Notebook

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0.1 King County House Regression - Project#2

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- Scheduled project review date/time: ***August, 2022***
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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, Homoscadescacity 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]:
```
# Read the Data
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]:
```
# Checking to see how many null values are present
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]:
```
# Are there any rows duplicated?
df.duplicated().sum()
```

[6]:
```
0
```

[7]:
```
# Are there any house IDs duplicated?
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]:
```python
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 and keep the last sale in the dataset:

[9]:
```python
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]:
```python
df.shape
```

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

Handling NaN values:

[11]:
```python
# How many null values?
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]:
```python
df.waterfront.value_counts()
```

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

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

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

[14]:
```python
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]:
```python
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]:
```python
# What percentage of View is Null?
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
# Let's fill null with 0
df['yr_renovated'] = df['yr_renovated'].fillna(0)
```

[23]:
```
df.isnull().sum()
# No null values any more!
```

[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]:
```
# Which one of these variables are encoded in string format?
df_fixed.columns.to_series().groupby(df_fixed.dtypes).groups
```

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

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

[28]:
```
# Replacing NO and YES with 0 and 1
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]:
```
# Making sure datatype is now numerical
df_fixed["waterfront"].dtype
```

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

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

[30]:
```
NONE         19316
AVERAGE        956
```

```
GOOD           505
FAIR           329
EXCELLENT      314
Name: view, dtype: int64
```

[31]:
```python
# Replacing the string values with numerical values.
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]:
```python
df['condition'].value_counts()
```

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

[33]:
```python
# Replacing the string values with numerical values.
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]:
```python
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]:
```
# Replacing the string values with numerical values.
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
```

- For condition and grade I chose to leave them as ordinal with assumption that the categories of 1-5 or 3-13 could be defined by a numerical relationship.
- If I had assigned dummy variables I would lose the order but instead treat them all as separate categories. This was also an option but I chose to leave them as ordinal since I wanted to preserve the numerical relationship between the category levels.

[36]:
```
# What are the unique values for sqft_basement?
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]:
```python
# Replace ? with 0 and then convert to numerical data
df_fixed['sqft_basement'].replace('?', '0.0', inplace = True)
df_fixed['sqft_basement'] = pd.to_numeric(df_fixed['sqft_basement'])
df_fixed['sqft_basement'].dtype
```

[37]:
```
dtype('float64')
```

[38]:
```python
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
```

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

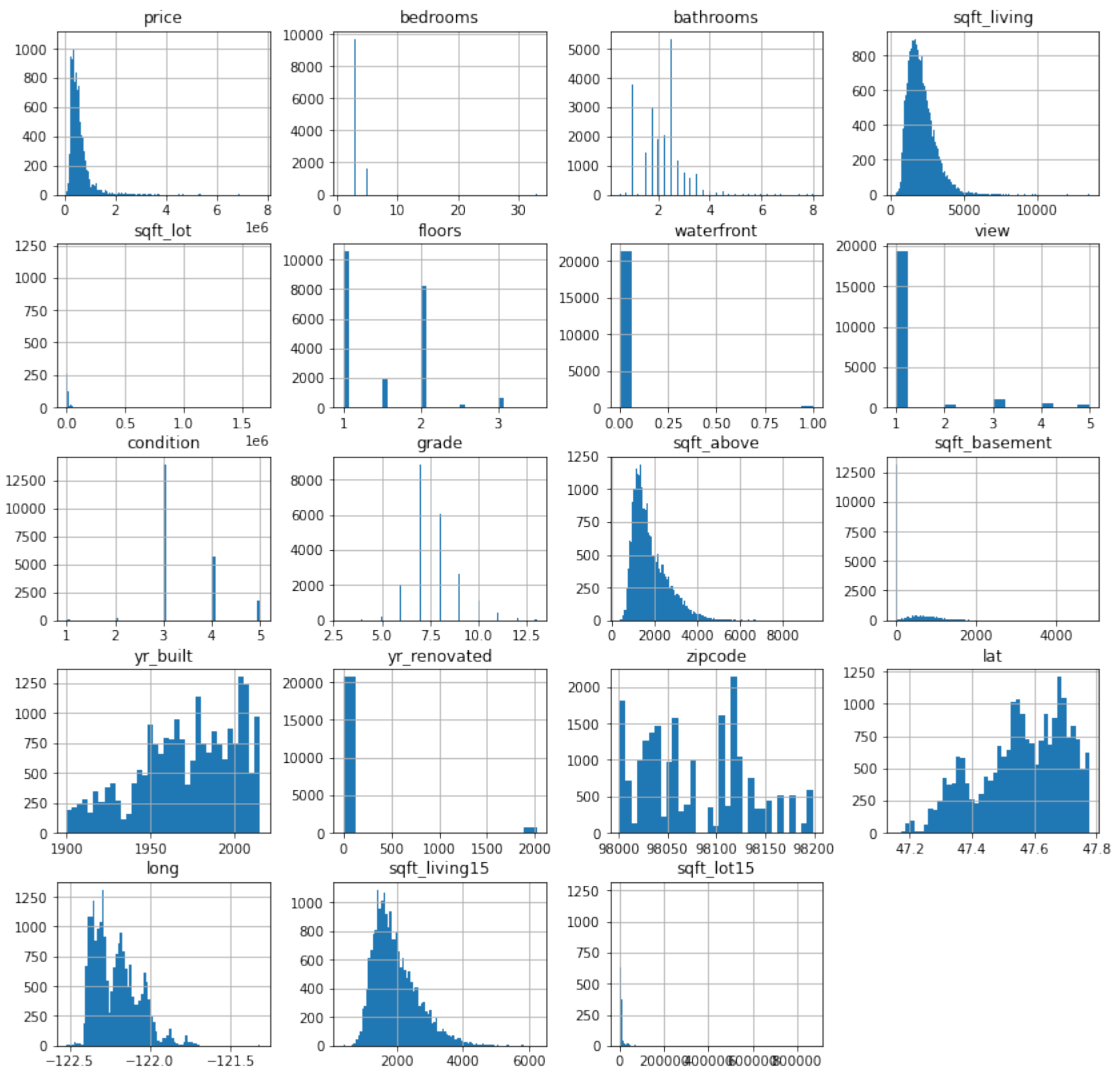
0.7 Feature Engineering:

[39]:
```
df_new = df_fixed.copy()
```

- Drop `id` column since it has no meaning

[40]:
```
df_new.drop(columns=['id'], inplace = True, axis=1)
```

[41]:
```
# Check out the distribution of all variables:
df_new.hist(bins='auto', edgecolor='none', figsize=(14,14));
```



The target / dependent variable:

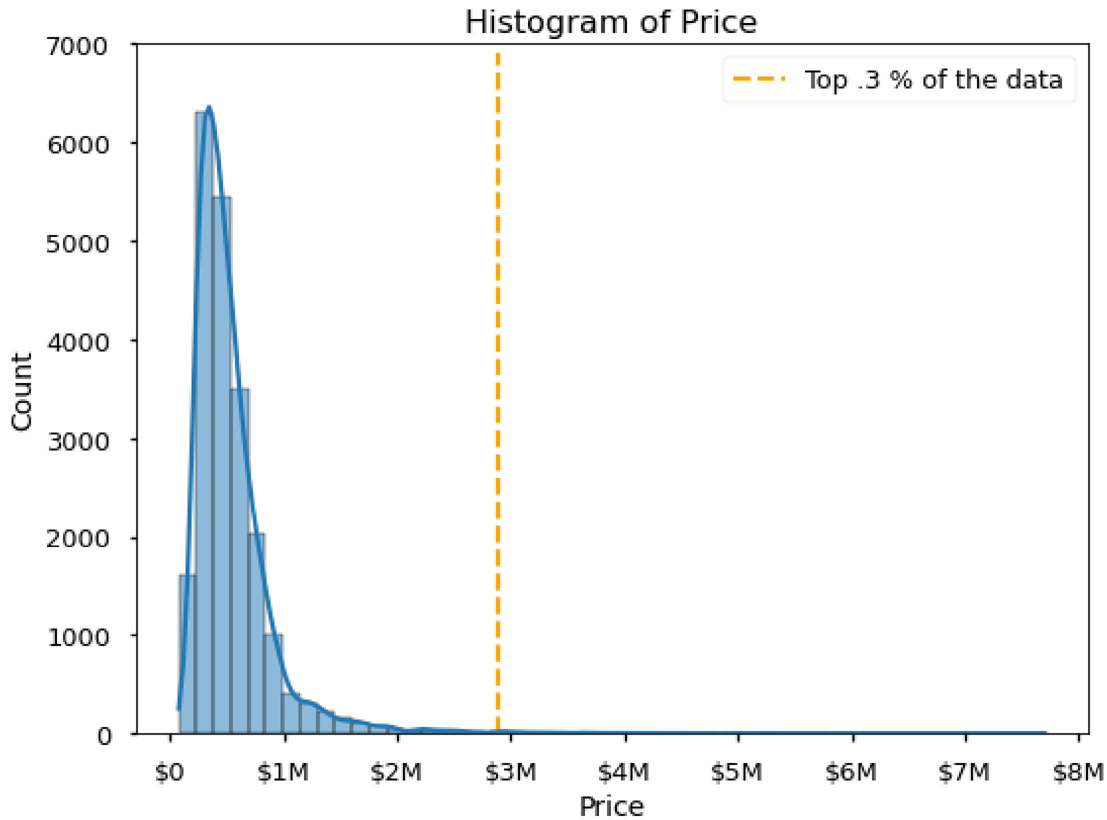
- The sale prices have a negative skew, meaning the majority of the data is in the lower values, and there are fewer very high values.
- We might also benefit from (log) transforming this variable.

[42]:
```python
# 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):
```

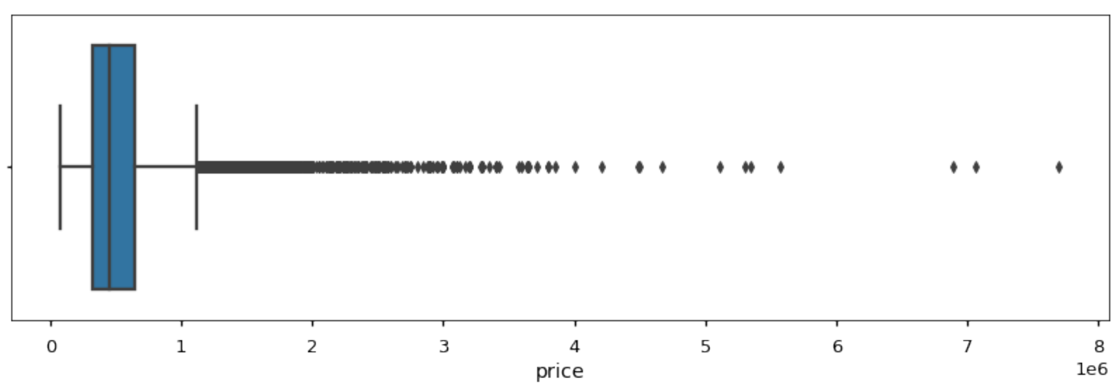
```
    magnitude = 0
    while abs(num) >= 1000:
        magnitude += 1
        num /= 1000.0
    return '$%.0f%s' % (num, ['', 'K', 'M', 'B', 'T', 'P'][magnitude])

formatter = FuncFormatter(human_format)
```

[43]:

```
# Histogram of Price:
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)
```



[44]:
```python
# Boxplot of Price:
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.

[45]:
```
# Checking to see what percentage of data we have removed in total:

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.
```

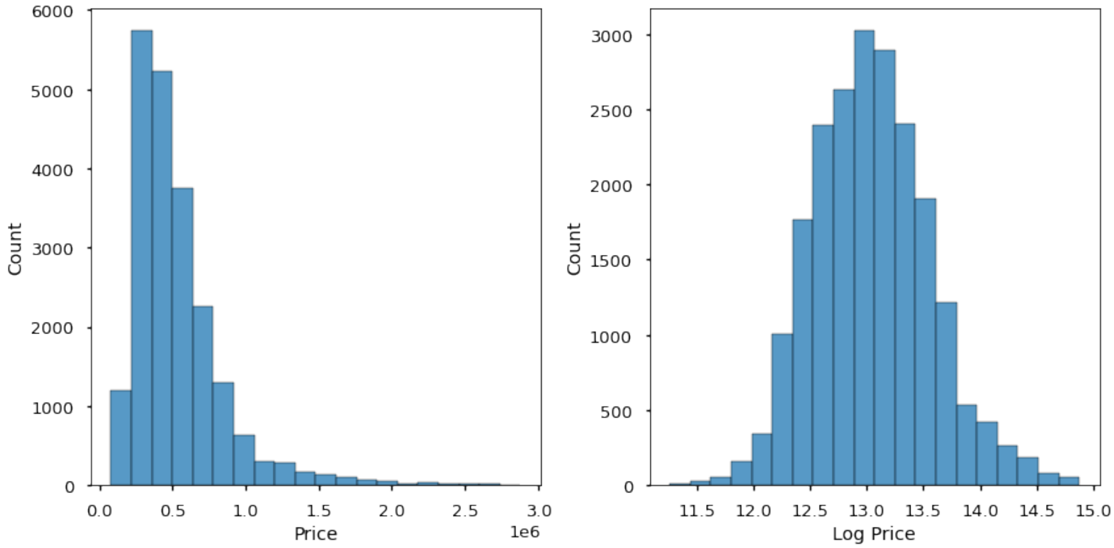
```
oldshape: (21420, 20)
newshape: (21355, 20)
65
0.30437836572231325
```

Log Transform the target variable:

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

[46]:
```
df_new['log_price'] = np.log(df_new['price'])
```

[47]:
```
# Price distribution before and after log transformation:

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.

[48]:
```
df_new['view'].value_counts()
```

[48]:
```
1    19297
3      950
4      499
2      325
5      284
Name: view, dtype: int64
```

[49]:
```
# Regrouping 1 to 0 (no view) and 2-5 into 1 (has view)
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()
```

[49]:
```
0    19297
1     2058
Name: has_view, dtype: int64
```

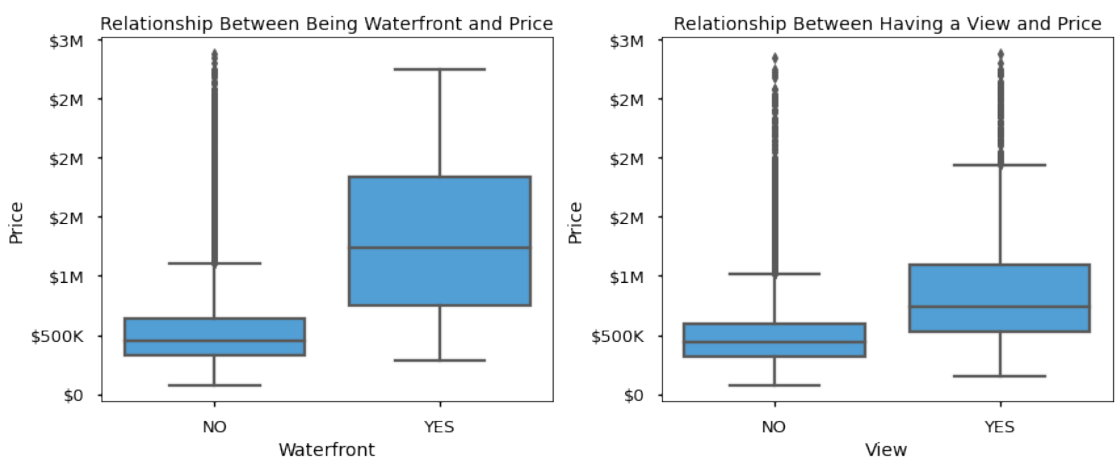
[50]:
```
print(df_new.corr()['price']['view'])
print(df_new.corr()['price']['has_view'])
```

```
# Let's use `has_view` instead of `view` since the correlation to price is␣
↪similar and it is more meaningful.
```

```
0.37483613089845086
0.3500682990327732
```

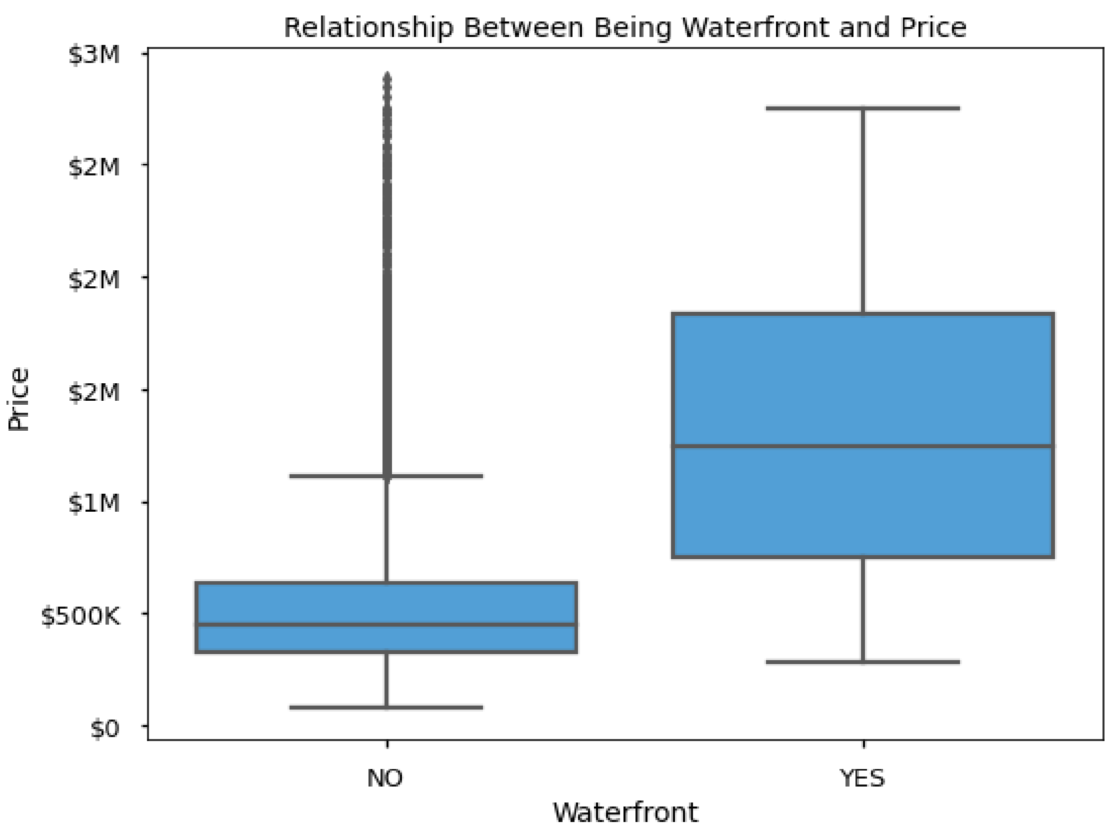
Visualizing Waterfront and View binary variables in relation to price:

[51]:
```
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);
```



[52]:

```
# Extra graph for the presentation only.
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, (ax) = plt.subplots(figsize=(8, 6))
    fig.set_tight_layout(True)

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

    fig.savefig('./images/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.

