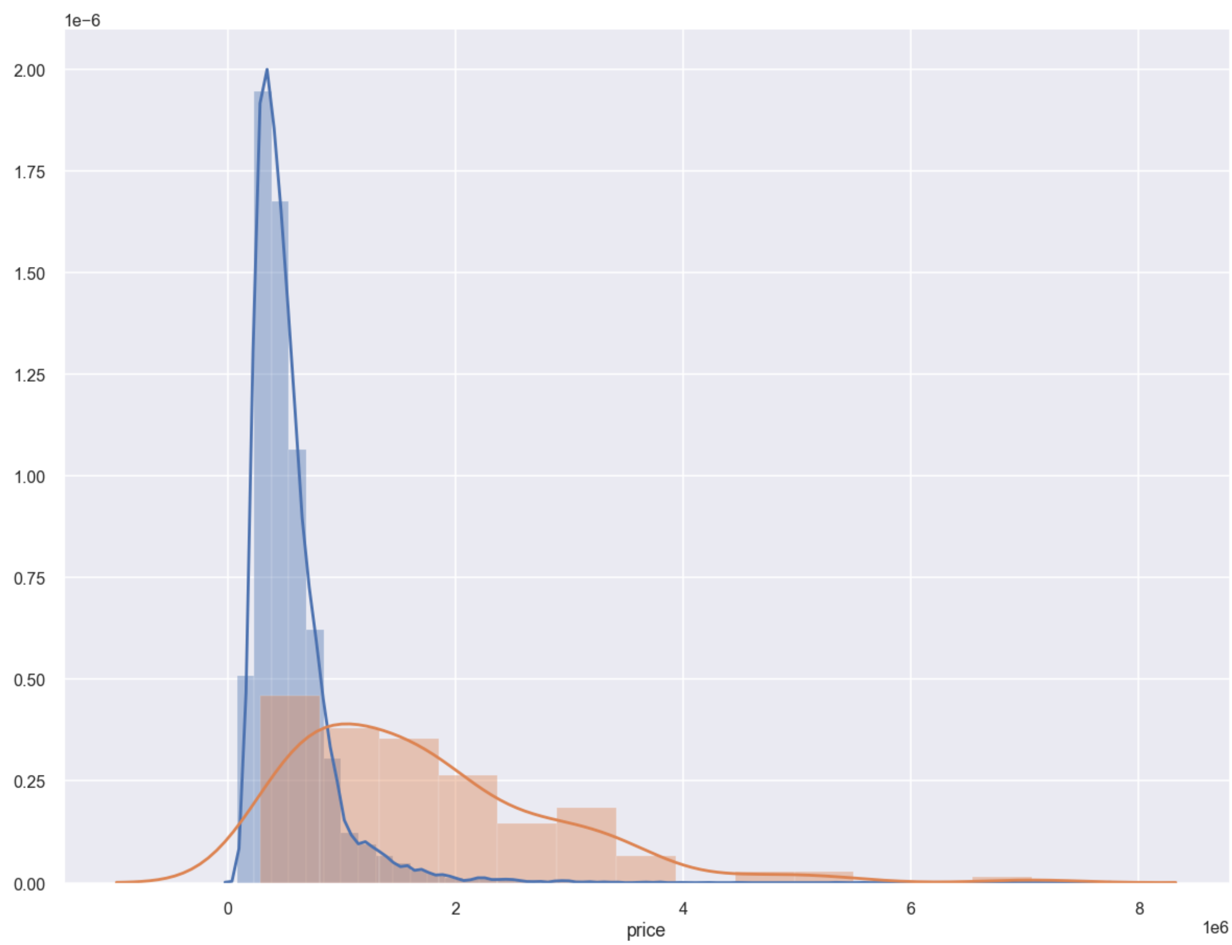
Out[129]:
```
0        nan
1    0.00000
2    0.00000
3    0.00000
4    0.00000
Name: waterfront, dtype: float64
```

In [130]:
```
df_cleaned['waterfront'].value_counts(normalize=True, dropna=False)
```

Out[130]:
```
0.00000    0.88322
nan        0.11002
1.00000    0.00676
Name: waterfront, dtype: float64
```

In [131]:
```
# Does waterfront have an effect on price?
df_no_waterfront = df_cleaned[df_cleaned['waterfront'] == 0]
df_yes_waterfront = df_cleaned[df_cleaned['waterfront'] == 1]
sns.distplot(df_no_waterfront['price'], label='no waterfront')
sns.distplot(df_yes_waterfront['price'], label='with waterfront')
```

Out[131]: <AxesSubplot:xlabel='price'>



4.0.4 Seems like sale price increases due to waterfront, therefore, this feature will stay. We will get rid of null values by replacing the nulls with 0 assuming they don't have a waterfront if it's unavailable.

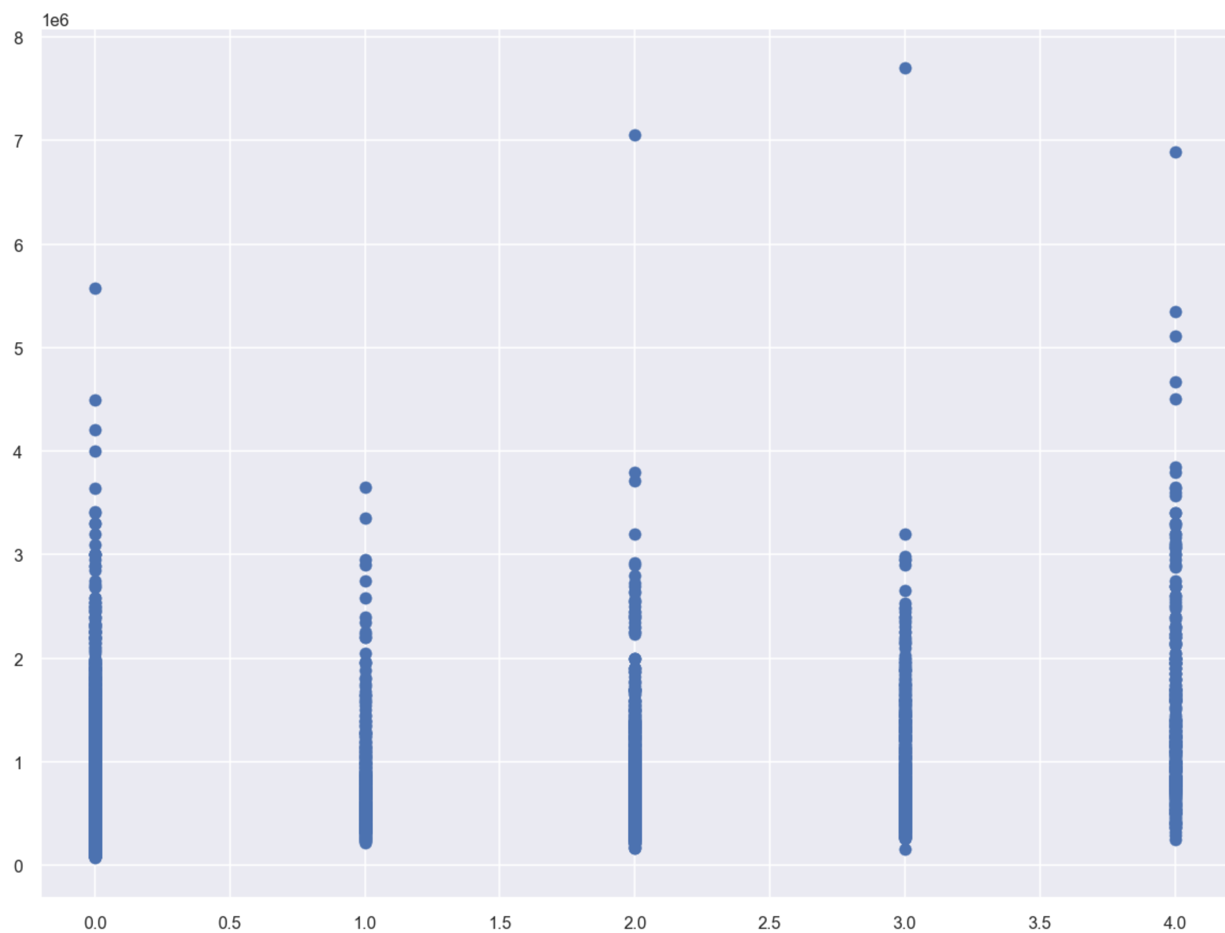
In [132]:
```
# replace null values with zero
df_cleaned['waterfront'].fillna(0, inplace=True)
```

In [133]:
```
df_cleaned['waterfront'].value_counts(normalize=True, dropna=False)
```
Out[133]:
```
0.00000    0.99324
1.00000    0.00676
Name: waterfront, dtype: float64
```

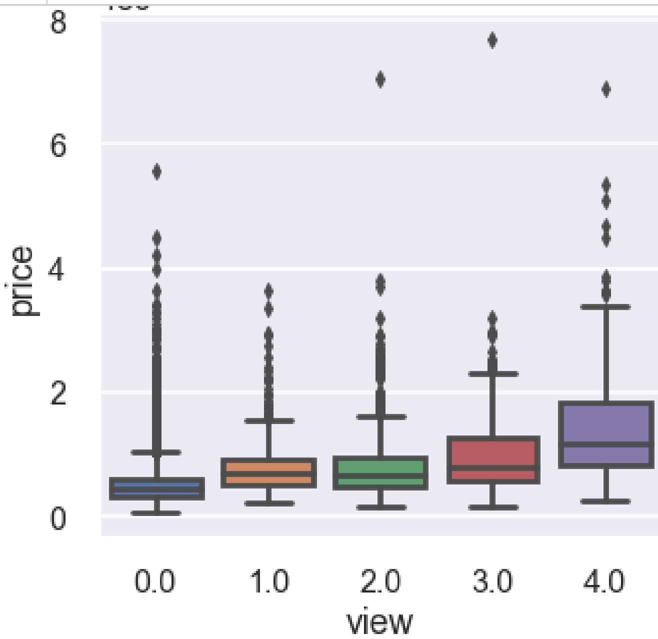
4.0.5 Now let's anylize the null values in view column

In [134]:
```
df_cleaned['view'].value_counts(normalize=True, dropna=False)
```
Out[134]:
```
0.00000    0.89929
2.00000    0.04431
3.00000    0.02352
1.00000    0.01528
4.00000    0.01468
nan        0.00292
Name: view, dtype: float64
```

In [135]:
```
fig, ax = plt.subplots()
ax.scatter(df_cleaned['view'], df_cleaned['price'])
```
Out[135]: <matplotlib.collections.PathCollection at 0x1f5614bbda0>



In [136]:
```
sns.catplot(data=df_cleaned, x='view', y='price', kind='box')
```



4.0.6 There doesn't seem to be a significant correlation between how many times the house has been viewed and the price. Dropping column

In [137]:
```
df_cleaned.drop(['view'], axis=1, inplace=True)
df_cleaned.isna().sum()
```

