KingCountySales

August 23, 2022

0.1 King County House Regression - Project#2

- Student name: ***Aysu Erdemir***
- Student pace: ***Flex***
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- Instructor name: ***Claude Fried***

0.2 Overview

- This project analyzes house sale data from King County WA to provide insights and recommendations about the kind of houses "We Buy Ugly Houses" should invest on for their business.

0.3 Business Problem

- We Buy Ugly Houses is a real estate investor (House Flipper) thay operates in King County WA. They purchase properties with the intention of remodeling to add value, then resell those properties for a profit.

- They want to know what type of houses to invest on for higher profit.

0.4 Data

King County House Sales dataset from Kaggle which contains house sale prices for King County sold between May 2014 and May 2015.

The variables/features included in the dataset are:

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
- `view` - Quality of view from house
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
  - See the King County Assessor Website for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.

  - See the King County Assessor Website for further explanation of each building grade code
- sqft_above - Square footage of house apart from basement
- sqft_basement - Square footage of the basement
- yr_built - Year when house was built
- yr_renovated - Year when house was renovated
- zipcode - ZIP Code used by the United States Postal Service
- 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

0.5 Methods

1. Clean the dataset.
2. Conduct feature engineering to come up with meaningful variables to be used in linear regression.
3. Build a series of linear regression models to come up with the best model to describe the relationship between the independent variables and the target/dependent variable (house price).
4. Check the linear regression assumptions to make sure normality, homoscadecity are not violated and multicollinearity does not present.
5. Draw conclusions and make suggestions about the kind of houses to invest on.

[1]:
```
# Import standard packages

import numpy as np
import pandas as pd
import statsmodels.api as sm
import scipy.stats as stats
from statsmodels.formula.api import ols
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
df = pd.read_csv("./data/kc_house_data.csv")
df.head()
```

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

   sqft_lot  floors waterfront  view  …          grade sqft_above  \
```

```
0      5650     1.0         NaN  NONE  …       7 Average       1180
1      7242     2.0          NO  NONE  …       7 Average       2170
2     10000     1.0          NO  NONE  …  6 Low Average         770
3      5000     1.0          NO  NONE  …       7 Average       1050
4      8080     1.0          NO  NONE  …          8 Good       1680

   sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
0            0.0     1955           0.0    98178  47.5112 -122.257
1          400.0     1951        1991.0    98125  47.7210 -122.319
2            0.0     1933           NaN    98028  47.7379 -122.233
3          910.0     1965           0.0    98136  47.5208 -122.393
4            0.0     1987           0.0    98074  47.6168 -122.045

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

[5 rows x 21 columns]
```

[3]:
```
df.shape
```

[3]:
```
(21597, 21)
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  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  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
```

```
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

[5]:
```python
df.isna().sum()
```

[5]:
```
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
```

- There are null values for `waterfront`, `view` and `yr_renovated`.

[6]:
```python
df.duplicated().sum()
```

[6]:
```
0
```

[7]:
```python
df[df.duplicated('id')]
```

[7]:
```
             id        date      price  bedrooms  bathrooms  sqft_living  \
94   6021501535  12/23/2014   700000.0         3       1.50         1580
314  4139480200   12/9/2014  1400000.0         4       3.25         4290
325  7520000520   3/11/2015   240500.0         2       1.00         1240
346  3969300030  12/29/2014   239900.0         4       1.00         1000
```

```
372    2231500030   3/24/2015   530000.0          4       2.25          2180
…           …           …          …          …          …        …
20165  7853400250   2/19/2015   645000.0          4       3.50          2910
20597  2724049222   12/1/2014   220000.0          2       2.50          1000
20654  8564860270   3/30/2015   502000.0          4       2.50          2680
20764  6300000226    5/4/2015   380000.0          4       1.00          1200
21565  7853420110    5/4/2015   625000.0          3       3.00          2780

       sqft_lot  floors waterfront  view  …          grade sqft_above  \
94         5000     1.0         NO  NONE  …         8 Good       1290
314       12103     1.0         NO  GOOD  …    11 Excellent      2690
325       12092     1.0         NO  NONE  …  6 Low Average        960
346        7134     1.0         NO  NONE  …  6 Low Average       1000
372       10754     1.0         NO  NONE  …      7 Average       1100
…           …       …          …    …   …             …          …
20165      5260     2.0         NO  NONE  …       9 Better       2910
20597      1092     2.0         NO  NONE  …      7 Average        990
20654      5539     2.0        NaN  NONE  …         8 Good       2680
20764      2171     1.5         NO  NONE  …      7 Average       1200
21565      6000     2.0         NO  NONE  …       9 Better       2780

       sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
94             290.0     1939           0.0    98117  47.6870 -122.386
314           1600.0     1997           0.0    98006  47.5503 -122.102
325            280.0     1922        1984.0    98146  47.4957 -122.352
346              0.0     1943           NaN    98178  47.4897 -122.240
372           1080.0     1954           0.0    98133  47.7711 -122.341
…                …        …            …        …        …       …
20165            0.0     2012           0.0    98065  47.5168 -121.883
20597           10.0     2004           0.0    98118  47.5419 -122.271
20654            0.0     2013           0.0    98045  47.4759 -121.734
20764            0.0     1933           0.0    98133  47.7076 -122.342
21565            0.0     2013           NaN    98065  47.5184 -121.886

       sqft_living15  sqft_lot15
94              1570        4500
314             3860       11244
325             1820        7460
346             1020        7138
372             1810        6929
…                …          …
20165           2910        5260
20597           1330        1466
20654           2680        5992
20764           1130        1598
21565           2850        6000
```

```
[177 rows x 21 columns]
```

[8]:
```
df[df['id'] == 6021501535]
```

[8]:
```
            id        date     price  bedrooms  bathrooms  sqft_living  \
93  6021501535   7/25/2014  430000.0         3        1.5         1580
94  6021501535  12/23/2014  700000.0         3        1.5         1580

    sqft_lot  floors waterfront  view  …   grade sqft_above  sqft_basement  \
93      5000     1.0         NO  NONE  …  8 Good       1290          290.0
94      5000     1.0         NO  NONE  …  8 Good       1290          290.0

   yr_built  yr_renovated  zipcode     lat     long  sqft_living15  sqft_lot15
93     1939           0.0    98117  47.687 -122.386           1570        4500
94     1939           0.0    98117  47.687 -122.386           1570        4500

[2 rows x 21 columns]
```

- The same house was probably sold multiple times in the same year.
- Let's take only the most recent sell for those 177 duplicated house IDs.

0.6 DATA CLEANING:

Drop Duplicates:

[9]:
```
df = df.drop_duplicates(subset ='id', keep = 'last').reset_index(drop=True)
df[df['id'] == 6021501535]
```

[9]:
```
            id        date     price  bedrooms  bathrooms  sqft_living  \
93  6021501535  12/23/2014  700000.0         3        1.5         1580

    sqft_lot  floors waterfront  view  …   grade sqft_above  sqft_basement  \
93      5000     1.0         NO  NONE  …  8 Good       1290          290.0

   yr_built  yr_renovated  zipcode     lat     long  sqft_living15  sqft_lot15
93     1939           0.0    98117  47.687 -122.386           1570        4500

[1 rows x 21 columns]
```

[10]:
```
df.shape
```

[10]:
```
(21420, 21)
```

Handling NaN values:

[11]:
```
nulls = ['waterfront', 'view', 'yr_renovated']
print(*(f"{item}: {df[item].isnull().sum()}" for item in nulls), sep='\n' )
```

```
waterfront: 2353
view: 63
yr_renovated: 3813
```

[12]:
```
df.waterfront.value_counts()
```

[12]:
```
NO     18921
YES      146
Name: waterfront, dtype: int64
```

[13]:
```
df.view.value_counts()
```

[13]:
```
NONE         19253
AVERAGE        956
GOOD           505
FAIR           329
EXCELLENT      314
Name: view, dtype: int64
```

[14]:
```
df.yr_renovated.value_counts()
```

[14]:
```
0.0       16867
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          …
1934.0        1
1971.0        1
1954.0        1
1950.0        1
1944.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

[15]:
```
df.waterfront.isna().sum()/len(df)
```

[15]:
```
0.10985060690943044
```

- 11% of `waterfront` is NaN.
- Let's convert that to 0, because if a house had waterfront, it would likely be known and marked as YES.

[16]:
```
df.view.isna().sum()/len(df.view)
```

[16]:
```
0.0029411764705882353
```

- .003 % of `view` is NaN.
- Let's convert that to NONE, because if a house had view, it would likely be known.

[17]:
```python
# We would expect houses with NaN on view also to be NaN or NO on waterfront,␣
↪let's double check that:

len(df[((df["waterfront"] == 'NO') | (df["waterfront"].isnull())) &
       (df["view"].isnull())])
# 62 out of 63 fits the criteria
```

[17]: 62

[18]:
```python
# Let's replace null with NONE
df['view'] = df['view'].fillna('NONE')
```

[19]:
```python
# We would expect houses with NaN on waterview also to be NONE on view, let's␣
↪double check that:
len(df[ (df["view"] == 'NONE')  & (df["waterfront"].isnull())])
# Majority of the data (2093/2353) fits the criteria.
```

[19]: 2093

[20]:
```python
# Let's replace null with NO
df['waterfront'] = df['waterfront'].fillna('NO')
```

[21]:
```python
df['yr_renovated'].describe()
# Minimum is 0 most likely meaning that house has not been renovated.
# We will replace all NaNs with 0 to mean the same thing.
```

[21]:
```
count    17607.000000
mean        83.890101
std        400.534473
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max       2015.000000
Name: yr_renovated, dtype: float64
```

[22]:
```python
df['yr_renovated'] = df['yr_renovated'].fillna(0)
```

[23]:
```python
df.isnull().sum()
```

[23]:
```
id                 0
date               0
price              0
bedrooms           0
bathrooms          0
sqft_living        0
sqft_lot           0
```

```
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

Fixing variable types:

[24]:
```
df_fixed = df.copy()
```

[25]:
```
df_fixed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21420 entries, 0 to 21419
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  object
 2   price          21420 non-null  float64
 3   bedrooms       21420 non-null  int64
 4   bathrooms      21420 non-null  float64
 5   sqft_living    21420 non-null  int64
 6   sqft_lot       21420 non-null  int64
 7   floors         21420 non-null  float64
 8   waterfront     21420 non-null  object
 9   view           21420 non-null  object
 10  condition      21420 non-null  object
 11  grade          21420 non-null  object
 12  sqft_above     21420 non-null  int64
 13  sqft_basement  21420 non-null  object
 14  yr_built       21420 non-null  int64
 15  yr_renovated   21420 non-null  float64
 16  zipcode        21420 non-null  int64
 17  lat            21420 non-null  float64
 18  long           21420 non-null  float64
 19  sqft_living15  21420 non-null  int64
 20  sqft_lot15     21420 non-null  int64
```

```
dtypes: float64(6), int64(9), object(6)
memory usage: 3.4+ MB
```

[26]:
```python
df_fixed.columns.to_series().groupby(df_fixed.dtypes).groups
# object: ['date', 'waterfront', 'view', 'condition', 'grade', 'sqft_basement']}
```

[26]:
```
{int64: ['id', 'bedrooms', 'sqft_living', 'sqft_lot', 'sqft_above', 'yr_built',
'zipcode', 'sqft_living15', 'sqft_lot15'], float64: ['price', 'bathrooms',
'floors', 'yr_renovated', 'lat', 'long'], object: ['date', 'waterfront', 'view',
'condition', 'grade', 'sqft_basement']}
```

These variables were coded as **string** and they need to be fixed (converted to **numerical**) for linear regression: - object: `date`, `waterfront`, `view`, `condition`, `grade`, `sqft_basement`

[27]:
```python
df_fixed.waterfront.value_counts()
```

[27]:
```
NO     21274
YES      146
Name: waterfront, dtype: int64
```

[28]:
```python
dic = {"NO":0, "YES":1}
df_fixed.replace({"waterfront": dic}, inplace=True)
df_fixed["waterfront"].value_counts()
```

[28]:
```
0    21274
1      146
Name: waterfront, dtype: int64
```

[29]:
```python
df_fixed["waterfront"].dtype
```

[29]:
```
dtype('int64')
```

[30]:
```python
df_fixed['view'].value_counts()
```

[30]:
```
NONE         19316
AVERAGE        956
GOOD           505
FAIR           329
EXCELLENT      314
Name: view, dtype: int64
```

[31]:
```python
dic = {"NONE":1, "FAIR":2 ,"AVERAGE":3 ,"GOOD":4 ,"EXCELLENT":5}
df_fixed.replace({"view": dic}, inplace=True)
df_fixed["view"].value_counts()
```

[31]:
```
1    19316
3      956
4      505
```

```
2      329
5      314
Name: view, dtype: int64
```

[32]:
```
df['condition'].value_counts()
```

[32]:
```
Average      13900
Good          5643
Very Good     1687
Fair           162
Poor            28
Name: condition, dtype: int64
```

[33]:
```
dic = {"Poor":1, "Fair":2 ,"Average":3 ,"Good":4 ,"Very Good":5}
df_fixed.replace({"condition": dic}, inplace=True)
df_fixed["condition"].value_counts()
```

[33]:
```
3    13900
4     5643
5     1687
2      162
1       28
Name: condition, dtype: int64
```

[34]:
```
df_fixed['grade'].value_counts()
```

[34]:
```
7 Average        8889
8 Good           6041
9 Better         2606
6 Low Average    1995
10 Very Good     1130
11 Excellent      396
5 Fair            234
12 Luxury          88
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

[35]:
```
dic = {"3 Poor":3, "4 Low":4, "5 Fair":5, "6 Low Average":6, "7 Average":7, "8␣
↪Good":8, \
       "9 Better":9, "10 Very Good":10, "11 Excellent":11, "12 Luxury":12,  "13␣
↪Mansion":13}
df_fixed.replace({"grade": dic}, inplace=True)
df_fixed["grade"].value_counts()
```

[35]:
```
7     8889
8     6041
9     2606
6     1995
10    1130
11     396
5      234
12      88
4       27
13      13
3        1
Name: grade, dtype: int64
```

[36]:
```
df_fixed['sqft_basement'].unique()
```

[36]:
```
array(['0.0', '400.0', '910.0', '1530.0', '?', '730.0', '1700.0', '300.0',
       '970.0', '760.0', '720.0', '700.0', '820.0', '780.0', '790.0',
       '330.0', '1620.0', '360.0', '588.0', '1510.0', '410.0', '990.0',
       '600.0', '560.0', '550.0', '1000.0', '1600.0', '500.0', '1040.0',
       '880.0', '1010.0', '240.0', '265.0', '290.0', '800.0', '540.0',
       '710.0', '840.0', '380.0', '770.0', '480.0', '570.0', '1490.0',
       '620.0', '1250.0', '1270.0', '120.0', '650.0', '180.0', '1130.0',
       '450.0', '1640.0', '1460.0', '1020.0', '1030.0', '750.0', '640.0',
       '1070.0', '490.0', '1310.0', '630.0', '2000.0', '390.0', '430.0',
       '850.0', '210.0', '1430.0', '1950.0', '440.0', '220.0', '1160.0',
       '860.0', '580.0', '2060.0', '1820.0', '1180.0', '200.0', '1150.0',
       '1200.0', '680.0', '530.0', '1450.0', '1170.0', '1080.0', '960.0',
       '280.0', '870.0', '1100.0', '460.0', '1400.0', '660.0', '1220.0',
       '900.0', '420.0', '1580.0', '1380.0', '475.0', '690.0', '270.0',
       '350.0', '935.0', '1370.0', '980.0', '1470.0', '160.0', '950.0',
       '50.0', '740.0', '1780.0', '1900.0', '340.0', '470.0', '370.0',
       '140.0', '1760.0', '130.0', '520.0', '890.0', '1110.0', '150.0',
       '1720.0', '810.0', '190.0', '1290.0', '670.0', '1800.0', '1120.0',
       '1810.0', '60.0', '1050.0', '940.0', '310.0', '930.0', '1390.0',
       '610.0', '1830.0', '1300.0', '510.0', '1330.0', '1590.0', '920.0',
       '1320.0', '1420.0', '1240.0', '1960.0', '1560.0', '2020.0',
       '1190.0', '2110.0', '1280.0', '250.0', '2390.0', '1230.0', '170.0',
       '830.0', '1260.0', '1410.0', '1340.0', '590.0', '1500.0', '1140.0',
       '260.0', '100.0', '320.0', '1480.0', '1060.0', '1284.0', '1670.0',
       '1350.0', '2570.0', '1090.0', '110.0', '2500.0', '90.0', '1940.0',
       '1550.0', '2350.0', '2490.0', '1481.0', '1360.0', '1135.0',
       '1520.0', '1850.0', '1660.0', '2130.0', '2600.0', '1690.0',
       '243.0', '1210.0', '1024.0', '1798.0', '1610.0', '1440.0',
       '1570.0', '1650.0', '704.0', '1910.0', '1630.0', '2360.0',
       '1852.0', '2090.0', '2400.0', '1790.0', '2150.0', '230.0', '70.0',
       '1680.0', '2100.0', '3000.0', '1870.0', '1710.0', '2030.0',
       '875.0', '1540.0', '2850.0', '2170.0', '506.0', '906.0', '145.0',
```

```
       '2040.0', '784.0', '1750.0', '374.0', '518.0', '2720.0', '2730.0',
       '1840.0', '3480.0', '2160.0', '1920.0', '2330.0', '1860.0',
       '2050.0', '4820.0', '1913.0', '80.0', '2010.0', '3260.0', '2200.0',
       '415.0', '1730.0', '652.0', '2196.0', '1930.0', '515.0', '40.0',
       '2080.0', '2580.0', '1548.0', '1740.0', '235.0', '861.0', '1890.0',
       '2220.0', '792.0', '2070.0', '4130.0', '2250.0', '2240.0',
       '1990.0', '768.0', '2550.0', '435.0', '1008.0', '2300.0', '2610.0',
       '666.0', '3500.0', '172.0', '1816.0', '2190.0', '1245.0', '1525.0',
       '1880.0', '862.0', '946.0', '1281.0', '414.0', '2180.0', '276.0',
       '1248.0', '602.0', '516.0', '176.0', '225.0', '1275.0', '266.0',
       '283.0', '65.0', '2310.0', '10.0', '1770.0', '2120.0', '295.0',
       '207.0', '915.0', '556.0', '417.0', '143.0', '508.0', '2810.0',
       '20.0', '274.0', '248.0'], dtype=object)
```

[37]:
```
# Replace ? with 0 and then convert to numerical data
df_fixed['sqft_basement'].replace('?', '0.0', inplace = True)
```

[38]:
```
df_fixed['sqft_basement'] = pd.to_numeric(df_fixed['sqft_basement'])
df_fixed['sqft_basement'].dtype
```

[38]:
```
dtype('float64')
```

[39]:
```
df_fixed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21420 entries, 0 to 21419
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  object
 2   price          21420 non-null  float64
 3   bedrooms       21420 non-null  int64
 4   bathrooms      21420 non-null  float64
 5   sqft_living    21420 non-null  int64
 6   sqft_lot       21420 non-null  int64
 7   floors         21420 non-null  float64
 8   waterfront     21420 non-null  int64
 9   view           21420 non-null  int64
 10  condition      21420 non-null  int64
 11  grade          21420 non-null  int64
 12  sqft_above     21420 non-null  int64
 13  sqft_basement  21420 non-null  float64
 14  yr_built       21420 non-null  int64
 15  yr_renovated   21420 non-null  float64
 16  zipcode        21420 non-null  int64
 17  lat            21420 non-null  float64
```

```
 18  long           21420 non-null  float64
 19  sqft_living15  21420 non-null  int64
 20  sqft_lot15     21420 non-null  int64
dtypes: float64(7), int64(13), object(1)
memory usage: 3.4+ MB
```

- We are **not** changing `date` datatype because we will derive another variable from it, and then we will drop it.

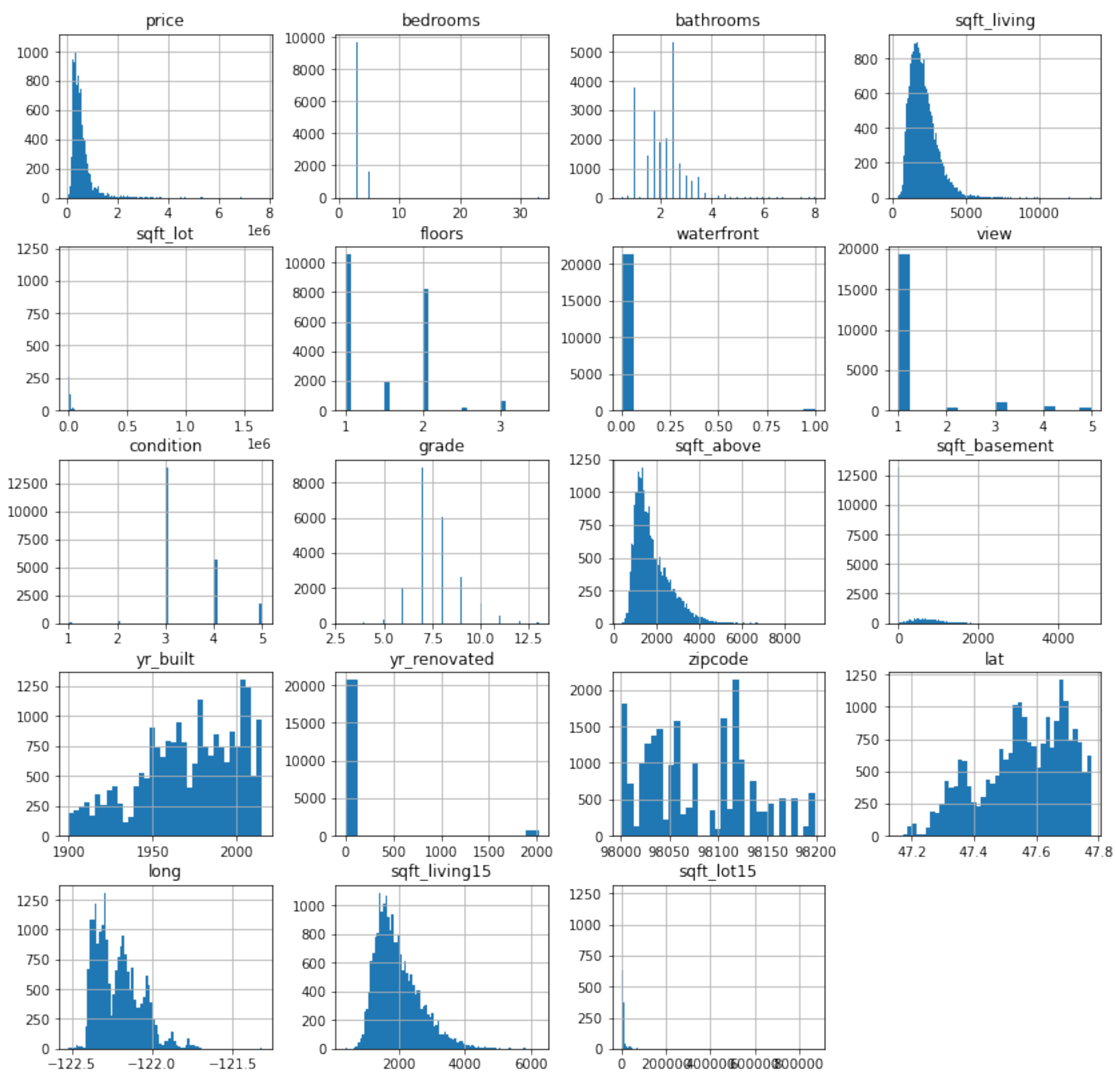
0.7 Feature Engineering:

[40]:
```
df_new = df_fixed.copy()
```

- Drop `id` column since it has no meaning

[41]:
```
df_new.drop(columns=['id'], inplace = True, axis=1)
```

[42]:
```
df_new.hist(bins='auto', edgecolor='none', figsize=(14,14));
```

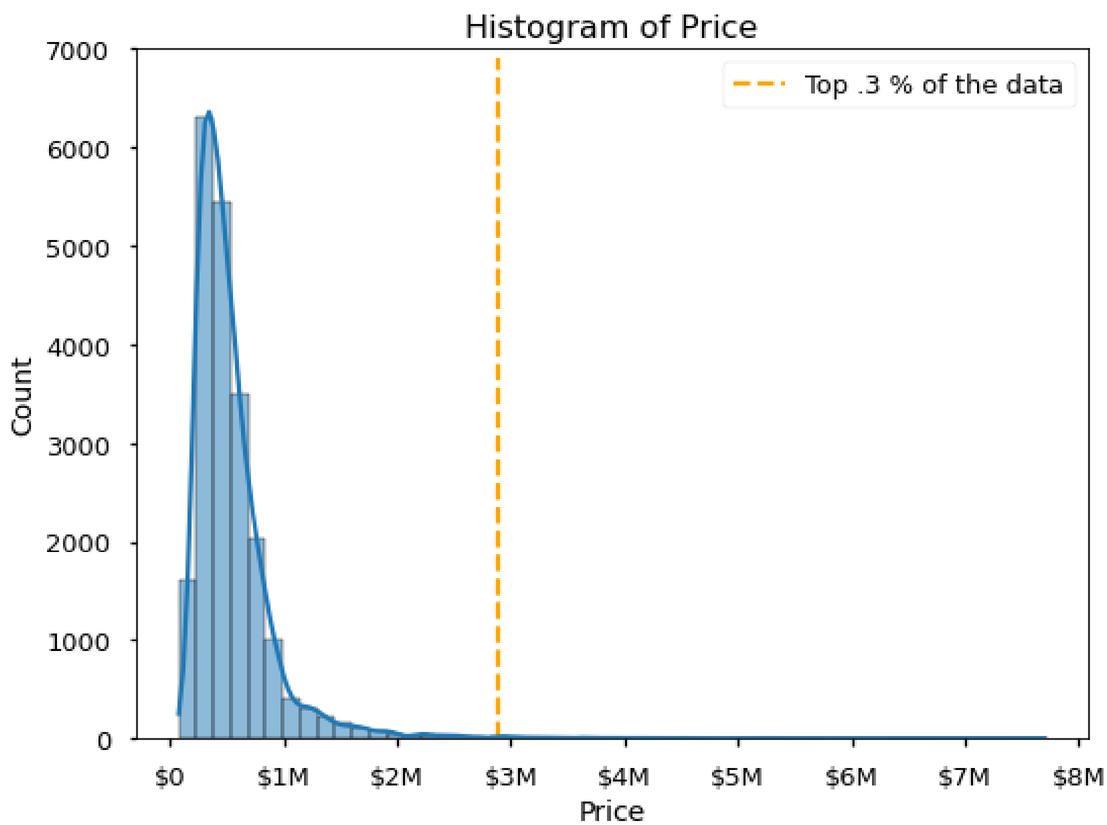


The target / dependent variable:

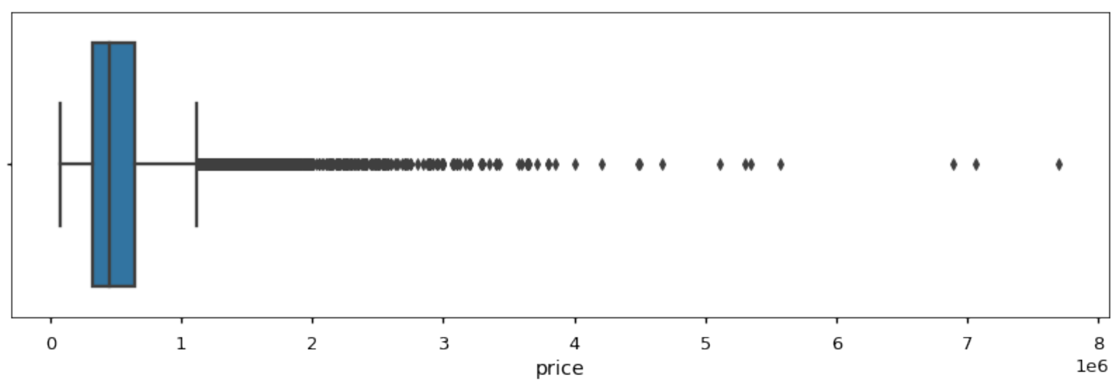
- The sale prices have a negative skew, meaning the majority of the data is in the lower values, and there are fewer very high values.
- We might benefit from (log) transforming this variable.

[43]:
```
# Code copied from: https://stackoverflow.com/questions/61330427/
↪set-y-axis-in-millions and modified a bit.
# Use the function below to get rid of 1e8s etc on graphs and to format numbers␣
↪in thousands, millions, etc in visualizations..:

from matplotlib.ticker import FuncFormatter

def human_format(num, pos):
    magnitude = 0
    while abs(num) >= 1000:
        magnitude += 1
        num /= 1000.0
    return '$%.0f%s' % (num, ['', 'K', 'M', 'B', 'T', 'P'][magnitude])

formatter = FuncFormatter(human_format)
```

[44]:
```
with plt.style.context('seaborn-talk'):
    fig, ax  = plt.subplots(figsize=(8, 6))

    sns.histplot(x = df_new['price'], bins=50, ax=ax, kde =True)
    ax.xaxis.set_major_formatter(formatter)
    plt.ylim(0, 7000)
    ax.set_title('Histogram of Price', fontsize=16)
    ax.set_xlabel("Price", fontsize=14)
    ax.set_ylabel("Count", fontsize=14)
    ax.vlines(df['price'].quantile(0.997), 0, 6900, color= 'orange',␣
↪linestyle='--', label = "Top .3 % of the data")
    ax.legend(loc = 'upper right')
    fig.tight_layout();

    fig.savefig('./images/Histogram_DependentMeasure.png', dpi=300)
```



[45]:
```
with plt.style.context('seaborn-talk'):
    fig, ax  = plt.subplots(figsize=(14, 4))
    sns.boxplot(x = df_new['price'], ax=ax);
```



Remove the extreme outliers from the data:

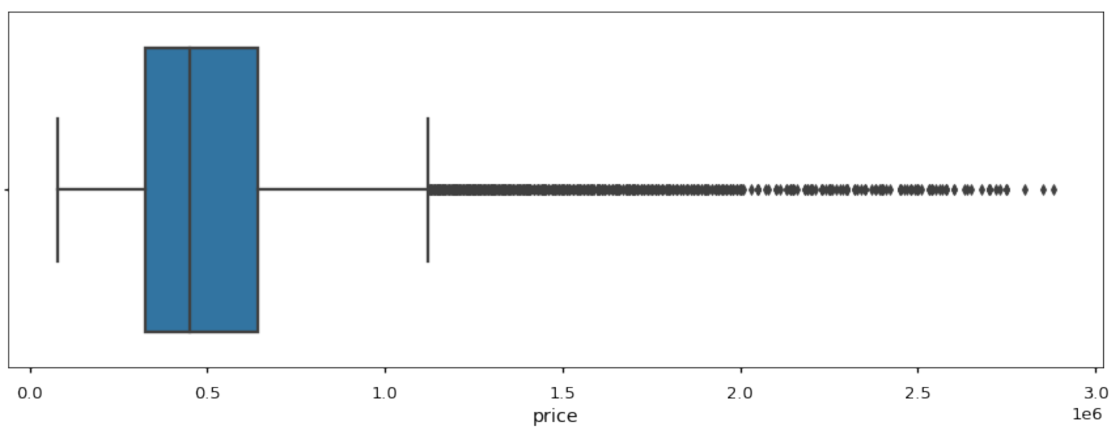
- Since the distribution is highly skewed I will remove the top .3% of the data.

- We will only be dealing with houses up to ~3M in price.

[46]:
```
oldshape = df_new.shape
print(f"oldshape: {oldshape}")

df_new = df_new[(df_new['price'] < df_new['price'].quantile(.997))]
print(f"newshape: {df_new.shape}")
print(oldshape[0] - df_new.shape[0])
print(((oldshape[0] - df_new.shape[0]) *100) /df_new.shape[0])

# we removed only 65 data points and .3 % of data.
```

```
oldshape: (21420, 20)
newshape: (21355, 20)
65
0.30437836572231325
```

[47]:
```
with plt.style.context('seaborn-talk'):
    fig, ax  = plt.subplots(figsize=(15, 5))
    sns.boxplot(x = df_new['price'], ax=ax)
```



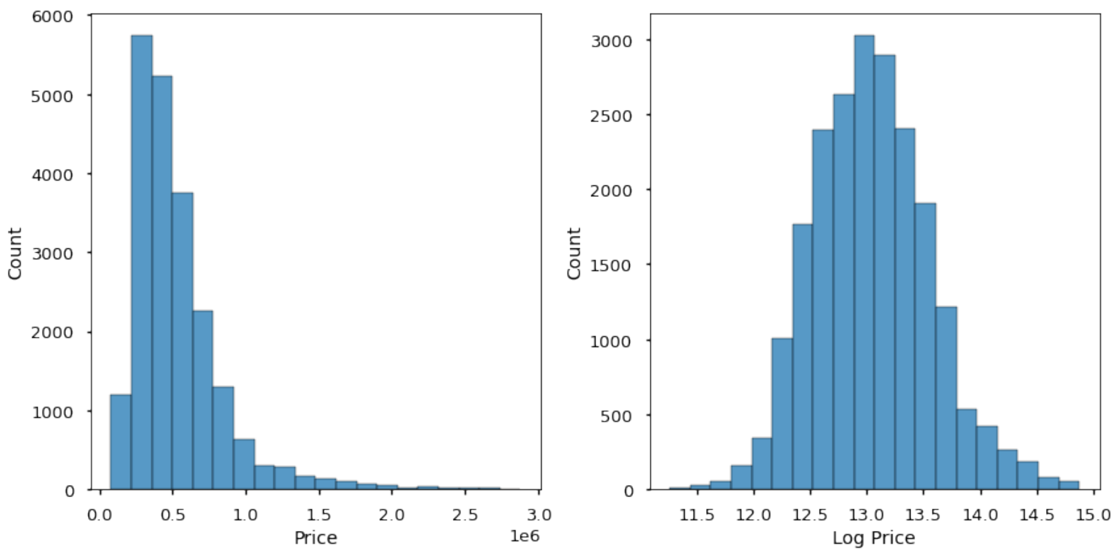
Log Transform the target variable:

- Price distribution is still highly skewed so let's log transform the variable as well.

[48]:
```
df_new['log_price'] = np.log(df_new['price'])
```

[49]:
```
with plt.style.context('seaborn-talk'):

    fig, (ax1, ax2) = plt.subplots(ncols=2,  figsize=(12, 6))
    fig.set_tight_layout(True)

    sns.histplot(x = df_new['price'], ax= ax1, bins=20);
```

```
sns.histplot(x = df_new['log_price'], ax= ax2, bins=20);

ax1.set_xlabel("Price", fontsize=14)
ax2.set_xlabel("Log Price", fontsize=14)
ax1.set_ylabel("Count", fontsize=14)
ax2.set_ylabel("Count", fontsize=14)

fig.savefig('./images/price_before_after_log.png', dpi=300);
```



- The price distribution looks NORMAL after log transformation.

Creating a Binary View variable:

- The majority of the houses don't have a view and very few have ratings of 2-5.
- So let's impute a new variable to indicate whether or not a house has a view.

[50]:
```
df_new['view'].value_counts()
```

[50]:
```
1    19297
3      950
4      499
2      325
5      284
Name: view, dtype: int64
```

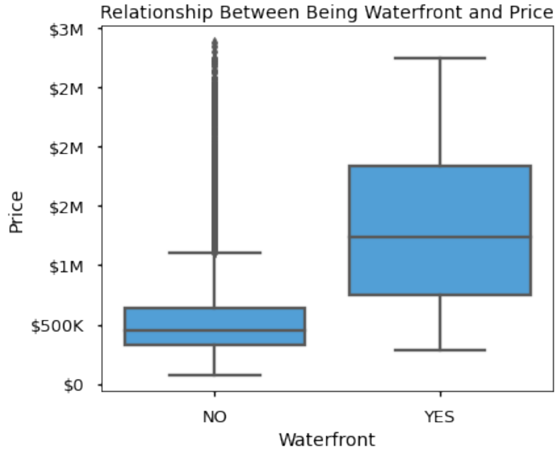
[51]:
```
dic = {1:0, 2:1 ,3:1 ,4:1 ,5:1}
df_new['has_view'] = df_new['view'].map(dic)
df_new['has_view'].value_counts()
```

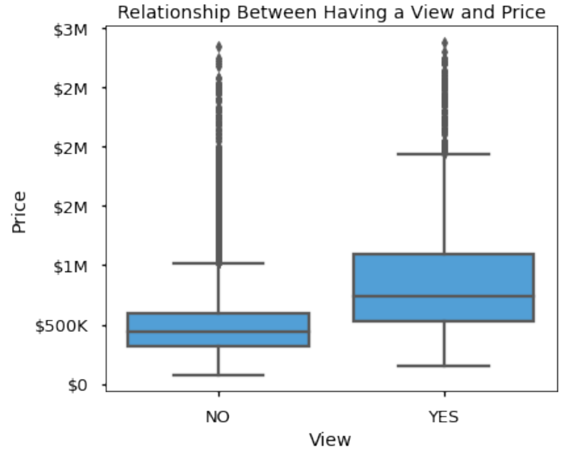
[51]:
```
0    19297
1     2058
Name: has_view, dtype: int64
```

[52]:
```
print(df_new.corr()['price']['view'])
print(df_new.corr()['price']['has_view'])

# Let's use `has_view` instead of `view`
```

```
0.37483613089845086
0.3500682990327732
```

[55]:
```
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, (ax1, ax2) = plt.subplots(ncols = 2, nrows=1, figsize=(12, 5))
    fig.set_tight_layout(True)

    sns.boxplot(x="waterfront", y="price", ax=ax1, data=df_new, color =␣
↪base_color)
    ax1.yaxis.set_major_formatter(formatter)
    ax1.set_xticklabels(labels=['NO', 'YES'])
    ax1.set_title('Relationship Between Being Waterfront and Price',␣
↪fontsize=14)
    ax1.set_xlabel("Waterfront",fontsize=14)
    ax1.set_ylabel("Price",fontsize=14)

    sns.boxplot(x="has_view", y="price", ax=ax2, data=df_new, color =␣
↪base_color)
    ax2.yaxis.set_major_formatter(formatter)
    ax2.set_xticklabels(labels=['NO', 'YES'])
    ax2.set_title('Relationship Between Having a View and Price', fontsize=14)
    ax2.set_xlabel("View",fontsize=14)
    ax2.set_ylabel("Price",fontsize=14)

    fig.savefig('./images/view_waterfront _to_Price.png', dpi=300);
```





Creating a Month variable:

- Date a house is sold cannot be significant in predicting house price so I will add a `month` column to indicate which month of the year the house was sold and drop the date.

[56]:
```
df_new['month'] = pd.to_datetime(df_new['date']).dt.month
df_new.drop(columns=['date'], inplace = True, axis=1)
```

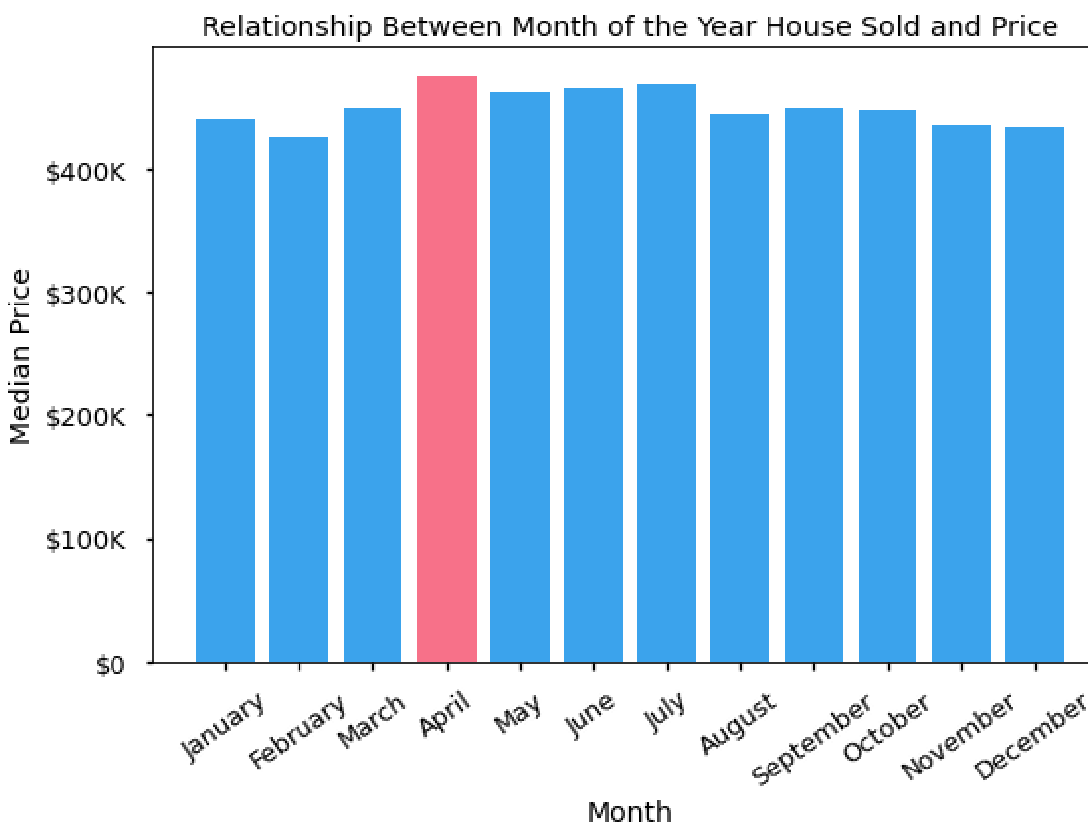
[57]:
```
mean_month = pd.DataFrame(df_new.groupby('month')['price'].median())  # median␣
 ↪because price is skewed
mean_month.head()
```

[57]:

month	price
1	440000.0
2	426045.0
3	450000.0
4	475000.0
5	462000.0

[58]:
```
mean_month = pd.DataFrame(df_new.groupby('month')['price'].median())  # median␣
 ↪because price is skewed

with plt.style.context('seaborn-talk'):
    base_color = [sns.color_palette("husl", 9)[0] if month == 4 else sns.
 ↪color_palette("husl", 9)[6] for month in mean_month.index]
    fig, ax  = plt.subplots(figsize=(8, 6))
    #sns.barplot(x = mean_month.index, y= mean_month['price'], ax=ax, color =␣
 ↪base_color)
    bars = plt.bar(x=mean_month.index, height=mean_month['price'], color =␣
 ↪base_color)
```

```
    plt.xticks(np.arange(1, 13, 1))
    ax.set_xticklabels(labels=['January', 'February', 'March', 'April',
                               'May', 'June', 'July', 'August',
                              'September', 'October', 'November', 'December'],␣
↪rotation = 35)
    ax.yaxis.set_major_formatter(formatter)
    ax.set_title('Relationship Between Month of the Year House Sold and␣
↪Price',fontsize=14)
    ax.set_xlabel("Month",fontsize=14)
    ax.set_ylabel("Median Price",fontsize=14)
    fig.tight_layout();

    fig.savefig('./images/month_price-relationship.png', dpi=300);
```



[59]:
```
dic = {1: 'january', 2:'february',3:'march',4:'april',5:'may',
       6:'june',7:'july',8:'august',9:'september',
       10:'october',11:'november',12:'december'}

df_new.replace({"month": dic}, inplace=True)
```

Dummy coding `month` variable:

- Months appear as distinct categories with no meaningful numerical relationship to one another.

[60]:
```
month_dummies = pd.get_dummies(df_new['month']).drop(['january'], axis=1)
df_new = pd.concat([df_new, month_dummies], axis=1)
df_new = df_new.drop(['month'], axis=1)
df_new.head()
```

[60]:
```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
0  221900.0         3       1.00         1180      5650     1.0           0
1  538000.0         3       2.25         2570      7242     2.0           0
2  180000.0         2       1.00          770     10000     1.0           0
3  604000.0         4       3.00         1960      5000     1.0           0
4  510000.0         3       2.00         1680      8080     1.0           0

   view  condition  grade  …  august  december  february  july  june  march  \
0     1          3      7  …       0         0         0     0     0      0
1     1          3      7  …       0         1         0     0     0      0
2     1          3      6  …       0         0         1     0     0      0
3     1          5      7  …       0         1         0     0     0      0
4     1          3      8  …       0         0         1     0     0      0

   may  november  october  september
0    0         0        1          0
1    0         0        0          0
2    0         0        0          0
3    0         0        0          0
4    0         0        0          0

[5 rows x 32 columns]
```

Creating an age related variable:

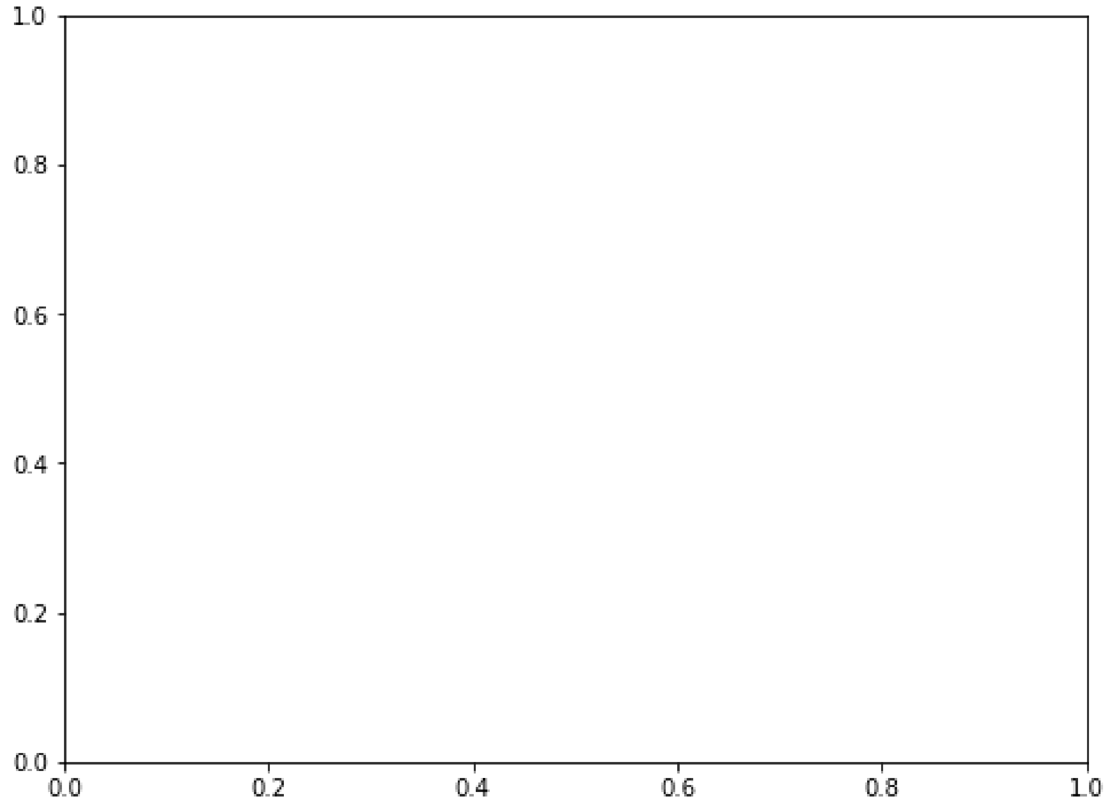
- Let's create a new variable called `age` to represent the age of an house from the time it was built or renovated using `yr_built` and `yr_renovated`.

[61]:
```
# Because all houses were sold in 2014 and 2015 we will take 2015 as the current year.

df_new['age'] = 2015 - df_new['yr_built'] # Set all age based on yr_built initially.
mask = df_new['yr_renovated'] != 0 # create a mask for those rows with a value in yr_renovated.
df_new.loc[mask, "age"] = (2015 - df_new['yr_renovated']) # Set age based on yr_renovation where the mask condition is true
```

[62]:
```python
fig, ax = plt.subplots(figsize=(8, 6))
sns.regplot(x="age", y="price", ax=ax, data=df_new, color = base_color,␣
 ↪line_kws={"color": "orange"})
print(df_new.corr()['price']['age'])

# not much of a correlation but let's still keep this variable.
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-62-cb84da805dc2> in <module>
      1 fig, ax = plt.subplots(figsize=(8, 6))
----> 2 sns.regplot(x="age", y="price", ax=ax, data=df_new, color = base_color,␣
 ↪line_kws={"color": "orange"})
      3 print(df_new.corr()['price']['age'])
      4 
      5 # not much of a correlation but let's still keep this variable.

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/_decorators.py␣
 ↪in inner_f(*args, **kwargs)
     44             )
     45         kwargs.update({k: arg for k, arg in zip(sig.parameters, args)})
---> 46         return f(**kwargs)
     47     return inner_f
     48 

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/regression.py␣
 ↪in regplot(x, y, data, x_estimator, x_bins, x_ci, scatter, fit_reg, ci,␣
 ↪n_boot, units, seed, order, logistic, lowess, robust, logx, x_partial,␣
 ↪y_partial, truncate, dropna, x_jitter, y_jitter, label, color, marker,␣
 ↪scatter_kws, line_kws, ax)
    833     scatter_kws["marker"] = marker
    834     line_kws = {} if line_kws is None else copy.copy(line_kws)
--> 835     plotter.plot(ax, scatter_kws, line_kws)
    836     return ax
    837 

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/regression.py␣
 ↪in plot(self, ax, scatter_kws, line_kws)
    357 
    358         # Ensure that color is hex to avoid matplotlib weirdness
--> 359         color = mpl.colors.rgb2hex(mpl.colors.colorConverter.
 ↪to_rgb(color))
    360 
    361         # Let color in keyword arguments override overall plot color

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/matplotlib/colors.py␣
 ↪in to_rgb(c)
    344 def to_rgb(c):
```

```
    345     """Convert *c* to an RGB color, silently dropping the alpha channel
 ↪"""
--> 346     return to_rgba(c)[:3]
    347
    348

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/matplotlib/colors.py␣
 ↪in to_rgba(c, alpha)
    187         rgba = None
    188     if rgba is None:  # Suppress exception chaining of cache lookup␣
 ↪failure.
--> 189         rgba = _to_rgba_no_colorcycle(c, alpha)
    190         try:
    191             _colors_full_map.cache[c, alpha] = rgba

/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/matplotlib/colors.py␣
 ↪in _to_rgba_no_colorcycle(c, alpha)
    263         raise ValueError(f"Invalid RGBA argument: {orig_c!r}")
    264     if len(c) not in [3, 4]:
--> 265         raise ValueError("RGBA sequence should have length 3 or 4")
    266     if not all(isinstance(x, Number) for x in c):
    267         # Checks that don't work: `map(float, ...)`, `np.array(..., float)`␣
 ↪and

ValueError: RGBA sequence should have length 3 or 4
```



- Let's create a new binary variable `age<30` where we group older versus younger houses.
- We pick age 30 as the criterion for a house that most likely needs repair.

[63]:
```
df_new['age<30'] = df_new['age'] < 30
df_new['age<30'].value_counts()
```

[63]:
```
False    12809
True      8546
Name: age<30, dtype: int64
```

[64]:
```
dic = {False:"0", True:"1"}
df_new.replace({"age<30": dic}, inplace=True)
df_new["age<30"] = df_new["age<30"].astype(int)
df_new["age<30"].value_counts()
```

[64]:
```
0    12809
1     8546
Name: age<30, dtype: int64
```

[65]:
```
print(df_new.corr()['price']['age'])
print(df_new.corr()['price']['age<30'])
```