[53]:
```python
df_new['month'] = pd.to_datetime(df_new['date']).dt.month
df_new.drop(columns=['date'], inplace = True, axis=1)
```

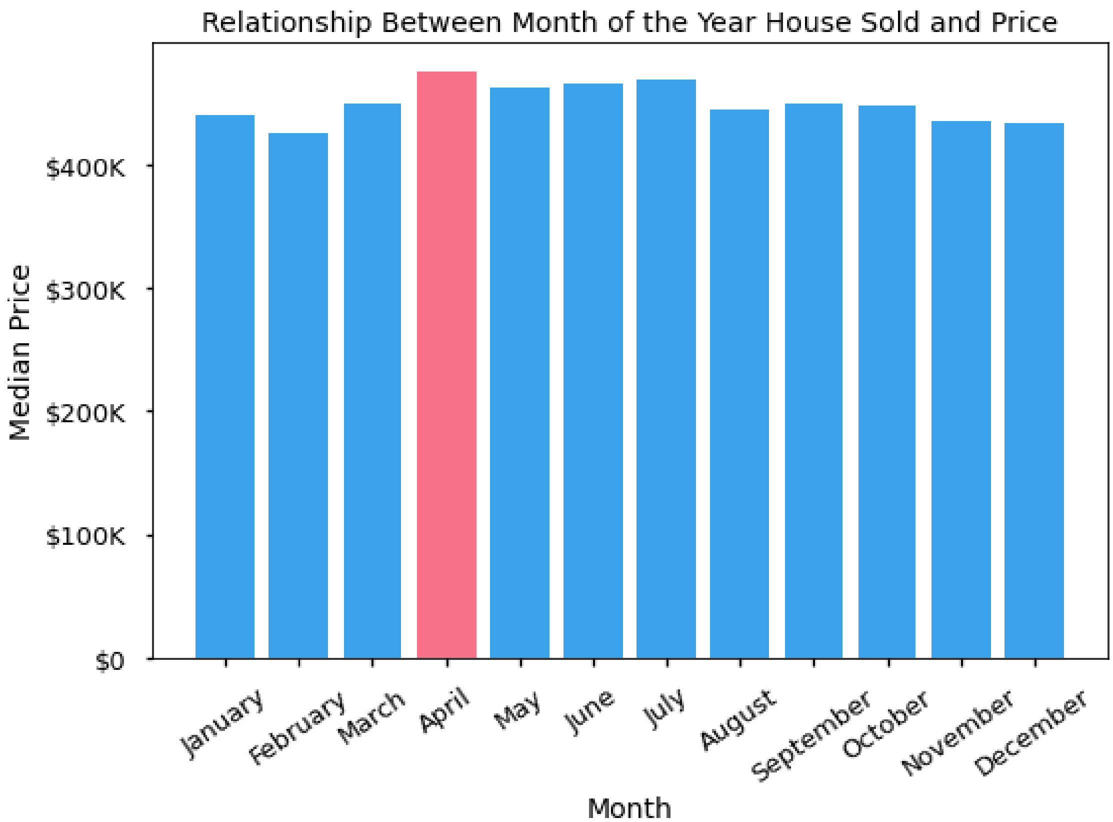
[54]:
```python
median_month = pd.DataFrame(df_new.groupby('month')['price'].median())  #␣
↪median because price is skewed
median_month
```

[54]:

month	price
1	440000.0
2	426045.0
3	450000.0
4	475000.0
5	462000.0
6	465000.0
7	469000.0
8	444000.0
9	450000.0
10	448000.0
11	435000.0
12	433250.0

[55]:
```python
# Barplot of median house price for each month:

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

with plt.style.context('seaborn-talk'):
    colors = [sns.color_palette("husl", 9)[0] if month == 4 else sns.
↪color_palette("husl", 9)[6] for month in median_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=median_month.index, height=median_month['price'], color =␣
↪colors)
    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);
```



- Replacing month number with month name, so that the 'month name' would appear as the 'column name' when we dummy code this variable:

[56]:
```
# Replacing month number with month name:
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.

[57]:
```
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()
```

[57]:
```
      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]
```

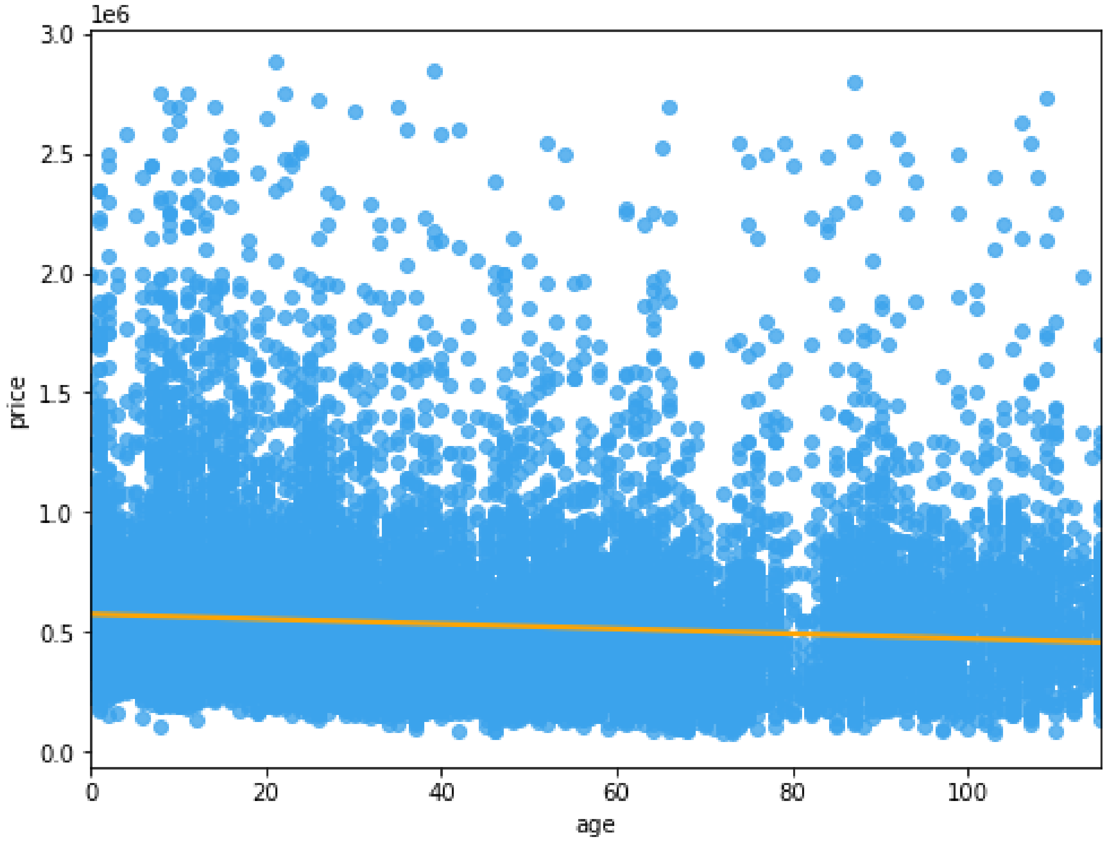
Creating an age related variable:

- 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`.

[58]:
```
# 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
```

[59]:
```
fig, ax = plt.subplots(figsize=(8, 6))
base_color = sns.color_palette("husl", 9)[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.
```

```
-0.09219731443044772
```



- 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.

[60]:
```python
# Creating a new binary variable `age<30` ro represent houses younger and older␣
↪than 30 years.
df_new['age<30'] = df_new['age'] < 30
df_new['age<30'].value_counts()
```

[60]:
```
False    12809
True      8546
Name: age<30, dtype: int64
```

[61]:
```python
# Renaming True and False with 0 and 1.
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()
```

[61]:
```
0    12809
1     8546
Name: age<30, dtype: int64
```

[62]:
```
print(df_new.corr()['price']['age'])
print(df_new.corr()['price']['age<30'])
```

```
-0.09219731443044772
0.16020160020637306
```

- Improvement in correlation with price when we binary code the age variable. Let's pick `age<30` over `age`.

[63]:
```
# Dropping unnecessary columns:
df_new = df_new.drop(['yr_built', 'yr_renovated', 'age', 'view'], axis=1)
```

Creating a location based variable:

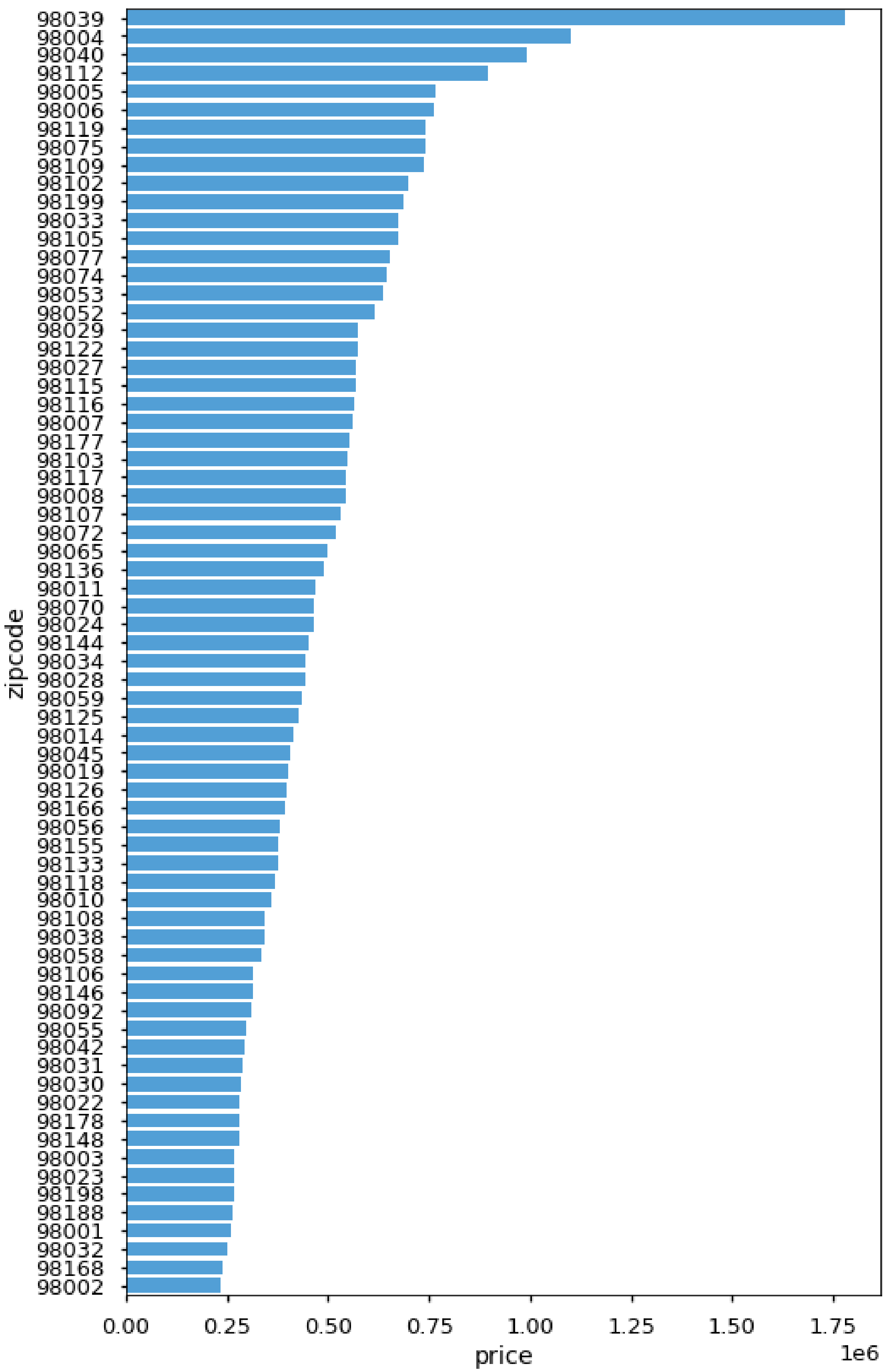
- There are 70 Zipcodes! Too many levels if we go for One Hot Encoding.
- We cannot leave it as label encoded either, zip numbers do not have a meaningful numerical relationship to one another.
- I will engineer a new "location" variable with more meaningful categorical distinctions using Longitude-Latitude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

[68]:
```
# Creating a dataframe to show median price for each Zipcode.
zipmedians = df_new.groupby('zipcode')['price'].median().
 ↪sort_values(ascending=False)
zipmedians = pd.DataFrame(zipmedians).reset_index()
zipmedians.head()
```

[68]:

	zipcode	price
0	98039	1780000.0
1	98004	1100000.0
2	98040	990000.0
3	98112	897500.0
4	98005	765475.0

[69]:
```
# Plotting the median price for each zipcode:
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ax  = plt.subplots(figsize=(8, 14))
    sns.barplot(x = zipmedians['price'], y= zipmedians['zipcode'],
                order = zipmedians.sort_values('price',ascending = False).
 ↪zipcode, ax=ax, color = base_color, orient = "h")
```



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

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

Upload city data to be able to superimpose on the map:

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

[70]:
```
# Read the data:
dfzip = pd.read_csv("./data/uszips.csv")
dfzip.head()
```

[70]:
```
   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
```

[71]:
```python
# 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
```

[71]:
```
         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]
```

[72]:

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

[72]:

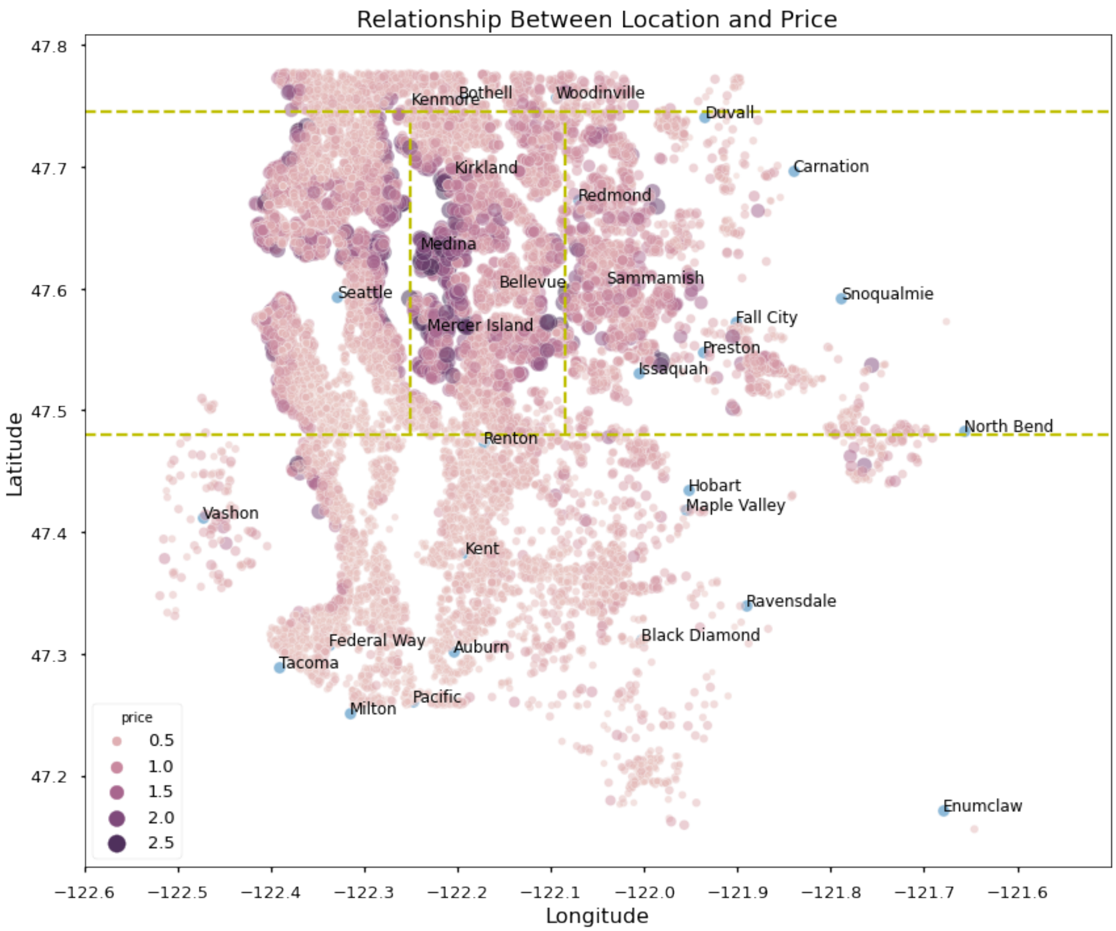
```
               city        lat         lng
0            Auburn  47.301967 -122.203720
1            Baring  47.735700 -121.568590
2          Bellevue  47.602148 -122.155832
3     Black Diamond  47.311730 -122.003260
4           Bothell  47.757360 -122.198710
5         Carnation  47.696640 -121.840240
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:

[73]:
```python
# For the purpose of graphing only remove far east cities of Baring, Skykomish,␣
↪Snoqualmie Pass:
dfzip_table.drop(index=[1,27,29], axis=0, inplace=True)
```

[74]:
```python
# 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.

[75]:
```
# Group latitude and longitude togetger to create a new variable called␣
↪`coordinates`
df_new['coordinates'] = list(zip(df_new.lat, df_new.long))

# Write a function to extract the region information based on coordinates
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])
```

[75]: 'west'

[76]:
```
# Apply the function on the coordinates to come up with a new variable called␣
 ↪`region`:
df_new['region'] = df_new['coordinates'].apply(region)
df_new['region'].head()
```

[76]:
```
0       west
1       west
2       east
3       west
4    fareast
Name: region, dtype: object
```

[77]:
```
# Check out median price for each region:
df_new.groupby('region')['price'].median()
```

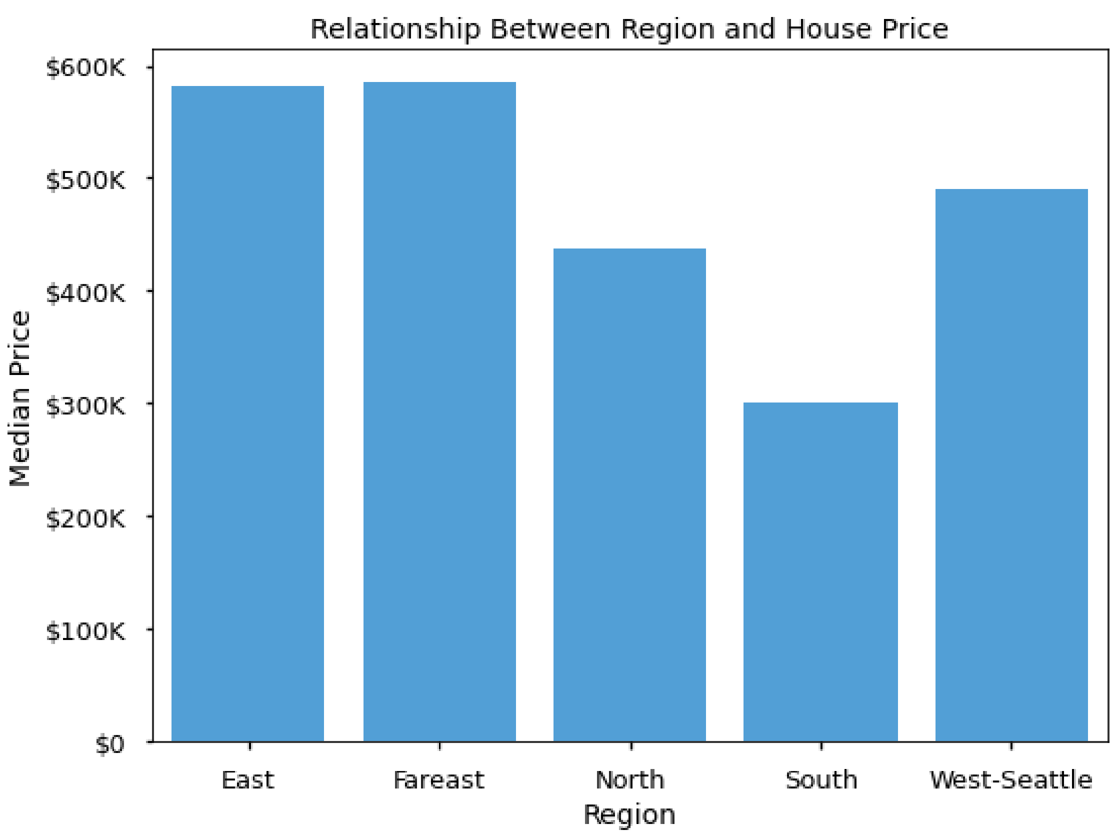
[77]:
```
region
east       582250.0
fareast    585000.0
north      437000.0
south      299900.0
west       490000.0
Name: price, dtype: float64
```

[78]:
```
df_new['region'].value_counts()
```

[78]:
```
west       7344
south      5661
east       4448
fareast    2665
north      1237
Name: region, dtype: int64
```

[79]:

```python
# Extract DataFrame of Median price for each region:
median_region = pd.DataFrame(df_new.groupby('region')['price'].median())  #␣
↪median because price is skewed

# Plot as a bar plot:
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ax  = plt.subplots(figsize=(8, 6))
    sns.barplot(x = median_region.index, y= median_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.

Dummy code region:

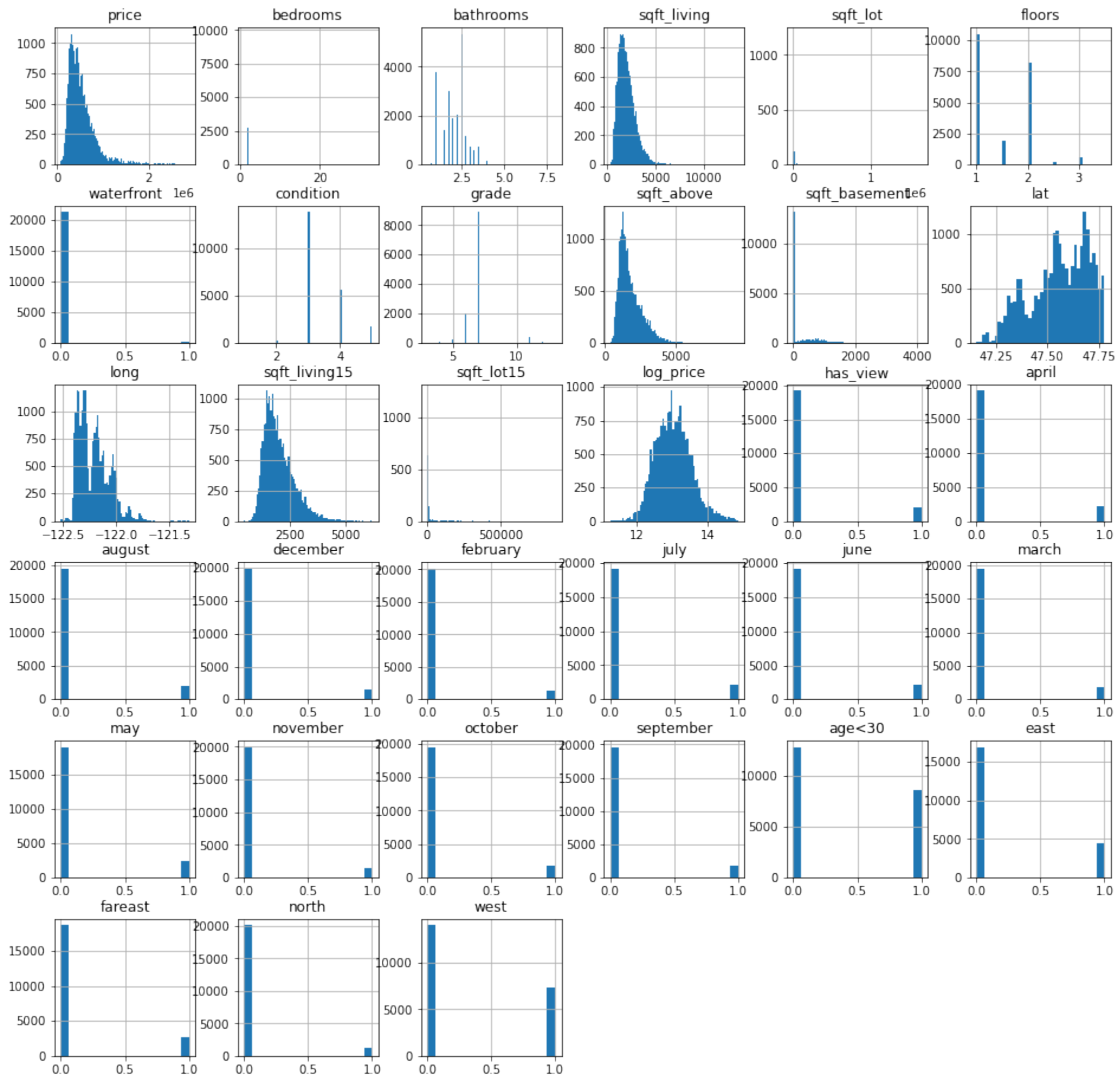
[80]:
```
# South region is the reference point:
region_dummies = pd.get_dummies(df_new['region']).drop(['south'],axis=1)
df_new = pd.concat([df_new, region_dummies], axis=1)
df_new.head()
```

[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]:
```
# Drop unnecessary variables:
df_new = df_new.drop(['region','coordinates', 'zipcode'], axis=1)
```

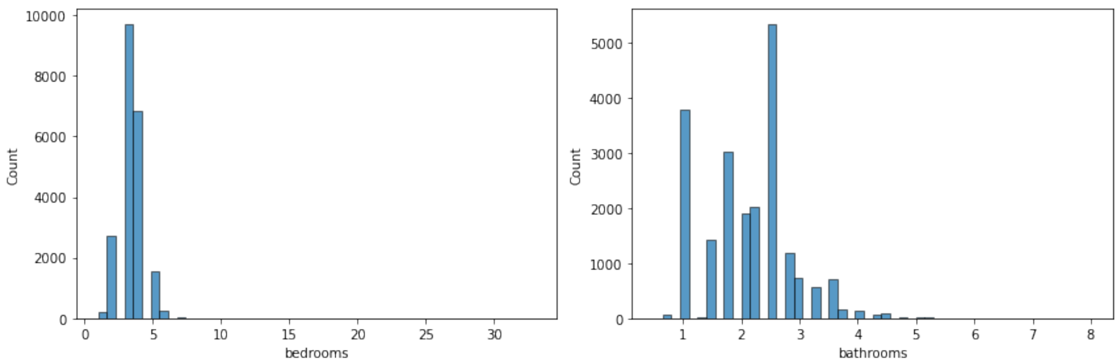
0.8 Feature Engineering Continued:

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



Remove outliers from bedrooms and bathrooms:

[83]:
```
# Histogram of bathrooms and bedrooms:
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
```

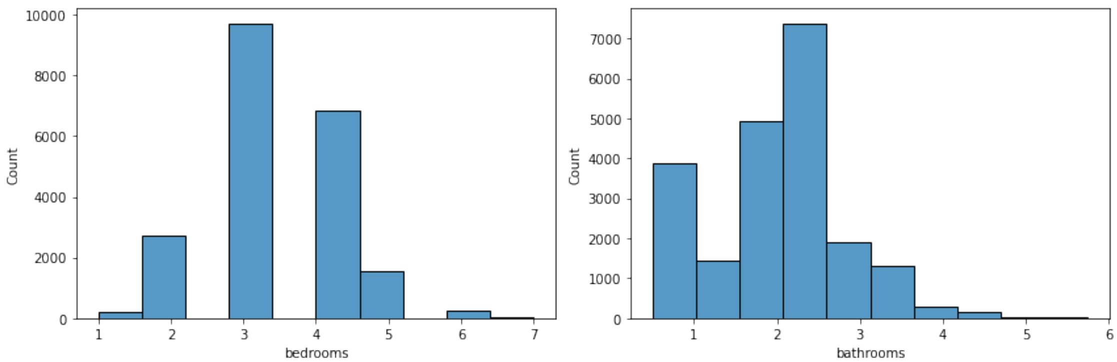
[86]:
```
# Let's check out what value the top .1 percent of the data corresponds to:
print(df_new['bedrooms'].quantile(.999))
print(df_new['bathrooms'].quantile(.999))
```

```
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]
```

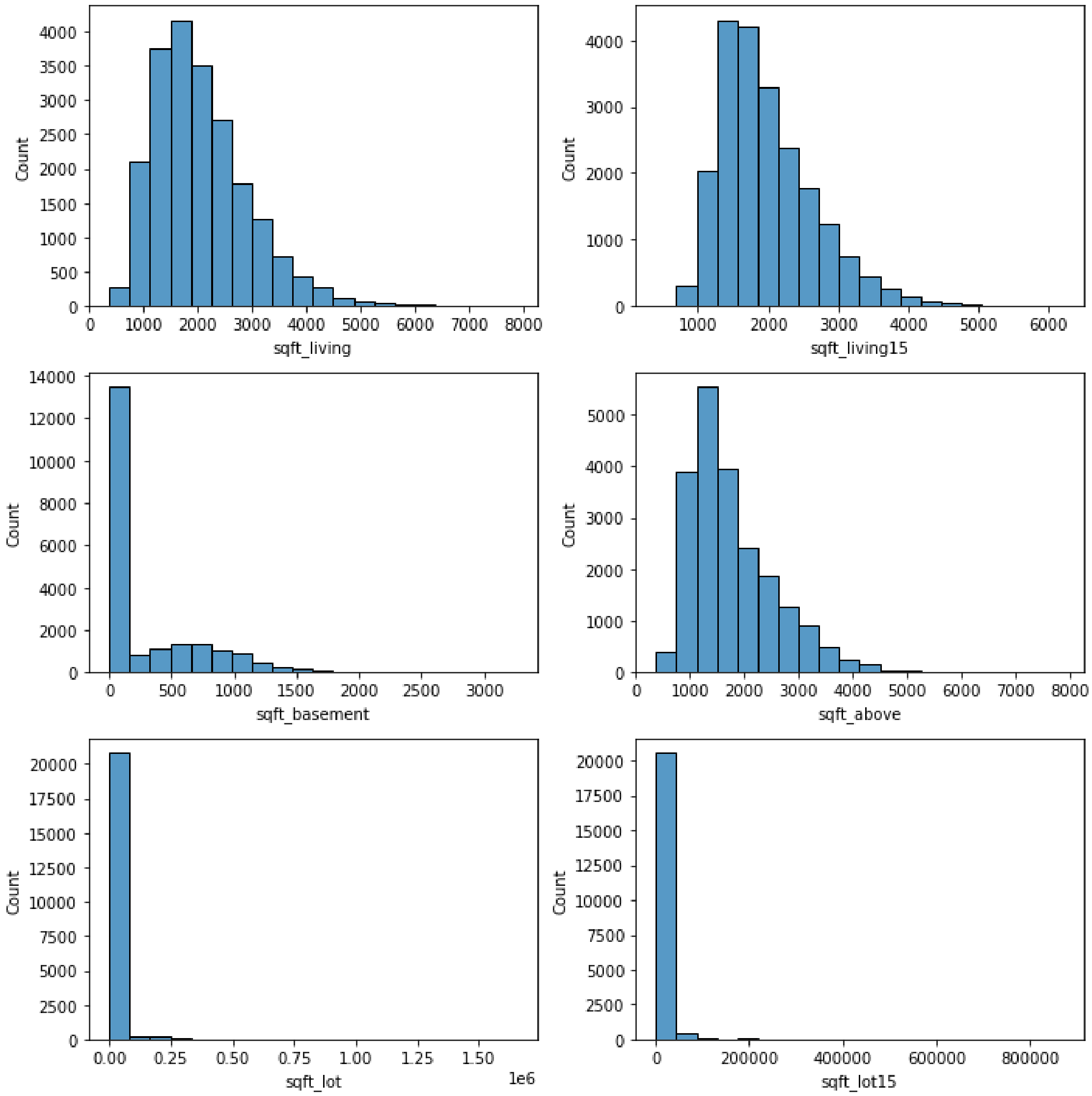
[88]:

```python
# Check out the histograms after removing the outliers:
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]:

```python
# Check out the distribution of other area related numerical variables:

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=20);
sns.histplot(x = df_new['sqft_lot15'], ax= ax6, bins=20);

# Lots of outliers in sqft_lot and sqft_lot15
```



What if we use IQR to come up with an upper cutoff value for `sqft_lot`?:

[90]:
```
df_new['sqft_lot'].describe()
```

[90]:
```
count    2.132600e+04
mean     1.507740e+04
std      4.151363e+04
min      5.200000e+02
25%      5.038500e+03
50%      7.600000e+03
75%      1.062500e+04
max      1.651359e+06
Name: sqft_lot, dtype: float64
```

[91]:
```python
# What value would we use as cutoff using IQR:
Q1 = df_new['sqft_lot'].quantile(0.25)
Q3 = df_new['sqft_lot'].quantile(0.75)
IQR = Q3 - Q1
print(Q3 + (1.5 * IQR))
```

```
19004.75
```

[92]:
```python
# What percentile does this score correspond to?:
stats.percentileofscore(df_new['sqft_lot'], 19004, kind='rank')
```

[92]:
```
88.82115727281253
```

- If we use IQR to exclude the high values we would be removing 11% of the data which is A LOT!
- Let's adopt another criteria to remove a smaller upper portion of the data:

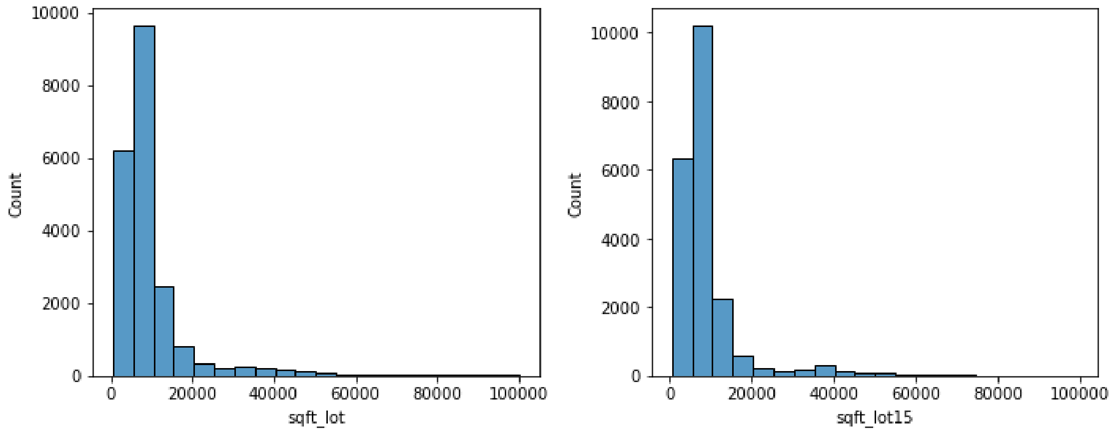
[93]:
```python
print(stats.percentileofscore(df_new['sqft_lot'], 100000, kind='rank'))
print(stats.percentileofscore(df_new['sqft_lot15'], 100000, kind='rank'))
# If we remove those values above 100000 sqft, we would be removing about top␣
↪2% of the data.
```

```
97.84300853418362
98.41976929569539
```

Remove outliers from sqft_lot, and sqft_lot15:

[94]:
```python
# Remove some high values from sqft_lot and sqft_lot15
df_new =  df_new[df_new['sqft_lot'] < 100000]
df_new =  df_new[df_new['sqft_lot15'] < 100000]
```

[95]:
```python
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.

[96]:
```
# What proportion of data has NO basement?
(len(df_new[df_new['sqft_basement'] == 0]) *100 )/  len(df_new['sqft_basement'])
```

[96]:
```
61.38013945660015
```

[97]:
```
# Impute the new variable `has_basement` to describe whether or not a house has␣
↪basement:
df_new['has_basement'] = df_new['sqft_basement'] > 0
df_new['has_basement'].value_counts()
```

[97]:
```
False    12764
True      8031
Name: has_basement, dtype: int64
```

[98]:
```
# Renaming False and True to 0 and 1:
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()
```

[98]:
```
0    12764
1     8031
Name: has_basement, dtype: int64
```

[99]:
```
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'
```

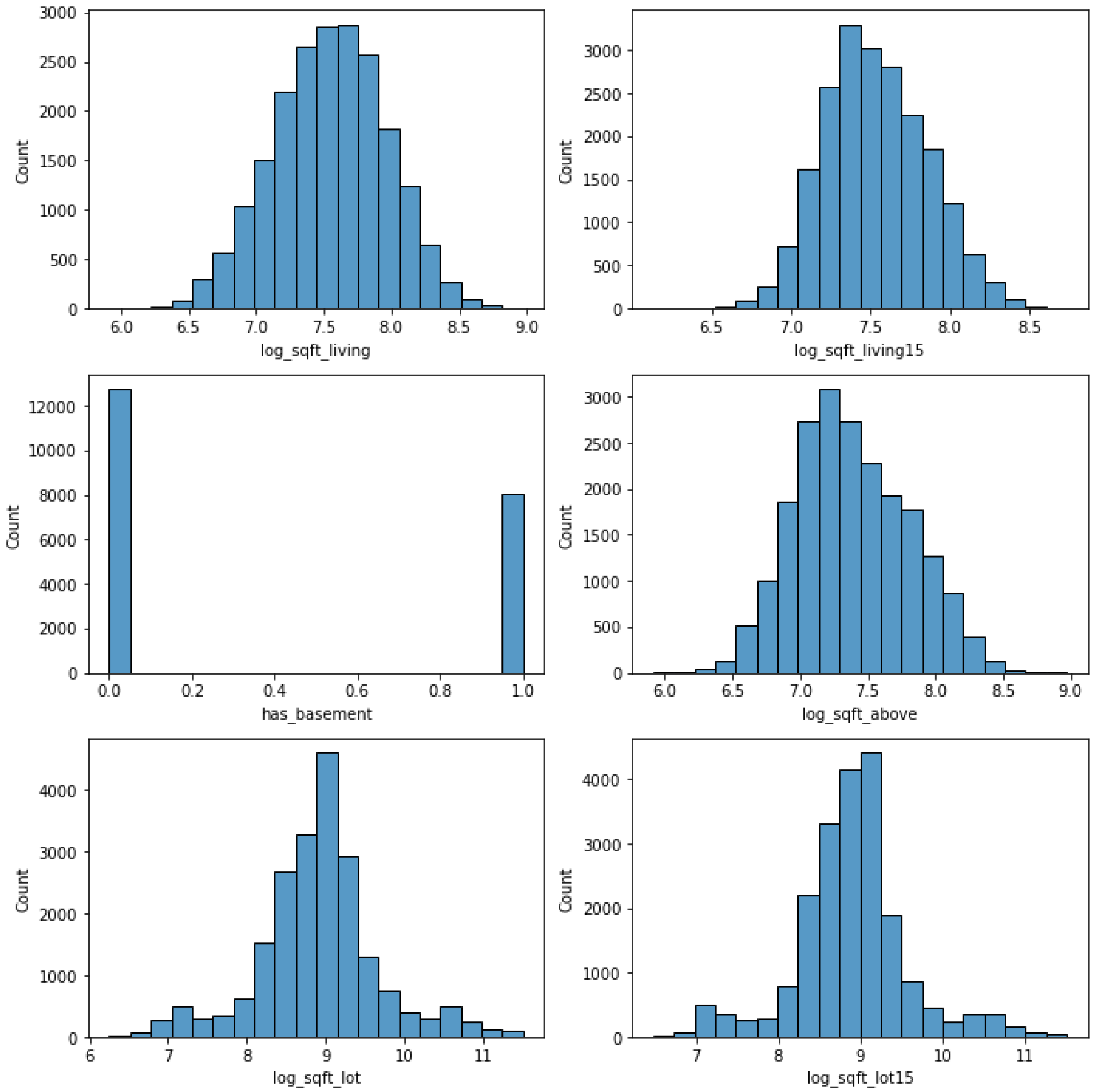
```
0.3001634928370975
0.18426400416449712
```

[100]:
```
df_new.drop('sqft_basement', axis=1, inplace=True )
```

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

[101]:
```
# Create log_transformed version of the variables below:
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])
```

[102]:
```
# Plot the log_transformed variables (except has_basement which is binary):
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);
```



- The log transformed versions looks NORMAL now.

[103]:
```
# Print the shape before and after data engineering:

print(df.shape)
print(df_new.shape)
```

```
(21420, 21)
(20795, 38)
```

In the end we lost ~ 2.9% of the data during data engineering process:

[104]:
```
total_dataloss = ((df_fixed.shape[0] - df_new.shape[0]) * 100 ) /  df_fixed.
 ↪shape[0]
```

```
total_dataloss
```

[104]: 2.917833800186741

0.9 Feature Selection:

[105]:
```
data = df_new.copy()
data.head()
```

[105]:
```
      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]
```

[106]:
```
data.columns
```

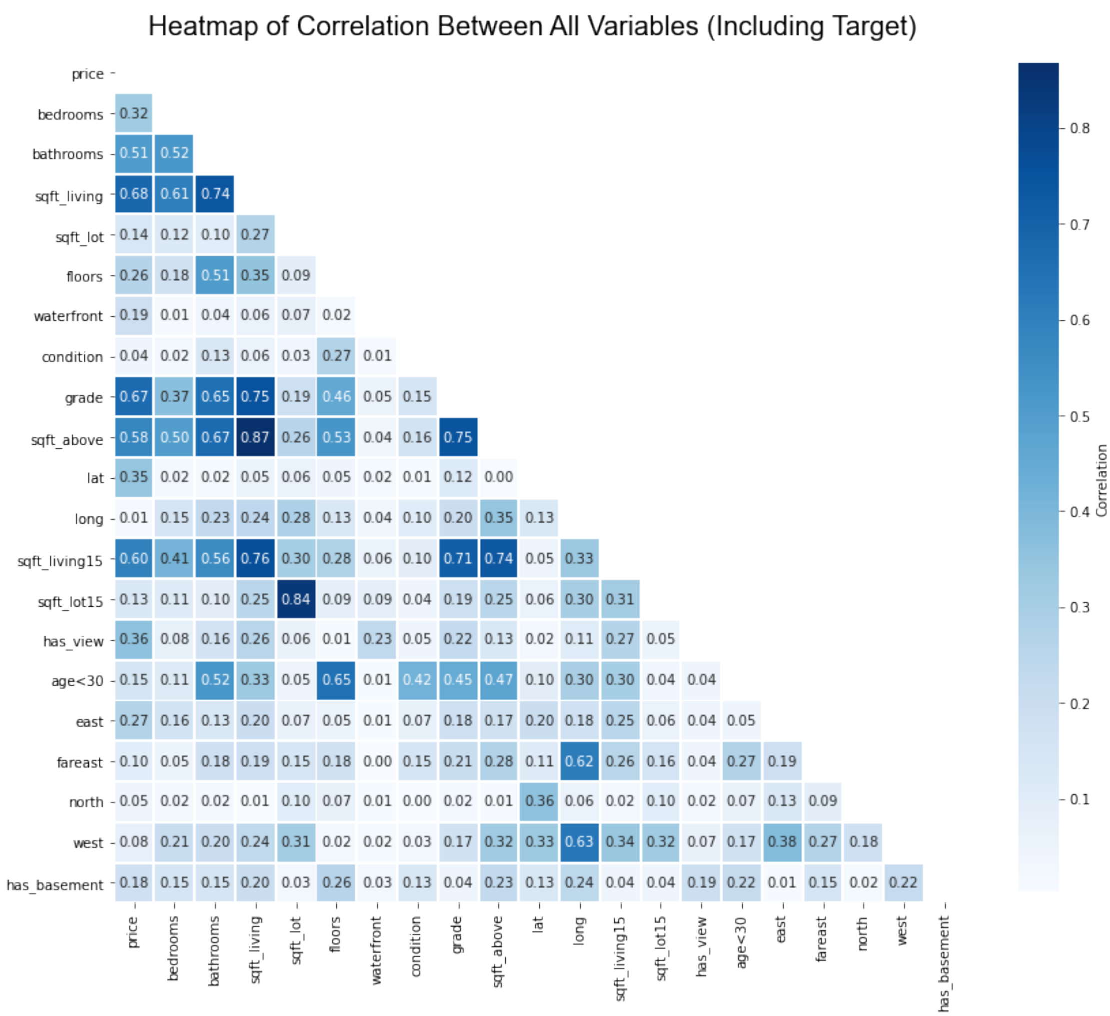
[106]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'log_price', 'has_view', 'april',
       'august', 'december', 'february', 'july', 'june', 'march', 'may',
       '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:

- Create a correlation matrix to see the intercorrelation of all variables:

[107]:
```python
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:

[108]:
```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
```

[109]:
```python
show_corr_pairs(variables)
```

[109]:
```
            var1         var2  corrcoef
39    sqft_above  sqft_living  0.867206
82    sqft_lot15     sqft_lot  0.837811
69  sqft_living15  sqft_living  0.763508
31         grade  sqft_living  0.754432
44    sqft_above        grade  0.746833
5    sqft_living    bathrooms  0.742071
75  sqft_living15   sqft_above  0.735328
74  sqft_living15        grade  0.710579
```

What are mostly inter-correlated variables?:

- `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`.

[110]:
```
variables.corr()['price'].map(abs).sort_values(ascending=False)
```

[110]:
```
price            1.000000
sqft_living      0.684657
grade            0.674439
sqft_living15    0.599341
sqft_above       0.584023
bathrooms        0.506821
has_view         0.357703
lat              0.345269
bedrooms         0.320176
east             0.271447
floors           0.263646
waterfront       0.190387
has_basement     0.184264
age<30           0.151822
sqft_lot         0.137853
sqft_lot15       0.128145
fareast          0.098088
west             0.076611
north            0.045607
condition        0.044216
long             0.013770
Name: price, dtype: float64
```

Which variable correlates highest with `price`?:

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

[111]:
```
df_corr = abs(variables.corr()) > 0.7
df_corr.sum()
```

[111]:
```
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
```

Which variable has the most number of correlations to other variables?:

- `sqft_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:

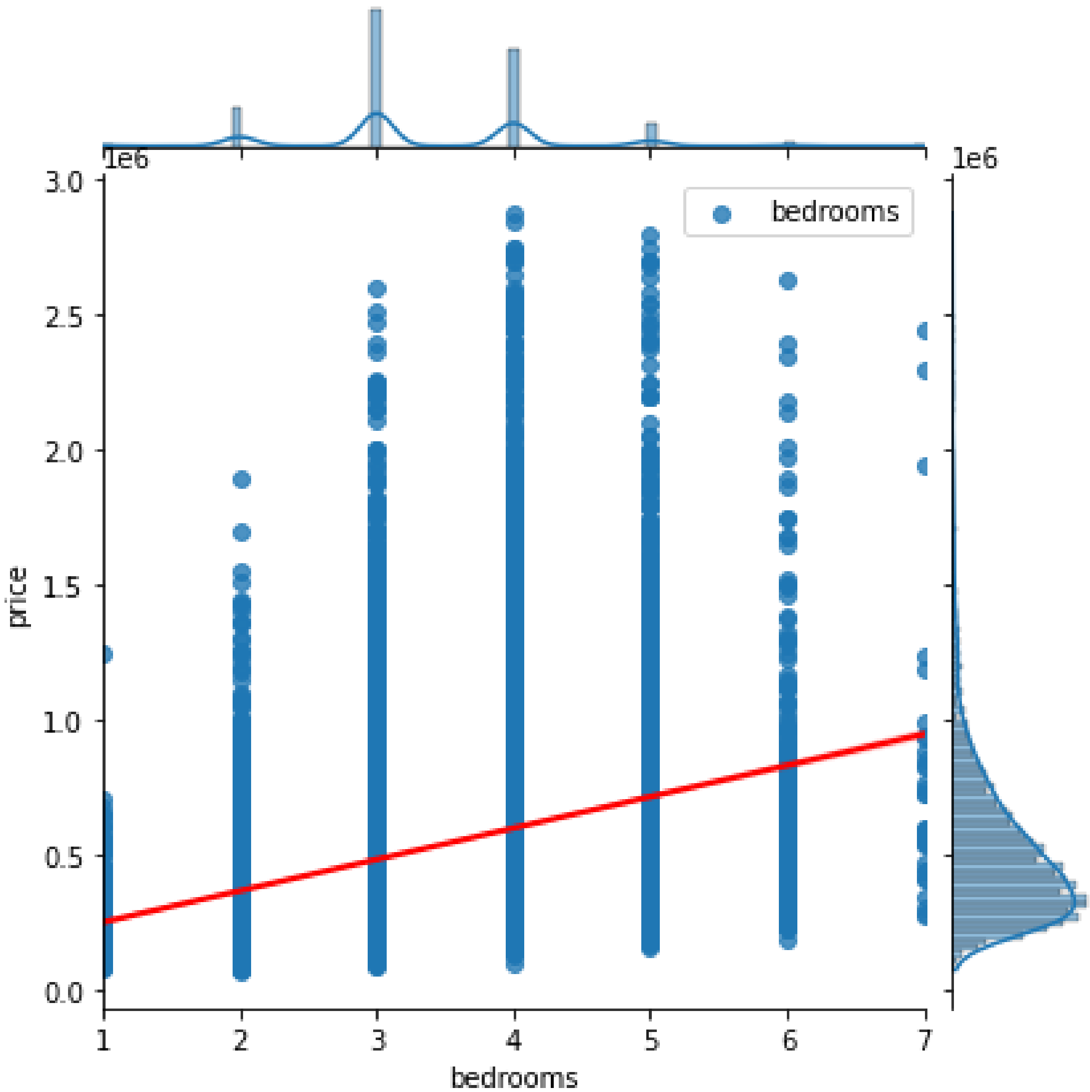
0.10.1 Linearity:

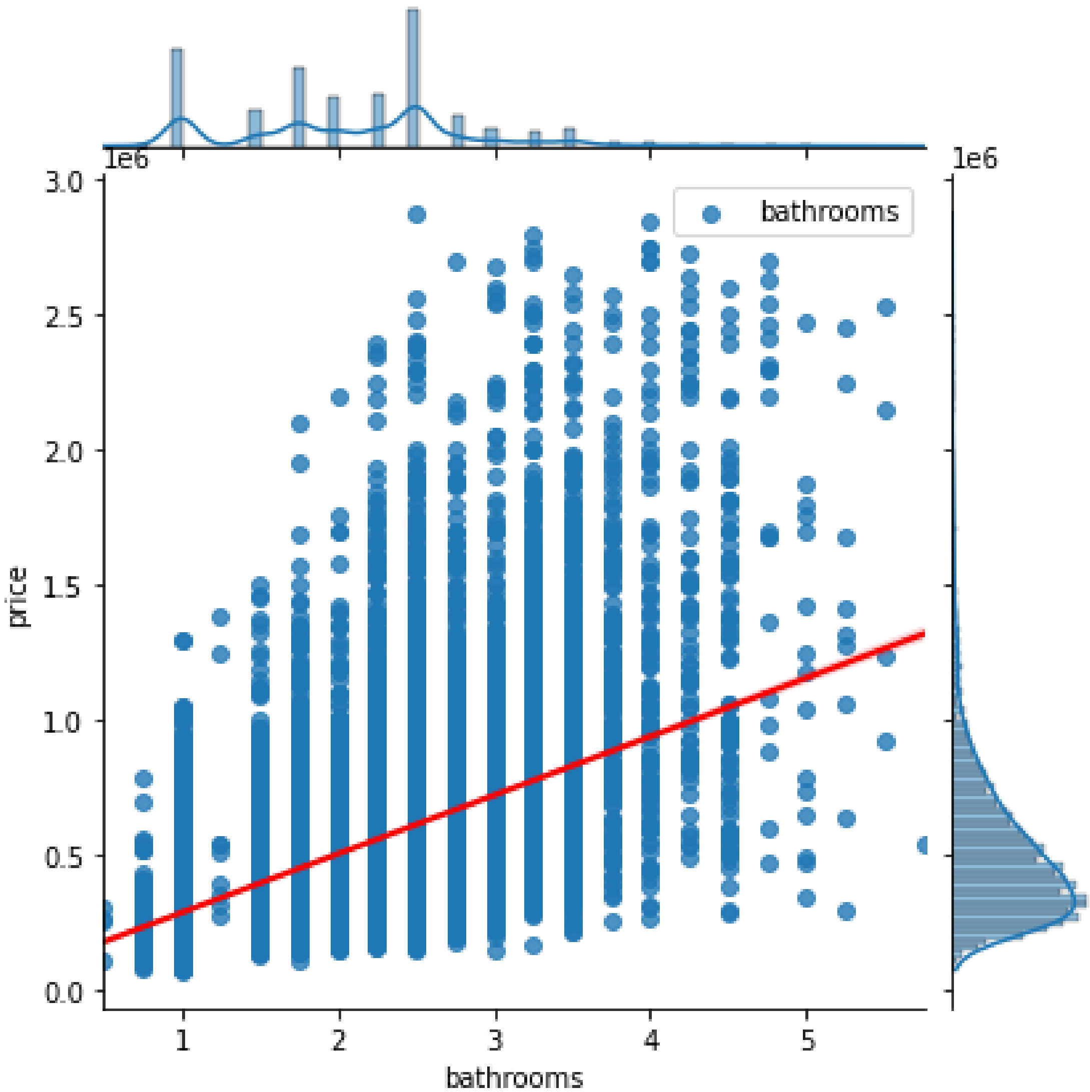
- There should be a linear relationship between the response/target variable and predictors.
- Check for this once using scatterplots and then visually inspecting the scatterplots for linearity..

[112]:
```
data.columns
```

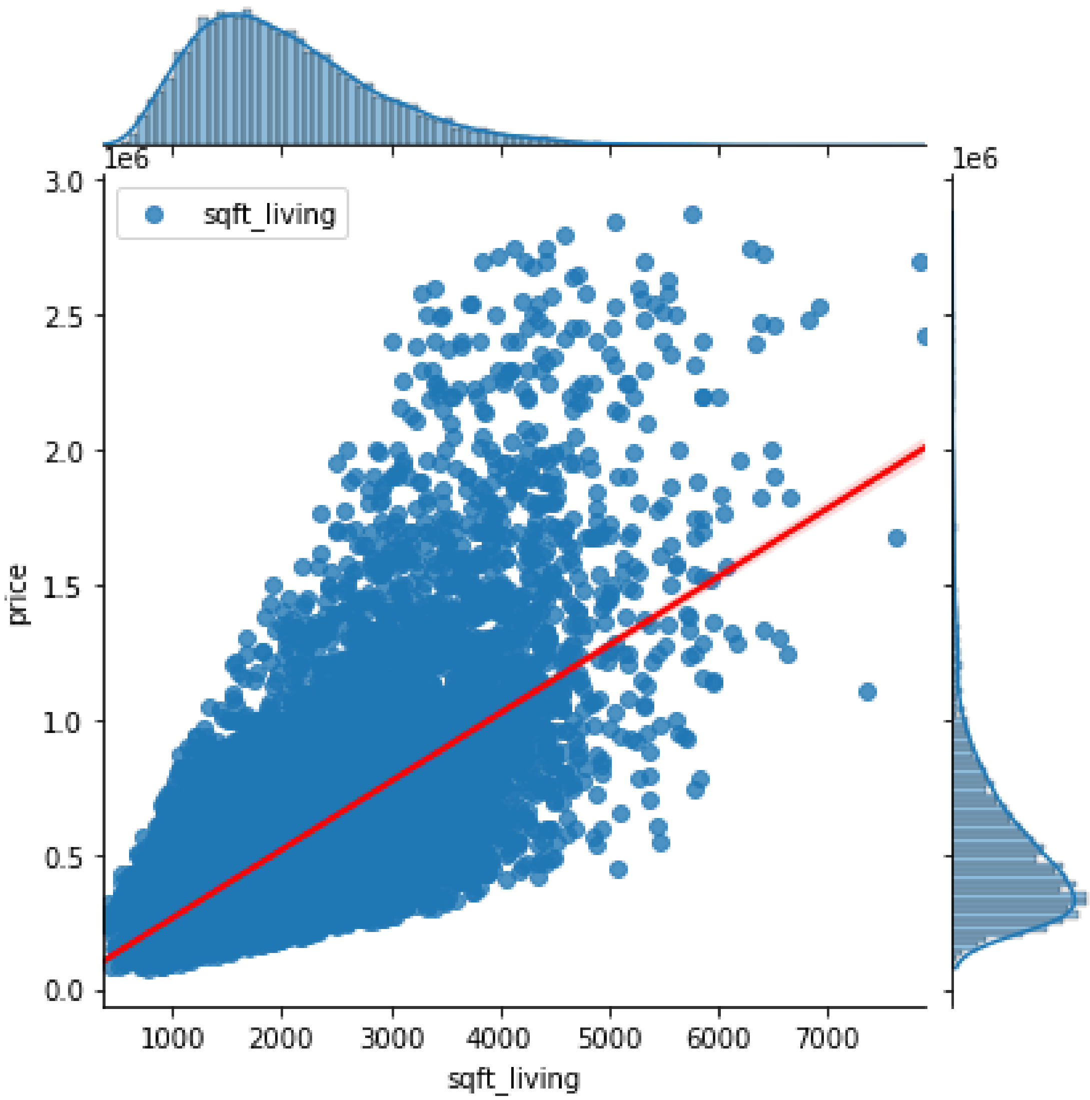
[112]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'log_price', 'has_view', 'april',
       'august', 'december', 'february', 'july', 'june', 'march', 'may',
       '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')
```

[113]:
```
# 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()
```

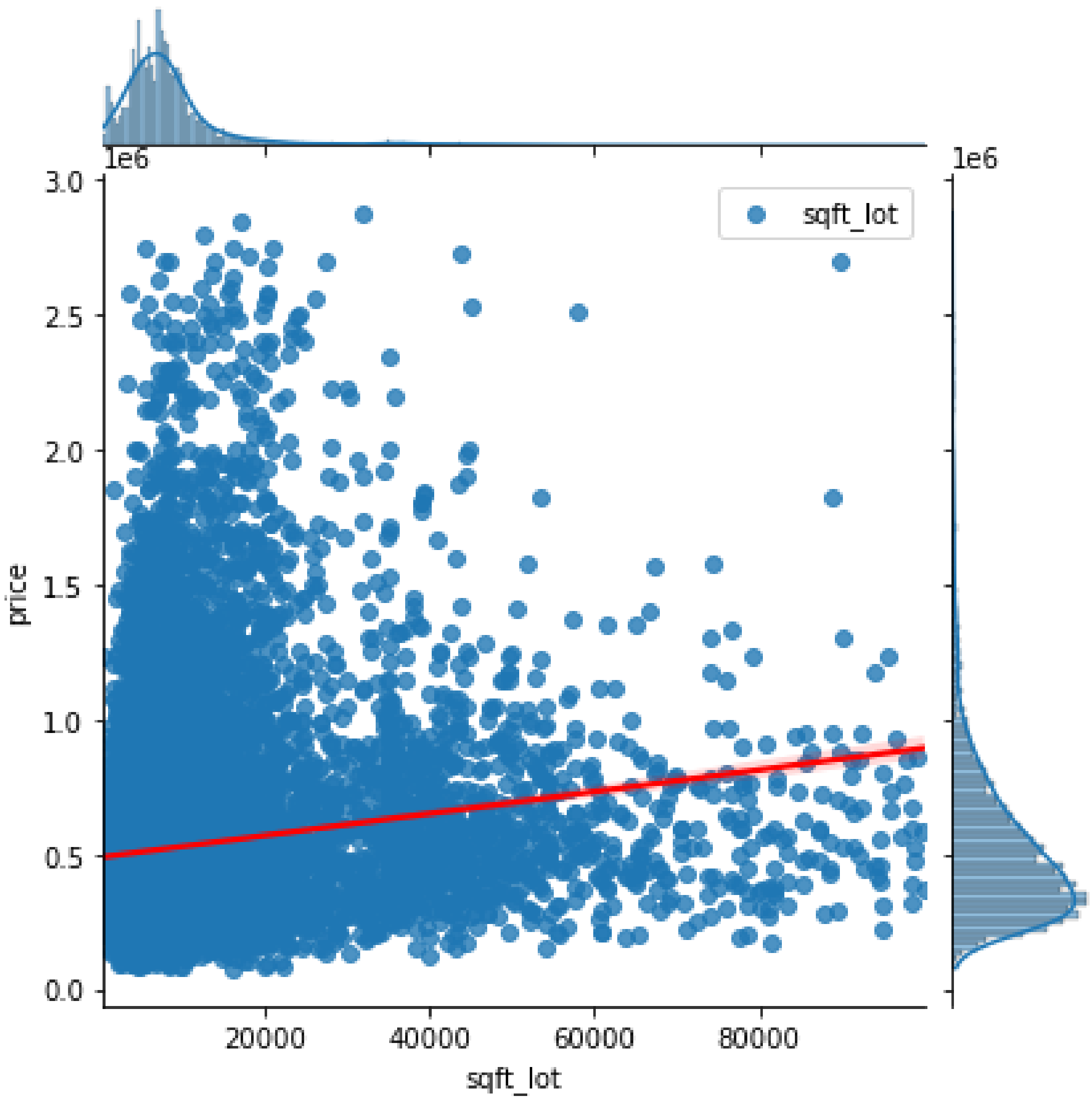

1e6
1e6
bedrooms
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
1
2
3
4
5
6
7
bedrooms