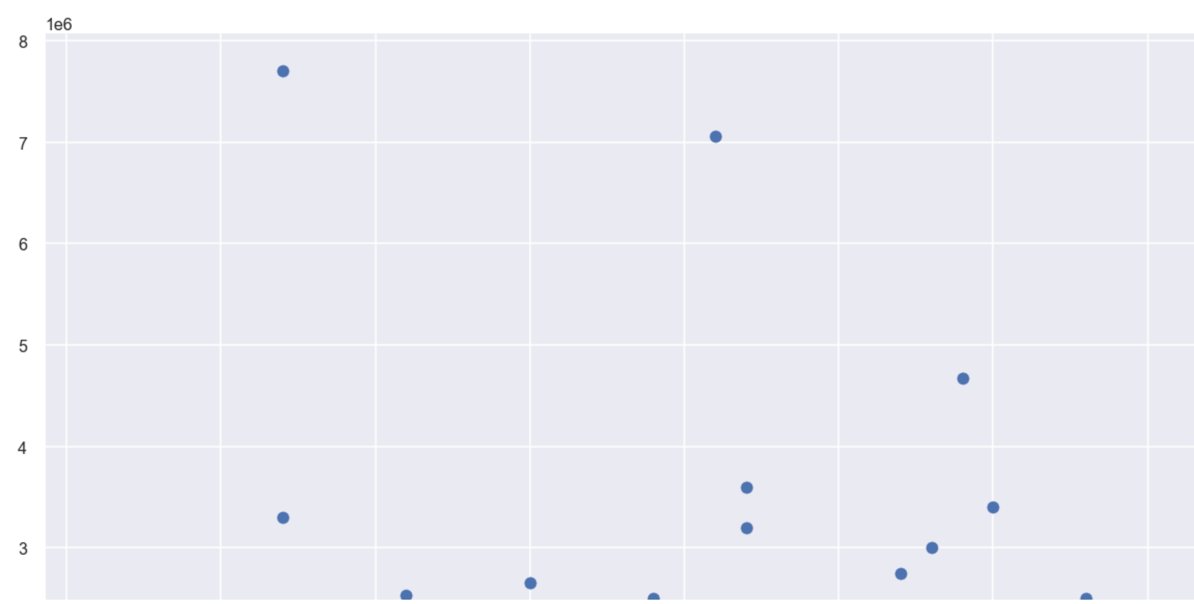
Out[137]:
```
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront          0
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In [138]:
```python
# Lets see how much of yr_renovated column consists of null values
df_cleaned['yr_renovated'].value_counts(normalize=True, dropna=False)
```

Out[138]:
```
0.00000      0.78766
nan          0.17790
2014.00000   0.00338
2003.00000   0.00144
2013.00000   0.00144
               ...
1944.00000   0.00005
1948.00000   0.00005
1976.00000   0.00005
1934.00000   0.00005
1953.00000   0.00005
Name: yr_renovated, Length: 71, dtype: float64
```

In [139]:
```python
# Check if the year it was renovated makes a significant difference
fig, ax = plt.subplots()
ax.scatter(df_cleaned['yr_renovated'][df_cleaned['yr_renovated'] > 1980], df_c
```

Out[139]:
```
<matplotlib.collections.PathCollection at 0x1f553ec22e8>
```



Because 78% of these houses were not renovated, we will make this column into a 0 and 1's column based on whether each particular house was renovated or not. Especially because the specific year that it was renovated doesn't seem to affect the price

In [140]:
```python
def convert_to_bool(x):
    if x > 0:
        x = 1
    else:
        x = 0
    return x
```

In [141]:
```
df_cleaned['yr_renovated'] = df_cleaned['yr_renovated'].map(convert_to_bool)
```

In [142]:
```
df_cleaned['yr_renovated'].value_counts(normalize=True, dropna=False)
```

Out[142]:
```
0    0.96555
1    0.03445
Name: yr_renovated, dtype: float64
```

In [143]:
```
# column will represent if it was renovated or not
df_cleaned.rename(columns={'yr_renovated': 'renovated'}, inplace=True)
df_cleaned
```

Out[143]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grad
0	221900.00000	3	1.00000	1180	5650	1.00000	0.00000	3	
1	538000.00000	3	2.25000	2570	7242	2.00000	0.00000	3	
2	180000.00000	2	1.00000	770	10000	1.00000	0.00000	3	
3	604000.00000	4	3.00000	1960	5000	1.00000	0.00000	5	
4	510000.00000	3	2.00000	1680	8080	1.00000	0.00000	3	
...	...	...	...	...	...	...	...	...	.
21592	360000.00000	3	2.50000	1530	1131	3.00000	0.00000	3	
21593	400000.00000	4	2.50000	2310	5813	2.00000	0.00000	3	
21594	402101.00000	2	0.75000	1020	1350	2.00000	0.00000	3	
21595	400000.00000	3	2.50000	1600	2388	2.00000	0.00000	3	
21596	325000.00000	2	0.75000	1020	1076	2.00000	0.00000	3	

21597 rows × 18 columns

In [144]:
```
df_cleaned['renovated'].value_counts(normalize=True, dropna=False)
```

Out[144]:
```
0    0.96555
1    0.03445
Name: renovated, dtype: float64
```

In [145]:
```
df_cleaned.isna().sum()
```

Out[145]:
```
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
renovated        0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

We now got rid of all known null values!

4.0.7 Convert sqft_basement from String to Float data type

In [146]:
```
df_cleaned['sqft_basement'] = pd.to_numeric(df_cleaned['sqft_basement'], error
df_cleaned['sqft_basement']
```

Out[146]:
```
0          0.00000
1        400.00000
2          0.00000
3        910.00000
4          0.00000
           ...
21592      0.00000
21593      0.00000
21594      0.00000
21595      0.00000
21596      0.00000
Name: sqft_basement, Length: 21597, dtype: float64
```

In [147]:
```
#check for nulls
df_cleaned['sqft_basement'].value_counts(normalize=True, dropna=False)
```

Out[147]:
```
0.00000      0.59388
nan          0.02102
600.00000    0.01005
500.00000    0.00968
700.00000    0.00963
               ...
588.00000    0.00005
1920.00000   0.00005
2390.00000   0.00005
1245.00000   0.00005
1135.00000   0.00005
Name: sqft_basement, Length: 304, dtype: float64
```

4.0.8 Something must be done about these newly discovered null values. We will assume that a null value means no basement. Partially because the mode is zero anyhow.

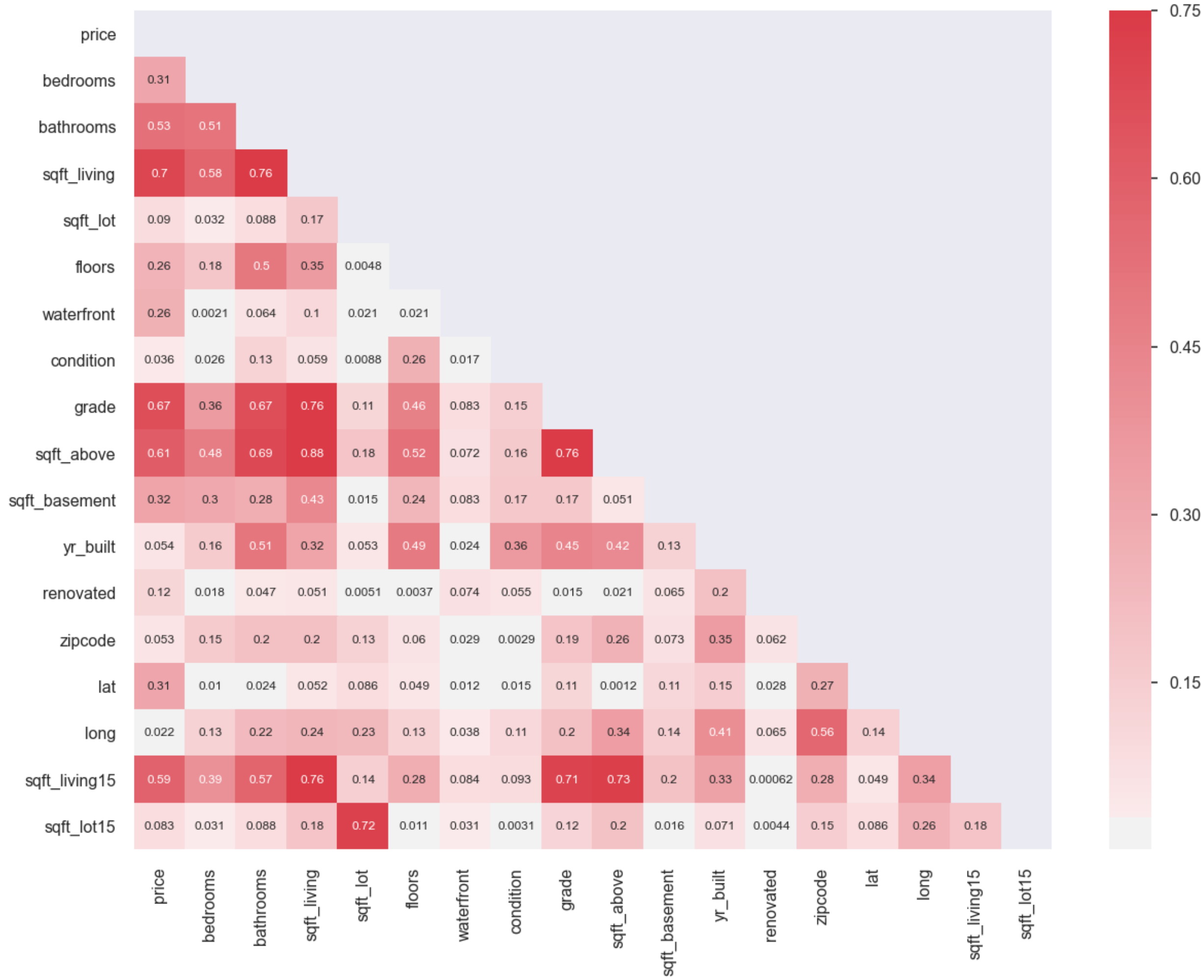
In [148]:
```
df_cleaned['sqft_basement'].fillna(0, inplace=True)
df_cleaned['sqft_basement'].value_counts(normalize=True, dropna=False)
```

Out[148]:
```
0.00000      0.61490
600.00000    0.01005
500.00000    0.00968
700.00000    0.00963
800.00000    0.00931
               ...
915.00000    0.00005
295.00000    0.00005
1281.00000   0.00005
2130.00000   0.00005
906.00000    0.00005
Name: sqft_basement, Length: 303, dtype: float64
```

In [149]:
```
def check_multicol(df):

    corr = df.corr().abs()
    mask = np.triu(np.ones_like(corr, dtype=bool))
    cmap = sns.diverging_palette(220, 10, as_cmap=True)
    sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.75, center=0, annot=True)
```

In [150]:
```
plt.rcParams['figure.figsize'] = (20,15)
check_multicol(df_cleaned)
```



4.0.9 Multicollinearity found in following combinations:

- sqft_above and sqft_living
- sqft_living and bathrooms
- grade and sqft_living
- sqft_above and sqft_living
- sqft_above and grade
- sqft_living15 and sqft_living
- sqft_living15 and sqft_above
- sqft_living15 and grade