```
-0.09219731443044772
0.16020160020637306
```

- Improvement in correlation with price. Let's pick `age<30` over `age`.

[66]:
```
df_new = df_new.drop(['yr_built', 'yr_renovated', 'age', 'view'], axis=1)
```

Creating a location based variable:

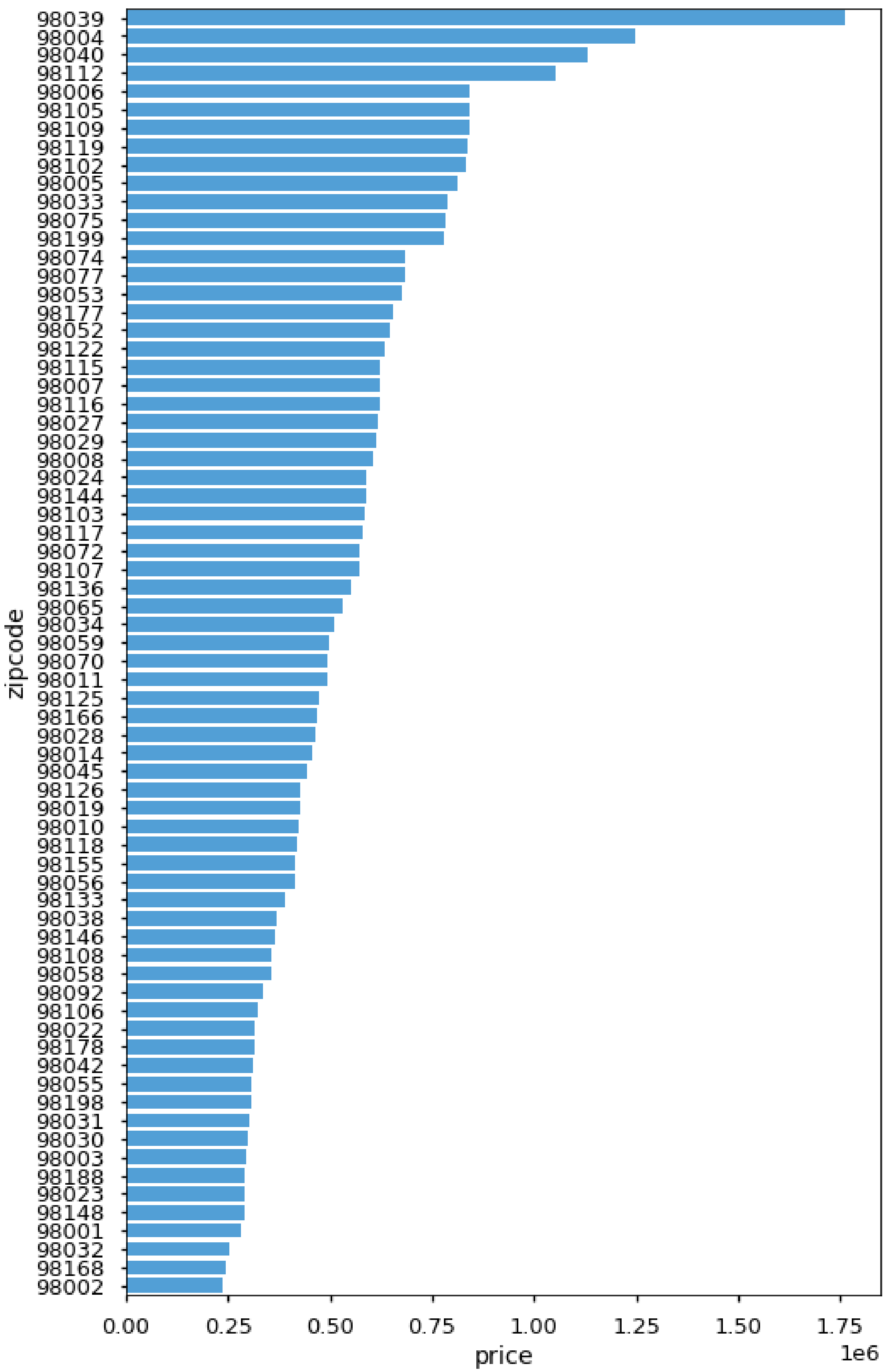
- There are 70 Zipcodes! Too many levels if we go for One Hot Encoding.
- We cannot leave it as label encoded either, zip numbers do not have a meaninful numerical relationship to one another.
- I will engineer a new "location" variable with more meaningful categorical distinctions using Longitude-Latitude - I will then dummy code this variable.

[67]:
```
zipmeans = df_new.groupby('zipcode')['price'].mean().
↪sort_values(ascending=False)
zipmeans = pd.DataFrame(zipmeans).reset_index()
zipmeans.head()
```

[67]:

	zipcode	price
0	98039	1.761750e+06
1	98004	1.245386e+06
2	98040	1.129398e+06
3	98112	1.051826e+06
4	98006	8.418961e+05

[68]:
```
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ax  = plt.subplots(figsize=(8, 14))
    sns.barplot(x = zipmeans['price'], y= zipmeans['zipcode'],
                order = zipmeans.sort_values('price',ascending = False).
↪zipcode, ax=ax, color = base_color, orient = "h")
```


98039
98004
98040
98112
98006
98105
98109
98119
98102
98005
98033
98075
98199
98074
98077
98053
98177
98052
98122
98115
98007
98116
98027
98029
98008
98024
98144
98103
98117
98072
98107
98136
98065
98034
98059
98070
98011
98125
98166
98028
98014
98045
98126
98019
98010
98118
98155
98056
98133
98038
98146
98108
98058
98092
98106
98022
98178
98042
98055
98198
98031
98030
98003
98188
98023
98148
98001
98032
98168
98002
zipcode
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
price

The most expensive 4 zipcodes: - Medina, Bellevue, Mercer Island and Seattle

Upload city data to use on the map:

- Upload US Zip Codes Database here which contains `city` info in relation to `zipcodes`:

[69]:
```
dfzip = pd.read_csv("./data/uszips.csv")
dfzip.head()
```

[69]:
```
   zip       lat       lng        city state_id   state_name  zcta  \
0  601  18.18027 -66.75266    Adjuntas       PR  Puerto Rico  True
1  602  18.36075 -67.17541      Aguada       PR  Puerto Rico  True
2  603  18.45744 -67.12225   Aguadilla       PR  Puerto Rico  True
3  606  18.16585 -66.93716     Maricao       PR  Puerto Rico  True
4  610  18.29110 -67.12243      Anasco       PR  Puerto Rico  True

   parent_zcta  population  density  county_fips county_name  \
0          NaN     16773.0    100.5        72001    Adjuntas
1          NaN     37083.0    472.1        72003      Aguada
2          NaN     45652.0    513.2        72005   Aguadilla
3          NaN      6231.0     54.3        72093     Maricao
4          NaN     26502.0    275.7        72011      Añasco

                                    county_weights  \
0                   {"72001": 98.76, "72141": 1.24}
1                                   {"72003": 100}
2                   {"72005": 99.76, "72099": 0.24}
3   {"72093": 82.28, "72153": 11.67, "72121": 6.05}
4  {"72011": 96.71, "72099": 2.81, "72083": 0.37,…

                county_names_all          county_fips_all  imprecise  \
0                Adjuntas|Utuado              72001|72141      False
1                         Aguada                    72003      False
2                 Aguadilla|Moca              72005|72099      False
3   Maricao|Yauco|Sabana Grande        72093|72153|72121      False
4  Añasco|Moca|Las Marías|Aguada  72011|72099|72083|72003      False

   military             timezone
0     False  America/Puerto_Rico
1     False  America/Puerto_Rico
2     False  America/Puerto_Rico
3     False  America/Puerto_Rico
4     False  America/Puerto_Rico
```

[70]:
```
# subsetting the dataset to include those cities in KingCounty only:

dfzip = dfzip[(dfzip['county_names_all'].str.contains('King')) &
 ↪(dfzip['state_id'] == 'WA') ]
print(dfzip.zip.nunique())
dfzip
```

```
89
```

[70]:
```
         zip       lat        lng         city state_id  state_name  zcta  \
32938  98001  47.30919 -122.26426       Auburn       WA  Washington  True
32939  98002  47.30820 -122.21567       Auburn       WA  Washington  True
32940  98003  47.30596 -122.31465  Federal Way       WA  Washington  True
32941  98004  47.61865 -122.20548     Bellevue       WA  Washington  True
32942  98005  47.61494 -122.16814     Bellevue       WA  Washington  True
…        …        …          …          …        …           …   …
33031  98199  47.65139 -122.40223      Seattle       WA  Washington  True
33041  98224  47.73570 -121.56859       Baring       WA  Washington  True
33092  98288  47.65204 -121.35740    Skykomish       WA  Washington  True
33132  98354  47.25113 -122.31557       Milton       WA  Washington  True
33178  98422  47.28907 -122.39123       Tacoma       WA  Washington  True

       parent_zcta  population  density  county_fips county_name  \
32938          NaN     34455.0    713.9        53033        King
32939          NaN     33947.0   1829.6        53033        King
32940          NaN     49445.0   1659.9        53033        King
32941          NaN     37265.0   1979.1        53033        King
32942          NaN     21414.0   1126.7        53033        King
…             …          …       …          …           …
33031          NaN     23444.0   2137.3        53033        King
33041          NaN       243.0      1.5        53033        King
33092          NaN       225.0      0.3        53033        King
33132          NaN      7551.0   1029.0        53053      Pierce
33178          NaN     21732.0   1197.8        53053      Pierce

                          county_weights county_names_all county_fips_all  \
32938                     {"53033": 100}             King           53033
32939                     {"53033": 100}             King           53033
32940                     {"53033": 100}             King           53033
32941                     {"53033": 100}             King           53033
32942                     {"53033": 100}             King           53033
…                                     …                …               …
33031                     {"53033": 100}             King           53033
33041                     {"53033": 100}             King           53033
33092                     {"53033": 100}             King           53033
33132  {"53053": 80.02, "53033": 19.98}      Pierce|King     53053|53033
33178   {"53053": 97.78, "53033": 2.22}      Pierce|King     53053|53033
```

```
      imprecise  military             timezone
32938     False     False  America/Los_Angeles
32939     False     False  America/Los_Angeles
32940     False     False  America/Los_Angeles
32941     False     False  America/Los_Angeles
32942     False     False  America/Los_Angeles
…           …       …                    …
33031     False     False  America/Los_Angeles
33041     False     False  America/Los_Angeles
33092     False     False  America/Los_Angeles
33132     False     False  America/Los_Angeles
33178     False     False  America/Los_Angeles

[89 rows x 18 columns]
```

[71]:

```python
# For cities with multiple zipcodes find an average location latitude and␣
↪longitude
dfzip_table = dfzip.groupby('city')[['lat', 'lng']].mean()
dfzip_table = dfzip_table.reset_index()
dfzip_table
```

[71]:

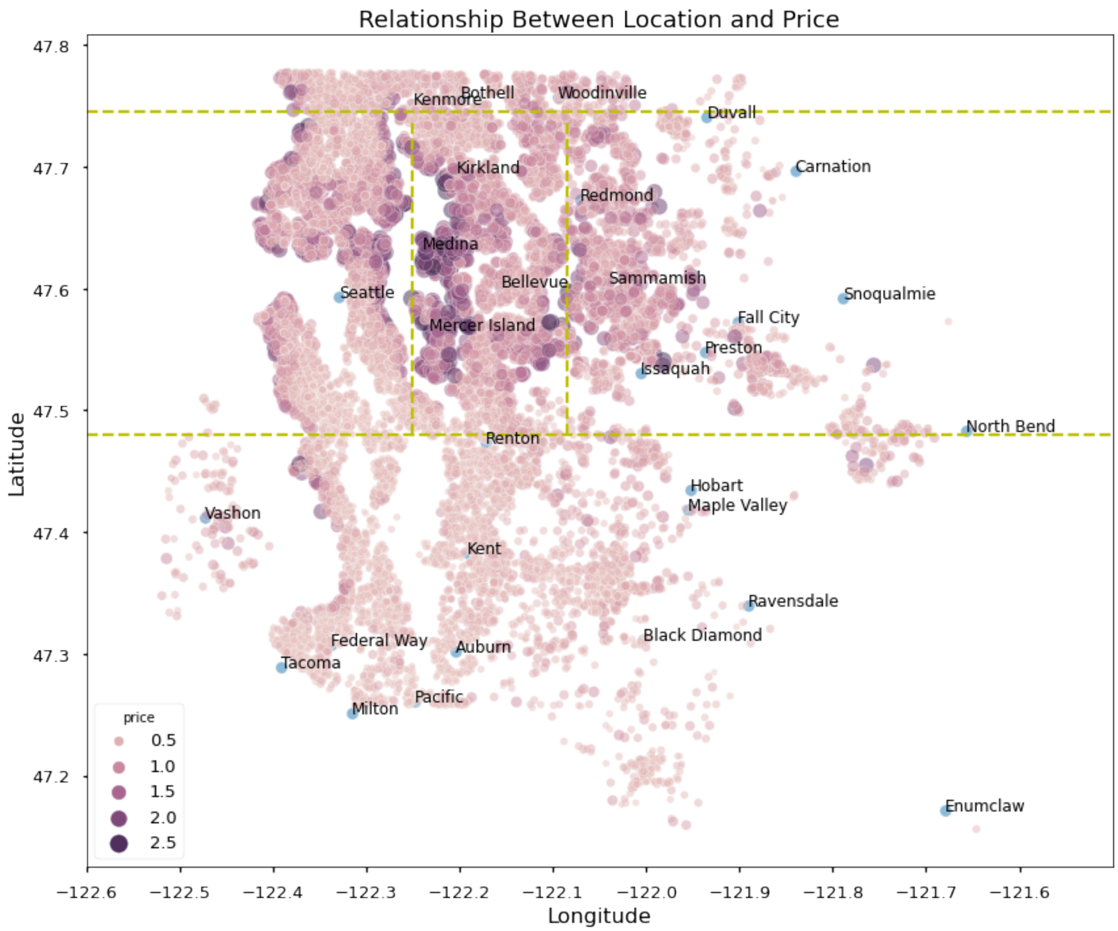
```
             city        lat         lng
0          Auburn  47.301967 -122.203720
1          Baring  47.735700 -121.568590
2        Bellevue  47.602148 -122.155832
3   Black Diamond  47.311730 -122.003260
4         Bothell  47.757360 -122.198710
5       Carnation  47.696640 -121.840240
6          Duvall  47.740830 -121.934940
7        Enumclaw  47.171400 -121.679580
8       Fall City  47.573010 -121.902190
9     Federal Way  47.307385 -122.338315
10         Hobart  47.434410 -121.952400
11       Issaquah  47.530735 -122.005430
12        Kenmore  47.751620 -122.248920
13           Kent  47.382738 -122.191553
14       Kirkland  47.696140 -122.202995
15   Maple Valley  47.418610 -121.955890
16         Medina  47.633080 -122.239630
17  Mercer Island  47.566110 -122.232000
18         Milton  47.251130 -122.315570
19     North Bend  47.482760 -121.656780
20        Pacific  47.260790 -122.248220
21        Preston  47.547640 -121.936630
22     Ravensdale  47.339600 -121.890490
23        Redmond  47.673195 -122.070505
```

```
24            Renton  47.473778 -122.172132
25         Sammamish  47.604445 -122.041165
26           Seattle  47.593588 -122.329591
27         Skykomish  47.652040 -121.357400
28        Snoqualmie  47.592340 -121.789310
29   Snoqualmie Pass  47.451540 -121.357950
30            Tacoma  47.289070 -122.391230
31            Vashon  47.412190 -122.472600
32       Woodinville  47.757070 -122.094535
```

- We have a total of 32 cities in KingCounty WA which we can superimpose on the map below:

[72]:
```
# For the purpose of graphing removing far east cities of Baring, Skykomish,␣
↪Snoqualmie Pass:
dfzip_table.drop(index=[1,27,29], axis=0, inplace=True)
```

[73]:
```
# Scatterplot of longitude and latitude with a hue of price, city names are␣
↪superimposed to the map:
# Superimposed data is from: https://www.communitiescount.org/
↪king-county-geographies
# The shape is the shape of King County, WA

with plt.style.context('seaborn-talk'):

    fig, ax = plt.subplots(figsize=(12, 10))
    sns.scatterplot(data=dfzip_table, x='lng', y='lat',  alpha = .5, ax=ax)
    [plt.text(x=row['lng'], y=row['lat'], s=row['city'], size='large',␣
↪color='black') for k,row in dfzip_table.iterrows()]

    sns.scatterplot(data=df_new, x='long', y='lat', hue='price',␣
↪size="price",sizes=(20, 200),  alpha = .5, ax=ax)
    ax.axhline(y= 47.48, xmin=0, xmax=1, color='y', linestyle='--')
    ax.axvline(x= -122.25, ymin=0.52, ymax=0.9, color='y', linestyle='--')
    ax.axvline(x= -122.085, ymin=0.52, ymax=0.9, color='y', linestyle='--')
    ax.axhline(y= 47.745, xmin=0, xmax=1, color='y', linestyle='--')
    plt.xticks(np.arange(-122.6, -121.5, 0.1))

    plt.xlim(-122.6, -121.5)
    ax.set_title('Relationship Between Location and Price',fontsize=18)
    ax.set_xlabel("Longitude",fontsize=16)
    ax.set_ylabel("Latitude",fontsize=16)
    fig.tight_layout();

    fig.savefig('./images/LocationMap.png', dpi=300);
```



Extract 5 regions based on coordinates:

- North - Kenmore, Bothell, Woodinville
- East - Medina, Bellevue, Mercer Island and Kirkland
- Far East - Redmond, Sammamish etc.
- West - Seattle.
- South - Tacoma, Renton, Kent etc.

[74]:
```
df_new['coordinates'] = list(zip(df_new.lat, df_new.long))

def region(coordinate):
    if (coordinate[0] > 47.745):
        return 'north'
    elif (coordinate[0] > 47.48) and (coordinate[0] < 47.745) and␣
 ↪(coordinate[1] < -122.25):
        return 'west'
    elif (coordinate[0] > 47.48) and (coordinate[0] < 47.745) and␣
 ↪(coordinate[1] > -122.25) and  (coordinate[1] < -122.085):
```

```
        return 'east'
    elif (coordinate[0] > 47.48) and (coordinate[0] < 47.745) and␣
 ↪(coordinate[1] > -122.085):
        return 'fareast'
    else:
        return 'south'

region([47.5112, -122.257])
```

[74]: 'west'

[75]:
```
df_new['region'] = df_new['coordinates'].apply(region)
df_new['region'].head()
```

[75]:
```
0        west
1        west
2        east
3        west
4     fareast
Name: region, dtype: object
```

[76]:
```
df_new.groupby('region')['price'].median()
```

[76]:
```
region
east       582250.0
fareast    585000.0
north      437000.0
south      299900.0
west       490000.0
Name: price, dtype: float64
```

[77]:
```
df_new['region'].value_counts()
```

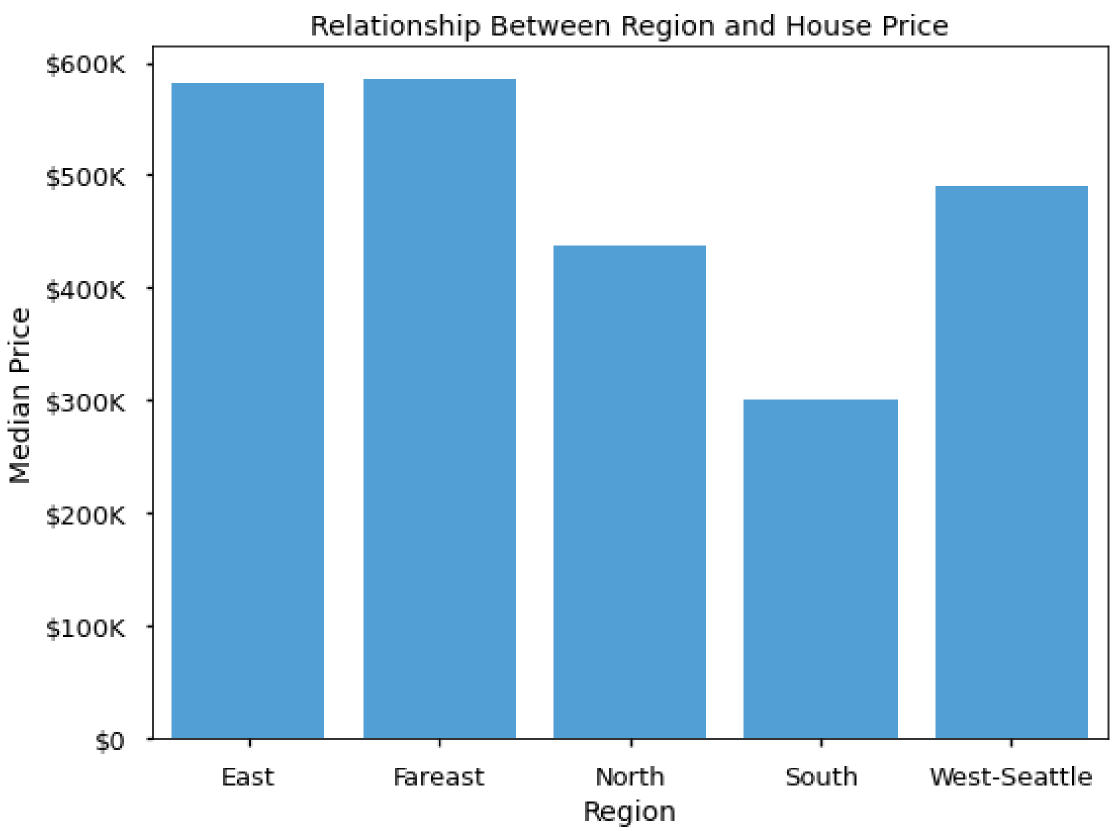
[77]:
```
west       7344
south      5661
east       4448
fareast    2665
north      1237
Name: region, dtype: int64
```

[78]:
```
mean_region = pd.DataFrame(df_new.groupby('region')['price'].median())
mean_region['price']
```

[78]:
```
region
east       582250.0
fareast    585000.0
north      437000.0
```

```
south      299900.0
west       490000.0
Name: price, dtype: float64
```

[79]:
```
mean_region = pd.DataFrame(df_new.groupby('region')['price'].median())   #␣
↪median because price is skewed

with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ax  = plt.subplots(figsize=(8, 6))
    sns.barplot(x = mean_region.index, y= mean_region['price'], ax=ax, color =␣
↪base_color)
    ax.set_xticklabels(labels=['East', 'Fareast', 'North', 'South',␣
↪'West-Seattle'])
    ax.yaxis.set_major_formatter(formatter)
    ax.set_title('Relationship Between Region and House Price',fontsize=14)
    ax.set_xlabel("Region",fontsize=14)
    ax.set_ylabel("Median Price",fontsize=14)
    fig.tight_layout();

    fig.savefig('./images/region_price-relationship.png', dpi=300);
```



- East regions appear as the most expensive area, followed by Seattle and then north. South is the cheapest.

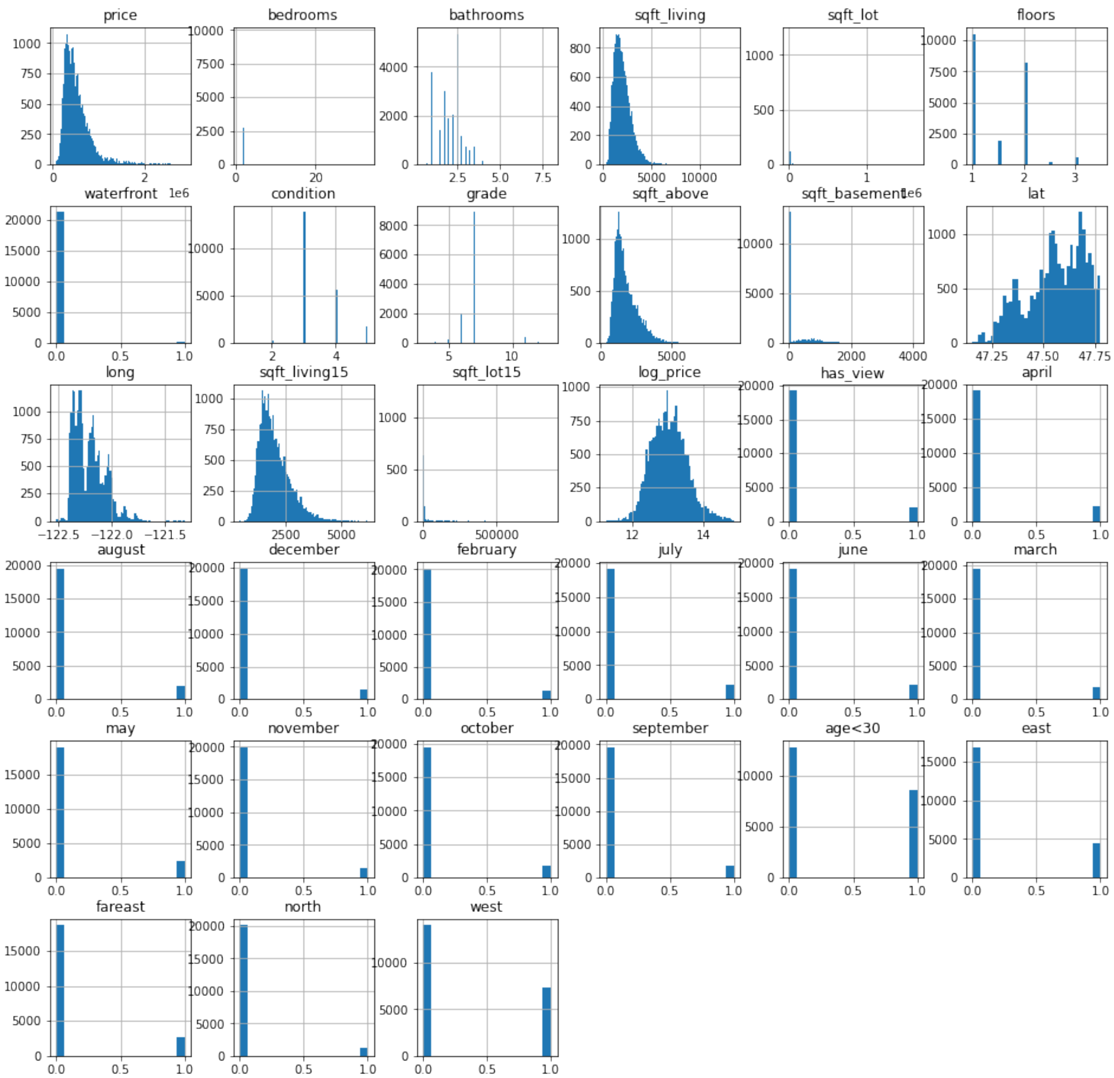
[80]:
```
# South region is the reference point
region_dummies = pd.get_dummies(df_new['region']).drop(['south'],axis=1)
df_new = pd.concat([df_new, region_dummies], axis=1)
df_new.head()
```

[80]:
```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
0  221900.0         3       1.00         1180      5650     1.0           0
1  538000.0         3       2.25         2570      7242     2.0           0
2  180000.0         2       1.00          770     10000     1.0           0
3  604000.0         4       3.00         1960      5000     1.0           0
4  510000.0         3       2.00         1680      8080     1.0           0

   condition  grade  sqft_above  …  november  october  september  age<30  \
0          3      7        1180  …         0        1          0       0
1          3      7        2170  …         0        0          0       1
2          3      6         770  …         0        0          0       0
3          5      7        1050  …         0        0          0       0
4          3      8        1680  …         0        0          0       1

          coordinates   region  east  fareast  north  west
0  (47.5112, -122.257)     west     0        0      0     1
1   (47.721, -122.319)     west     0        0      0     1
2  (47.7379, -122.233)     east     1        0      0     0
3  (47.5208, -122.393)     west     0        0      0     1
4  (47.6168, -122.045)  fareast     0        1      0     0