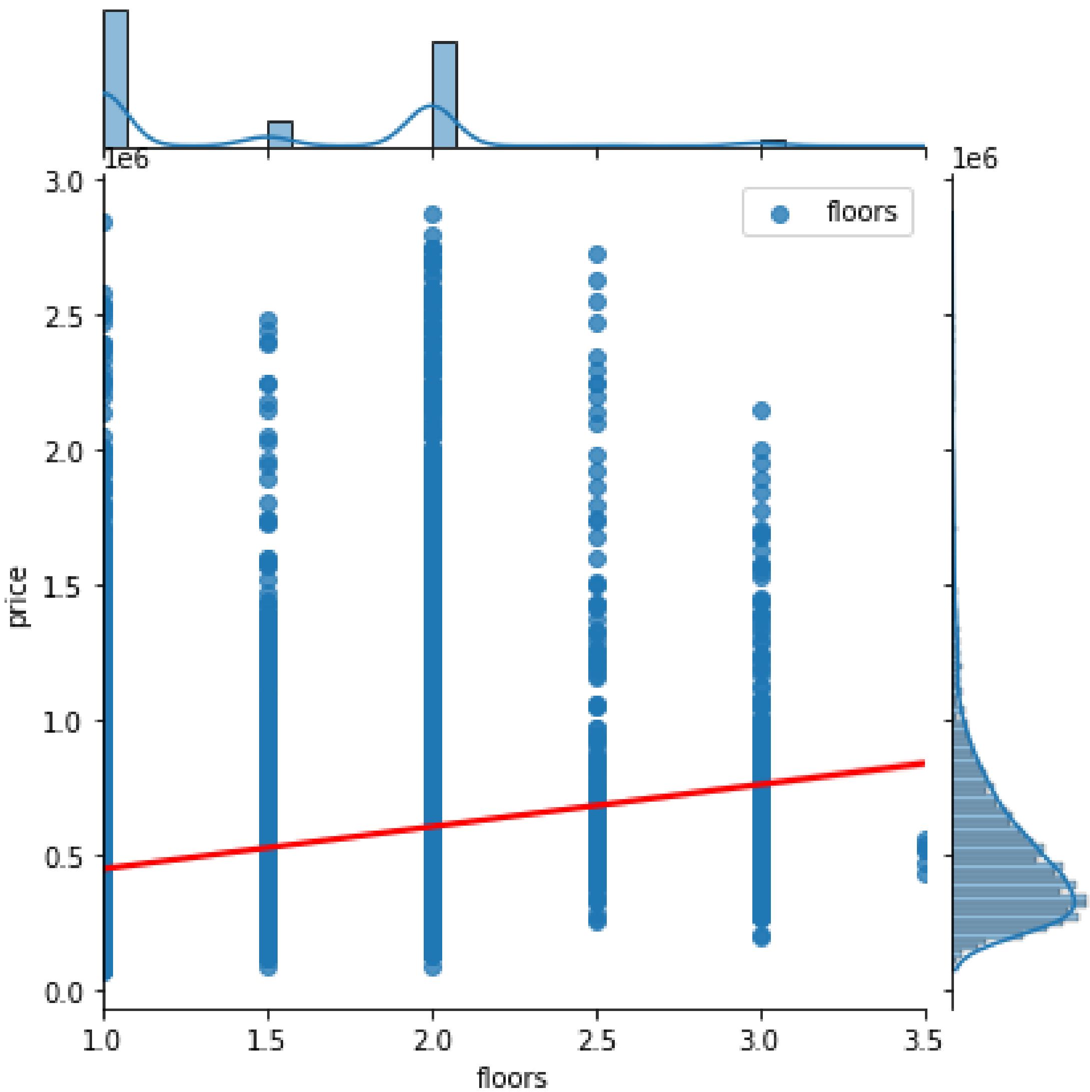


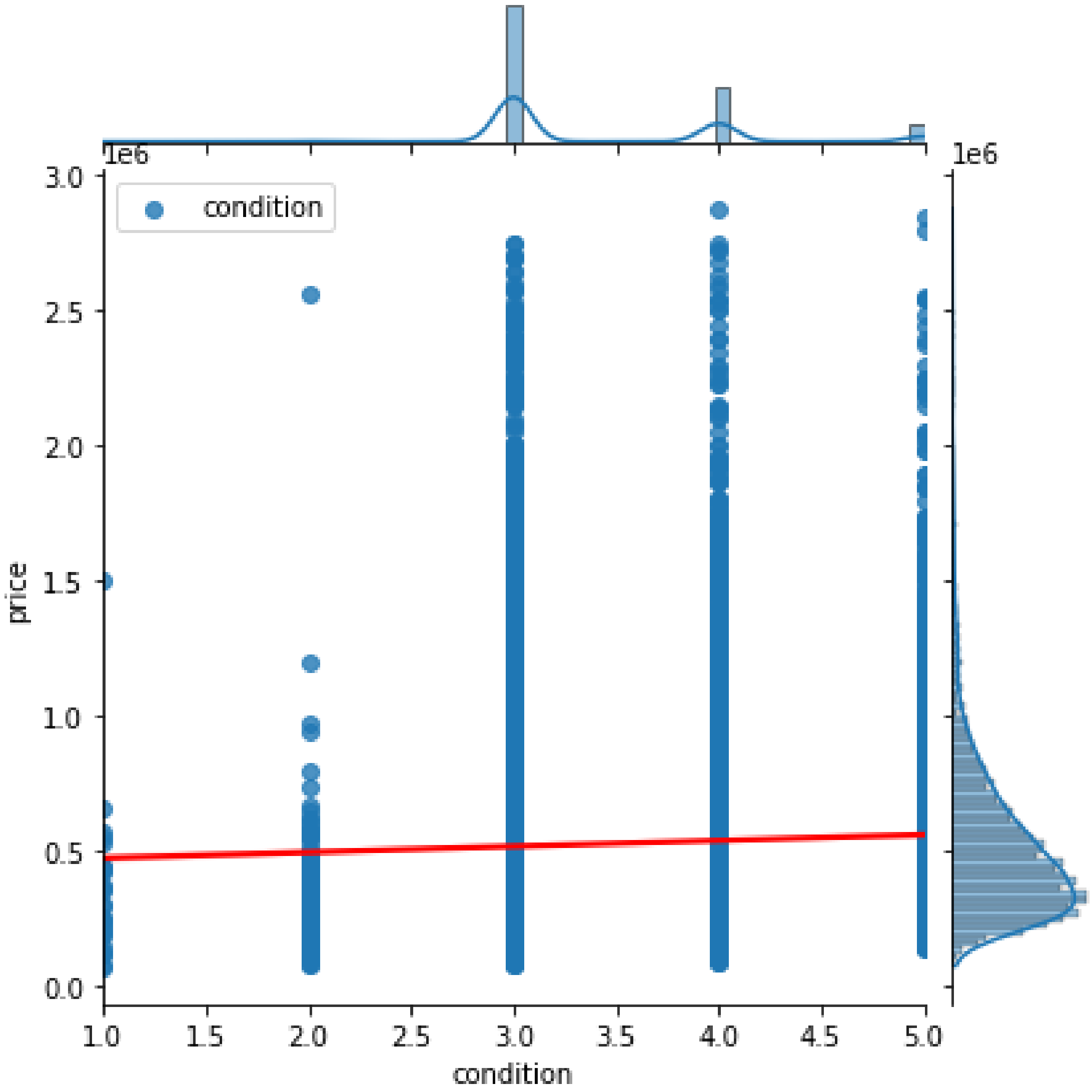
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
bathrooms
1
2
3
4
5
bathrooms
1e6



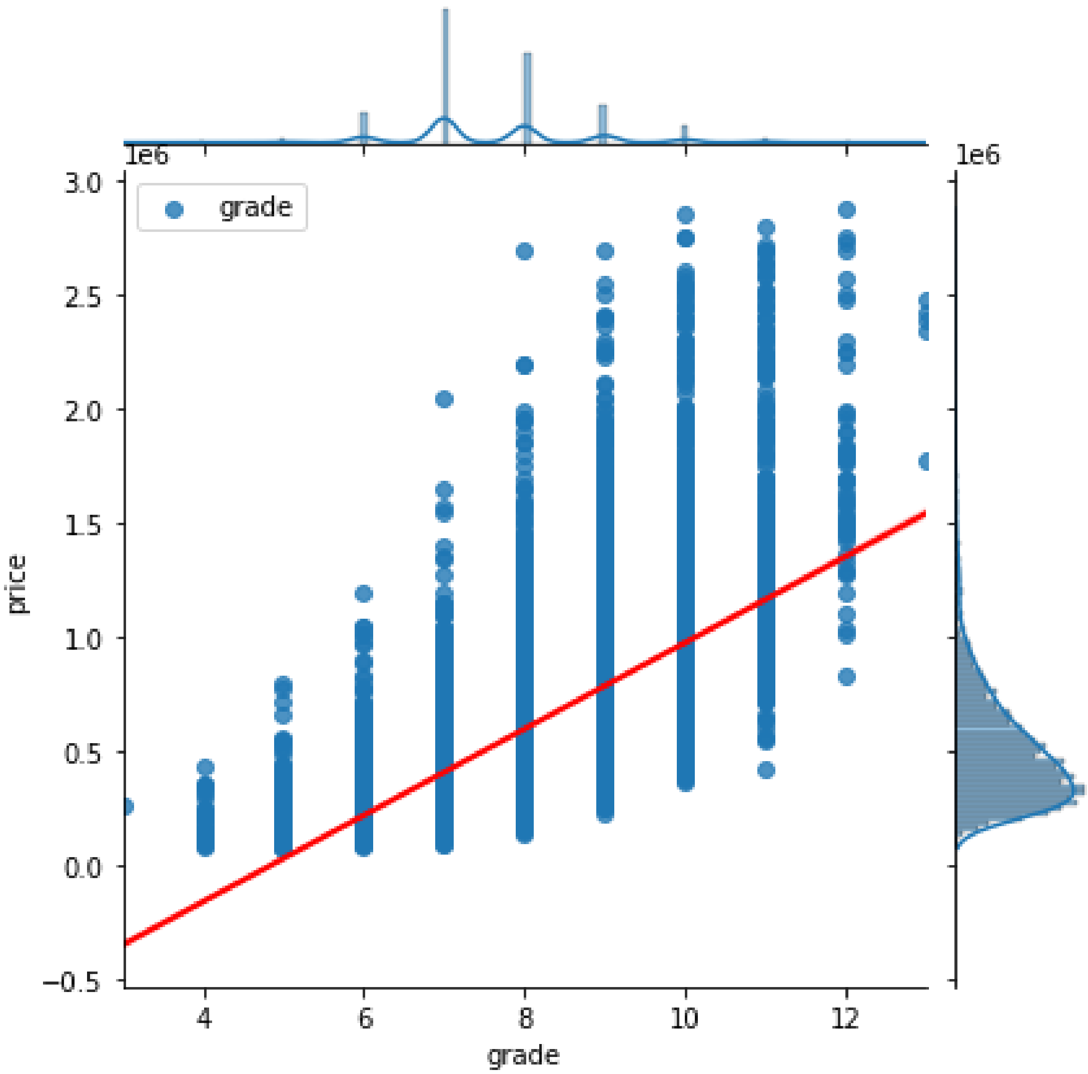
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
sqft_living
1000
2000
3000
4000
5000
6000
7000
sqft_living
1e6


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


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

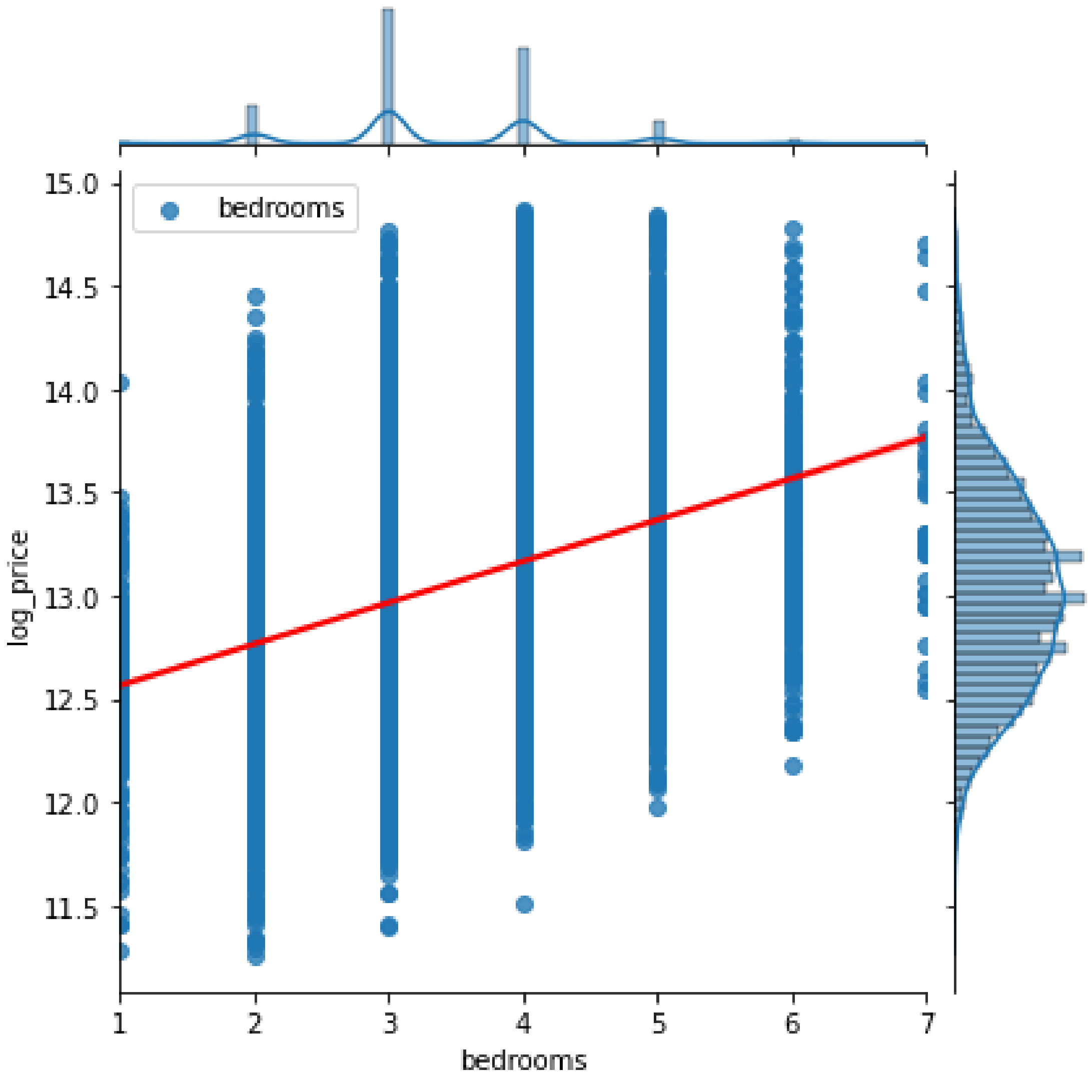


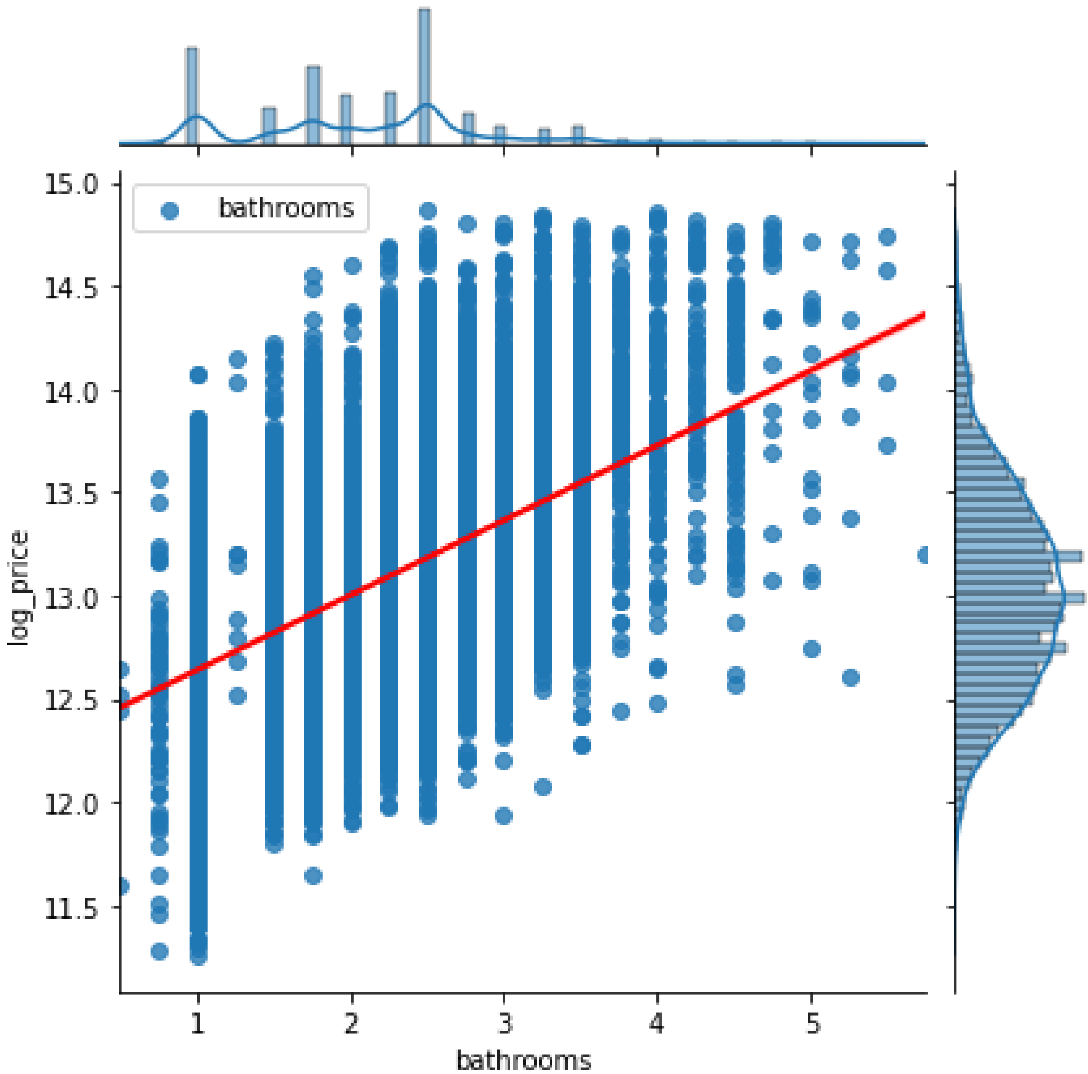
1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
price
condition
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
condition
1e6