- sqft_lot15 and sqft_lot

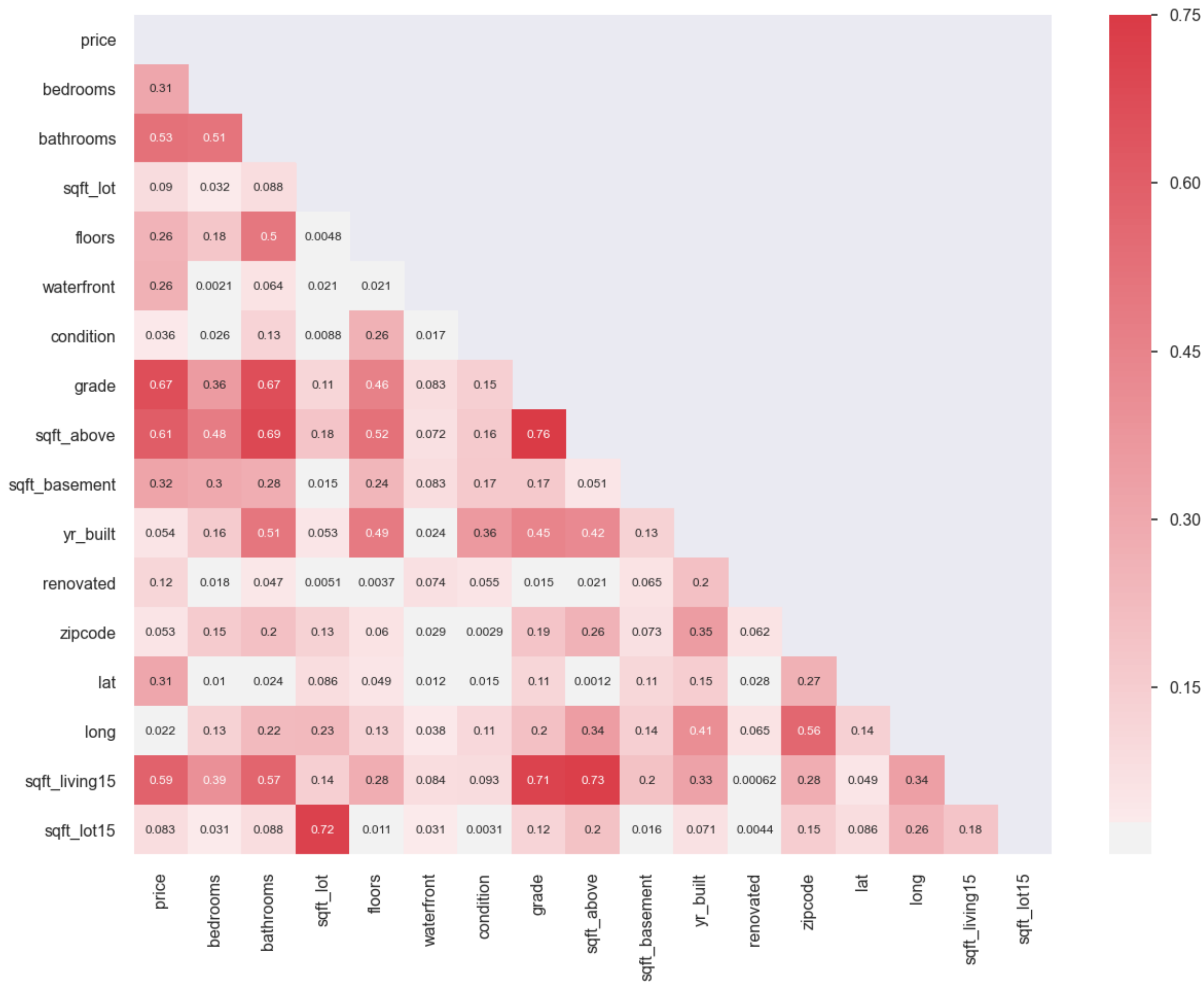
In [151]:
```
# High multicolinearity occuring in sqft_living
# Check if it adds any value to dataset
sqft_sample = df_cleaned[df_cleaned['sqft_basement'] > 0].sample(5, random_sta
sqft_sample[['sqft_above', 'sqft_living', 'sqft_basement']]
```

Out[151]:

	sqft_above	sqft_living	sqft_basement
8367	1080	1370	290.00000
20021	2242	3490	1248.00000
16657	1100	2110	1010.00000
20430	1140	1405	265.00000
12953	1500	2750	1250.00000

4.0.10 Drop sqft_living - can be calculated by adding basement and above square footage

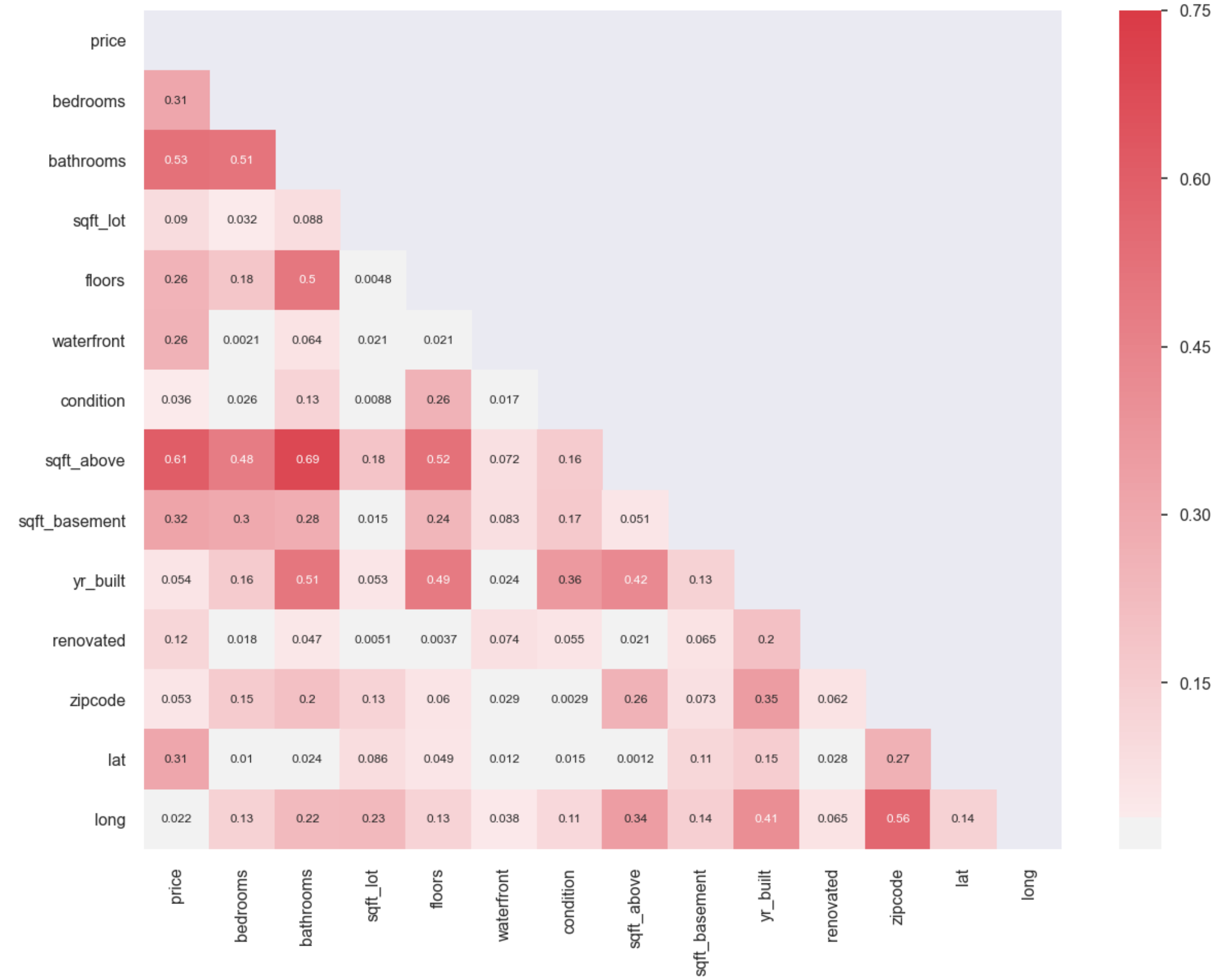
In [152]:
```
df_cleaned.drop(['sqft_living'], axis=1, inplace=True)
check_multicol(df_cleaned)
```



4.0.11 Drop some other columns that aren't so important in the bigger scheme of things

In [153]:

```
df_cleaned.drop(['sqft_living15'], inplace=True, axis=1)
df_cleaned.drop(['sqft_lot15'], inplace=True, axis=1)
df_cleaned.drop(['grade'], inplace=True, axis=1)
check_multicol(df_cleaned)
```