[5 rows x 36 columns]
```

[81]:
```
df_new = df_new.drop(['region','coordinates', 'zipcode'], axis=1)
# Zipcodes cannot be left as label encoded since the levels do not have a␣
↪numerical relationship.
```

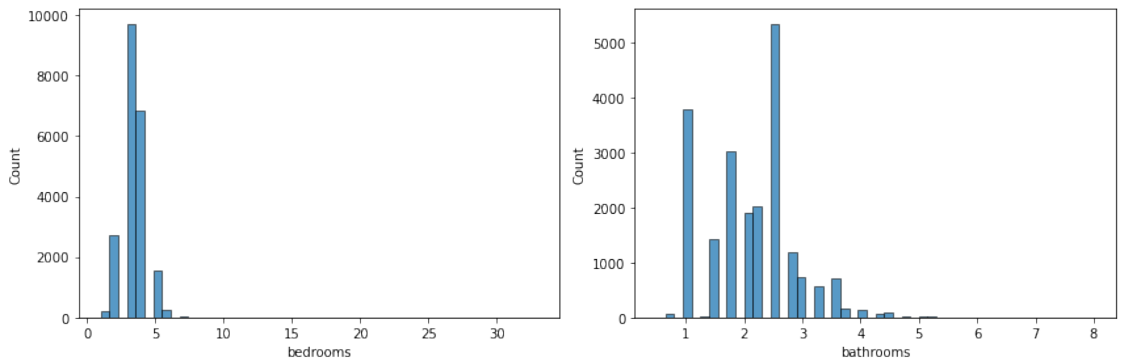
0.8 Feature Engineering Continued:

[82]:
```
df_new.hist(bins='auto', edgecolor='none', figsize=(16,16));
```



Remove outliers from bedrooms and bathrooms:

[83]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, nrows=1, figsize=(12, 4))
fig.set_tight_layout(True)

sns.histplot(x = df_new['bedrooms'], ax= ax1, bins=50);
sns.histplot(x = df_new['bathrooms'], ax =ax2, bins=50);

# There are outliers in both bathrooms and bedrooms.
```



[84]:
```
df_new['bedrooms'].describe()
```

[84]:
```
count    21355.000000
mean         3.370265
std          0.922473
min          1.000000
25%          3.000000
50%          3.000000
75%          4.000000
max         33.000000
Name: bedrooms, dtype: float64
```

[85]:
```
df_new['bathrooms'].describe()
```

[85]:
```
count    21355.000000
mean         2.111672
std          0.757100
min          0.500000
25%          1.750000
50%          2.250000
75%          2.500000
max          8.000000
Name: bathrooms, dtype: float64
```

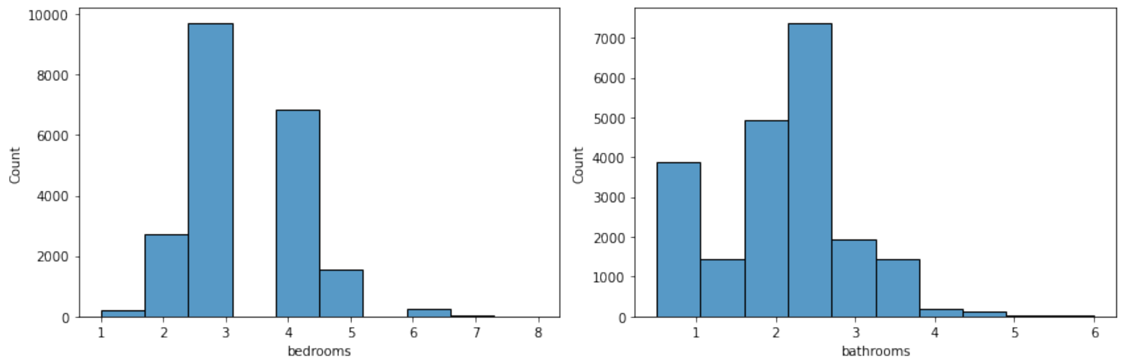
[86]:
```
print(df_new['bedrooms'].quantile(.999))
print(df_new['bathrooms'].quantile(.999))
```

```
8.0
5.25
```

[87]:
```
# Let's remove some very high values visible in the histogram ~ top 1 percent.
df_new =  df_new[df_new['bedrooms'] <= 8]
df_new =  df_new[df_new['bathrooms'] <= 6]
```

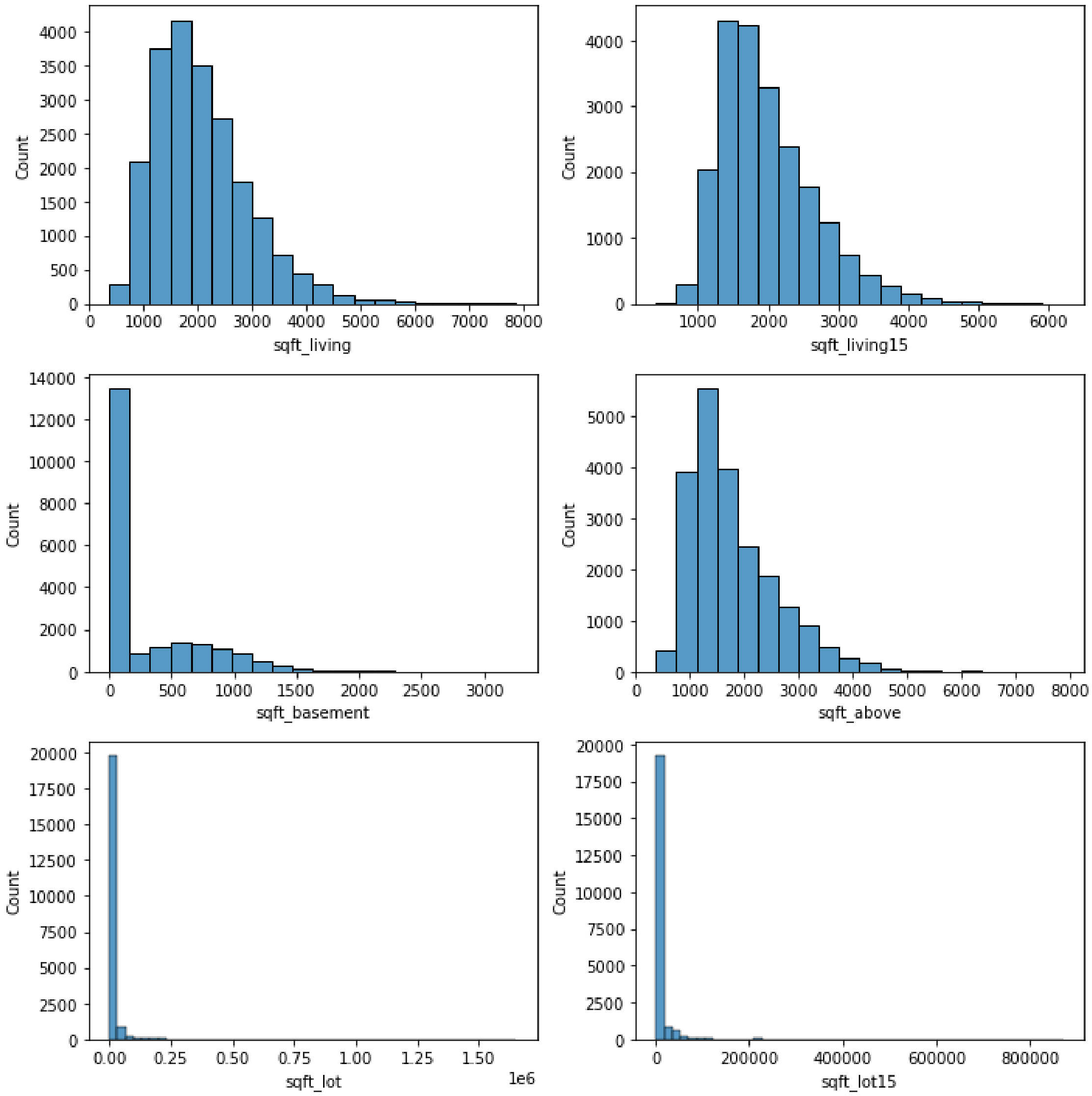
[88]:

```
fig, (ax1, ax2) = plt.subplots(ncols=2, nrows=1, figsize=(12, 4))
fig.set_tight_layout(True)

sns.histplot(x = df_new['bedrooms'], ax= ax1, bins=10);
sns.histplot(x = df_new['bathrooms'], ax =ax2, bins=10);
```



[89]:

```
fig, ((ax1, ax2),(ax3,ax4),(ax5,ax6)) = plt.subplots(ncols=2, nrows=3,␣
↪figsize=(10, 10))
fig.set_tight_layout(True)

sns.histplot(x = df_new['sqft_living'], ax= ax1, bins=20);
sns.histplot(x = df_new['sqft_living15'], ax= ax2, bins=20);
sns.histplot(x = df_new['sqft_basement'], ax =ax3, bins=20);
sns.histplot(x = df_new['sqft_above'], ax= ax4, bins=20);
sns.histplot(x = df_new['sqft_lot'], ax =ax5, bins=50);
sns.histplot(x = df_new['sqft_lot15'], ax= ax6, bins=50);
```



[90]:
```
df_new.shape
```

[90]: (21340, 33)

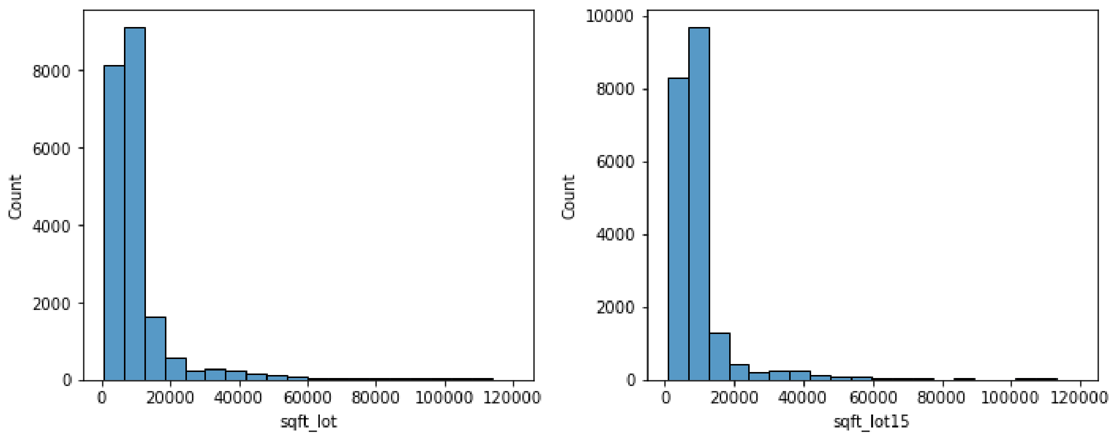
[91]:
```
print(df_new['sqft_lot'].quantile(.99)) # np.percentile(df_new['sqft_lot'],98)
print(df_new['sqft_lot15'].quantile(.99))
```

```
213008.0
157687.0
```

Remove outliers from `sqft_lot`, and `sqft_lot15`:

[92]:
```
# Remove some high values from sqft_lot and sqft_lot15
df_new =  df_new[df_new['sqft_lot'] < 120000]
df_new =  df_new[df_new['sqft_lot15'] < 120000]
```

[93]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(10, 4))
fig.set_tight_layout(True)

sns.histplot(x = df_new['sqft_lot'], ax= ax1, bins=20);
sns.histplot(x = df_new['sqft_lot15'], ax= ax2, bins=20);
```



Create a new `sqft_basement` variable:

- `has_basement` will define precence or absence of `sqft_basement` since more than half of the houses don't have a basement.

[94]:
```
len(df_new[df_new['sqft_basement'] == 0])
```

[94]:
```
12834
```

[95]:
```
df_new['has_basement'] = df_new['sqft_basement'] > 0
df_new['has_basement'].value_counts()
```

[95]:
```
False    12834
True      8070
Name: has_basement, dtype: int64
```

[96]:
```
dic = {False:"0", True:"1"}
df_new.replace({"has_basement": dic}, inplace=True)
df_new["has_basement"] = df_new["has_basement"].astype(int)
df_new["has_basement"].value_counts()
```

[96]:
```
0    12834
1     8070
Name: has_basement, dtype: int64
```

[97]:
```
print(df_new.corr()['price']['sqft_basement'])
print(df_new.corr()['price']['has_basement'])
# correlation coef is smaller for has_basement but since this variable is more␣
↪meaningful let's use it and drop 'sqft_basement'
```

```
0.2983845422940022
0.18230767995993896
```

[98]:
```
len(df_new[df_new['sqft_lot'] == 0])
```

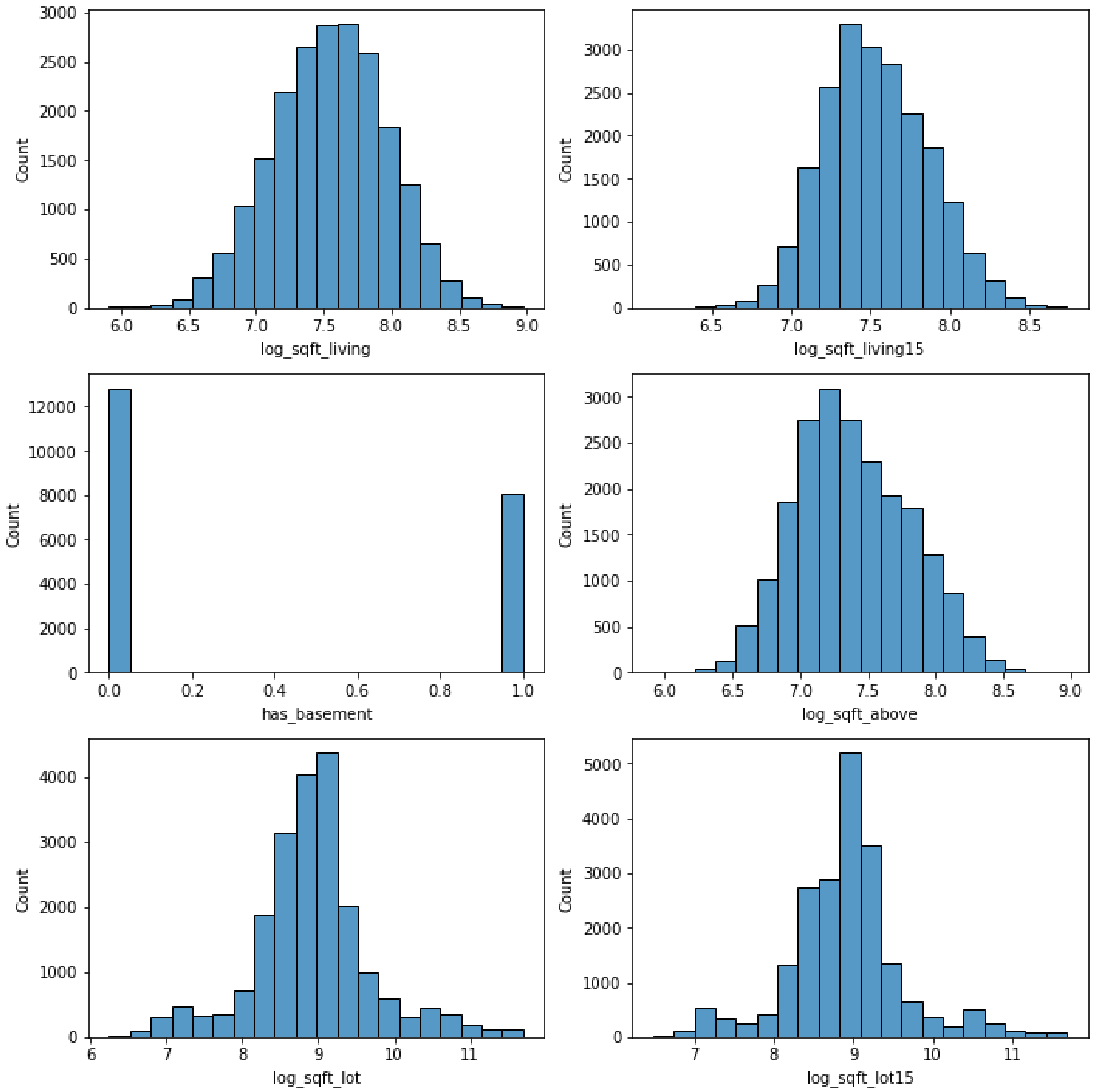
[98]:
```
0
```

[99]:
```
df_new.drop('sqft_basement', axis=1, inplace=True )
```

Log transform skewed variables in case we need to use them in regression:

[100]:
```
for var in ['sqft_living','sqft_living15','sqft_above','sqft_lot','sqft_lot15']:
    df_new[f"log_"+var] = np.log(df_new[var])  # df_new[f"log{var}"] = np.
↪log(df_new[var])
```

[101]:
```
fig, ((ax1, ax2),(ax3, ax4),(ax5,ax6)) = plt.subplots(ncols=2, nrows=3,␣
↪figsize=(10, 10))
fig.set_tight_layout(True)

sns.histplot(x = df_new['log_sqft_living'], ax= ax1, bins=20);
sns.histplot(x = df_new['log_sqft_living15'], ax= ax2, bins=20);
sns.histplot(x = df_new['has_basement'], ax= ax3, bins=20);
sns.histplot(x = df_new['log_sqft_above'], ax= ax4, bins=20);
sns.histplot(x = df_new['log_sqft_lot'], ax =ax5, bins=20);
sns.histplot(x = df_new['log_sqft_lot15'], ax= ax6, bins=20);
```




```
[102]: print(df.shape)
       print(df_new.shape)
```

```
(21420, 21)
(20904, 38)
```

- In the end we lost ~ 2.5% of the data during data engineering process:

```
[103]: total_dataloss = ((df_fixed.shape[0] - df_new.shape[0]) * 100 ) /  df_fixed.
        ↪shape[0]
       total_dataloss
```

```
[103]: 2.4089635854341735
```

0.9 Feature Selection:

[104]:
```
data = df_new.copy()
data.head()
```

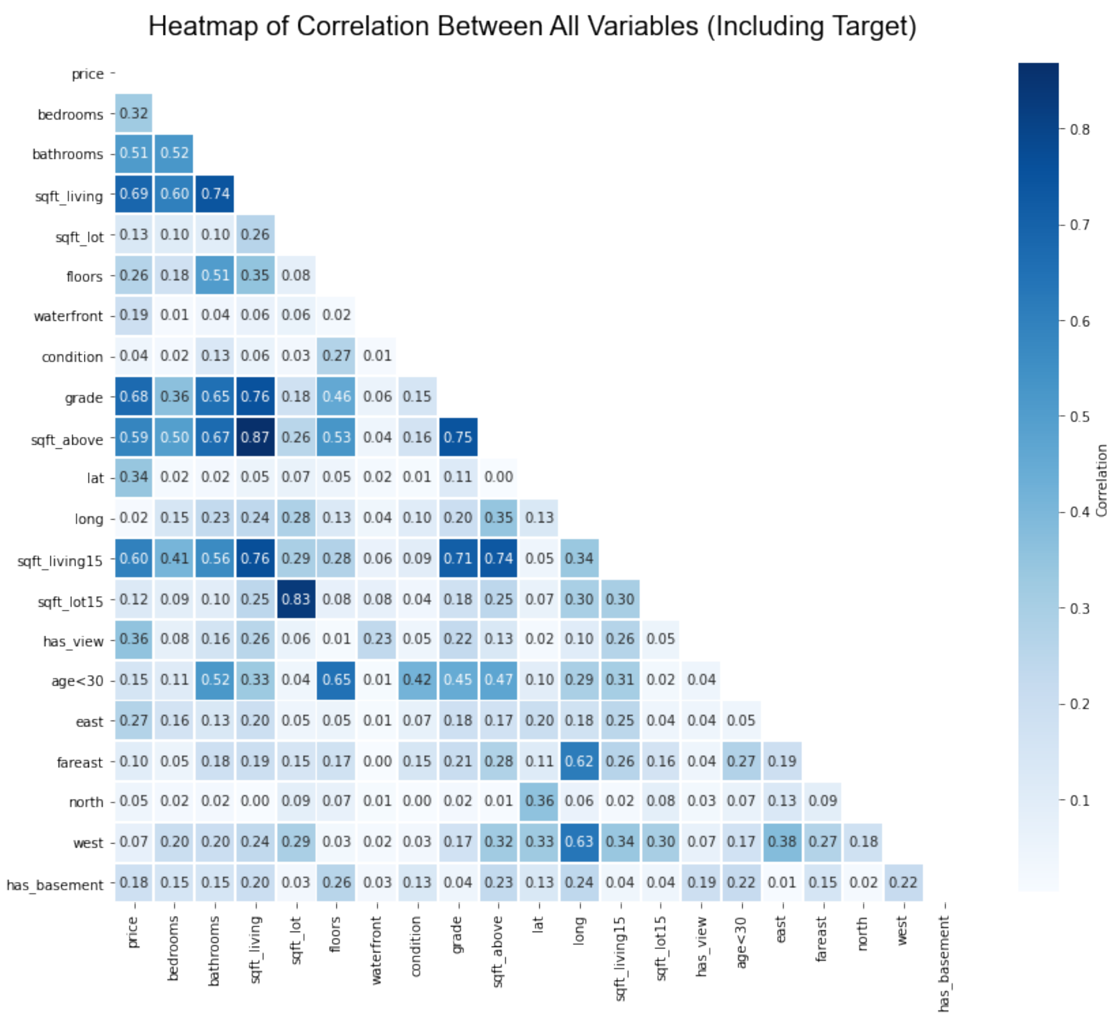
[104]:
```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
0  221900.0         3       1.00         1180      5650     1.0           0
1  538000.0         3       2.25         2570      7242     2.0           0
2  180000.0         2       1.00          770     10000     1.0           0
3  604000.0         4       3.00         1960      5000     1.0           0
4  510000.0         3       2.00         1680      8080     1.0           0

   condition  grade  sqft_above  …  east  fareast  north  west  \
0          3      7        1180  …     0        0      0     1
1          3      7        2170  …     0        0      0     1
2          3      6         770  …     1        0      0     0
3          5      7        1050  …     0        0      0     1
4          3      8        1680  …     0        1      0     0

   has_basement  log_sqft_living  log_sqft_living15  log_sqft_above  \
0             0         7.073270           7.200425        7.073270
1             1         7.851661           7.432484        7.682482
2             0         6.646391           7.908387        6.646391
3             1         7.580700           7.215240        6.956545
4             0         7.426549           7.495542        7.426549

   log_sqft_lot  log_sqft_lot15
0      8.639411        8.639411
1      8.887653        8.941022
2      9.210340        8.994917
3      8.517193        8.517193
4      8.997147        8.923058

[5 rows x 38 columns]
```

[105]:
```
data.columns
```

[105]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'log_price', 'has_view', 'april',
       'august', 'december', 'february', 'july', 'june', 'march', 'may',
       'november', 'october', 'september', 'age<30', 'east', 'fareast',
       'north', 'west', 'has_basement', 'log_sqft_living', 'log_sqft_living15',
       'log_sqft_above', 'log_sqft_lot', 'log_sqft_lot15'],
      dtype='object')
```

0.9.1 HEATMAP

[106]:
```
variables = data[['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',␣
↪'floors',
       'waterfront', 'condition', 'grade', 'sqft_above',
       'lat', 'long', 'sqft_living15', 'sqft_lot15',  'has_view',
        'age<30', 'east', 'fareast',
       'north', 'west', 'has_basement']]

corr = variables.corr().abs()

fig, ax=plt.subplots(figsize=(14,14))
matrix = np.triu(corr) # Getting the Upper Triangle of the correlation matrix
cbar_kws={"label": "Correlation", "shrink":0.8}
heatmap = sns.heatmap(data = corr, cmap='Blues', linewidths = 1, square= True, ␣
↪ax=ax, annot=True, mask=matrix, fmt= ".2f", cbar_kws=cbar_kws)
fig.suptitle('Heatmap of Correlation Between All Variables (Including Target)',␣
↪fontsize=20, y=.84, x = .43, fontname='Arial');
heatmap;

fig.savefig('./images/Heatmap_Correlation.png', dpi=300);
```



Write a function to show the most correlated pairs:

[107]:
```python
def show_corr_pairs(data):
    dataCorr = data.corr().abs()
    dataCorr = dataCorr.mask(np.triu(np.ones(dataCorr.shape)).astype(np.bool))␣
 ↪# convert upper triangle of values to NaN to remove repeated values from the␣
 ↪table
    dataCorr = dataCorr.stack().reset_index().sort_values(0, ascending=False)␣
 ↪#0 is the column automatically generated by the stacking
    dataCorr = dataCorr[(dataCorr[0]>.7) & (dataCorr[0]<1)]
    dataCorr =  dataCorr.rename(columns = {'level_0': 'var1', 'level_1':␣
 ↪'var2', 0:'corrcoef'})
    return dataCorr
```

[108]:
```python
show_corr_pairs(variables)
```

[108]:
```
            var1         var2  corrcoef
39    sqft_above  sqft_living  0.867865
82    sqft_lot15     sqft_lot  0.832800
69  sqft_living15  sqft_living  0.763589
31         grade  sqft_living  0.755051
44    sqft_above        grade  0.747496
5    sqft_living    bathrooms  0.743058
75  sqft_living15   sqft_above  0.735825
74  sqft_living15        grade  0.711495
```

- `sqft_living` correlates highly with `sqft_above` and `sqft_living`.
- `sqft_living` correlates highly with `grade` and `bathrooms` too.
- `sqft_lot15` correlates highly with `sqft_lot`.

[109]:
```
variables.corr()['price'].map(abs).sort_values(ascending=False)
```

[109]:
```
price            1.000000
sqft_living      0.685533
grade            0.675277
sqft_living15    0.600749
sqft_above       0.586275
bathrooms        0.508569
has_view         0.355573
lat              0.344114
bedrooms         0.321149
east             0.270383
floors           0.264440
waterfront       0.191616
has_basement     0.182308
age<30           0.152268
sqft_lot         0.133435
sqft_lot15       0.122568
fareast          0.100217
west             0.074890
north            0.045800
condition        0.043828
long             0.015586
Name: price, dtype: float64
```

- `sqft_living` seems to have the greatest correlation with `price`.

[110]:
```
df_corr = abs(variables.corr()) > 0.7
df_corr.sum()
```

[110]:
```
price            1
bedrooms         1
bathrooms        2
sqft_living      5
```

```
sqft_lot         2
floors           1
waterfront       1
condition        1
grade            4
sqft_above       4
lat              1
long             1
sqft_living15    4
sqft_lot15       2
has_view         1
age<30           1
east             1
fareast          1
north            1
west             1
has_basement     1
dtype: int64
```

- `Square Foot Living` is the variable with the greatest collinearity to others too.