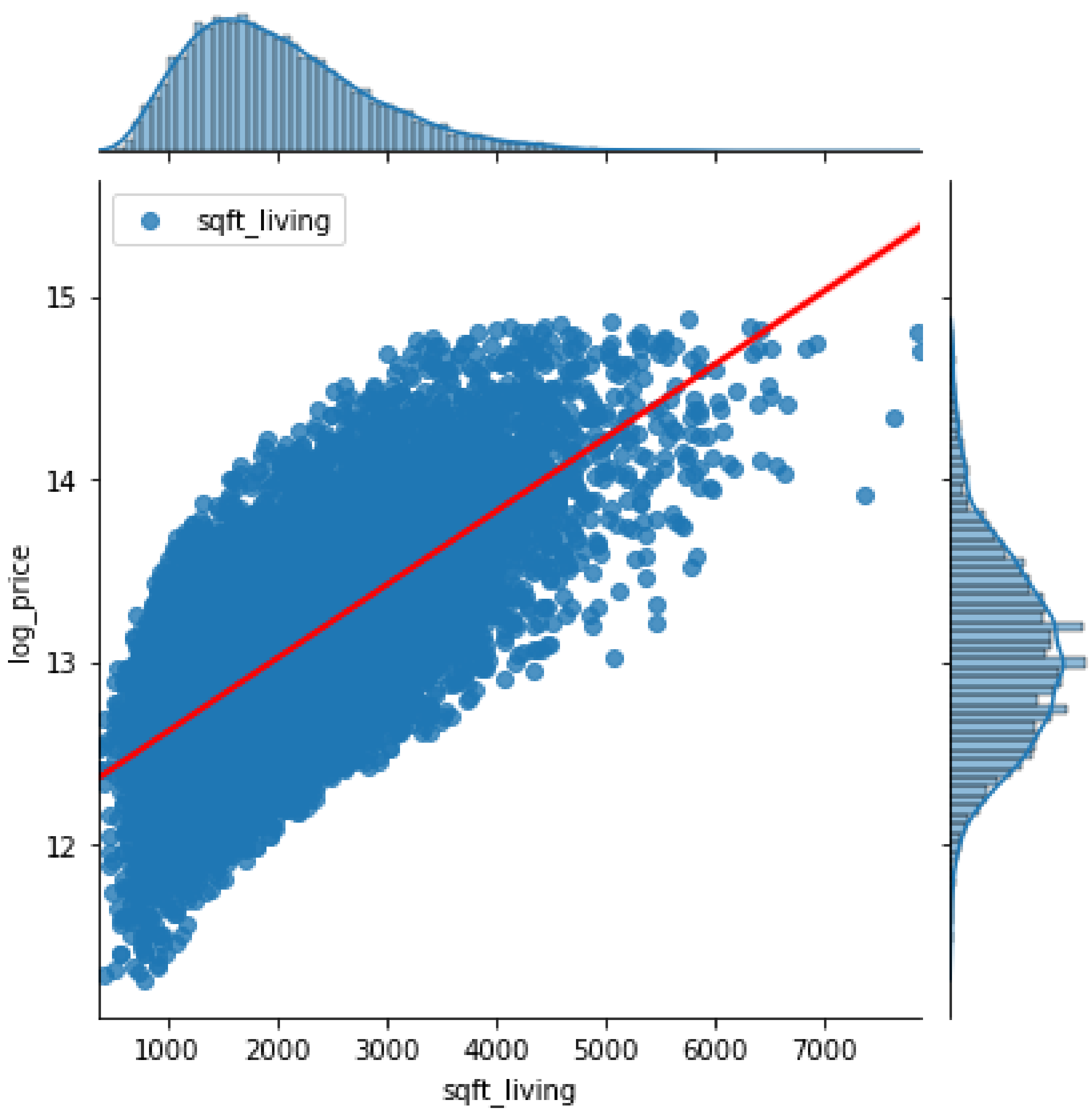


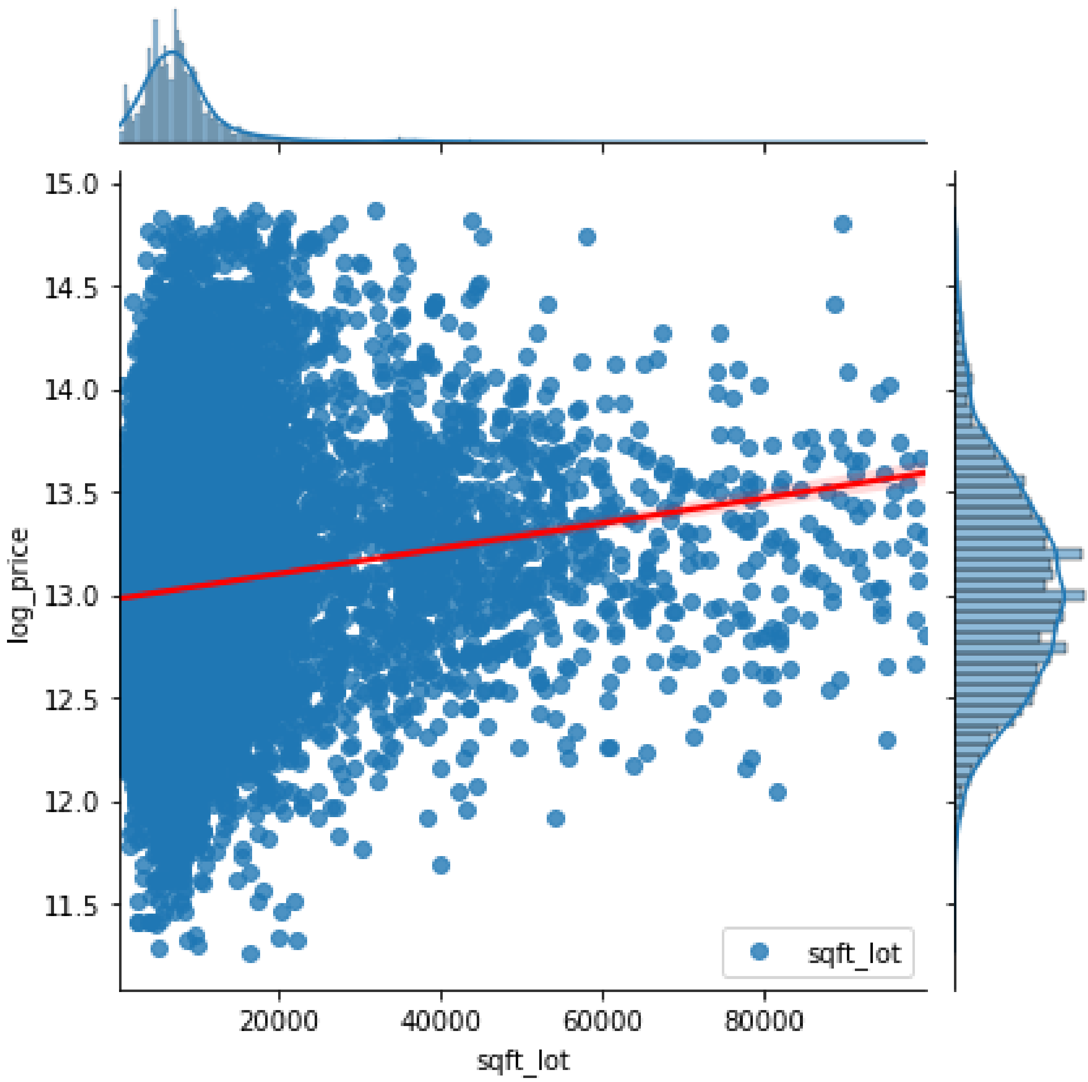
- Looks like a linear relationship except `sqft_lot`

[114]:
```
# 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()
```

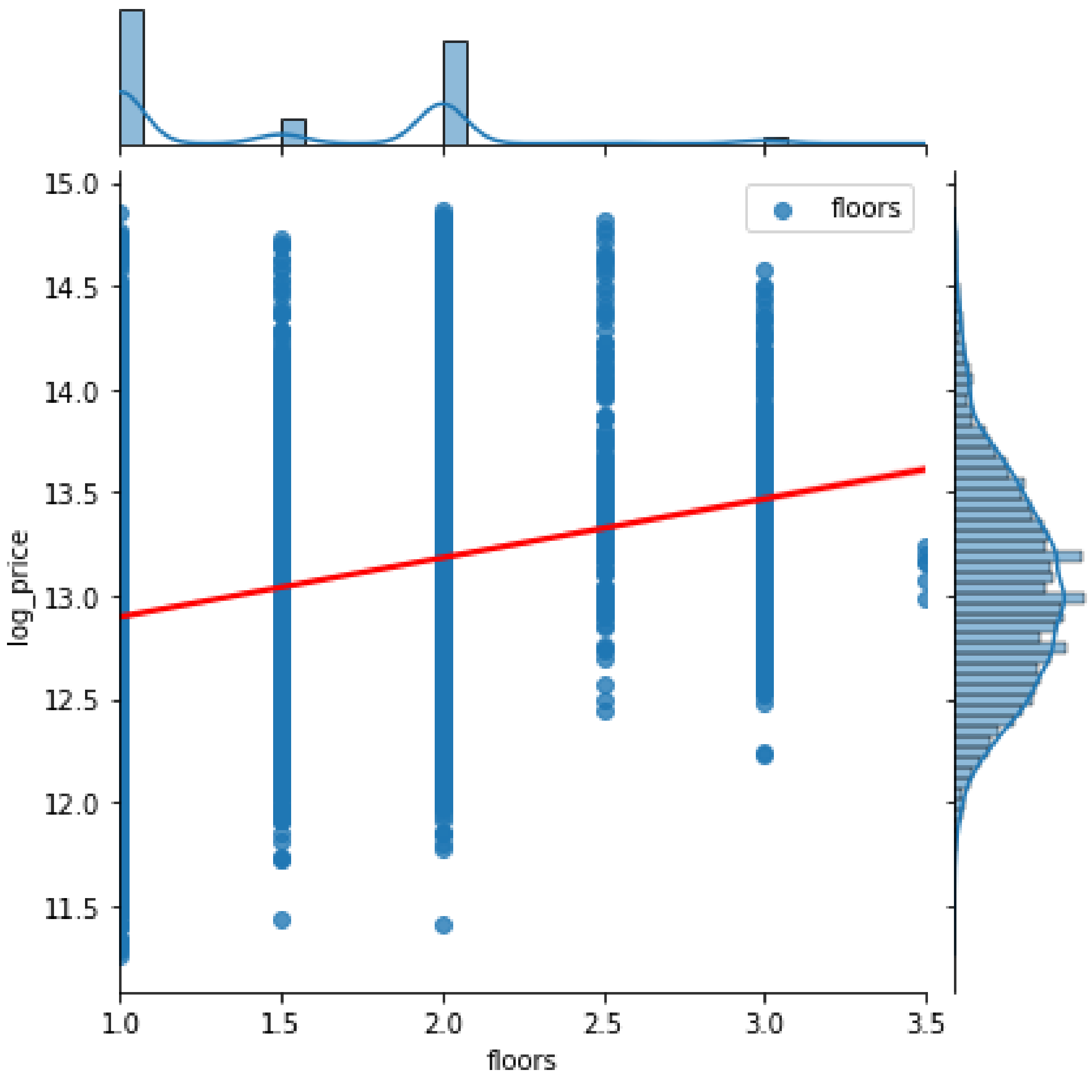

bedrooms
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
1
2
3
4
5
6
7
bedrooms

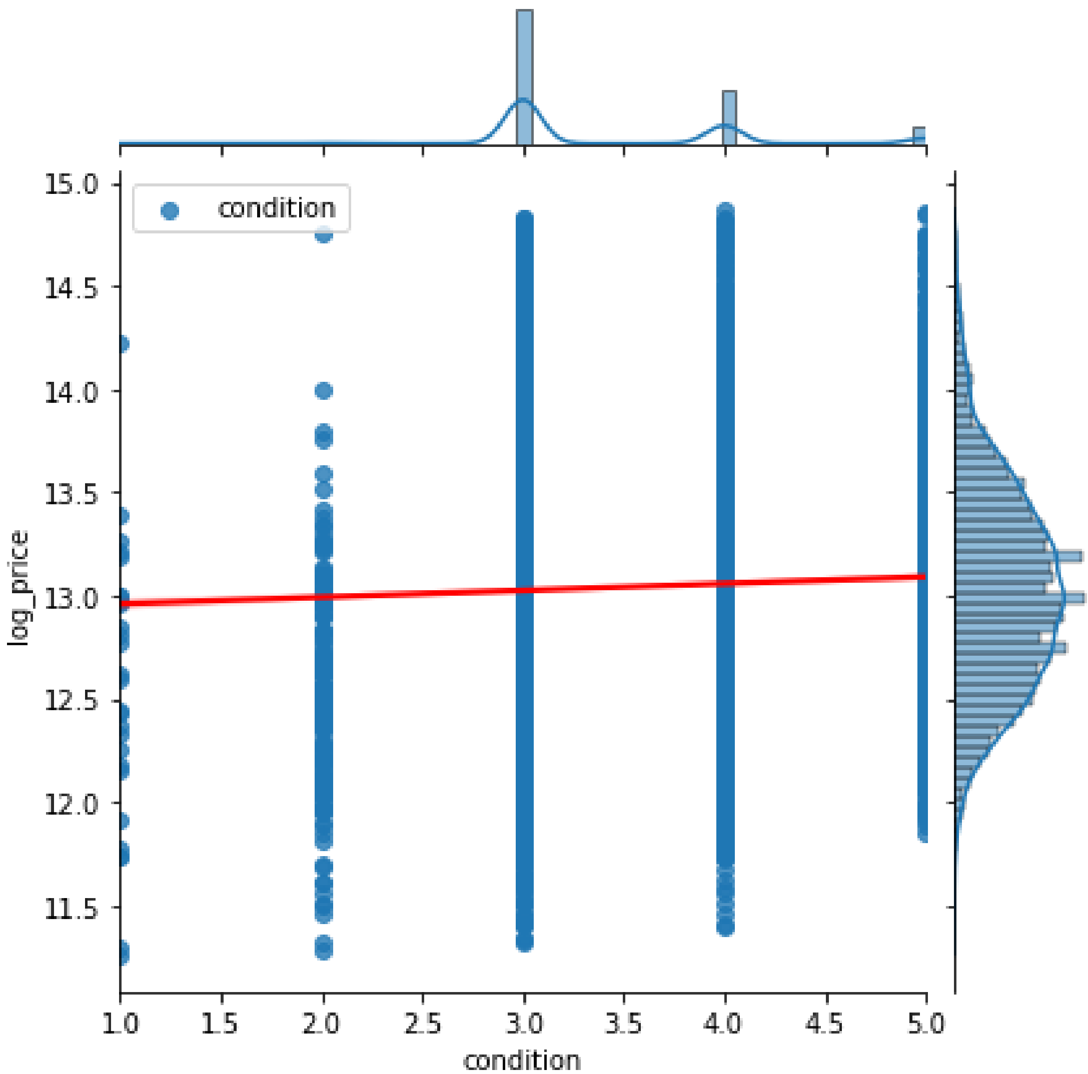

bathrooms
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
1
2
3
4
5
bathrooms


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

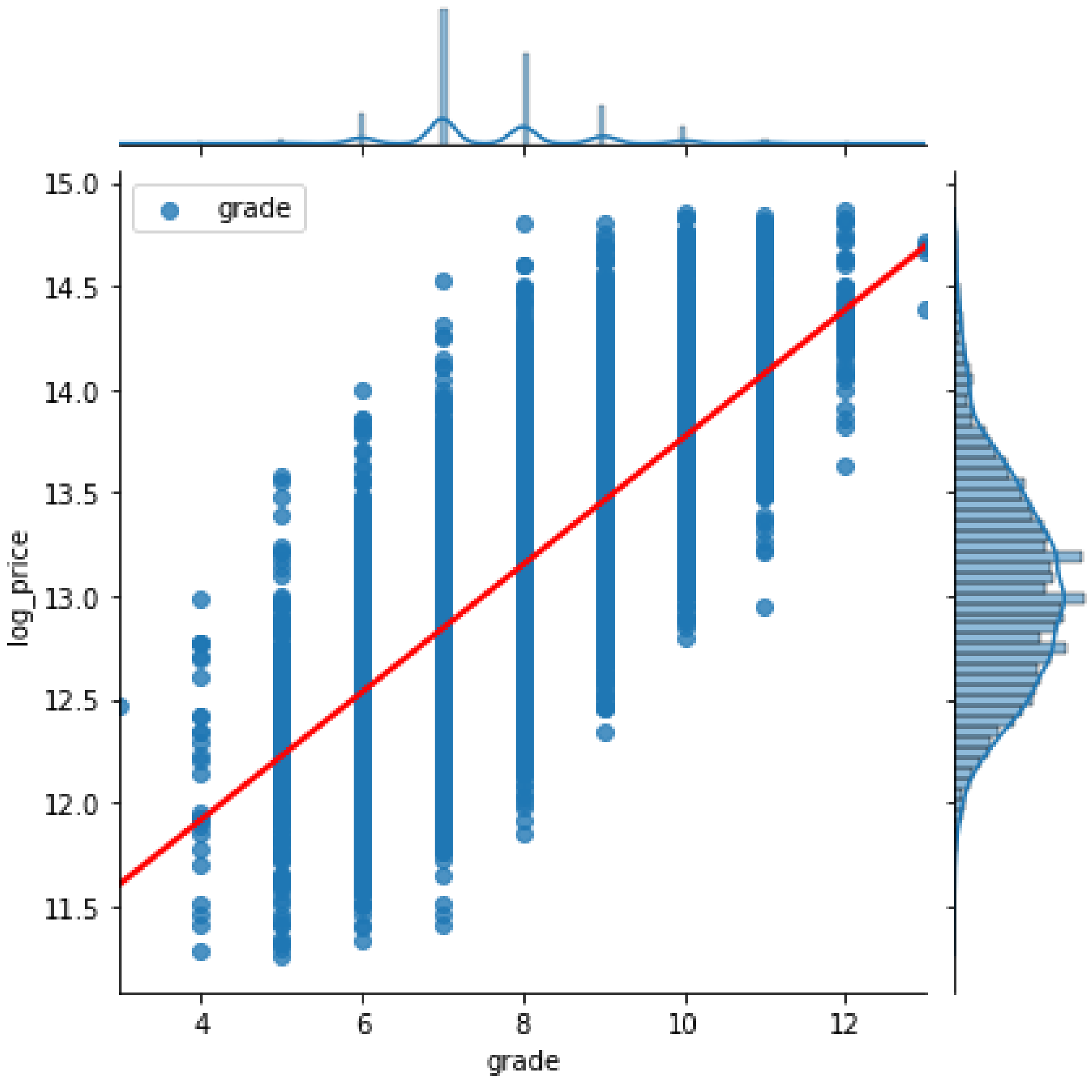


15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
log_price
sqft_lot
20000
40000
60000
80000
sqft_lot