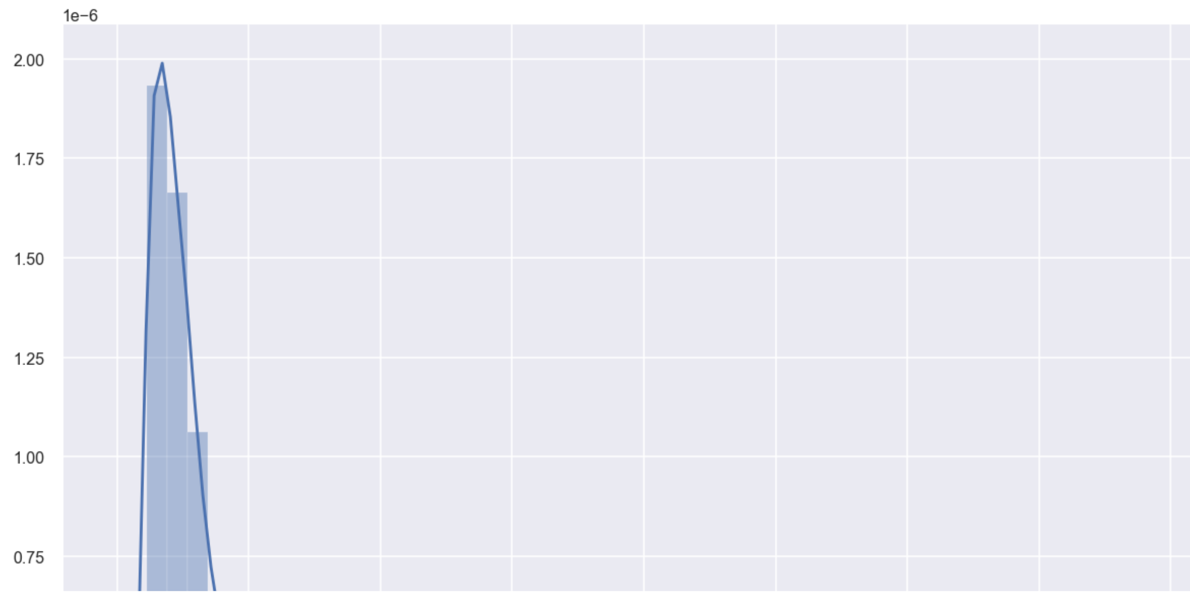


5 EXPLORE

5.0.1 Identify outliers

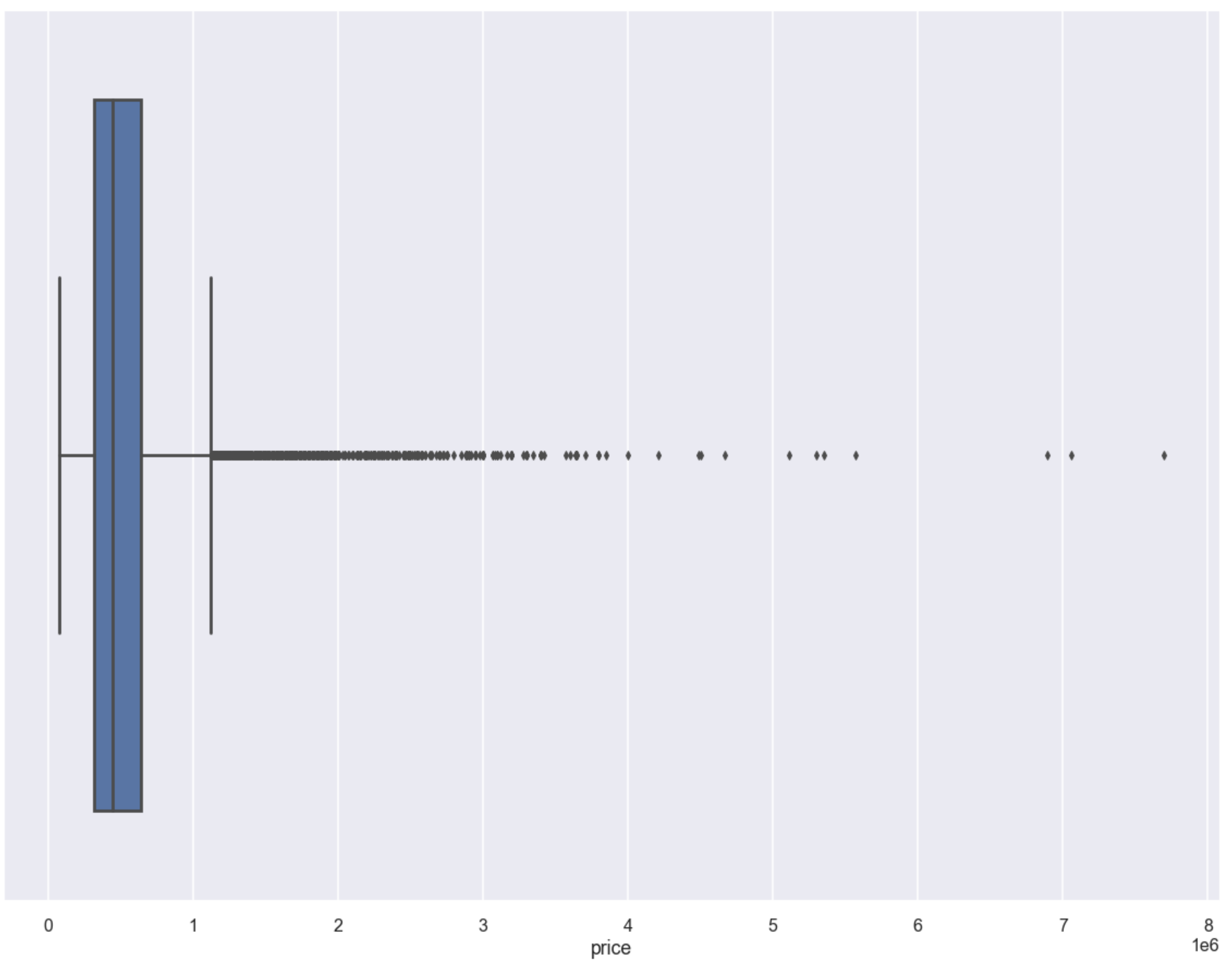
In [154]:
```
target = 'price'
sns.distplot(df_cleaned[target])
```

Out[154]: <AxesSubplot:xlabel='price'>



In [155]:
```
sns.boxplot(df_cleaned[target])
```

Out[155]: <AxesSubplot:xlabel='price'>



We see clearly from both the histogram and the whisker plot that there are many outliers for price column

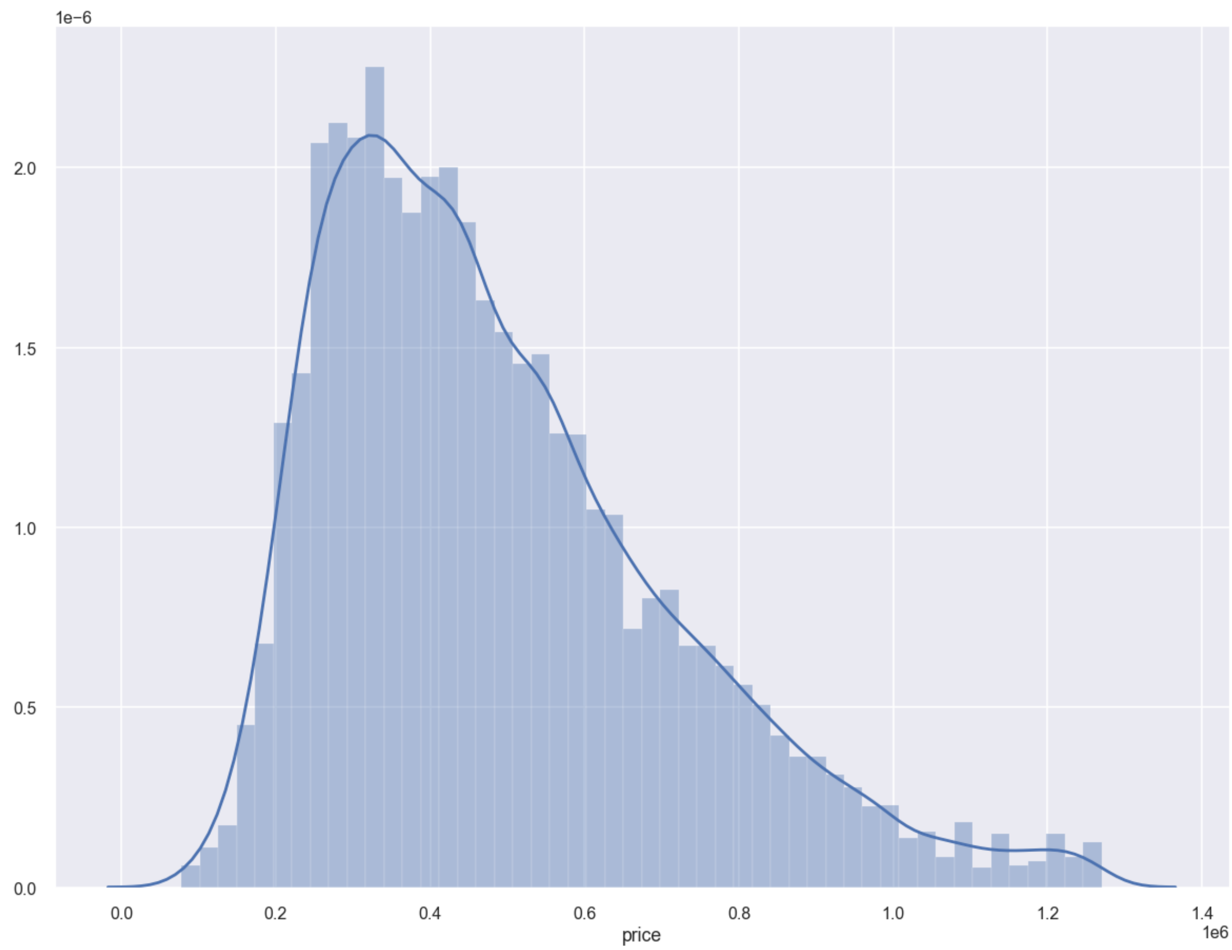
5.0.2 Remove outliers

In [156]:
```
import scipy
z_price = scipy.stats.zscore(df_cleaned['price'])
z_price = np.abs(z_price)
z_price
```

Out[156]:
```
array([0.86671627, 0.00625157, 0.98077344, ..., 0.37618606, 0.38190525,
       0.58606486])
```

In [157]:
```
# Preview histogram before changing
sns.distplot(df_cleaned[z_price < 2]['price'])
```

Out[157]:
```
<AxesSubplot:xlabel='price'>
```



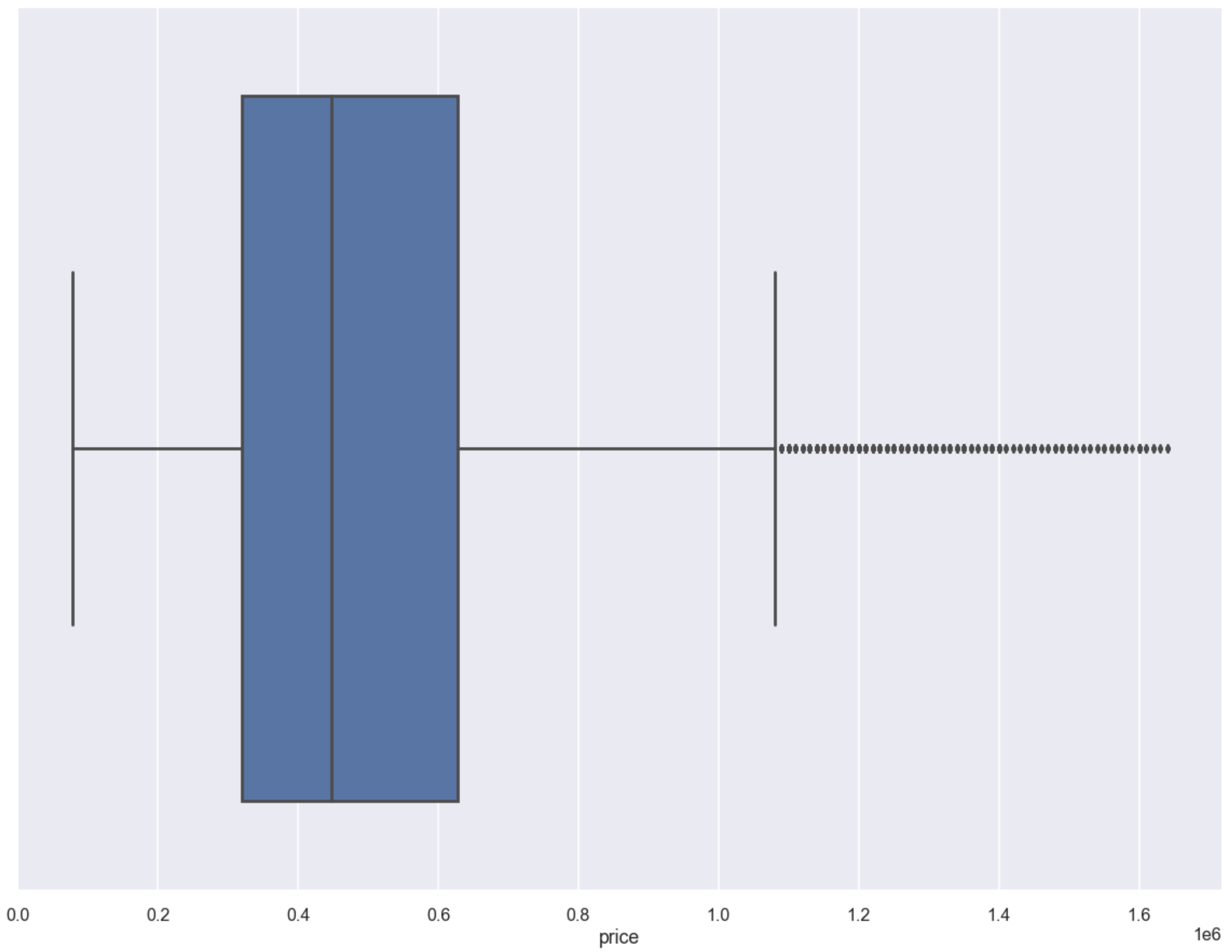
In [158]:
```
# Make changes
df_cleaned = df_cleaned[z_price < 3]
df_cleaned.shape

# Maybe go back and remove more outliers from other cols based on modeling
```

Out[158]:
```
(21191, 14)
```

In [159]:
```
sns.boxplot(df_cleaned[target])
```

Out[159]:
```
<AxesSubplot:xlabel='price'>
```



5.0.3 Make sure data is accurate

In [160]:
```
1 df_cleaned.describe().round(2)
```

Out[160]:

	price	bedrooms	bathrooms	sqft_lot	floors	waterfront	conditio
count	21191.00000	21191.00000	21191.00000	21191.00000	21191.00000	21191.00000	21191.0000
mean	507010.29000	3.36000	2.09000	14826.73000	1.49000	0.00000	3.4100
std	259462.21000	0.92000	0.74000	40400.95000	0.54000	0.06000	0.6500
min	78000.00000	1.00000	0.50000	520.00000	1.00000	0.00000	1.0000
25%	320000.00000	3.00000	1.50000	5005.50000	1.00000	0.00000	3.0000
50%	447000.00000	3.00000	2.25000	7560.00000	1.00000	0.00000	3.0000
75%	627650.00000	4.00000	2.50000	10490.50000	2.00000	0.00000	4.0000
max	1640000.00000	33.00000	7.50000	1651359.00000	3.50000	1.00000	5.0000