0.9.2 Take away from the Heat Map

- `sqft_living`, `sqft_above` ,`sqft_living15` correlate highly. Keep `sqft_living` as it correlates with price the highest.
- `grade` and `bathrooms` also correlate highly with `sqft_living`. But let's keep these variables since they give a different type of information.
- Do not use `lat` and `long` since they are redundant with location variables.
- `sqft_lot15`and `sqft_lot` correlate highly. Keep `sqft_lot` as it correlates with price a bit more.

0.10 Regression Assumptions Check Functions:

0.10.1 Linearity:

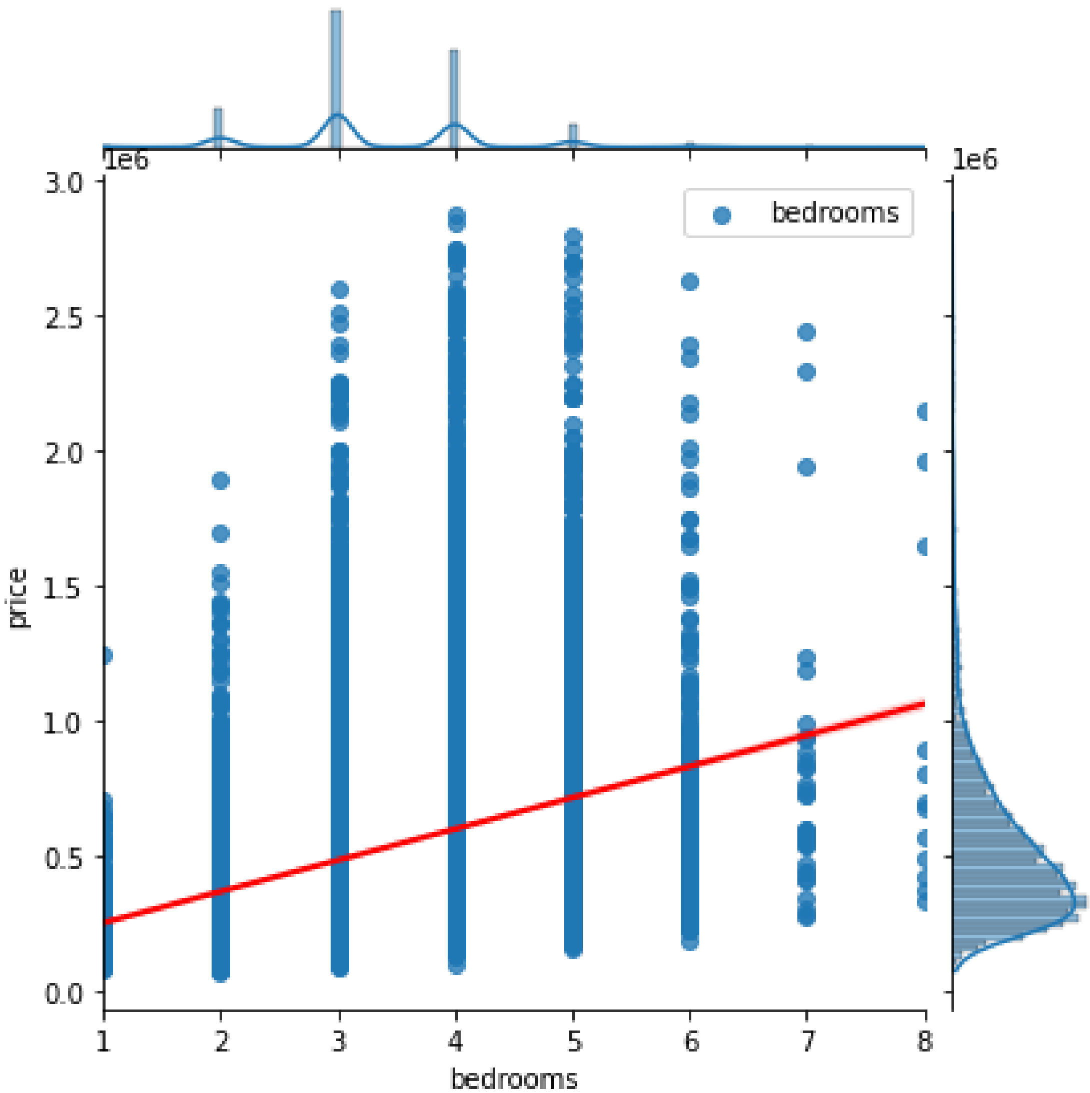
- There should be a linear relationship between the response/target variable and predictors.
- Check for this once using scatterplots and then visually inspecting the scatterplots for linearity..

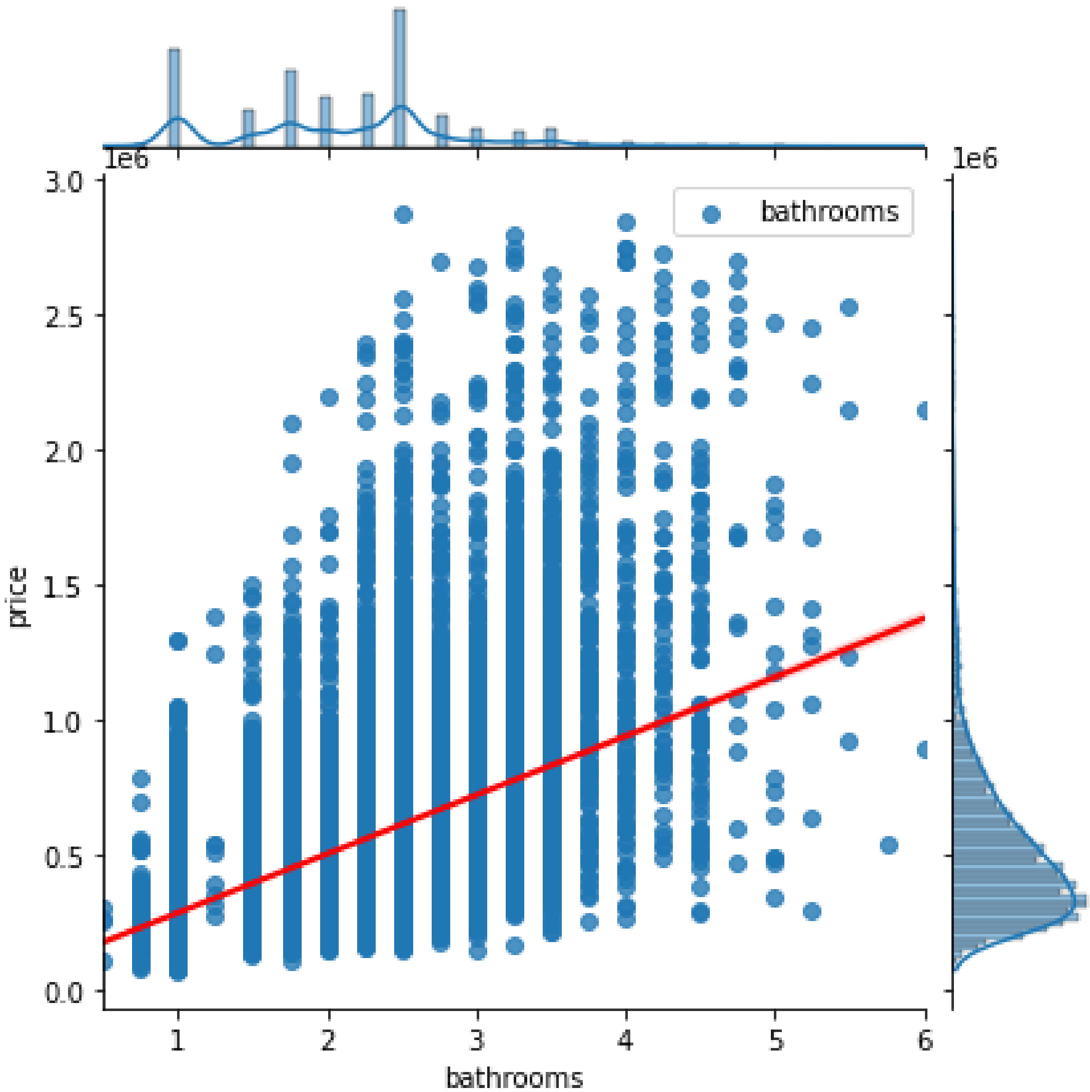
[111]:
```
data.columns
```

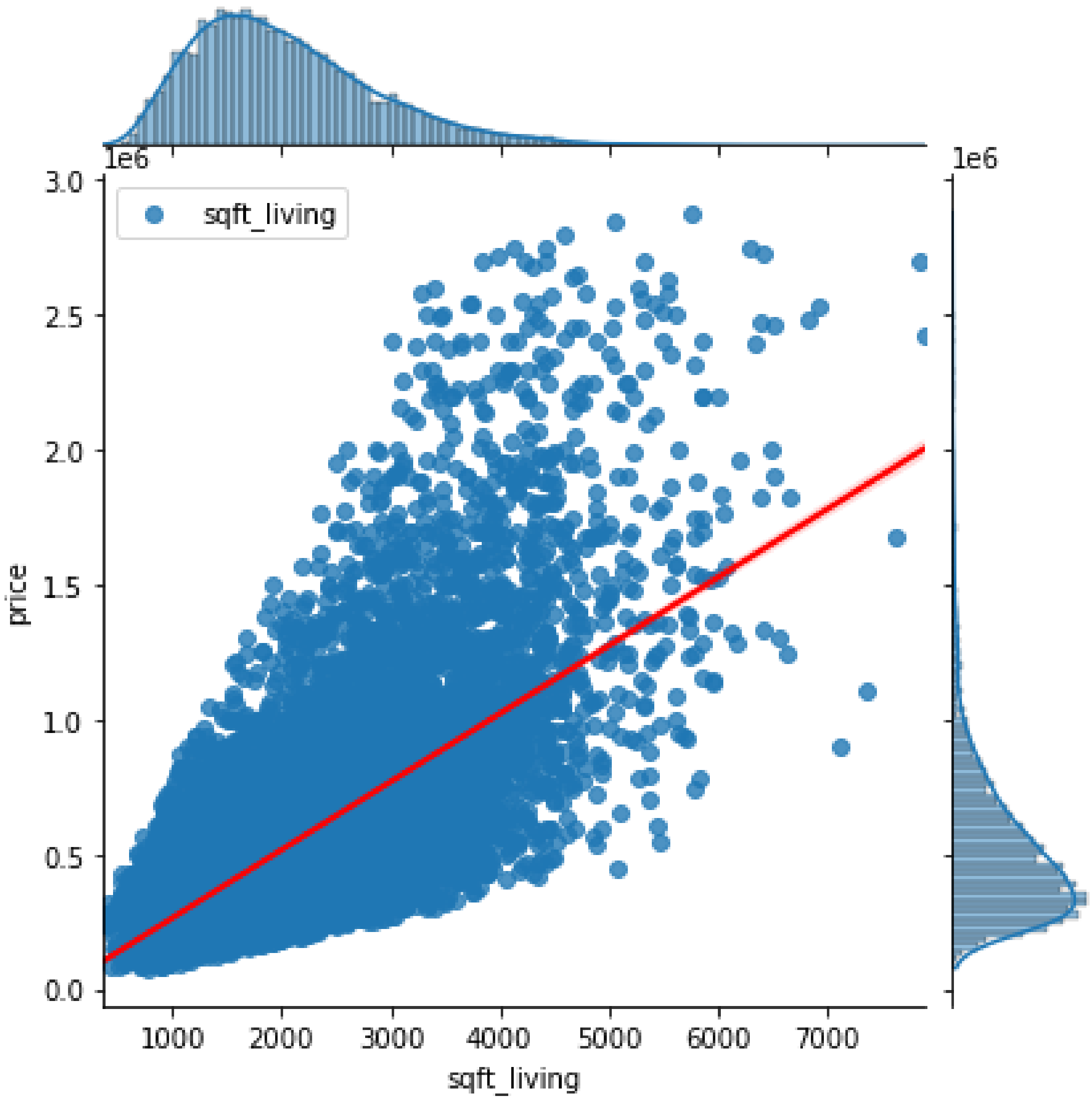
[111]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'log_price', 'has_view', 'april',
       'august', 'december', 'february', 'july', 'june', 'march', 'may',
       'november', 'october', 'september', 'age<30', 'east', 'fareast',
       'north', 'west', 'has_basement', 'log_sqft_living', 'log_sqft_living15',
       'log_sqft_above', 'log_sqft_lot', 'log_sqft_lot15'],
      dtype='object')
```

[112]:

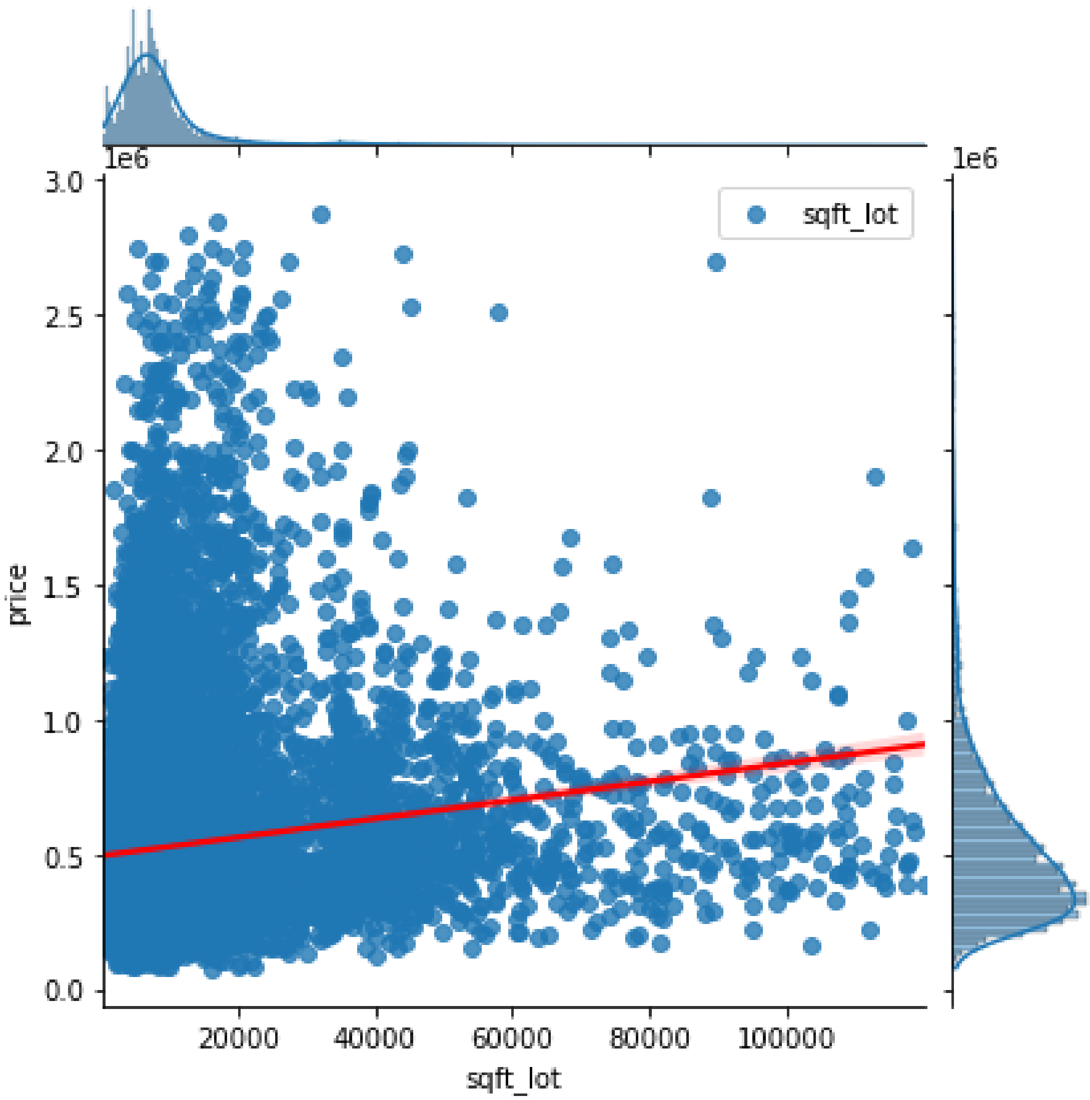
```python
# Linearity against `price`:
continuous = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
              'condition', 'grade']