5.0.4 Doesn't seem likely that a house will contain 33 bedrooms. Let's inspect that row

In [161]:
```
1 df_cleaned[df_cleaned['bedrooms'] == 33]
```

Out[161]:

	price	bedrooms	bathrooms	sqft_lot	floors	waterfront	condition	sqft_above	sqft
15856	640000.00000	33	1.75000	6000	1.00000	0.00000	5	1040	

In [162]:
```
1 with 3 bedrooms to see if it meant to say 3
2 d['bedrooms'] == 3) & (df_cleaned['bathrooms'] == 2) & (df_cleaned['floors'] == 1)
```

Out[162]:

	price	bedrooms	bathrooms	sqft_lot	floors	waterfront	condition	sqft_above	sqft_
164	420000.00000	3	2.00000	38332	1.00000	0.00000	4	1010	1
221	279950.00000	3	2.00000	9750	1.00000	0.00000	3	1350	
236	416000.00000	3	2.00000	94300	1.00000	0.00000	5	1640	
250	260000.00000	3	2.00000	7209	1.00000	0.00000	4	1240	
316	487000.00000	3	2.00000	14052	1.00000	0.00000	5	1720	
387	252350.00000	3	2.00000	7352	1.00000	0.00000	3	1160	
427	1300000.00000	3	2.00000	15021	1.00000	0.00000	4	1770	
468	340500.00000	3	2.00000	28025	1.00000	0.00000	4	1920	
494	397500.00000	3	2.00000	6710	1.00000	0.00000	3	1070	
608	223000.00000	3	2.00000	6824	1.00000	0.00000	3	1300	

In [163]:
```
# Delete row
df_cleaned = df_cleaned[df_cleaned['bedrooms'] != 33]
df_cleaned.describe().round(2)
```

Out[163]:

	price	bedrooms	bathrooms	sqft_lot	floors	waterfront	conditio
count	21190.00000	21190.00000	21190.00000	21190.00000	21190.00000	21190.00000	21190.0000
mean	507004.02000	3.35000	2.09000	14827.15000	1.49000	0.00000	3.4100
std	259466.72000	0.89000	0.74000	40401.85000	0.54000	0.06000	0.6500
min	78000.00000	1.00000	0.50000	520.00000	1.00000	0.00000	1.0000
25%	320000.00000	3.00000	1.50000	5005.25000	1.00000	0.00000	3.0000
50%	447000.00000	3.00000	2.25000	7560.00000	1.00000	0.00000	3.0000
75%	627500.00000	4.00000	2.50000	10490.75000	2.00000	0.00000	4.0000
max	1640000.00000	11.00000	7.50000	1651359.00000	3.50000	1.00000	5.0000

5.0.5 One hot encode zip code

In [175]:
```
cat_cols = ['zipcode']
df_preproccesed_ohe = pd.get_dummies(data=df_cleaned, columns= cat_cols, drop_
df_preproccesed_ohe.head()
```

Out[175]:

	price	bedrooms	bathrooms	sqft_lot	floors	waterfront	condition	sqft_above	sqft_bas
0	221900.00000	3	1.00000	5650	1.00000	0.00000	3	1180	0
1	538000.00000	3	2.25000	7242	2.00000	0.00000	3	2170	400
2	180000.00000	2	1.00000	10000	1.00000	0.00000	3	770	0
3	604000.00000	4	3.00000	5000	1.00000	0.00000	5	1050	910
4	510000.00000	3	2.00000	8080	1.00000	0.00000	3	1680	0

6 MODEL

6.1 Train test split

In [210]:
```
from sklearn.model_selection import train_test_split
```

In [211]:
```
target = 'price'
x_cols = list(df_preproccesed_ohe.columns)
x_cols.remove(target)
```

In [212]:
```
train, test = train_test_split(df_preproccesed_ohe, random_state=52)
```

In [213]:
```
def model_data(df_ohe_, target='price'):

    df_ohe = df_ohe_.copy()

    feat = '+'.join(df_ohe.drop(columns=target).columns)
    f = target + '~'+ feat
    model = ols(formula=f, data=df_ohe).fit()
    return model
```

In [214]:

```
model = model_data(train)
model.summary()
```

Out[214]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.799
Model:	OLS	**Adj. R-squared:**	0.798
Method:	Least Squares	**F-statistic:**	778.3
Date:	Sun, 29 Nov 2020	**Prob (F-statistic):**	0.00
Time:	22:48:04	**Log-Likelihood:**	-2.0792e+05
No. Observations:	15892	**AIC:**	4.160e+05
Df Residuals:	15810	**BIC:**	4.166e+05
Df Model:	81		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-2.399e+07	5.17e+06	-4.641	0.000	-3.41e+07	-1.39e+07
bedrooms	-2.133e+04	1353.811	-15.757	0.000	-2.4e+04	-1.87e+04
bathrooms	2.427e+04	2248.474	10.795	0.000	1.99e+04	2.87e+04
sqft_lot	0.2803	0.025	11.356	0.000	0.232	0.329
floors	-2.572e+04	2700.977	-9.523	0.000	-3.1e+04	-2.04e+04
waterfront	4.28e+05	1.57e+04	27.306	0.000	3.97e+05	4.59e+05
condition	2.516e+04	1623.832	15.493	0.000	2.2e+04	2.83e+04
sqft_above	213.3397	2.066	103.266	0.000	209.290	217.389
sqft_basement	133.4232	2.915	45.767	0.000	127.709	139.137
yr_built	-117.0635	52.567	-2.227	0.026	-220.101	-14.026
renovated	4.301e+04	5413.771	7.944	0.000	3.24e+04	5.36e+04
lat	2.018e+05	5.35e+04	3.769	0.000	9.69e+04	3.07e+05
long	-1.189e+05	3.84e+04	-3.098	0.002	-1.94e+05	-4.37e+04
zipcode_98002	-43.3948	1.19e+04	-0.004	0.997	-2.34e+04	2.33e+04
zipcode_98003	1200.8238	1.07e+04	0.112	0.911	-1.98e+04	2.22e+04
zipcode_98004	5.928e+05	2.01e+04	29.503	0.000	5.53e+05	6.32e+05
zipcode_98005	3.009e+05	2.1e+04	14.322	0.000	2.6e+05	3.42e+05
zipcode_98006	2.984e+05	1.72e+04	17.316	0.000	2.65e+05	3.32e+05
zipcode_98007	2.321e+05	2.13e+04	10.878	0.000	1.9e+05	2.74e+05
zipcode_98008	2.329e+05	2.07e+04	11.241	0.000	1.92e+05	2.74e+05
zipcode_98010	8.444e+04	1.83e+04	4.623	0.000	4.86e+04	1.2e+05
zipcode_98011	5.508e+04	2.7e+04	2.043	0.041	2238.147	1.08e+05
zipcode_98014	6.676e+04	2.93e+04	2.277	0.023	9279.803	1.24e+05
zipcode_98019	3.194e+04	2.92e+04	1.094	0.274	-2.53e+04	8.92e+04

zipcode_98022	6.343e+04	1.6e+04	3.954	0.000	3.2e+04	9.49e+04
zipcode_98023	-2.386e+04	9943.942	-2.400	0.016	-4.34e+04	-4373.086
zipcode_98024	1.453e+05	2.59e+04	5.615	0.000	9.46e+04	1.96e+05
zipcode_98027	1.788e+05	1.77e+04	10.120	0.000	1.44e+05	2.13e+05
zipcode_98028	5.84e+04	2.62e+04	2.229	0.026	7036.248	1.1e+05
zipcode_98029	2.267e+05	2.02e+04	11.231	0.000	1.87e+05	2.66e+05
zipcode_98030	-4763.6027	1.17e+04	-0.407	0.684	-2.77e+04	1.82e+04
zipcode_98031	-626.2128	1.23e+04	-0.051	0.959	-2.47e+04	2.35e+04
zipcode_98032	-9986.8859	1.39e+04	-0.717	0.473	-3.73e+04	1.73e+04
zipcode_98033	3.091e+05	2.25e+04	13.753	0.000	2.65e+05	3.53e+05
zipcode_98034	1.268e+05	2.41e+04	5.268	0.000	7.96e+04	1.74e+05
zipcode_98038	3.729e+04	1.34e+04	2.792	0.005	1.11e+04	6.35e+04
zipcode_98039	7.832e+05	3.54e+04	22.150	0.000	7.14e+05	8.53e+05
zipcode_98040	4.969e+05	1.76e+04	28.288	0.000	4.63e+05	5.31e+05
zipcode_98042	9409.2183	1.14e+04	0.826	0.409	-1.29e+04	3.17e+04
zipcode_98045	1.326e+05	2.5e+04	5.313	0.000	8.37e+04	1.82e+05
zipcode_98052	2.093e+05	2.29e+04	9.144	0.000	1.64e+05	2.54e+05
zipcode_98053	1.738e+05	2.47e+04	7.050	0.000	1.25e+05	2.22e+05
zipcode_98055	2.17e+04	1.39e+04	1.563	0.118	-5517.090	4.89e+04
zipcode_98056	6.981e+04	1.5e+04	4.655	0.000	4.04e+04	9.92e+04
zipcode_98058	2.473e+04	1.3e+04	1.902	0.057	-753.642	5.02e+04
zipcode_98059	7.865e+04	1.47e+04	5.358	0.000	4.99e+04	1.07e+05
zipcode_98065	1.082e+05	2.28e+04	4.753	0.000	6.36e+04	1.53e+05
zipcode_98070	3.586e+04	1.71e+04	2.094	0.036	2290.931	6.94e+04
zipcode_98072	1.189e+05	2.69e+04	4.425	0.000	6.62e+04	1.72e+05
zipcode_98074	1.982e+05	2.17e+04	9.118	0.000	1.56e+05	2.41e+05
zipcode_98075	2.213e+05	2.08e+04	10.641	0.000	1.81e+05	2.62e+05
zipcode_98077	1.2e+05	2.79e+04	4.309	0.000	6.54e+04	1.75e+05
zipcode_98092	-4617.5825	1.08e+04	-0.426	0.670	-2.59e+04	1.66e+04
zipcode_98102	4.204e+05	2.32e+04	18.140	0.000	3.75e+05	4.66e+05
zipcode_98103	2.743e+05	2.16e+04	12.687	0.000	2.32e+05	3.17e+05
zipcode_98105	4.028e+05	2.23e+04	18.092	0.000	3.59e+05	4.46e+05
zipcode_98106	7.651e+04	1.6e+04	4.791	0.000	4.52e+04	1.08e+05
zipcode_98107	2.73e+05	2.24e+04	12.181	0.000	2.29e+05	3.17e+05
zipcode_98108	6.881e+04	1.79e+04	3.842	0.000	3.37e+04	1.04e+05
zipcode_98109	4.494e+05	2.33e+04	19.319	0.000	4.04e+05	4.95e+05
zipcode_98112	4.866e+05	2.05e+04	23.685	0.000	4.46e+05	5.27e+05
zipcode_98115	2.816e+05	2.2e+04	12.811	0.000	2.39e+05	3.25e+05