for column in continuous:
    sns.jointplot(x=column, y="price", data=data, kind='reg',␣
 ↪label=column,joint_kws={'line_kws':{'color':'red'}})
    plt.legend()
    plt.show()
```



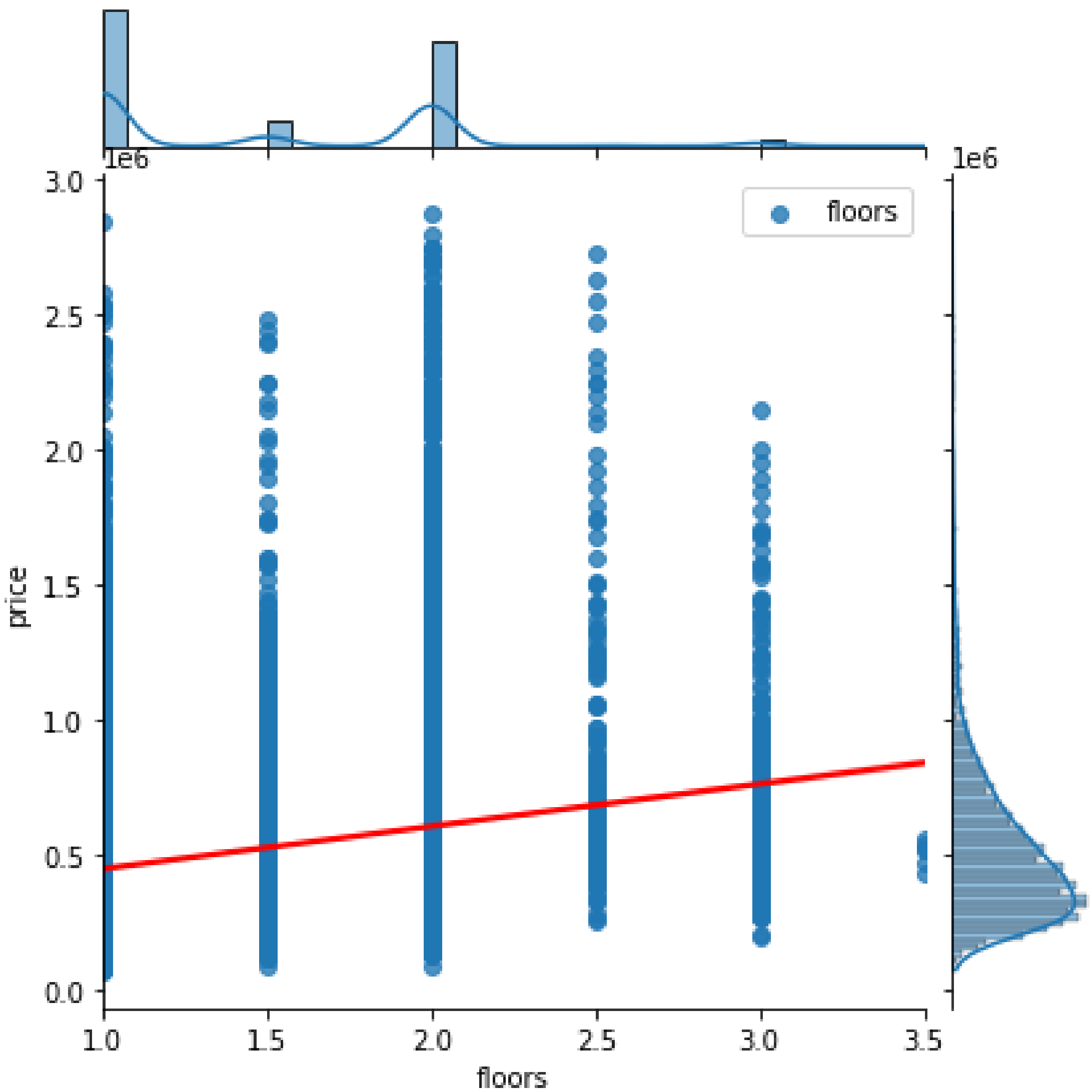

1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
bathrooms
1
2
3
4
5
6
bathrooms
1e6

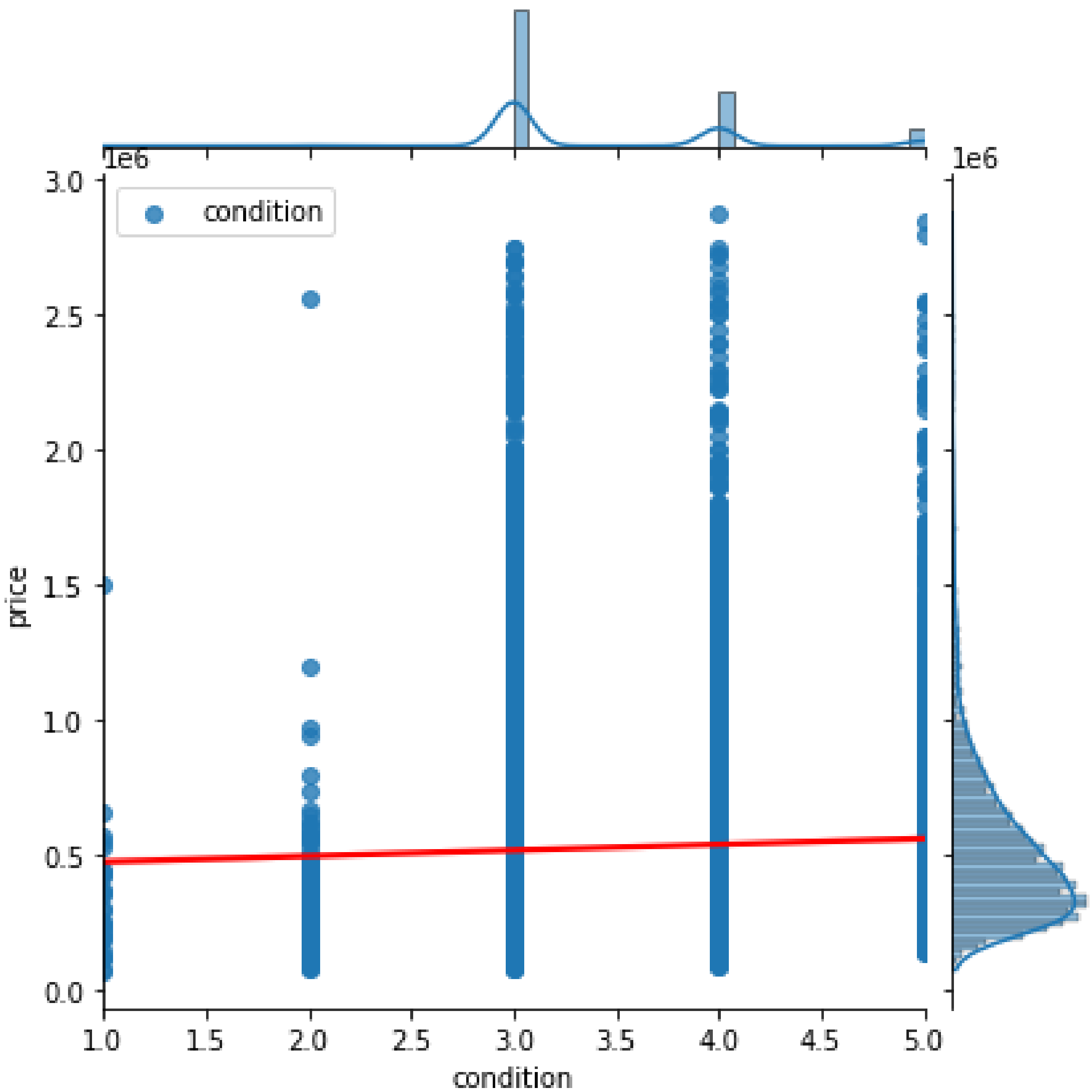


1e6
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
sqft_living
1000
2000
3000
4000
5000
6000
7000
sqft_living

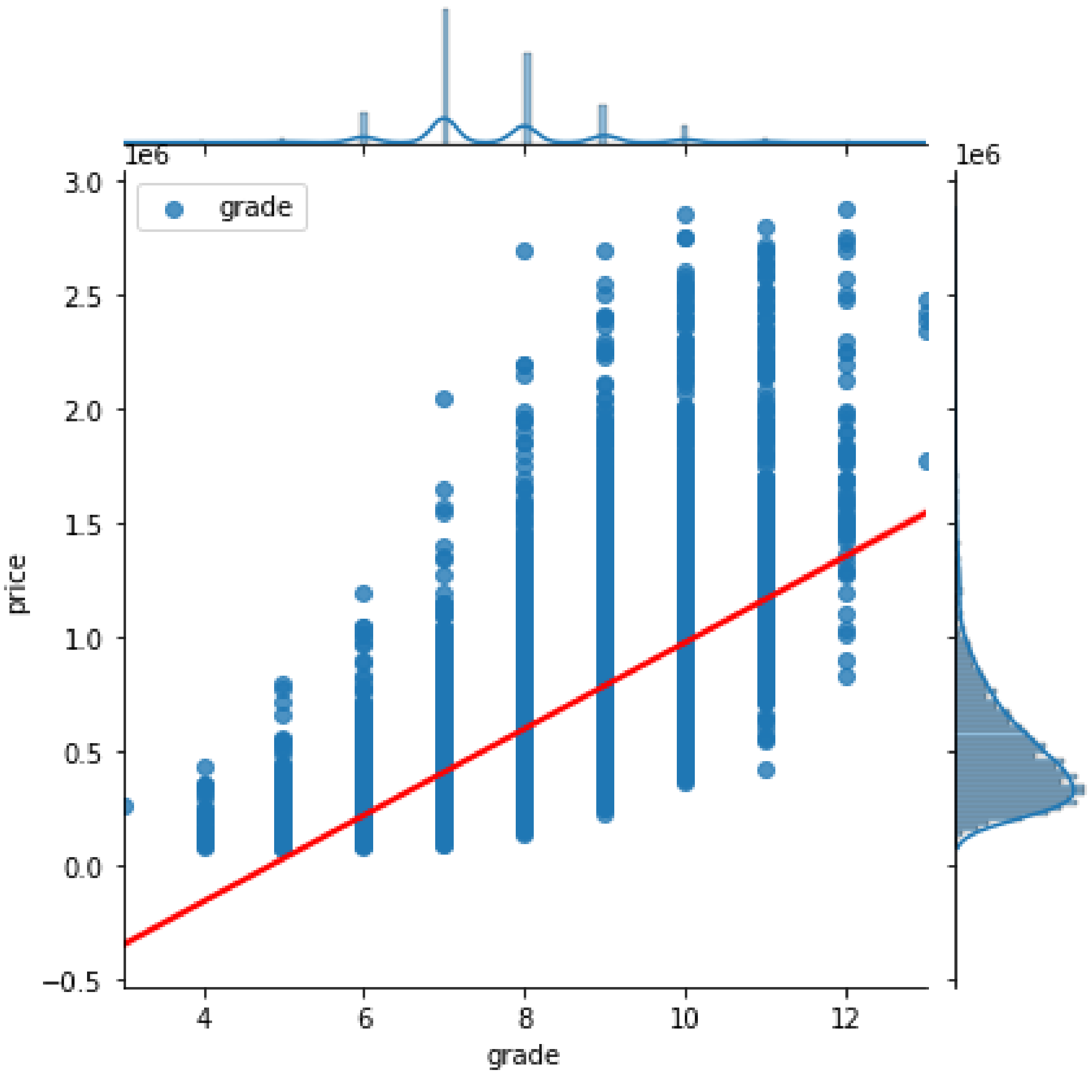


1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
sqft_lot
20000
40000
60000
80000
100000
sqft_lot
1e6


1e6
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
floors
1.0
1.5
2.0
2.5
3.0
3.5
floors

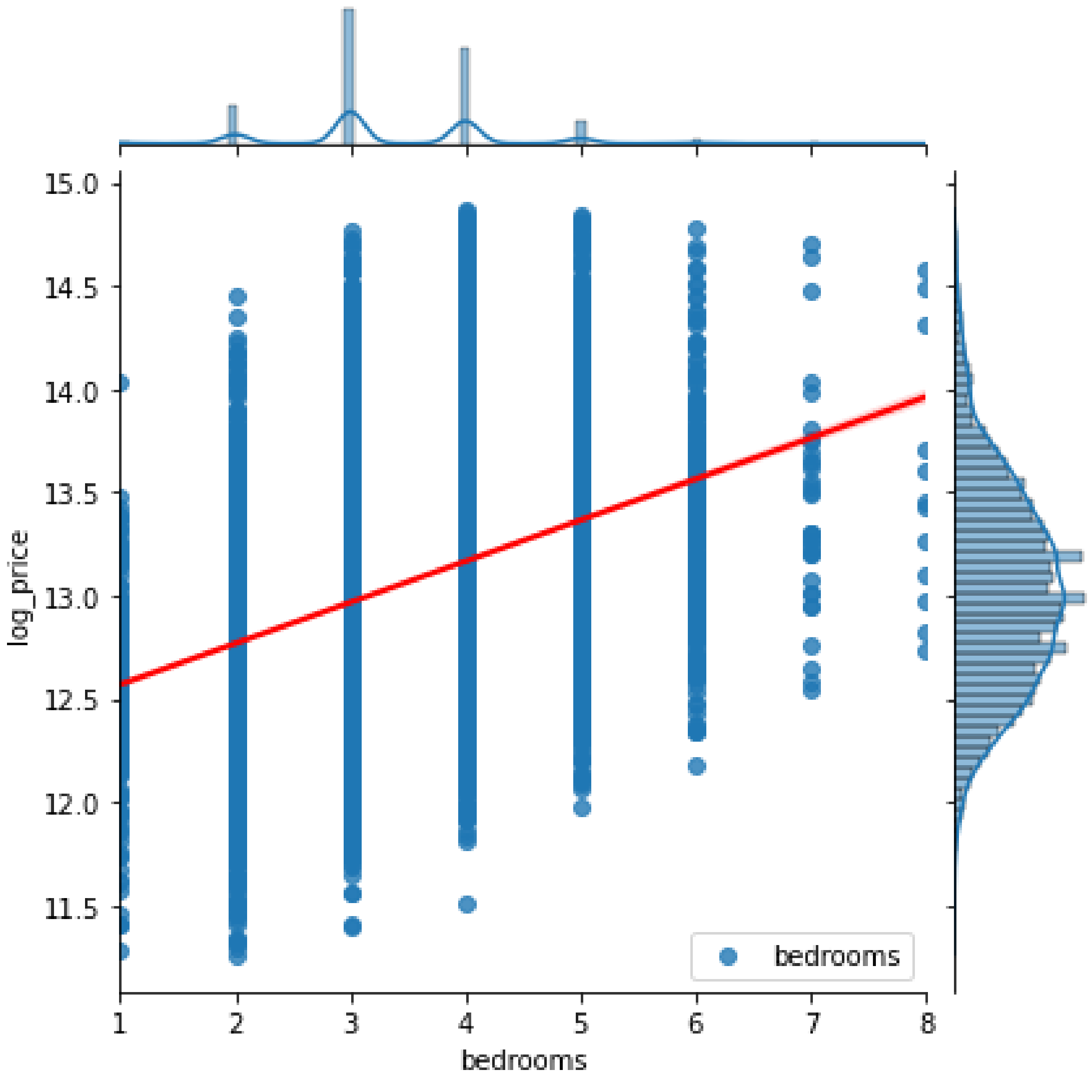


1e6
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
condition
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
condition

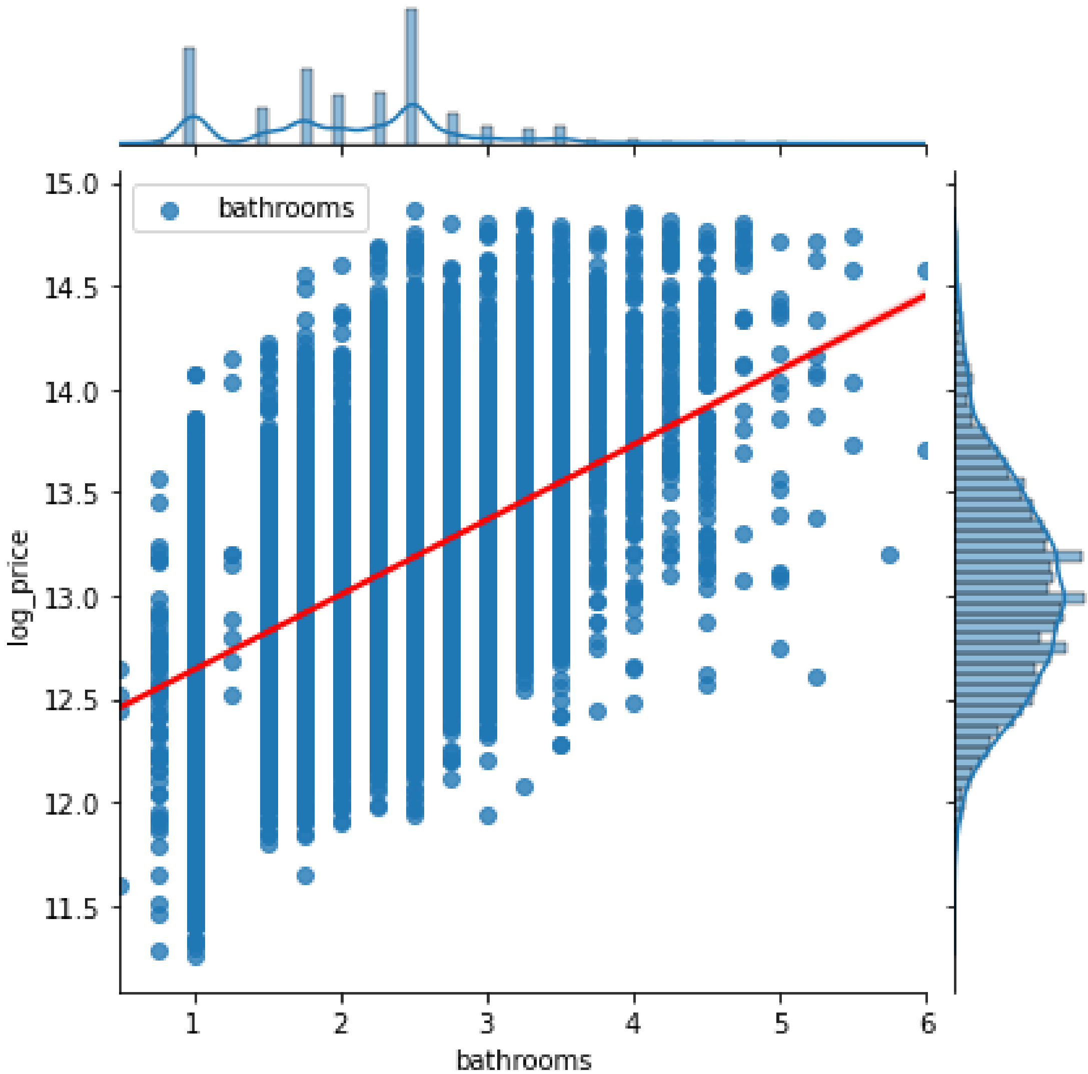


- Looks like a linear relationship except `sqft_lot`

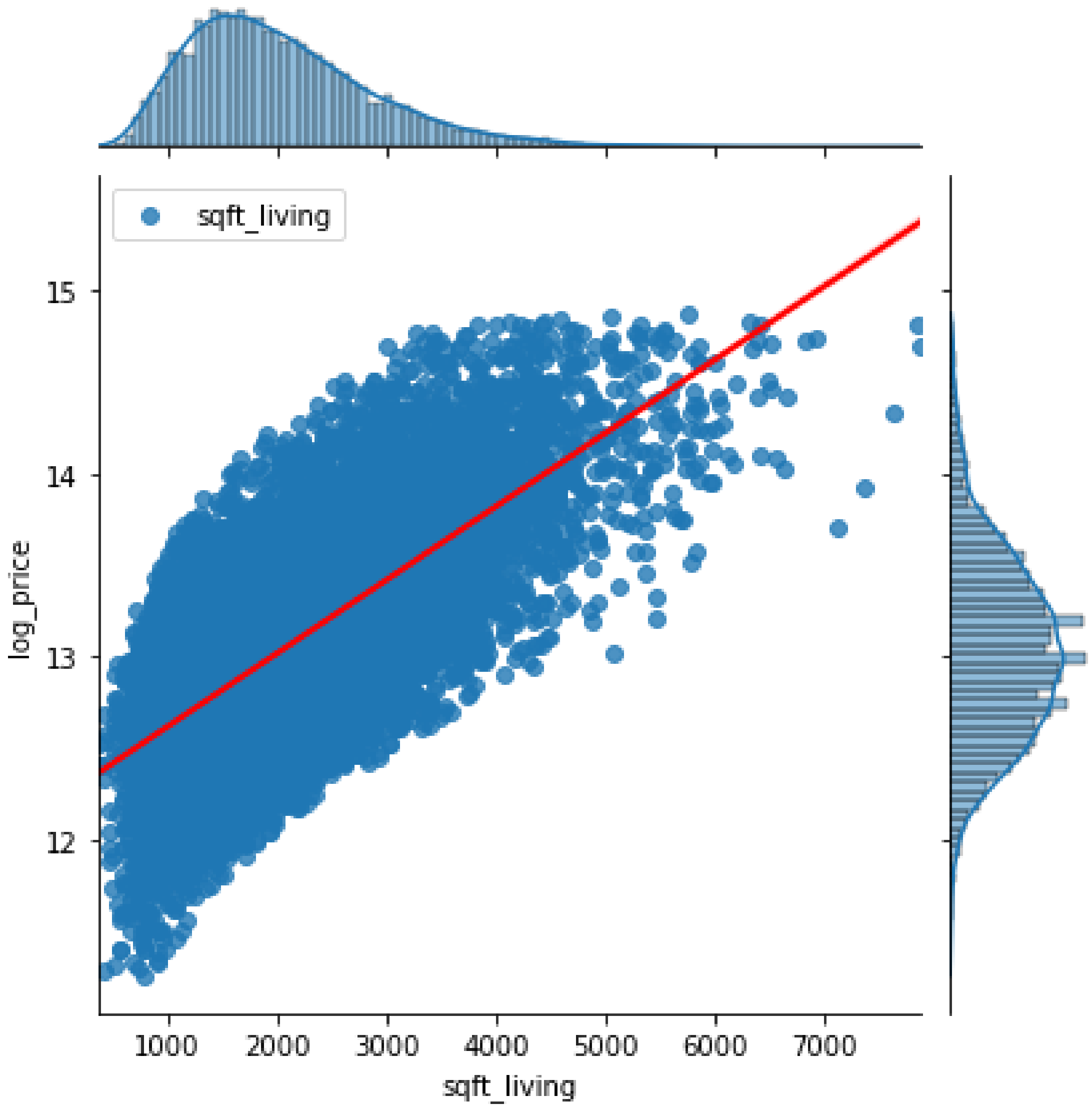
[113]:
```
# Linearity against `log_price`:

continuous = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
              'condition', 'grade']

for column in continuous:
    sns.jointplot(x=column, y="log_price", data=data, kind='reg',␣
 ↪label=column,joint_kws={'line_kws':{'color':'red'}})
    plt.legend()
    plt.show()
```



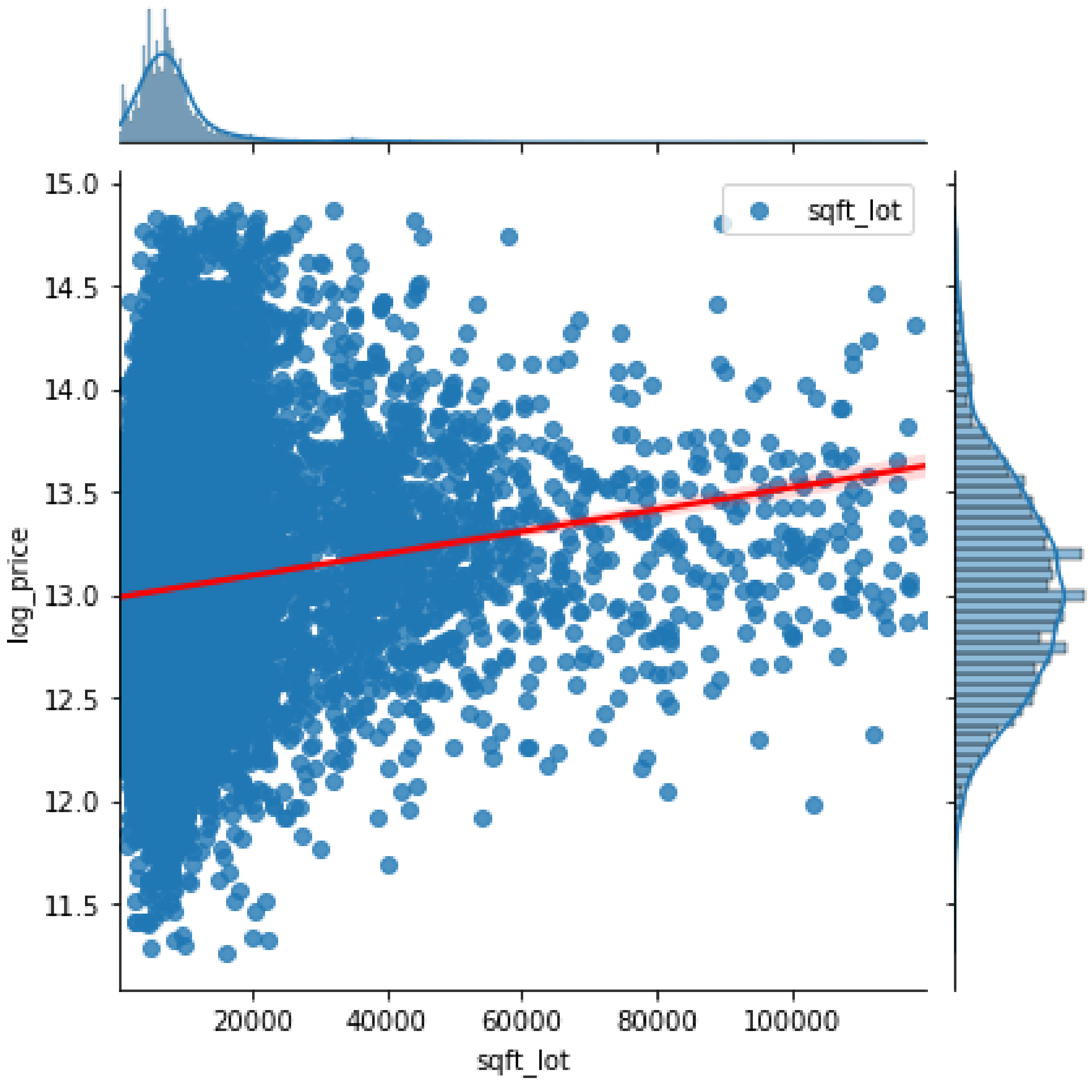
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
bedrooms
1
2
3
4
5
6
7
8
bedrooms

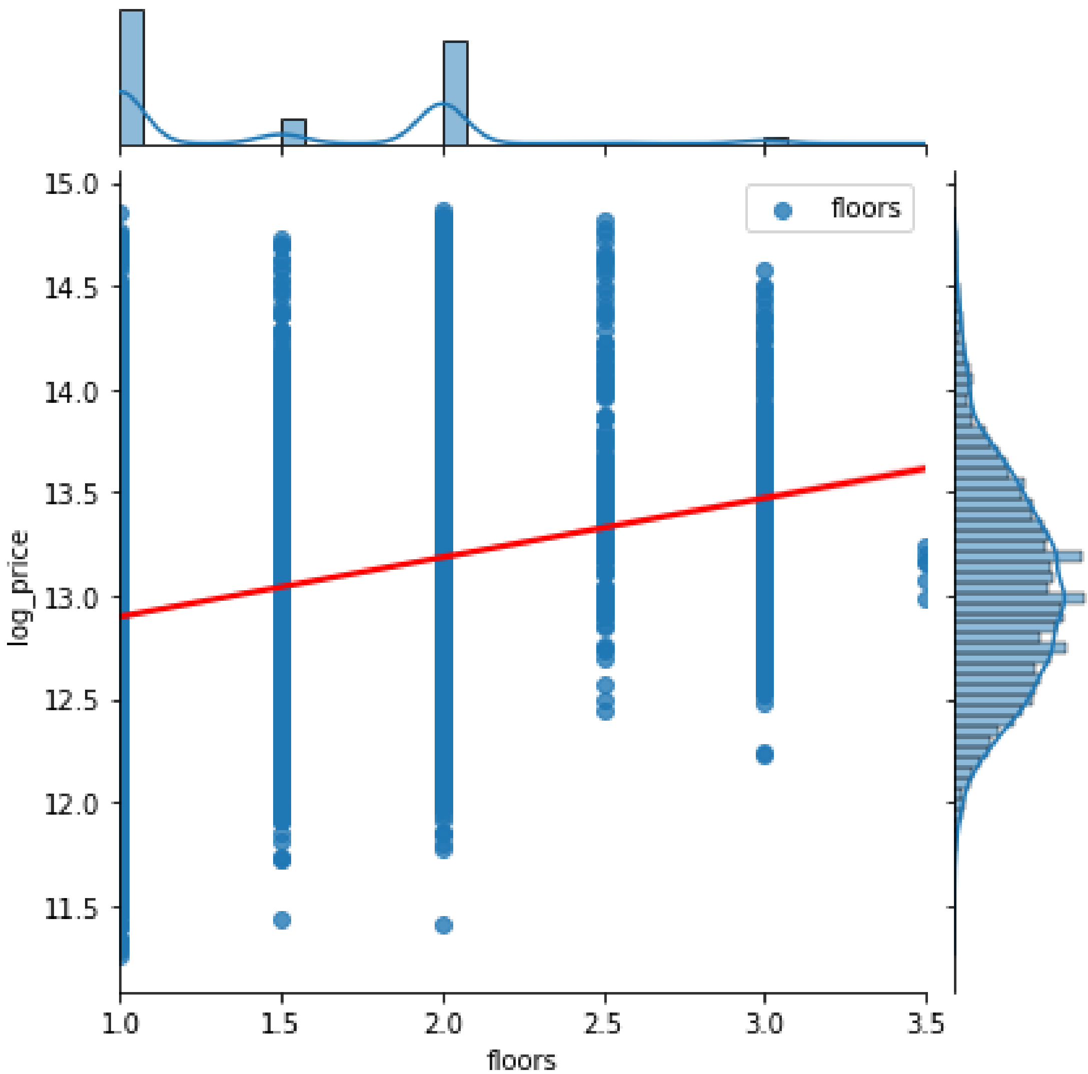


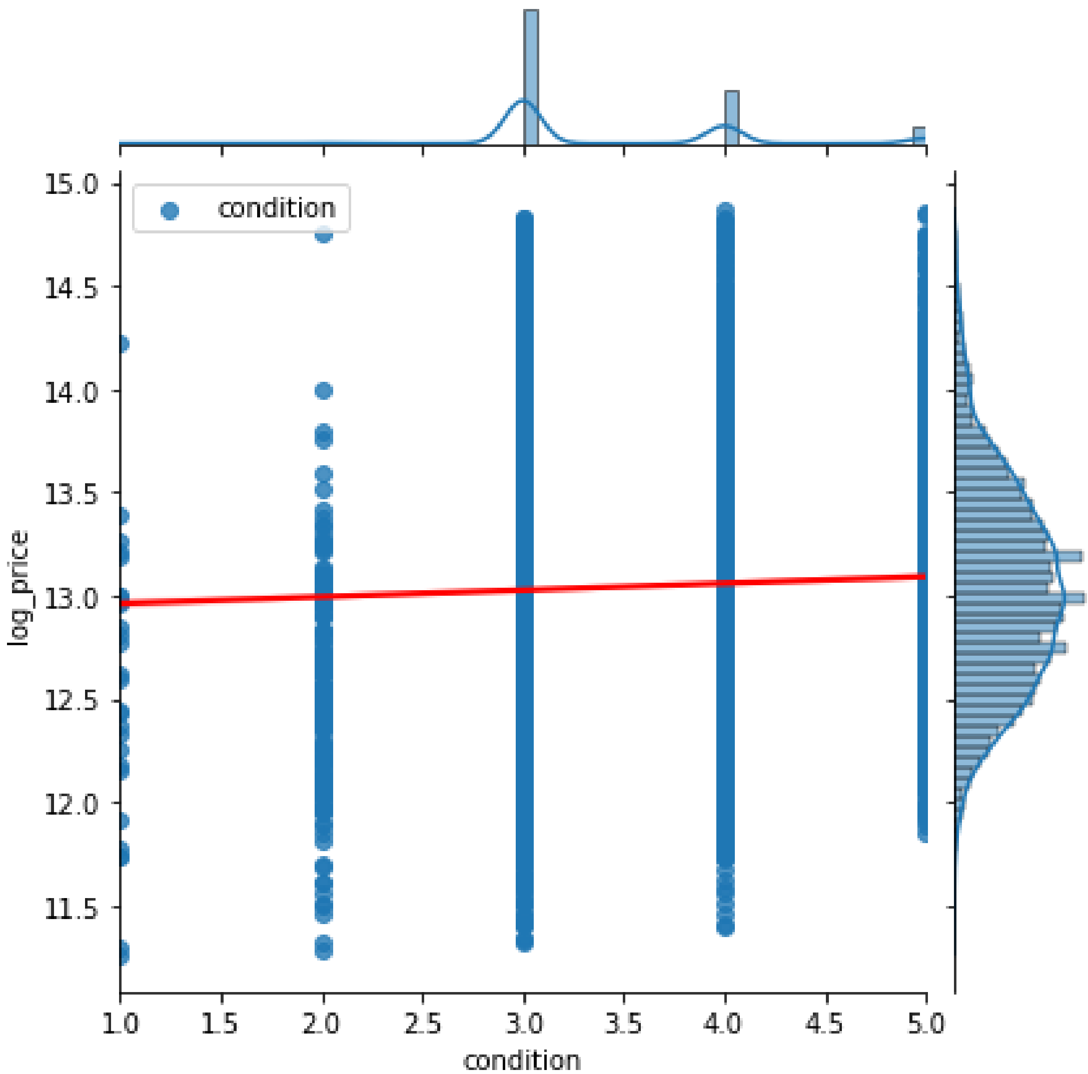
bathrooms
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
1
2
3
4
5
6
bathrooms

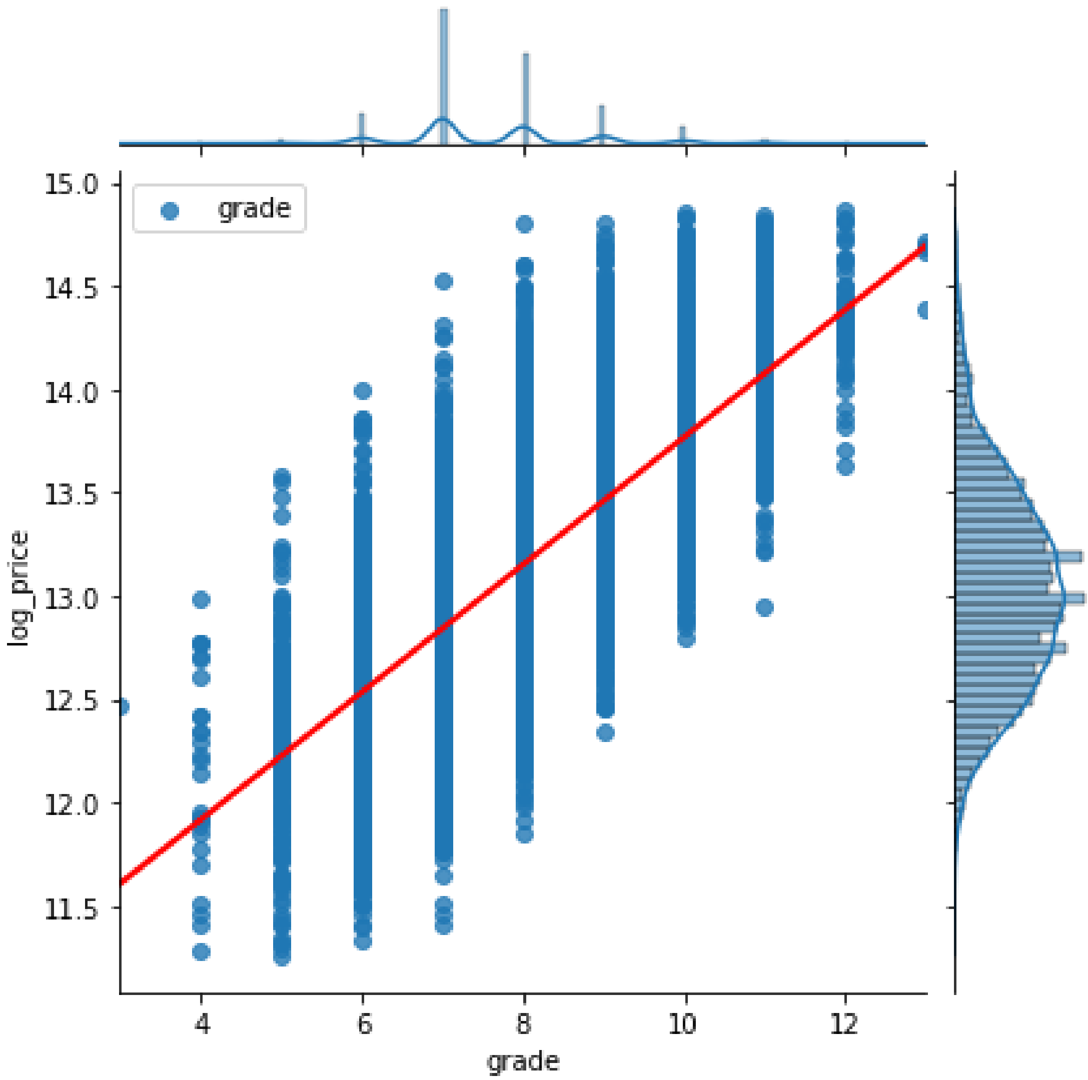


sqft_living
15
14
13
12
log_price
1000
2000
3000
4000
5000
6000
7000
sqft_living


15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
sqft_lot
20000
40000
60000
80000
100000
sqft_lot


floors
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
1.0
1.5
2.0
2.5
3.0
3.5
floors


condition
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
condition



- Looks like a linear realtionship for all variables.

0.10.2 Check for Normality and Homoscadecity:

- The model residuals should follow a normal distribution.
- The residuals should be evenly spread through range (The variance of residual is uniform).

[114]:
```
def normality_homoscadecity(model):
    fig, ((ax1, ax2, ax3)) = plt.subplots(ncols=3,  figsize=(16, 4))

    ax1.hist(model.resid_pearson,bins=20,edgecolor='k')
    ax1.set_xlabel("Normalized residuals",fontsize=14)
    ax1.set_ylabel("Count",fontsize=14)
    ax1.set_title("Histogram of normalized residuals (NORMALITY)", fontsize =11)
```