zipcode_98116	2.842e+05	1.78e+04	15.938	0.000	2.49e+05	3.19e+05
zipcode_98117	2.525e+05	2.23e+04	11.332	0.000	2.09e+05	2.96e+05
zipcode_98118	1.309e+05	1.56e+04	8.383	0.000	1e+05	1.62e+05
zipcode_98119	4.112e+05	2.17e+04	18.925	0.000	3.69e+05	4.54e+05
zipcode_98122	3.017e+05	1.93e+04	15.615	0.000	2.64e+05	3.4e+05
zipcode_98125	1.271e+05	2.38e+04	5.350	0.000	8.05e+04	1.74e+05
zipcode_98126	1.511e+05	1.64e+04	9.204	0.000	1.19e+05	1.83e+05
zipcode_98133	6.917e+04	2.45e+04	2.819	0.005	2.11e+04	1.17e+05
zipcode_98136	2.384e+05	1.68e+04	14.158	0.000	2.05e+05	2.71e+05
zipcode_98144	2.277e+05	1.8e+04	12.681	0.000	1.93e+05	2.63e+05
zipcode_98146	7.529e+04	1.49e+04	5.049	0.000	4.61e+04	1.05e+05
zipcode_98148	2.143e+04	2e+04	1.071	0.284	-1.78e+04	6.06e+04
zipcode_98155	5.213e+04	2.56e+04	2.040	0.041	2029.691	1.02e+05
zipcode_98166	7.56e+04	1.37e+04	5.508	0.000	4.87e+04	1.03e+05
zipcode_98168	3733.5582	1.47e+04	0.254	0.799	-2.5e+04	3.25e+04
zipcode_98177	1.631e+05	2.56e+04	6.370	0.000	1.13e+05	2.13e+05
zipcode_98178	2.307e+04	1.5e+04	1.538	0.124	-6332.252	5.25e+04
zipcode_98188	1.065e+04	1.56e+04	0.683	0.495	-1.99e+04	4.12e+04
zipcode_98198	1.584e+04	1.14e+04	1.386	0.166	-6563.441	3.82e+04
zipcode_98199	3.588e+05	2.12e+04	16.942	0.000	3.17e+05	4e+05

Omnibus:	3465.972	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	17948.473
Skew:	0.958	**Prob(JB):**	0.00
Kurtosis:	7.841	**Cond. No.**	2.45e+08

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.45e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

> Initial model showing high p-values in certain zip codes. The r squared is around 80% meaning that 80% of the model explains around 80% of the data points. This is certainly high enough. However, we need to check for some assumptions of linear regression.

6.2 Check homoscedasticity and normality

In [215]:

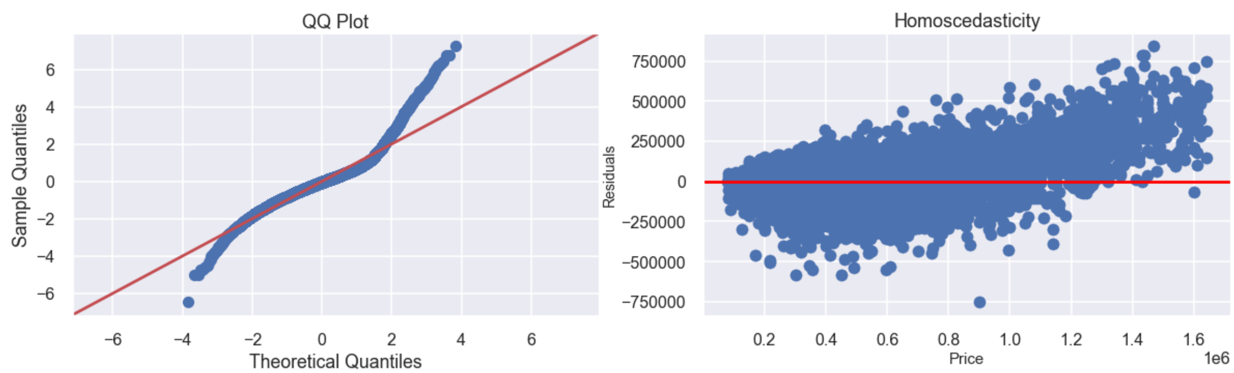
```
# Checking homoscedasticity and normality for initial model
def check_for_assumptions(residuals):

# make qq plot
    fig, axes = plt.subplots(ncols=2, figsize=(20, 5))
    sm.graphics.qqplot(model.resid, fit=True, line='45', ax=axes[0])
    axes[0].set_title('QQ Plot', fontsize=18)

# check for homoscedasticity
    ax=axes[1]
    ax.scatter(train['price'], model.resid)
    ax.axhline(0, color='red')
    axes[1].set_title('Homoscedasticity', fontsize=18)
    axes[1].set_xlabel('Price', fontsize=15)
    axes[1].set_ylabel('Residuals', fontsize=14)
    plt.show();
```

In [216]:

```
check_for_assumptions(model.resid)
```



There seems to be a curve in the qq-plot telling us that the data could be more normally distributed. Toward the higher price range houses, there seems to be an issue with homoscedasticity.

6.2.1 Feature selection

In [217]:

```
# Getting rid of high p values
summary = model.summary()
p_table = summary.tables[1]
p_table = pd.DataFrame(p_table.data)
p_table.columns = p_table.iloc[0]
p_table = p_table.drop(0)
p_table = p_table.set_index(p_table.columns[0])
p_table['P>|t|'] = p_table['P>|t|'].astype(float)
keep_cols = list(p_table[p_table['P>|t|'] < 0.05].index)
keep_cols.remove('Intercept')
keep_cols.append('price')
print(len(p_table), len(keep_cols))
print(keep_cols)
```

```
82 67
['bedrooms', 'bathrooms', 'sqft_lot', 'floors', 'waterfront', 'condition', 'sqft_
above', 'sqft_basement', 'yr_built', 'renovated', 'lat', 'long', 'zipcode_98004',
'zipcode_98005', 'zipcode_98006', 'zipcode_98007', 'zipcode_98008', 'zipcode_9801
0', 'zipcode_98011', 'zipcode_98014', 'zipcode_98022', 'zipcode_98023', 'zipcode_
98024', 'zipcode_98027', 'zipcode_98028', 'zipcode_98029', 'zipcode_98033', 'zipc
ode_98034', 'zipcode_98038', 'zipcode_98039', 'zipcode_98040', 'zipcode_98045',
'zipcode_98052', 'zipcode_98053', 'zipcode_98056', 'zipcode_98059', 'zipcode_9806
5', 'zipcode_98070', 'zipcode_98072', 'zipcode_98074', 'zipcode_98075', 'zipcode_
98077', 'zipcode_98102', 'zipcode_98103', 'zipcode_98105', 'zipcode_98106', 'zipc
ode_98107', 'zipcode_98108', 'zipcode_98109', 'zipcode_98112', 'zipcode_98115',
'zipcode_98116', 'zipcode_98117', 'zipcode_98118', 'zipcode_98119', 'zipcode_9812
2', 'zipcode_98125', 'zipcode_98126', 'zipcode_98133', 'zipcode_98136', 'zipcode_
98144', 'zipcode_98146', 'zipcode_98155', 'zipcode_98166', 'zipcode_98177', 'zipc
ode_98199', 'price']
```

In [218]:
```
train = train[list(keep_cols)]
model = model_data(train)
model.summary()
```

Out[218]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.799
Model:	OLS	**Adj. R-squared:**	0.798
Method:	Least Squares	**F-statistic:**	954.8
Date:	Sun, 29 Nov 2020	**Prob (F-statistic):**	0.00
Time:	22:48:08	**Log-Likelihood:**	-2.0793e+05
No. Observations:	15892	**AIC:**	4.160e+05
Df Residuals:	15825	**BIC:**	4.165e+05
Df Model:	66		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-2.609e+07	3.18e+06	-8.203	0.000	-3.23e+07	-1.99e+07
bedrooms	-2.138e+04	1352.219	-15.812	0.000	-2.4e+04	-1.87e+04
bathrooms	2.442e+04	2245.089	10.877	0.000	2e+04	2.88e+04
sqft_lot	0.2795	0.025	11.342	0.000	0.231	0.328
floors	-2.577e+04	2694.065	-9.567	0.000	-3.11e+04	-2.05e+04
waterfront	4.299e+05	1.56e+04	27.469	0.000	3.99e+05	4.61e+05
condition	2.52e+04	1617.159	15.583	0.000	2.2e+04	2.84e+04
sqft_above	213.3365	2.063	103.434	0.000	209.294	217.379
sqft_basement	133.4472	2.909	45.874	0.000	127.745	139.149
yr_built	-121.9746	52.168	-2.338	0.019	-224.229	-19.720
renovated	4.307e+04	5411.335	7.959	0.000	3.25e+04	5.37e+04
lat	2.751e+05	2.13e+04	12.911	0.000	2.33e+05	3.17e+05
long	-1.078e+05	2.18e+04	-4.944	0.000	-1.51e+05	-6.51e+04
zipcode_98004	5.685e+05	1.02e+04	55.992	0.000	5.49e+05	5.88e+05
zipcode_98005	2.766e+05	1.16e+04	23.796	0.000	2.54e+05	2.99e+05
zipcode_98006	2.775e+05	7381.978	37.597	0.000	2.63e+05	2.92e+05
zipcode_98007	2.073e+05	1.16e+04	17.946	0.000	1.85e+05	2.3e+05
zipcode_98008	2.077e+05	9536.511	21.776	0.000	1.89e+05	2.26e+05
zipcode_98010	7.858e+04	1.43e+04	5.477	0.000	5.05e+04	1.07e+05
zipcode_98011	2.038e+04	1.24e+04	1.643	0.100	-3933.029	4.47e+04
zipcode_98014	3.452e+04	1.43e+04	2.411	0.016	6459.966	6.26e+04
zipcode_98022	6.647e+04	1.15e+04	5.765	0.000	4.39e+04	8.91e+04
zipcode_98023	-2.403e+04	7257.440	-3.311	0.001	-3.83e+04	-9803.858