```
    from statsmodels.graphics.gofplots import qqplot
    qqplot(model.resid_pearson, line='45', fit='True', ax = ax2, alpha=0.8,␣
 ↪markerfacecolor='#1f77b4')
    ax2.set_xlabel("Theoretical quantiles",fontsize=14)
    ax2.set_ylabel("Ordered Values",fontsize=14)
    ax2.set_title("Q-Q plot of normalized residuals (NORMALITY)", fontsize =11)

    ax3.scatter(x=model.fittedvalues, y=model.resid)
    xmin=min(model.fittedvalues)
    xmax = max(model.fittedvalues)
    plt.hlines(y=0,xmin=xmin,xmax=xmax,color='red',linestyle='--',lw=3)
    ax3.set_xlabel("Fitted values",fontsize=14)
    ax3.set_ylabel("Residuals",fontsize=14)
    ax3.set_title("Fitted vs. residuals plot (HOMOSCADECITY)", fontsize =11)
    plt.grid(True)

    return(ax)
```

0.10.3 Check for absence of multicollinearity:

- Multicollinearity occurs when 2 or more of the independent variables are highly correlated with each other.
- VIF (variance inflation factor) is a measure for the increase of the variance of the parameter estimates if an additional variable is added to the linear regression.
- If VIF is greater than 5, then the explanatory variable is highly collinear with another explanatory variable.

[115]:
```
#https://github.com/cwf231/linear_regression_guided_practice
from statsmodels.stats.outliers_influence import variance_inflation_factor

def create_vif_dictionary(X):
    vif_dct = {}
    for i in range(len(X.columns)): # Loop through each row and set the␣
 ↪variable name to the VIF.
        vif = variance_inflation_factor(X.values, i) # Calculate VIF
        v = X.columns[i] # Extract column name for dictionary key.
        vif_dct[v] = vif # Set value in dictionary.
    return vif_dct

def multicollinearity(X):
    multicollinearity = pd.DataFrame(create_vif_dictionary(X), index=[0]).T
    return multicollinearity.sort_values(by = 0, ascending =False).apply(lambda␣
 ↪x: x.apply('{0:.4f}'.format))
```

0.11 Regression Modeling:

0.11.1 BASELINE MODEL #1

- The baseline model is using the most highly correlated variable with price: `sqft_living`

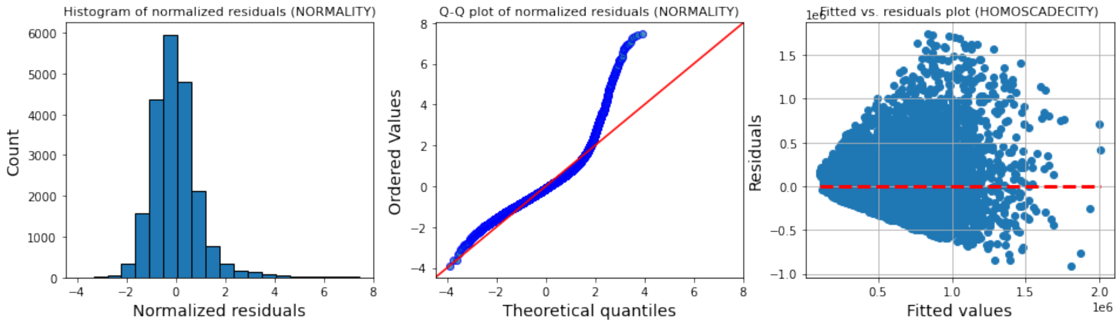
[116]:
```
y = data['price']
X = data['sqft_living']

X.shape, y.shape
```

[116]:
```
((20904,), (20904,))
```

[117]:
```
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[117]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.470
Model:                            OLS   Adj. R-squared:                  0.470
Method:                 Least Squares   F-statistic:                 1.853e+04
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:18:54   Log-Likelihood:            -2.8804e+05
No. Observations:               20904   AIC:                         5.761e+05
Df Residuals:                   20902   BIC:                         5.761e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        1.031e+04   4143.504      2.489      0.013    2191.002    1.84e+04
sqft_living   252.8318      1.857    136.134      0.000     249.192     256.472
==============================================================================
Omnibus:                     8006.855   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            52765.454
Skew:                           1.698   Prob(JB):                         0.00
Kurtosis:                      10.004   Cond. No.                     5.73e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.73e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[118]:
```
normality_homoscadecity(model);
```



Violation of normality and homoscadecity:

- The Distribution of the rediduals are NOT normal. The blue dots are the observed data while the red regression line is the prediction on the second graph. The residuals are NOT normally distributed as the blue dots are not falling on the red line. We may fix this by transforming the target variable and/or independent variables.
- There seems like a violation of Homoskedasticity as well since the dots around the red line are not symmetric and follow a cone-like shape. We can try log transforming the target variable.

0.11.2 MODEL #2

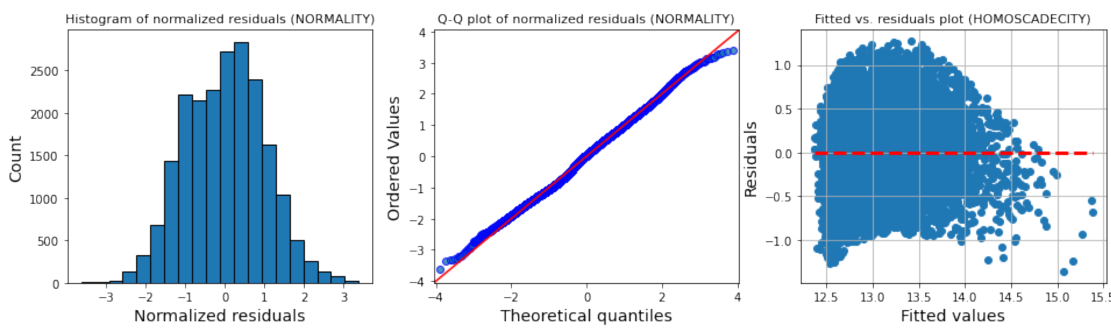
- Using log transformed `log_price` as the target variable.

[119]:
```
y = data['log_price']
X = data['sqft_living']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[119]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.463
Model:                            OLS   Adj. R-squared:                  0.463
Method:                 Least Squares   F-statistic:                 1.802e+04
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:18:55   Log-Likelihood:                -9171.7
No. Observations:               20904   AIC:                         1.835e+04
Df Residuals:                   20902   BIC:                         1.836e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
```

```
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          12.2174      0.007   1833.395      0.000      12.204      12.230
sqft_living     0.0004   2.99e-06    134.225      0.000       0.000       0.000
==============================================================================
Omnibus:                       76.821   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               61.899
Skew:                           0.057   Prob(JB):                     3.62e-14
Kurtosis:                       2.759   Cond. No.                     5.73e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.73e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[120]:
```
normality_homoscadecity(model);
```



- Normality and homoscadecity seem to be restored when we used log-transformed target variable!

Summary interpretation:

- p value for `sqft_living` is statistically significant, meaning we can reject the null hypothesis that `sqft_living` does not correlate with price. In other words we can also say: there is enough evidence in favor of the idea that change in `sqft_living` is associated with change in `price` at the population level. This variable is a worthwhile addition to our regression model.
- A Coefficient of Determination **R-Squared** value of .46 means that 46% of the variability in price is explained by sqft_living. R-Squared explains how good our model is when compared to a baseline model where y = mx. We need to boost this number.

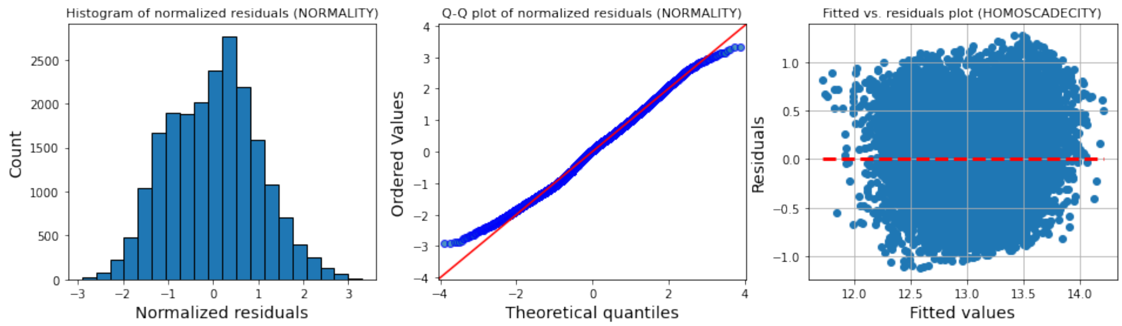
0.11.3 MODEL #3

- Using log transformed `log_sqft_living` as the predictor variable to see if it would improve R2.

[121]:
```
y = data['log_price']
X = data['log_sqft_living']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[121]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.437
Model:                            OLS   Adj. R-squared:                  0.437
Method:                 Least Squares   F-statistic:                 1.625e+04
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:18:55   Log-Likelihood:                -9658.4
No. Observations:               20904   AIC:                         1.932e+04
Df Residuals:                   20902   BIC:                         1.934e+04
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
const               6.9135      0.048    143.586      0.000       6.819
7.008
log_sqft_living     0.8124      0.006    127.459      0.000       0.800
0.825
==============================================================================
Omnibus:                      162.613   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              126.560
Skew:                           0.107   Prob(JB):                     3.29e-28
Kurtosis:                       2.685   Cond. No.                         139.
==============================================================================

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

[122]:
```
normality_homoscadecity(model);
```



- This was worse in terms of R2 and even normality. Let's go back to using un-transformed sqft_living.

0.11.4 MODEL #4

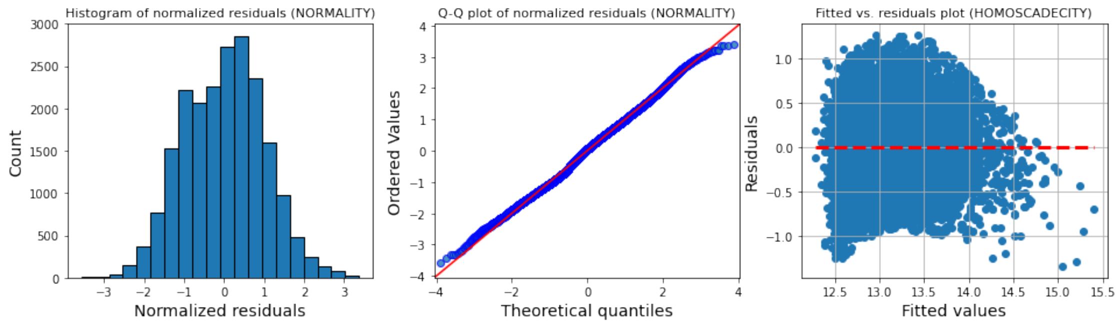
- Using `sqft_living` and `sqft_lot` as the 2 basic area variables.

[123]:
```
y = data['log_price']
X = data[['sqft_living', 'sqft_lot']]
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[123]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.466
Model:                            OLS   Adj. R-squared:                  0.465
Method:                 Least Squares   F-statistic:                     9102.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:18:56   Log-Likelihood:                -9121.3
No. Observations:               20904   AIC:                         1.825e+04
Df Residuals:                   20901   BIC:                         1.827e+04
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          12.2236      0.007   1830.876      0.000      12.210      12.237
sqft_living     0.0004   3.09e-06    132.479      0.000       0.000       0.000
sqft_lot    -2.175e-06   2.16e-07    -10.049      0.000    -2.6e-06   -1.75e-06
==============================================================================
Omnibus:                       65.587   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               53.110
Skew:                           0.047   Prob(JB):                     2.93e-12
```

```
Kurtosis:                       2.771   Cond. No.                    4.21e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.21e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[124]:
```
normality_homoscadecity(model);
```



[125]:
```
multicollinearity(X)
```

[125]:

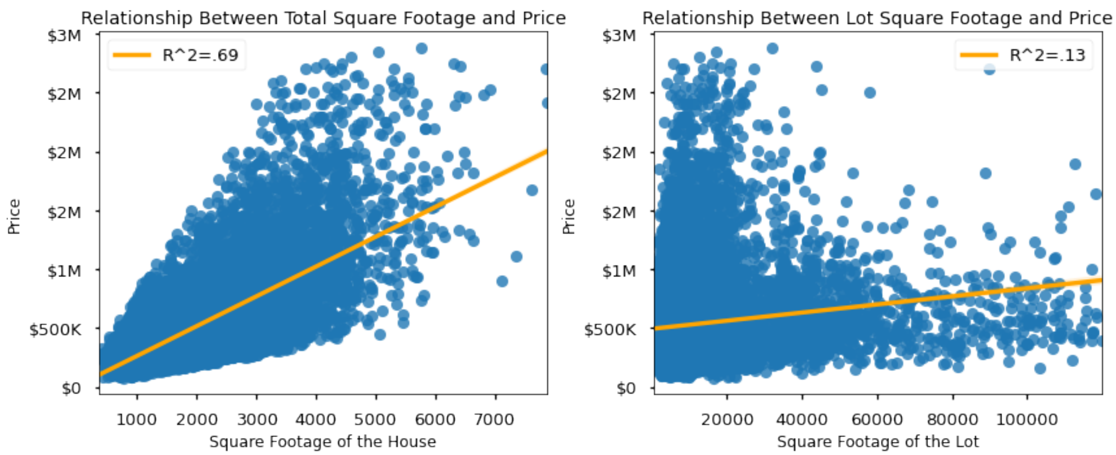
	0
const	6.6484
sqft_living	1.0737
sqft_lot	1.0737

[126]:
```
print(data.corr()['price']['sqft_living'])
print(data.corr()['price']['sqft_lot'])
```

```
0.6855331909828829
0.13343455593875633
```

[127]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(ncols=2, nrows=1, figsize=(12, 5))
    fig.set_tight_layout(True)

    sns.regplot(x="sqft_living", y="price", ax=ax1, data=data,␣
 ↪line_kws={"color": "orange","label":"R^2=.69"})
    ax1.legend()
    ax1.yaxis.set_major_formatter(formatter)
    ax1.set_title('Relationship Between Total Square Footage and␣
 ↪Price',fontsize=14)
```

```
    ax1.set_xlabel("Square Footage of the House",fontsize=12)
    ax1.set_ylabel("Price",fontsize=12)

    sns.regplot(x="sqft_lot", y="price", ax=ax2, data=data, line_kws={"color":
↪"orange","label":"R^2=.13"})
    ax2.legend()
    ax2.yaxis.set_major_formatter(formatter)
    ax2.set_title('Relationship Between Lot Square Footage and
↪Price',fontsize=14)
    ax2.set_xlabel("Square Footage of the Lot",fontsize=12)
    ax2.set_ylabel("Price",fontsize=12)

    fig.savefig('./images/sqft_living_sqft_lot.png', dpi=300);
```



- `sqft_lot` adds little to the model increasing R-squared slightly from 0.463 to 0.466.
- But this variable is still statistically significant, so it is still worthwhile adding it to the model.

0.11.5 MODEL #5

- Adding other meaningful variables except age, season and location

[128]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.rsquared
```

[128]: 0.552871437510315

[129]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',␣
↪'waterfront']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.rsquared
```

[129]: 0.5733582227842691

[130]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',␣
↪'waterfront',
             'bedrooms', 'bathrooms']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.rsquared
```

[130]: 0.5742774950797981

[131]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',␣
↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
print(model.rsquared)
```

```
0.5813996239007405
```

[132]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',␣
↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement', 'floors']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
```

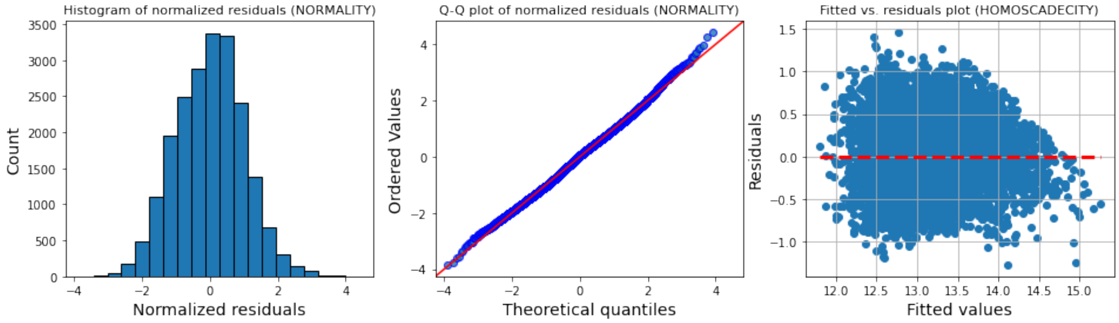
```python
print(model.rsquared)
```

```
0.5839041800981312
```

[133]:
```python
model.summary()
```

[133]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.584
Model:                            OLS   Adj. R-squared:                  0.584
Method:                 Least Squares   F-statistic:                     2932.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:00   Log-Likelihood:                -6504.1
No. Observations:               20904   AIC:                         1.303e+04
Df Residuals:                   20893   BIC:                         1.312e+04
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.8146      0.026    417.754      0.000      10.764      10.865
sqft_living      0.0002   5.43e-06     38.001      0.000       0.000       0.000
sqft_lot     -1.471e-06   1.98e-07     -7.413      0.000   -1.86e-06   -1.08e-06
condition        0.0954      0.004     25.884      0.000       0.088       0.103
grade            0.1911      0.003     57.642      0.000       0.185       0.198
has_view         0.1825      0.008     21.539      0.000       0.166       0.199
waterfront       0.4293      0.031     13.709      0.000       0.368       0.491
bedrooms        -0.0201      0.003     -5.965      0.000      -0.027      -0.013
bathrooms       -0.0279      0.005     -5.386      0.000      -0.038      -0.018
has_basement     0.1159      0.005     21.687      0.000       0.105       0.126
floors           0.0636      0.006     11.214      0.000       0.052       0.075
==============================================================================
Omnibus:                       11.677   Durbin-Watson:                   1.980
Prob(Omnibus):                  0.003   Jarque-Bera (JB):               11.672
Skew:                           0.058   Prob(JB):                      0.00292
Kurtosis:                       3.011   Cond. No.                     2.24e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.24e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[134]:
```
normality_homoscadecity(model);
```



[135]:
```
multicollinearity(X)
```

[135]:

	0
const	128.3504
sqft_living	4.2572
bathrooms	2.8699
grade	2.7510
floors	1.7974
bedrooms	1.7152
has_basement	1.2957
has_view	1.1752
sqft_lot	1.1586
condition	1.0991
waterfront	1.0628

- We increased R2 to 0.584 while still keeping normality and homoscadecity intact.
- All variables are statistically significant.

0.11.6 MODEL #6

- Adding the month the house was sold (January is reference) to the model.

[136]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',␣
 ↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement', 'floors',
             'april', 'august', 'december', 'february', 'july', 'june', 'march',
               'may', 'november', 'october', 'september']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
```

```python
model.summary()
```

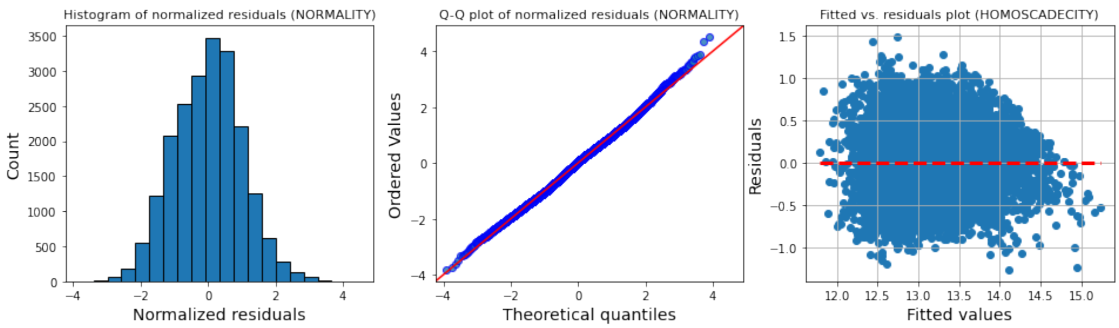
[136]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.586
Model:                            OLS   Adj. R-squared:                  0.586
Method:                 Least Squares   F-statistic:                     1409.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:00   Log-Likelihood:                -6446.0
No. Observations:               20904   AIC:                         1.294e+04
Df Residuals:                   20882   BIC:                         1.311e+04
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.7851      0.028    389.308      0.000      10.731      10.839
sqft_living      0.0002   5.41e-06     38.221      0.000       0.000       0.000
sqft_lot     -1.469e-06   1.98e-07     -7.424      0.000   -1.86e-06   -1.08e-06
condition        0.0964      0.004     26.187      0.000       0.089       0.104
grade            0.1908      0.003     57.690      0.000       0.184       0.197
has_view         0.1817      0.008     21.502      0.000       0.165       0.198
waterfront       0.4284      0.031     13.714      0.000       0.367       0.490
bedrooms        -0.0204      0.003     -6.085      0.000      -0.027      -0.014
bathrooms       -0.0277      0.005     -5.363      0.000      -0.038      -0.018
has_basement     0.1155      0.005     21.662      0.000       0.105       0.126
floors           0.0639      0.006     11.294      0.000       0.053       0.075
april            0.0813      0.013      6.341      0.000       0.056       0.106
august           0.0143      0.013      1.088      0.277      -0.011       0.040
december        -0.0041      0.014     -0.293      0.769      -0.031       0.023
february         0.0049      0.014      0.342      0.733      -0.023       0.033
july             0.0178      0.013      1.380      0.168      -0.007       0.043
june             0.0272      0.013      2.104      0.035       0.002       0.052
march            0.0571      0.013      4.324      0.000       0.031       0.083
may              0.0390      0.013      3.067      0.002       0.014       0.064
november         0.0033      0.014      0.236      0.813      -0.024       0.031
october          0.0191      0.013      1.442      0.149      -0.007       0.045
september        0.0160      0.013      1.200      0.230      -0.010       0.042
==============================================================================
Omnibus:                        9.523   Durbin-Watson:                   1.983
Prob(Omnibus):                  0.009   Jarque-Bera (JB):                9.509
Skew:                           0.052   Prob(JB):                      0.00861
Kurtosis:                       3.015   Cond. No.                     2.78e+05
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.78e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[137]:

```
normality_homoscadecity(model);
```



[138]:

```
multicollinearity(X)
```

[138]:

	0
const	147.7278
sqft_living	4.2592
may	3.0693
april	2.9614
july	2.9319
june	2.9041
bathrooms	2.8723
grade	2.7531
august	2.7078
march	2.6760
october	2.6552
september	2.5760
december	2.3326
november	2.2822
february	2.1584
floors	1.7988
bedrooms	1.7161
has_basement	1.2968
has_view	1.1760
sqft_lot	1.1589
condition	1.1038
waterfront	1.0632

- R2 increased very slightly from 0.584 to .586 - normality and homoscadecity are intact, and multicollinearity is absent.
- It seems like it is the months of spring that have an impact on price. But there are also a lot of non-signifcant months. Let's remove the nonsignificant months from the model to increase its performance (non-signifcance means that there is insufficient evidence in your sample to conclude that a correlation exists).