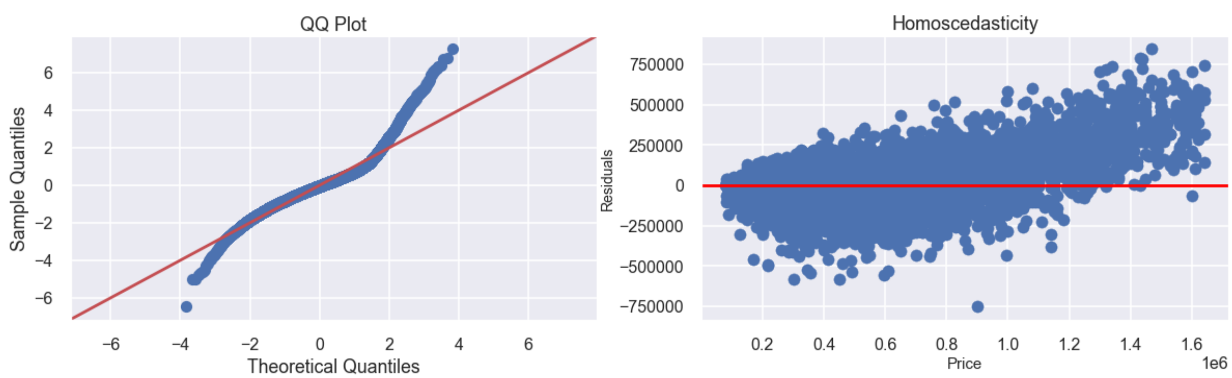
zipcode_98024	1.217e+05	1.63e+04	7.488	0.000	8.99e+04	1.54e+05
zipcode_98027	1.596e+05	7972.403	20.025	0.000	1.44e+05	1.75e+05
zipcode_98028	2.423e+04	1.15e+04	2.102	0.036	1638.381	4.68e+04
zipcode_98029	2.043e+05	9009.467	22.677	0.000	1.87e+05	2.22e+05
zipcode_98033	2.798e+05	9087.476	30.785	0.000	2.62e+05	2.98e+05
zipcode_98034	9.47e+04	9152.227	10.347	0.000	7.68e+04	1.13e+05
zipcode_98038	2.905e+04	7195.863	4.037	0.000	1.49e+04	4.32e+04
zipcode_98039	7.582e+05	3.06e+04	24.752	0.000	6.98e+05	8.18e+05
zipcode_98040	4.768e+05	9587.698	49.728	0.000	4.58e+05	4.96e+05
zipcode_98045	1.137e+05	1.33e+04	8.540	0.000	8.76e+04	1.4e+05
zipcode_98052	1.792e+05	8167.063	21.943	0.000	1.63e+05	1.95e+05
zipcode_98053	1.427e+05	9359.617	15.245	0.000	1.24e+05	1.61e+05
zipcode_98056	5.288e+04	7364.329	7.181	0.000	3.84e+04	6.73e+04
zipcode_98059	6.255e+04	6844.106	9.139	0.000	4.91e+04	7.6e+04
zipcode_98065	8.623e+04	1.05e+04	8.233	0.000	6.57e+04	1.07e+05
zipcode_98070	2.873e+04	1.41e+04	2.030	0.042	992.851	5.65e+04
zipcode_98072	8.379e+04	1.12e+04	7.514	0.000	6.19e+04	1.06e+05
zipcode_98074	1.714e+05	8445.641	20.290	0.000	1.55e+05	1.88e+05
zipcode_98075	1.97e+05	8788.346	22.413	0.000	1.8e+05	2.14e+05
zipcode_98077	8.448e+04	1.19e+04	7.070	0.000	6.11e+04	1.08e+05
zipcode_98102	3.958e+05	1.5e+04	26.329	0.000	3.66e+05	4.25e+05
zipcode_98103	2.469e+05	9496.185	25.999	0.000	2.28e+05	2.66e+05
zipcode_98105	3.756e+05	1.14e+04	32.905	0.000	3.53e+05	3.98e+05
zipcode_98106	5.957e+04	9112.330	6.537	0.000	4.17e+04	7.74e+04
zipcode_98107	2.464e+05	1.18e+04	20.940	0.000	2.23e+05	2.69e+05
zipcode_98108	5.024e+04	1.14e+04	4.411	0.000	2.79e+04	7.26e+04
zipcode_98109	4.249e+05	1.53e+04	27.859	0.000	3.95e+05	4.55e+05
zipcode_98112	4.621e+05	1.08e+04	42.684	0.000	4.41e+05	4.83e+05
zipcode_98115	2.53e+05	9145.268	27.669	0.000	2.35e+05	2.71e+05
zipcode_98116	2.648e+05	9986.962	26.518	0.000	2.45e+05	2.84e+05
zipcode_98117	2.246e+05	1.01e+04	22.161	0.000	2.05e+05	2.45e+05
zipcode_98118	1.125e+05	7491.688	15.011	0.000	9.78e+04	1.27e+05
zipcode_98119	3.866e+05	1.25e+04	30.868	0.000	3.62e+05	4.11e+05
zipcode_98122	2.786e+05	9934.876	28.046	0.000	2.59e+05	2.98e+05
zipcode_98125	9.625e+04	1.02e+04	9.405	0.000	7.62e+04	1.16e+05
zipcode_98126	1.337e+05	9334.248	14.321	0.000	1.15e+05	1.52e+05
zipcode_98133	3.754e+04	1.07e+04	3.503	0.000	1.65e+04	5.86e+04
zipcode_98136	2.216e+05	1.04e+04	21.343	0.000	2.01e+05	2.42e+05

zipcode_98144	2.063e+05	9072.043	22.746	0.000	1.89e+05	2.24e+05
zipcode_98146	6.079e+04	9224.738	6.590	0.000	4.27e+04	7.89e+04
zipcode_98155	1.855e+04	1.08e+04	1.722	0.085	-2561.743	3.97e+04
zipcode_98166	6.438e+04	9497.920	6.778	0.000	4.58e+04	8.3e+04
zipcode_98177	1.311e+05	1.25e+04	10.483	0.000	1.07e+05	1.56e+05
zipcode_98199	3.34e+05	1.11e+04	30.129	0.000	3.12e+05	3.56e+05

Omnibus:	3462.831	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	17862.447
Skew:	0.958	**Prob(JB):**	0.00
Kurtosis:	7.828	**Cond. No.**	1.51e+08

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.51e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [219]:
```
check_for_assumptions(model.resid)
```



We can see that model didn't change much as a result of removing high p-values

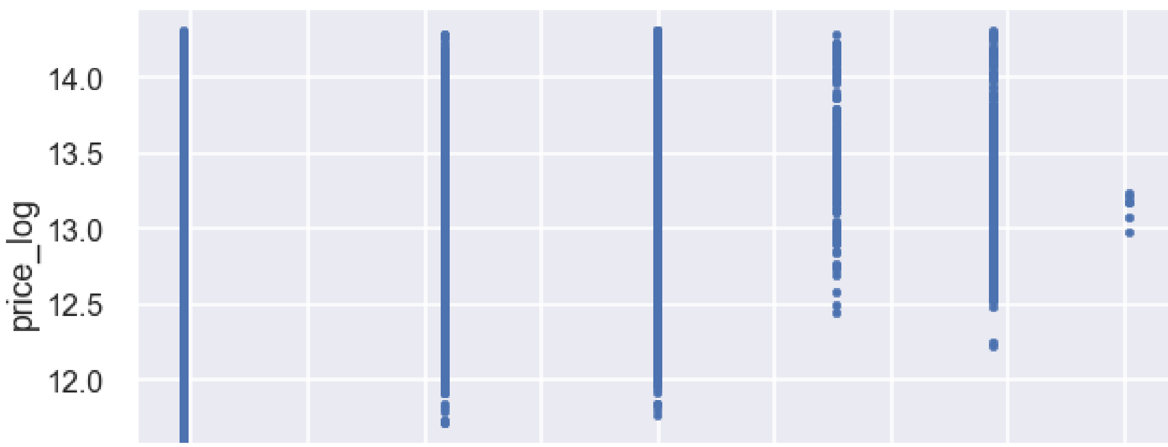
6.2.2 Going to log transform data to fit assumptions

In [65]:

```
# df_logged = pd.DataFrame([])

# for col in df_cleaned.drop(['zipcode', 'long', 'lat', 'yr_built'], axis=1).c
#     df_logged[col+'_log'] = np.log(df_cleaned[col]+1)

# for col in df_logged.columns:
#     df_logged.plot(kind='scatter', x=col, y= 'price_log', figsize=(10,5)  )
```



In [66]:

```
# df_logged.head()
```

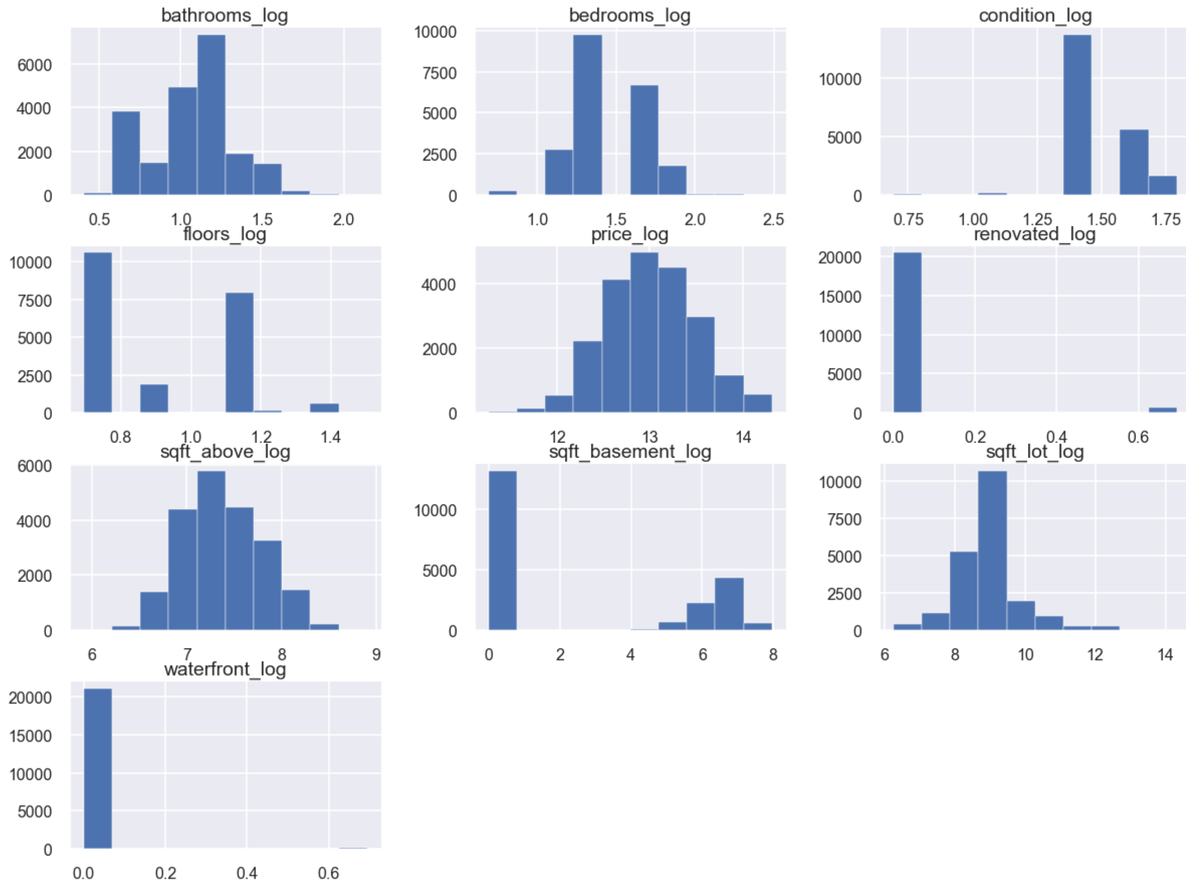
Out[66]:

	price_log	bedrooms_log	bathrooms_log	sqft_lot_log	floors_log	waterfront_log	condition_log	s
0	12.30999	1.38629	0.69315	8.63959	0.69315	0.00000	1.38629	
1	13.19562	1.38629	1.17865	8.88779	1.09861	0.00000	1.38629	
2	12.10072	1.09861	0.69315	9.21044	0.69315	0.00000	1.38629	
3	13.31133	1.60944	1.38629	8.51739	0.69315	0.00000	1.79176	
4	13.14217	1.38629	1.09861	8.99727	0.69315	0.00000	1.38629	

In [67]:
```python
# df_logged.hist(figsize=(20,15))
```

```
C:\Users\Joey\anaconda3\envs\learn-env\lib\site-packages\pandas\plotting\_matplot
lib\tools.py:307: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two min
or releases later. Use ax.get_subplotspec().rowspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
C:\Users\Joey\anaconda3\envs\learn-env\lib\site-packages\pandas\plotting\_matplot
lib\tools.py:307: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two min
or releases later. Use ax.get_subplotspec().colspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
C:\Users\Joey\anaconda3\envs\learn-env\lib\site-packages\pandas\plotting\_matplot
lib\tools.py:313: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two min
or releases later. Use ax.get_subplotspec().rowspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
C:\Users\Joey\anaconda3\envs\learn-env\lib\site-packages\pandas\plotting\_matplot
lib\tools.py:313: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two min
or releases later. Use ax.get_subplotspec().colspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
```