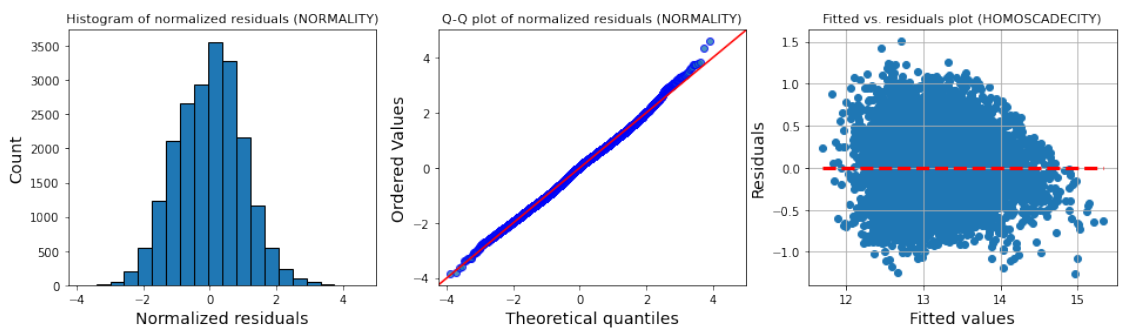
Removing nonsignificant months:

[139]:
```python
variables = ['sqft_living', 'log_sqft_lot', 'condition', 'grade', 'has_view',
 ↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement', 'floors',
             'april', 'march', 'may', 'june']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[139]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.591
Model:                            OLS   Adj. R-squared:                  0.591
Method:                 Least Squares   F-statistic:                     2157.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:01   Log-Likelihood:                -6322.2
No. Observations:               20904   AIC:                         1.267e+04
Df Residuals:                   20889   BIC:                         1.279e+04
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.3883      0.043    264.906      0.000      11.304      11.473
sqft_living      0.0002   5.66e-06     41.670      0.000       0.000       0.000
log_sqft_lot    -0.0665      0.004    -17.676      0.000      -0.074      -0.059
condition        0.0979      0.004     26.765      0.000       0.091       0.105
grade            0.1904      0.003     57.923      0.000       0.184       0.197
has_view         0.1827      0.008     21.762      0.000       0.166       0.199
waterfront       0.4553      0.031     14.648      0.000       0.394       0.516
bedrooms        -0.0171      0.003     -5.148      0.000      -0.024      -0.011
bathrooms       -0.0331      0.005     -6.432      0.000      -0.043      -0.023
has_basement     0.0890      0.006     16.043      0.000       0.078       0.100
floors           0.0194      0.006      3.097      0.002       0.007       0.032
```

```
april            0.0703      0.008      9.248      0.000       0.055       0.085
march            0.0462      0.008      5.626      0.000       0.030       0.062
may              0.0269      0.007      3.633      0.000       0.012       0.041
june             0.0181      0.008      2.349      0.019       0.003       0.033
==============================================================================
Omnibus:                        9.095   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.011   Jarque-Bera (JB):                9.121
Skew:                           0.045   Prob(JB):                       0.0105
Kurtosis:                       3.049   Cond. No.                     4.27e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.27e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[140]:
```
normality_homoscadecity(model);
```



[141]:
```
multicollinearity(X)
```

[141]:

	0
const	360.1094
sqft_living	4.7209
bathrooms	2.8832
grade	2.7509
floors	2.2386
bedrooms	1.7102
log_sqft_lot	1.6723
has_basement	1.4218
has_view	1.1746
condition	1.1024
waterfront	1.0657
may	1.0548

```
april            1.0535
june             1.0526
march            1.0483
```

- R2 increased from 0.584 to 0.591 with the addition of month variable.
- Normality and homoscadecity intact.
- All variables are statistically significant.

0.11.7 MODEL #7

- adding `age<30`

[142]:
```
variables = ['sqft_living', 'log_sqft_lot', 'condition', 'grade', 'has_view',␣
 ↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement', 'floors',
             'april', 'march', 'may', 'june',
             'age<30']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[142]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.602
Model:                            OLS   Adj. R-squared:                  0.601
Method:                 Least Squares   F-statistic:                     2104.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:02   Log-Likelihood:                -6045.4
No. Observations:               20904   AIC:                         1.212e+04
Df Residuals:                   20888   BIC:                         1.225e+04
Df Model:                          15
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.4741      0.043    269.472      0.000      11.391      11.558
sqft_living      0.0002   5.59e-06     42.195      0.000       0.000       0.000
log_sqft_lot    -0.0762      0.004    -20.405      0.000      -0.083      -0.069
condition        0.0684      0.004     17.914      0.000       0.061       0.076
grade            0.1988      0.003     60.928      0.000       0.192       0.205
has_view         0.1629      0.008     19.556      0.000       0.147       0.179
waterfront       0.4487      0.031     14.626      0.000       0.389       0.509
```

```
bedrooms        -0.0285      0.003     -8.570      0.000      -0.035      -0.022
bathrooms        0.0065      0.005      1.223      0.221      -0.004       0.017
has_basement     0.0657      0.006     11.809      0.000       0.055       0.077
floors           0.0656      0.006     10.114      0.000       0.053       0.078
april            0.0696      0.008      9.272      0.000       0.055       0.084
march            0.0456      0.008      5.627      0.000       0.030       0.061
may              0.0302      0.007      4.132      0.000       0.016       0.045
june             0.0178      0.008      2.339      0.019       0.003       0.033
age<30          -0.1664      0.007    -23.677      0.000      -0.180      -0.153
==============================================================================
Omnibus:                       17.606   Durbin-Watson:                   1.987
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20.068
Skew:                          -0.003   Prob(JB):                     4.39e-05
Kurtosis:                       3.152   Cond. No.                     4.28e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.28e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Remove bathrooms as it is not significant any more:

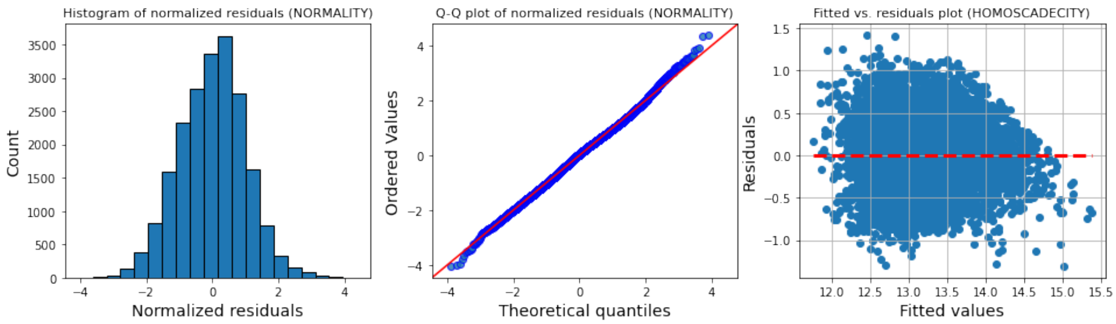
- It also correlates highly with `sqft_living`.

[143]:
```
variables = ['sqft_living', 'log_sqft_lot', 'condition', 'grade', 'has_view', 'waterfront',
             'bedrooms', 'has_basement', 'floors',
             'april', 'march', 'may', 'june',
             'age<30']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[143]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.602
Model:                            OLS   Adj. R-squared:                  0.601
Method:                 Least Squares   F-statistic:                     2254.
```

```
Date:                  Tue, 23 Aug 2022   Prob (F-statistic):                 0.00
Time:                          20:19:02   Log-Likelihood:                  -6046.1
No. Observations:                 20904   AIC:                           1.212e+04
Df Residuals:                     20889   BIC:                           1.224e+04
Df Model:                            14
Covariance Type:              nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.4737      0.043    269.467      0.000      11.390      11.557
sqft_living      0.0002   5.26e-06     45.307      0.000       0.000       0.000
log_sqft_lot    -0.0763      0.004    -20.467      0.000      -0.084      -0.069
condition        0.0687      0.004     18.039      0.000       0.061       0.076
grade            0.1992      0.003     61.375      0.000       0.193       0.206
has_view         0.1630      0.008     19.567      0.000       0.147       0.179
waterfront       0.4489      0.031     14.632      0.000       0.389       0.509
bedrooms        -0.0275      0.003     -8.516      0.000      -0.034      -0.021
has_basement     0.0670      0.005     12.278      0.000       0.056       0.078
floors           0.0670      0.006     10.472      0.000       0.054       0.080
april            0.0696      0.008      9.270      0.000       0.055       0.084
march            0.0455      0.008      5.619      0.000       0.030       0.061
may              0.0301      0.007      4.122      0.000       0.016       0.044
june             0.0179      0.008      2.353      0.019       0.003       0.033
age<30          -0.1638      0.007    -24.527      0.000      -0.177      -0.151
==============================================================================
Omnibus:                       17.640   Durbin-Watson:                   1.987
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20.104
Skew:                          -0.004   Prob(JB):                     4.31e-05
Kurtosis:                       3.152   Cond. No.                     4.28e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.28e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[144]:
```
normality_homoscadecity(model);
```



[145]:
```
multicollinearity(X)
```

[145]:
```
                      0
const          362.7151
sqft_living      4.1756
grade            2.7550
floors           2.3907
age<30           2.1350
log_sqft_lot     1.6902
bedrooms         1.6554
has_basement     1.4128
condition        1.2280
has_view         1.1866
waterfront       1.0657
may              1.0551
april            1.0535
june             1.0524
march            1.0483
```

- R2 increased from .591 to .602 with the addition of `age` variable.
- Normality and homoscadecity intact.

0.11.8 FINAL MODEL #8

- adding location variables

[146]:
```
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view'␣
↪,'waterfront',
             'bedrooms', 'has_basement', 'floors',
             'april', 'march', 'may', 'june',
             'age<30',
             'east', 'fareast','north', 'west']

y = data['log_price']
X = data[variables]
```

```python
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[146]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.752
Method:                 Least Squares   F-statistic:                     3531.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:02   Log-Likelihood:                -1066.0
No. Observations:               20904   AIC:                             2170.
Df Residuals:                   20885   BIC:                             2321.
Df Model:                          18
Covariance Type:            nonrobust
==============================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.6461      0.020    527.661      0.000      10.607      10.686
sqft_living      0.0002   3.98e-06     54.679      0.000       0.000       0.000
sqft_lot      1.462e-06   1.58e-07      9.252      0.000    1.15e-06    1.77e-06
condition        0.0834      0.003     27.687      0.000       0.077       0.089
grade            0.1608      0.003     62.077      0.000       0.156       0.166
has_view         0.1427      0.007     21.628      0.000       0.130       0.156
waterfront       0.5171      0.024     21.397      0.000       0.470       0.564
bedrooms        -0.0030      0.003     -1.155      0.248      -0.008       0.002
has_basement     0.0173      0.004      4.032      0.000       0.009       0.026
floors           0.0303      0.005      6.315      0.000       0.021       0.040
april            0.0677      0.006     11.452      0.000       0.056       0.079
march            0.0561      0.006      8.786      0.000       0.044       0.069
may              0.0169      0.006      2.939      0.003       0.006       0.028
june             0.0090      0.006      1.494      0.135      -0.003       0.021
age<30          -0.0246      0.005     -4.533      0.000      -0.035      -0.014
east             0.4867      0.005     90.505      0.000       0.476       0.497
fareast          0.4006      0.006     62.555      0.000       0.388       0.413
north            0.3322      0.008     40.583      0.000       0.316       0.348
west             0.5308      0.005    104.297      0.000       0.521       0.541
==============================================================================
Omnibus:                      581.185   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1409.328
Skew:                          -0.090   Prob(JB):                    9.30e-307
Kurtosis:                       4.259   Cond. No.                     2.25e+05
==============================================================================

Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.25e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

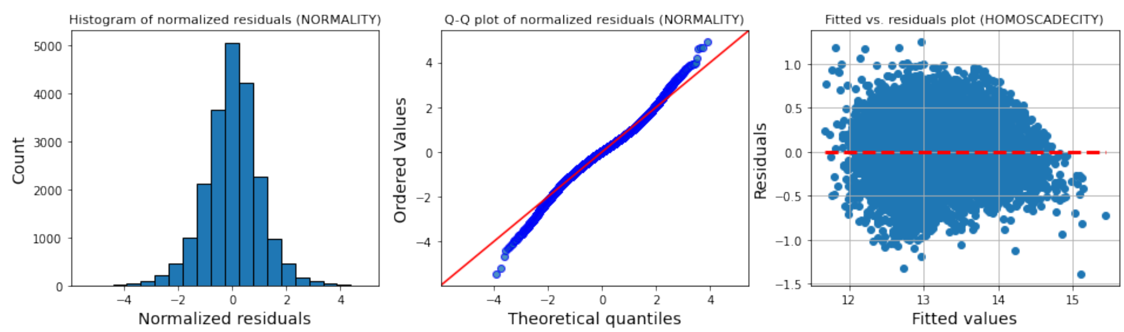
Remove bedrooms and june from the model:

[147]:
```python
variables = variables = ['sqft_living', 'sqft_lot', 'condition', 'grade',␣
↪'has_view' ,'waterfront',
             'has_basement', 'floors',
             'april', 'march', 'may',
             'age<30',
             'east', 'fareast','north', 'west']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[147]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.752
Method:                 Least Squares   F-statistic:                     3972.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:02   Log-Likelihood:                -1067.8
No. Observations:               20904   AIC:                             2170.
Df Residuals:                   20887   BIC:                             2305.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.6384      0.019    563.259      0.000      10.601      10.675
sqft_living      0.0002   3.43e-06     62.667      0.000       0.000       0.000
sqft_lot       1.48e-06   1.57e-07      9.407      0.000    1.17e-06    1.79e-06
condition        0.0834      0.003     27.712      0.000       0.078       0.089
grade            0.1612      0.003     62.788      0.000       0.156       0.166
has_view         0.1433      0.007     21.805      0.000       0.130       0.156
waterfront       0.5184      0.024     21.474      0.000       0.471       0.566
has_basement     0.0171      0.004      4.005      0.000       0.009       0.026
floors           0.0300      0.005      6.257      0.000       0.021       0.039
```

```
april            0.0664     0.006     11.346     0.000     0.055     0.078
march            0.0547     0.006      8.651     0.000     0.042     0.067
may              0.0156     0.006      2.742     0.006     0.004     0.027
age<30          -0.0240     0.005     -4.440     0.000    -0.035    -0.013
east             0.4868     0.005     90.527     0.000     0.476     0.497
fareast          0.4012     0.006     62.808     0.000     0.389     0.414
north            0.3324     0.008     40.612     0.000     0.316     0.348
west             0.5316     0.005    105.152     0.000     0.522     0.541
==============================================================================
Omnibus:                      579.603   Durbin-Watson:                   1.988
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1406.417
Skew:                          -0.088   Prob(JB):                    3.99e-306
Kurtosis:                       4.258   Cond. No.                     2.24e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.24e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[148]:
```
normality_homoscadecity(model);
```



[149]:
```
multicollinearity(X)
```

[149]:

	0
const	114.8988
sqft_living	2.8630
grade	2.7764
age<30	2.2580
floors	2.1560
west	1.8748
east	1.5564
has_basement	1.3967

```
fareast         1.3886
condition       1.2346
sqft_lot        1.2261
has_view        1.1903
north           1.1738
waterfront      1.0626
may             1.0318
april           1.0313
march           1.0295
```

- R2 increased from .602 to .753 with the addition of locations!
- Homoscadecity is still intact.
- Normality is worse with the addition of this variable but it is still acceptable.
- No multicollinearity.

Model with log-transformed independent variables to see if the normality will be improved:

[150]:
```
variables = variables = ['log_sqft_living', 'log_sqft_lot', 'condition',␣
↪'grade', 'has_view', 'waterfront',
             'has_basement', 'floors',
             'april', 'march', 'may',
             'age<30',
             'east', 'fareast','north', 'west']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[150]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.756
Model:                            OLS   Adj. R-squared:                  0.756
Method:                 Least Squares   F-statistic:                     4044.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:03   Log-Likelihood:                -927.26
No. Observations:               20904   AIC:                             1889.
Df Residuals:                   20887   BIC:                             2024.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
```

```
0.975]
--------------------------------------------------------------------------------
---
const               7.4255      0.044    170.017      0.000       7.340
7.511
log_sqft_living     0.4525      0.007     60.360      0.000       0.438
0.467
log_sqft_lot        0.0276      0.003      8.706      0.000       0.021
0.034
condition           0.0796      0.003     26.573      0.000       0.074
0.086
grade               0.1650      0.002     66.444      0.000       0.160
0.170
has_view            0.1568      0.007     24.087      0.000       0.144
0.170
waterfront          0.5308      0.024     22.115      0.000       0.484
0.578
has_basement       -0.0048      0.005     -1.051      0.293      -0.014
0.004
floors              0.0209      0.005      4.096      0.000       0.011
0.031
april               0.0656      0.006     11.284      0.000       0.054
0.077
march               0.0547      0.006      8.698      0.000       0.042
0.067
may                 0.0175      0.006      3.099      0.002       0.006
0.029
age<30             -0.0201      0.005     -3.663      0.000      -0.031
-0.009
east                0.4955      0.005     92.825      0.000       0.485
0.506
fareast             0.4097      0.006     64.674      0.000       0.397
0.422
north               0.3339      0.008     41.081      0.000       0.318
0.350
west                0.5638      0.005    105.623      0.000       0.553
0.574
==============================================================================
Omnibus:                      564.380   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1424.854
Skew:                           0.003   Prob(JB):                    3.95e-310
Kurtosis:                       4.279   Cond. No.                         366.
==============================================================================

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

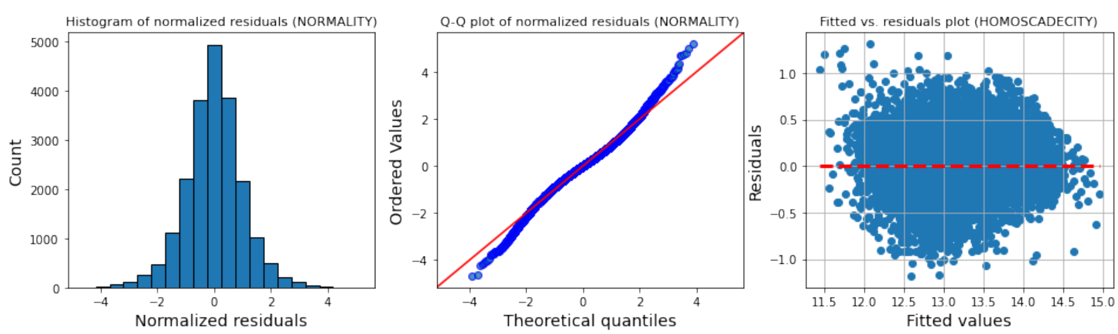
"""

[151]:
```
variables = variables = ['log_sqft_living', 'log_sqft_lot', 'condition',␣
↪'grade', 'has_view', 'waterfront',
             'floors',
             'april', 'march', 'may',
             'age<30',
             'east', 'fareast','north', 'west']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[151]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.756
Model:                            OLS   Adj. R-squared:                  0.756
Method:                 Least Squares   F-statistic:                     4313.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:03   Log-Likelihood:                -927.82
No. Observations:               20904   AIC:                             1888.
Df Residuals:                   20888   BIC:                             2015.
Df Model:                          15
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
const               7.4384      0.042    177.491      0.000       7.356
7.521
log_sqft_living     0.4489      0.007     67.003      0.000       0.436
0.462
log_sqft_lot        0.0285      0.003      9.297      0.000       0.022
0.034
condition           0.0796      0.003     26.573      0.000       0.074
0.086
grade               0.1652      0.002     66.689      0.000       0.160
0.170
has_view            0.1562      0.006     24.089      0.000       0.143
0.169
```

```
waterfront              0.5304        0.024       22.099       0.000        0.483
0.577
floors                  0.0230        0.005        4.859       0.000        0.014
0.032
april                   0.0656        0.006       11.284       0.000        0.054
0.077
march                   0.0547        0.006        8.700       0.000        0.042
0.067
may                     0.0175        0.006        3.096       0.002        0.006
0.029
age<30                 -0.0197        0.005       -3.602       0.000       -0.030
-0.009
east                    0.4955        0.005       92.819       0.000        0.485
0.506
fareast                 0.4100        0.006       64.788       0.000        0.398
0.422
north                   0.3335        0.008       41.080       0.000        0.318
0.349
west                    0.5627        0.005      107.414       0.000        0.552
0.573
==============================================================================
Omnibus:                      564.179   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1423.955
Skew:                           0.005   Prob(JB):                    6.20e-310
Kurtosis:                       4.279   Cond. No.                         351.
==============================================================================

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

[152]:
```
normality_homoscadecity(model);
```



- Slight imporovement in R2 but slight worsening in Kurtosis and Jarque-Bera (JB).

- For ease of interpretation let's keep the previous model.

[153]:
```
variables =  ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view'␣
 ↪,'waterfront',
             'has_basement', 'floors',
             'april', 'march', 'may',
             'age<30',
             'east', 'fareast','north', 'west']

y = data['log_price']
X = data[variables]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[153]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.752
Method:                 Least Squares   F-statistic:                     3972.
Date:                Tue, 23 Aug 2022   Prob (F-statistic):               0.00
Time:                        20:19:03   Log-Likelihood:                -1067.8
No. Observations:               20904   AIC:                             2170.
Df Residuals:                   20887   BIC:                             2305.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.6384      0.019    563.259      0.000      10.601      10.675
sqft_living      0.0002   3.43e-06     62.667      0.000       0.000       0.000
sqft_lot       1.48e-06   1.57e-07      9.407      0.000    1.17e-06    1.79e-06
condition        0.0834      0.003     27.712      0.000       0.078       0.089
grade            0.1612      0.003     62.788      0.000       0.156       0.166
has_view         0.1433      0.007     21.805      0.000       0.130       0.156
waterfront       0.5184      0.024     21.474      0.000       0.471       0.566
has_basement     0.0171      0.004      4.005      0.000       0.009       0.026
floors           0.0300      0.005      6.257      0.000       0.021       0.039
april            0.0664      0.006     11.346      0.000       0.055       0.078
march            0.0547      0.006      8.651      0.000       0.042       0.067
may              0.0156      0.006      2.742      0.006       0.004       0.027
age<30          -0.0240      0.005     -4.440      0.000      -0.035      -0.013
east             0.4868      0.005     90.527      0.000       0.476       0.497
fareast          0.4012      0.006     62.808      0.000       0.389       0.414
```

```
north             0.3324      0.008     40.612      0.000       0.316       0.348
west              0.5316      0.005    105.152      0.000       0.522       0.541
==============================================================================
Omnibus:                      579.603   Durbin-Watson:                   1.988
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1406.417
Skew:                          -0.088   Prob(JB):                    3.99e-306
Kurtosis:                       4.258   Cond. No.                     2.24e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.24e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[159]:
```python
coefs = model.params.apply('{0:.6f}'.format)
coefs = pd.DataFrame(coefs).reset_index()
coefs = coefs.rename({'index':'var', 0:'coef'}, axis =1)
coefs.coef = pd.to_numeric(coefs.coef)
coefs
```

[159]:

	var	coef
0	const	10.638372
1	sqft_living	0.000215
2	sqft_lot	0.000001
3	condition	0.083434
4	grade	0.161232
5	has_view	0.143341
6	waterfront	0.518445
7	has_basement	0.017130
8	floors	0.029957
9	april	0.066388
10	march	0.054738
11	may	0.015626
12	age<30	-0.024027
13	east	0.486775
14	fareast	0.401208
15	north	0.332381
16	west	0.531562

[155]:
```python
# https://data.library.virginia.edu/
↪interpreting-log-transformations-in-a-linear-model/
# Because the target variable is log-transformed let's exponentiate the␣
↪coefficients.
coefs['exp_coef'] = ((np.exp(coefs.coef) - 1) * 100).apply('{0:.6f}'.format)
coefs
```

[155]:

	var	coef	exp_coef
0	const	10.638372	4170382.047389
1	sqft_living	0.000215	0.021502
2	sqft_lot	0.000001	0.000100
3	condition	0.083434	8.701347
4	grade	0.161232	17.495753
5	has_view	0.143341	15.412329
6	waterfront	0.518445	67.941413
7	has_basement	0.017130	1.727756
8	floors	0.029957	3.041023
9	april	0.066388	6.864127
10	march	0.054738	5.626384
11	may	0.015626	1.574872
12	age<30	-0.024027	-2.374065
13	east	0.486775	62.706048
14	fareast	0.401208	49.362791
15	north	0.332381	39.428397
16	west	0.531562	70.158811

Model summary:

- R-squared of 0.753 means that the dependent variables explain 75% of the variability in price.
- All variables are statistically significnant (p <.05) meaning we can reject the null that are not related to price.
- Normality is acceptaple, homoscadecity is preserved, no presence of multicollinearity,
- Durbin-Watson score is between 1.5 and 2.5, meaning: no first-order autocorrelation.
- Skewness is between -0.5 and 0.5, it is approximately symmetric.
- Kurtosis is 4.2 which is not ideal but acceptable. An increased kurtosis (>3) can be visualized as a thinner "bell" with a higher peak. Hair et al. (2010) and Bryne (2010) argues that data is considered normal if skewness is between -2 to +2 and kurtosis is between -7 to +7.

Coefficient interpretation:

- For every 1 unit increase in `sqft_living` price increases by about 0.022 %
- For every 100 sqft increase in the house price increases by about 2.2 %.
- Average sqft of a house is 2000. Given all other variables are kept constant, if you increase a house size from 2000 to 3000 sqft you would increase price by 22%.
- For every 1 unit increase in `sqft_lot` price increases by 0.0001 %.
- For every 10000 sqft increase in the lot, price increases by about 1 %.
- For every 1 unit increase in `grade` price increases by 17 %.
- Being `waterfront` increases price by 68% compared to being non waterfront (given all other factors are same).
- Having `view` increases price by 15% compared to not having a view (given all other factors are same).

- For every `floor` added, price incrases by 3%.
- Houses sold in `April` are 6.8% more expensive than those sold in winter-fall or summer.
- Houses sold in `March` are 5.6% more expensive than those sold in winter-fall or summer.
- Houses sold in `May` are 1.5% more expensive than those sold in winter-fall or summer.
- Houses in `West-Seattle` are 70% more expensive than those in South (given all other factors are the same).
- Houses in `East` area are 62% more expensive than those in South.

0.11.9 Recommendations based on regression results:

1. Invest on increasing the total square footage of the house as much as possible (rather than investing on the lot size). For every 1000 sqft increase in the house price increases by about 22%.
2. Being on waterfront increases the house price by 67%, so invest on houses on waterfront. Having a view increases the house price by 15%, so invest on houses that has a view.
3. Put the house on the market in April which increases the price by 6.8%. The next best month is March with a 5.6% increase.
4. Invest on houses in Seattle for 70% increase in price, and Medina, Bellevue, Mercer Island and Kirkland for a 62% increase compared to the South.

0.11.10 Limitations

- Skewed data required outlier removal or data transformation which made the interpretations trickier.
- Although Zipcodes provided very useful information with regard to price, I did not feel comfortable using all 70 categories in the regression model.
- City to Zipcode mapping did not work due to the zipcode and city boundaries not being the same - many zipcodes belonging to various cities and vice versa. Total number of cities were also more than desired: 32.

0.11.11 Improvements

- Gather more detailed location info using API calls.
- Using cluster analysis group zipcodes into more meaningful clusters.

[160]:
```
./nbconvert.py --format=pdf KingCountySales.ipynb
```

```
  File "<ipython-input-160-745bf5d3884a>", line 1
    ./nbconvert.py --format=pdf KingCountySales.ipynb
    ^
SyntaxError: invalid syntax
```

[ ]:
```
```