Out[67]:
```
array([[<AxesSubplot:title={'center':'bathrooms_log'}>,
        <AxesSubplot:title={'center':'bedrooms_log'}>,
        <AxesSubplot:title={'center':'condition_log'}>],
       [<AxesSubplot:title={'center':'floors_log'}>,
        <AxesSubplot:title={'center':'price_log'}>,
        <AxesSubplot:title={'center':'renovated_log'}>],
       [<AxesSubplot:title={'center':'sqft_above_log'}>,
        <AxesSubplot:title={'center':'sqft_basement_log'}>,
        <AxesSubplot:title={'center':'sqft_lot_log'}>],
       [<AxesSubplot:title={'center':'waterfront_log'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



In [74]:

```
# # Put dataset back together
# df_preprocessed = df_logged.copy()
# for non_logged in df_cleaned[['zipcode', 'long', 'lat', 'yr_built']].columns
#     df_preprocessed[non_logged] = df_cleaned[non_logged]
# df_preprocessed
```

Out[74]:

	price_log	bedrooms_log	bathrooms_log	sqft_lot_log	floors_log	waterfront_log	condition_log
0	12.30999	1.38629	0.69315	8.63959	0.69315	0.00000	1.3862
1	13.19562	1.38629	1.17865	8.88779	1.09861	0.00000	1.3862
2	12.10072	1.09861	0.69315	9.21044	0.69315	0.00000	1.3862
3	13.31133	1.60944	1.38629	8.51739	0.69315	0.00000	1.7917
4	13.14217	1.38629	1.09861	8.99727	0.69315	0.00000	1.3862
...	...	...	...	...	...	...	..
21592	12.79386	1.38629	1.25276	7.03174	1.38629	0.00000	1.3862
21593	12.89922	1.60944	1.25276	8.66802	1.09861	0.00000	1.3862
21594	12.90446	1.09861	0.55962	7.20860	1.09861	0.00000	1.3862
21595	12.89922	1.38629	1.25276	7.77863	1.09861	0.00000	1.3862
21596	12.69158	1.09861	0.55962	6.98193	1.09861	0.00000	1.3862

21190 rows × 14 columns

In [96]:

```
# Bring price column back to beginning of df
# price = df_preproccesed_ohe['price_log']
# df_preproccesed_ohe.drop(labels=['price_log'], axis=1, inplace=True)
# df_preproccesed_ohe.insert(loc=0, column='price_log', value=price)
# df_preproccesed_ohe.head()
```

```
C:\Users\Joey\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:410
2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.o
rg/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  errors=errors,
```

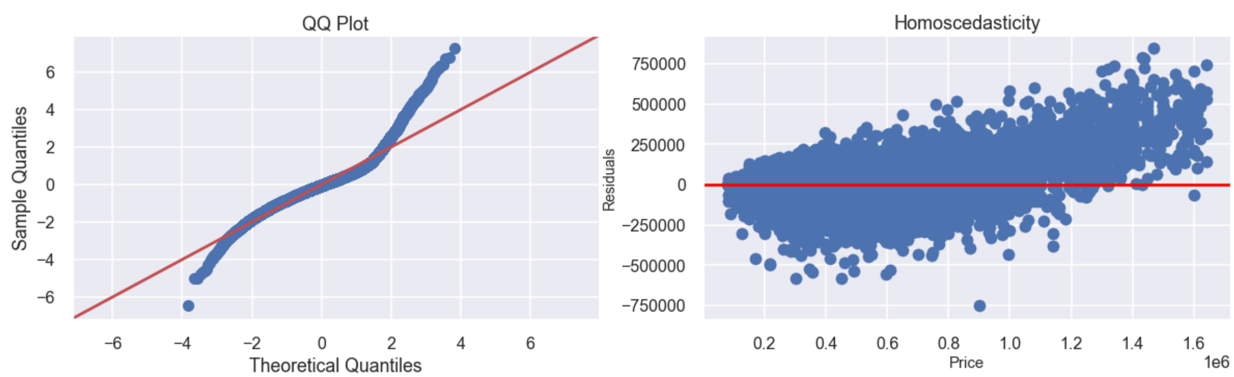
Out[96]:

	price_log	bedrooms_log	bathrooms_log	sqft_lot_log	floors_log	waterfront_log	condition_log	s(
0	12.30999	1.38629	0.69315	8.63959	0.69315	0.00000	1.38629	
1	13.19562	1.38629	1.17865	8.88779	1.09861	0.00000	1.38629	
2	12.10072	1.09861	0.69315	9.21044	0.69315	0.00000	1.38629	
3	13.31133	1.60944	1.38629	8.51739	0.69315	0.00000	1.79176	
4	13.14217	1.38629	1.09861	8.99727	0.69315	0.00000	1.38629	

6.2.3 Check assumption final time

In [221]:

```
check_for_assumptions(model.resid)
```



7 INTERPRET

7.0.1 Observations

- R2 is very high at .834 meaning over 80% of the data fit the regression model
- p-values are low enough to say that the predictors were statistically significant

In [225]:

```
# Train vs Test R^2
train_r2 = r2_score(train['price'], model.predict(train))
print(f'train r2 = {round(train_r2,3)}')

test_r2 = r2_score(test['price'], model.predict(test))
print(f'test r2 = {round(test_r2,3)}')
```

```
train r2 = 0.799
test r2 = 0.79
```

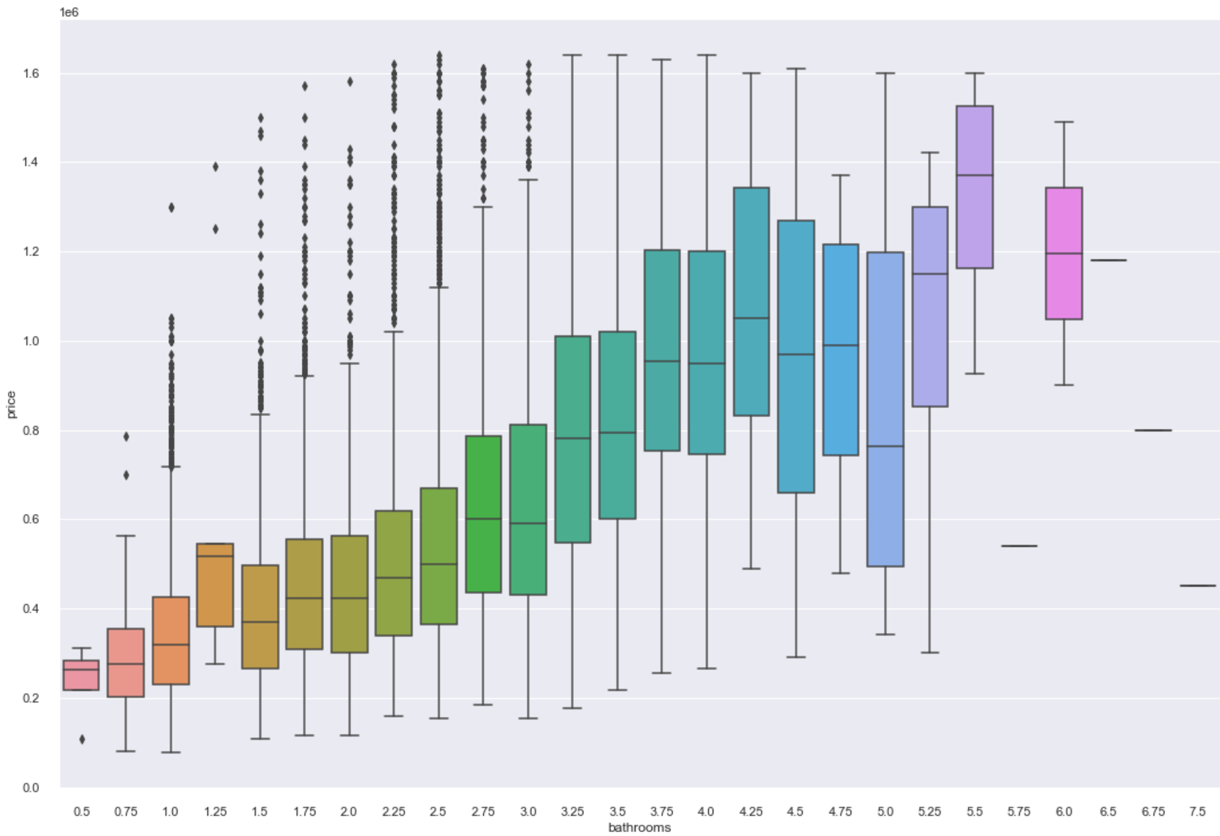
In [230]:

```
coeffs = model.params.sort_values(ascending=False)
no_zipcodes = [coef for coef in coeffs.index if 'zipcode' not in coef]
coeffs = coeffs[no_zipcodes]
frame = coeffs.to_frame('Coefficients')
styler = frame.style.background_gradient(cmap='Blues')
styler
```

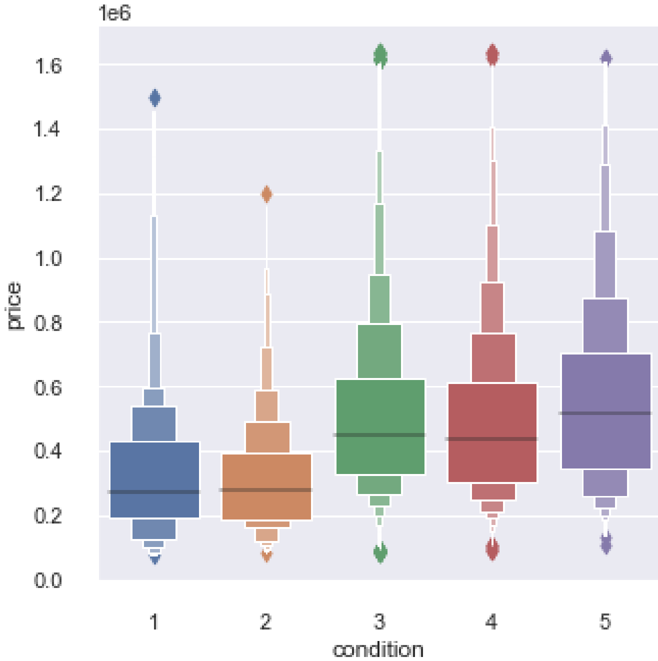
Out[230]:

	Coefficients
waterfront	429853
lat	275124
renovated	43070.7
condition	25200.1
bathrooms	24420.3
sqft_above	213.337
sqft_basement	133.447
sqft_lot	0.279454
yr_built	-121.975
bedrooms	-21381.7
floors	-25772.9
long	-107848
Intercept	-2.60941e+07

In [248]:
```
g = sns.catplot(data=df_preproccesed_ohe, x='bathrooms', y='price', kind='box'
g.fig.set_figwidth(18)
g.fig.set_figheight(12)
```



In [268]:
```
g = sns.catplot(data=df_preproccesed_ohe, x='condition', y='price', kind='boxe
```



In [282]:
```
plt.rcParams["axes.labelsize"] = 50
sns.scatterplot(data=df_preproccesed_ohe, x='sqft_above', y='price', s=100)
```

Out[282]: <AxesSubplot:xlabel='sqft_above', ylabel='price'>

8 CONCLUSIONS & RECOMMENDATIONS

- We have found that square footage is key in raising market selling price, therefore people should try to maximize the square footage of their home to increase their value
- We recommend that all of our customers increase the condition of their home. Each point increase in condition increases the value of the home on average by $25,200
- Putting a good number of bathrooms is proven to be a good way of increasing home value