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



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 Homoscadescacity:

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

[115]:
```
def normality_homoscadescacity(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 (HOMOSCADESCACITY)", 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.

[116]:
```
#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`

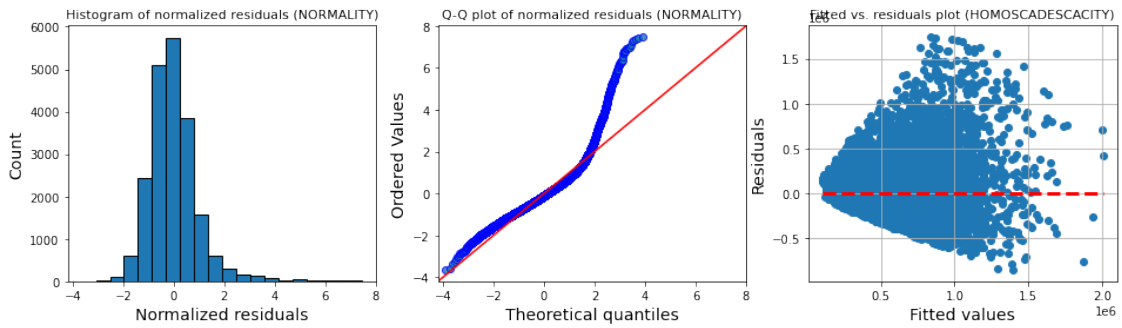
[117]:
```
y = data['price']
X = data['sqft_living']

X.shape, y.shape
```

[117]:
```
((20795,), (20795,))
```

[118]:
```
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[118]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.469
Model:                            OLS   Adj. R-squared:                  0.469
Method:                 Least Squares   F-statistic:                 1.835e+04
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:53   Log-Likelihood:            -2.8651e+05
No. Observations:               20795   AIC:                         5.730e+05
Df Residuals:                   20793   BIC:                         5.730e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        9734.4920   4160.152      2.340      0.019    1580.270    1.79e+04
sqft_living   253.2328      1.870    135.451      0.000     249.568     256.897
==============================================================================
Omnibus:                     7980.197   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            52673.868
Skew:                           1.701   Prob(JB):                         0.00
Kurtosis:                      10.016   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.
"""
```

[119]:
```
normality_homoscadescacity(model);
```



Violation of Normality and Homoscadescacity:

- 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 homoscadescacity 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

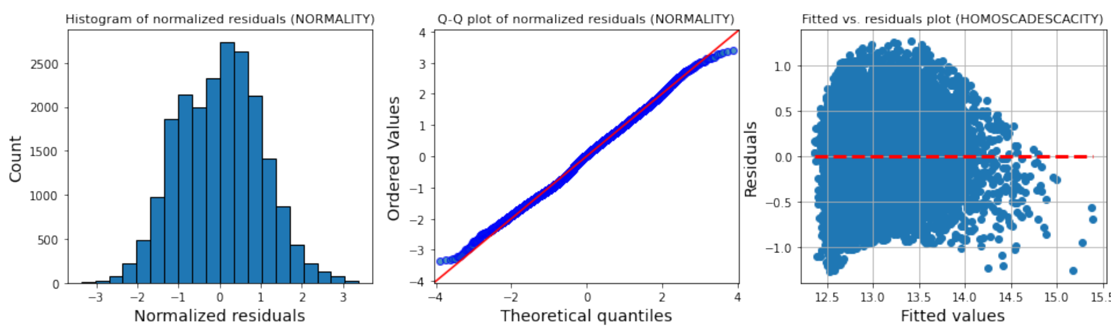
- Using log transformed `log_price` as the target variable.

[120]:
```
y = data['log_price']
X = data['sqft_living']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[120]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.462
Model:                            OLS   Adj. R-squared:                  0.462
Method:                 Least Squares   F-statistic:                 1.784e+04
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:54   Log-Likelihood:                -9129.5
No. Observations:               20795   AIC:                         1.826e+04
Df Residuals:                   20793   BIC:                         1.828e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
```

```
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          12.2151      0.007   1822.941      0.000      12.202      12.228
sqft_living     0.0004   3.01e-06    133.569      0.000       0.000       0.000
==============================================================================
Omnibus:                       81.946   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               65.464
Skew:                           0.058   Prob(JB):                     6.09e-15
Kurtosis:                       2.751   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.
"""
```

[121]:
```
normality_homoscadescacity(model);
```



- **Normality and Homoscadescacity are mostly 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 change 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.

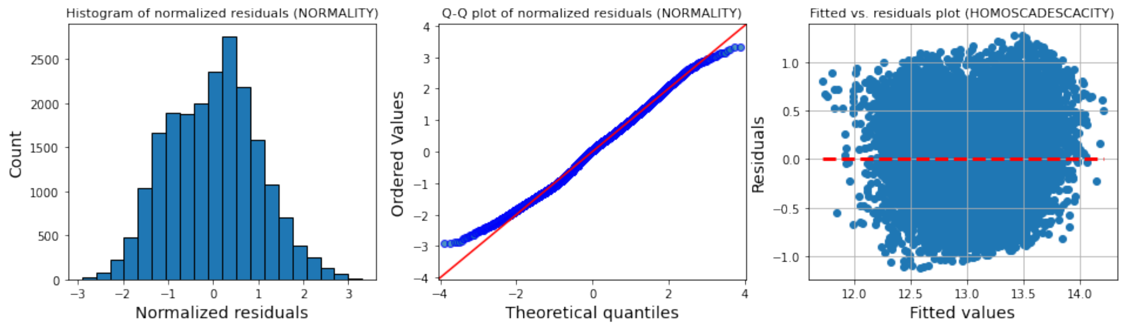
0.11.3 MODEL #3

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

[122]:
```
y = data['log_price']
X = data['log_sqft_living']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[122]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.436
Model:                            OLS   Adj. R-squared:                  0.436
Method:                 Least Squares   F-statistic:                 1.606e+04
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:54   Log-Likelihood:                -9620.7
No. Observations:               20795   AIC:                         1.925e+04
Df Residuals:                   20793   BIC:                         1.926e+04
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
const               6.9165      0.048    142.919      0.000       6.822
7.011
log_sqft_living     0.8120      0.006    126.720      0.000       0.799
0.825
==============================================================================
Omnibus:                      162.730   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              126.312
Skew:                           0.107   Prob(JB):                     3.73e-28
Kurtosis:                       2.683   Cond. No.                         140.
==============================================================================

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

[123]:
```
normality_homoscadescacity(model);
```



- This was worse in terms of R2, with a drop from .462 to .436.
- Normality is also slightly worse but homoscadescacity is better.
- 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.

[124]:
```
y = data['log_price']
X = data[['sqft_living', 'sqft_lot']]
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[124]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.465
Model:                            OLS   Adj. R-squared:                  0.465
Method:                 Least Squares   F-statistic:                     9032.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:54   Log-Likelihood:                -9069.5
No. Observations:               20795   AIC:                         1.815e+04
Df Residuals:                   20792   BIC:                         1.817e+04
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          12.2237      0.007   1816.812      0.000      12.211      12.237
sqft_living     0.0004   3.12e-06    131.935      0.000       0.000       0.000
sqft_lot    -2.726e-06   2.49e-07    -10.969      0.000   -3.21e-06   -2.24e-06
==============================================================================
Omnibus:                       67.767   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               54.733
```

```
Skew:                           0.048   Prob(JB):                     1.30e-12
Kurtosis:                       2.768   Cond. No.                     3.87e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.87e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

- Let's check the same model with log-transformed values again:

[125]:
```python
y = data['log_price']
X = data[['log_sqft_living', 'log_sqft_lot']]
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[125]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.448
Model:                            OLS   Adj. R-squared:                  0.447
Method:             Least Squares   F-statistic:                     8422.
Date:             Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                     13:48:55   Log-Likelihood:                -9401.3
No. Observations:            20795   AIC:                         1.881e+04
Df Residuals:                20792   BIC:                         1.883e+04
Df Model:                        2
Covariance Type:        nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
const               7.2609      0.051    143.486      0.000       7.162
7.360
log_sqft_living     0.8573      0.007    128.042      0.000       0.844
0.870
log_sqft_lot       -0.0770      0.004    -21.058      0.000      -0.084
-0.070
==============================================================================
Omnibus:                      103.248   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               93.067
```

```
Skew:                           0.123   Prob(JB):                     6.18e-21
Kurtosis:                       2.783   Cond. No.                         226.
==============================================================================

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

- R-square dropped to .448 from .465 when we used log-transformed values, so let's get back to untransformed independent variables.

[126]:
```python
y = data['log_price']
X = data[['sqft_living', 'sqft_lot']]
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

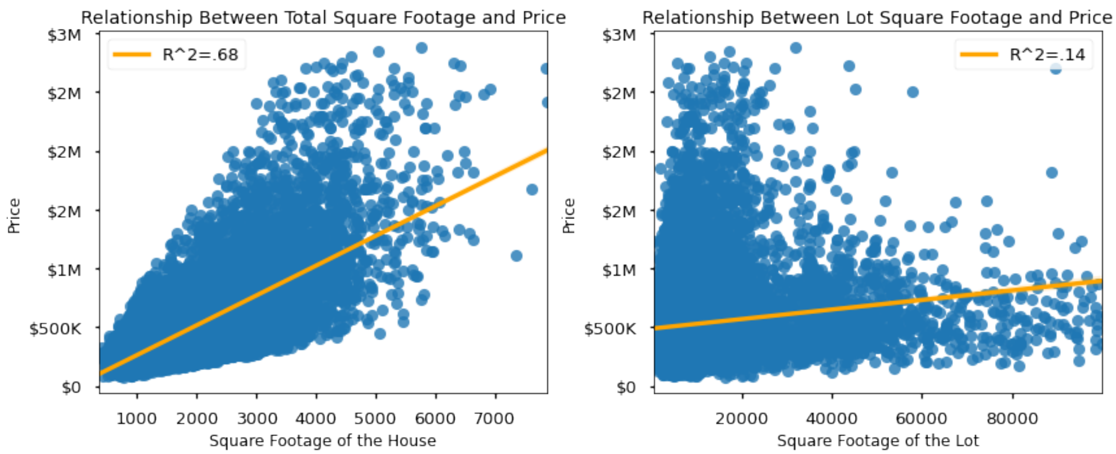
[126]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.465
Model:                            OLS   Adj. R-squared:                  0.465
Method:                 Least Squares   F-statistic:                     9032.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:55   Log-Likelihood:                -9069.5
No. Observations:               20795   AIC:                         1.815e+04
Df Residuals:                   20792   BIC:                         1.817e+04
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          12.2237      0.007   1816.812      0.000      12.211      12.237
sqft_living     0.0004   3.12e-06    131.935      0.000       0.000       0.000
sqft_lot    -2.726e-06   2.49e-07    -10.969      0.000   -3.21e-06   -2.24e-06
==============================================================================
Omnibus:                       67.767   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               54.733
Skew:                           0.048   Prob(JB):                     1.30e-12
Kurtosis:                       2.768   Cond. No.                     3.87e+04
==============================================================================

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

```
[2] The condition number is large, 3.87e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[127]:
```python
# Compare how sqft_living and sqft_lot (alone) correlates with price:
print(data.corr()['price']['sqft_living'])
print(data.corr()['price']['sqft_lot'])
```

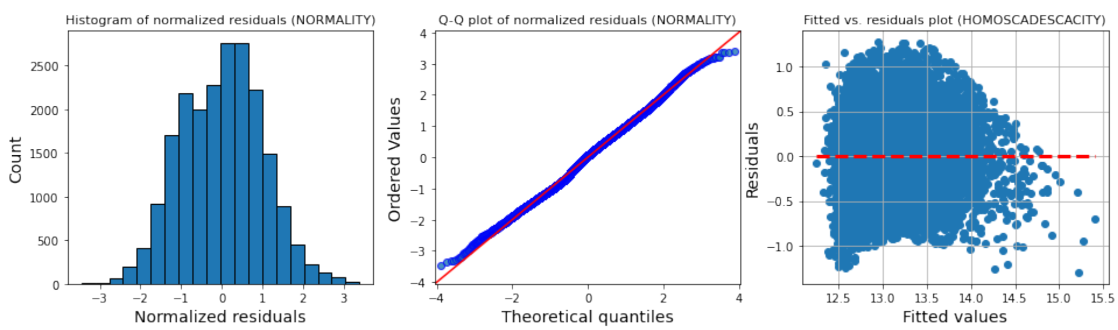
```
0.6846565855514448
0.13785310062451708
```

[128]:
```python
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=.68"})
    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=.14"})
    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_living` correlates very higly with `price` whereas `sqft_lot` correlates to a lower extent.
- However it is still important to keep them both in the regression model since `sqft_lot` is still significant.

[129]:
```
normality_homoscadescacity(model);
```



[130]:
```
multicollinearity(X).head()
```

[130]:
```
                  0
const        6.7194
sqft_living  1.0787
sqft_lot     1.0787
```

- Normality and homoscadescacity are acceptable.
- `sqft_lot` adds little to the model increasing R-squared slightly from 0.462 to 0.465.
- `sqft_lot` is still highly statistically significant, so it is still worthwhile keeping it in the model.

0.11.5 MODEL #5

- Adding other meaningful variables except age, season and location

[131]:
```python
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
```

[131]: 0.5524238302446016

[132]:
```python
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
```

[132]: 0.5732579679374332

[133]:
```python
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
```

[133]: 0.5743467319579401

[134]:
```python
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)
```

0.5814723680773605

[135]:
```
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()
print(model.rsquared)
```

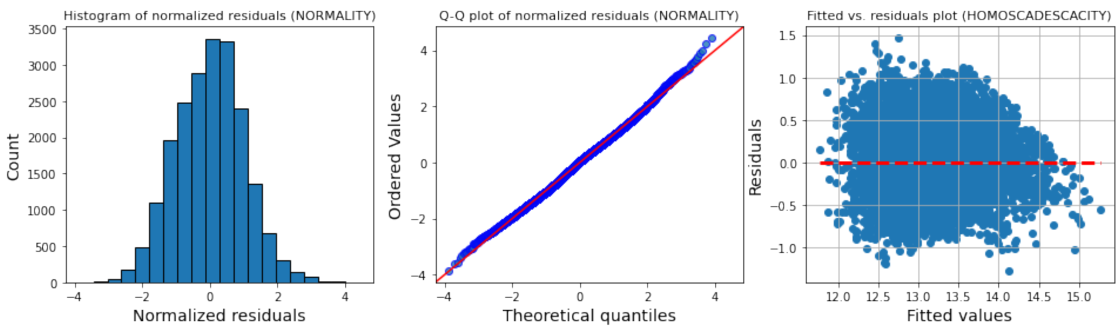
0.5838257541322789

[136]:
```
model.summary()
```

[136]:
```
<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:                     2916.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:48:59   Log-Likelihood:                -6455.9
No. Observations:               20795   AIC:                         1.293e+04
Df Residuals:                   20784   BIC:                         1.302e+04
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.8182      0.026    417.001      0.000      10.767      10.869
sqft_living      0.0002   5.46e-06     38.487      0.000       0.000       0.000
sqft_lot     -2.019e-06   2.29e-07     -8.825      0.000   -2.47e-06   -1.57e-06
condition        0.0957      0.004     25.927      0.000       0.088       0.103
grade            0.1917      0.003     57.632      0.000       0.185       0.198
has_view         0.1823      0.009     21.442      0.000       0.166       0.199
waterfront       0.4379      0.031     13.929      0.000       0.376       0.500
bedrooms        -0.0218      0.003     -6.414      0.000      -0.028      -0.015
bathrooms       -0.0298      0.005     -5.735      0.000      -0.040      -0.020
has_basement     0.1154      0.005     21.519      0.000       0.105       0.126
floors           0.0618      0.006     10.841      0.000       0.051       0.073
==============================================================================
Omnibus:                       11.124   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               11.127
```

```
Skew:                           0.057   Prob(JB):                      0.00384
Kurtosis:                       3.004   Cond. No.                     2.05e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.05e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[138]:
```python
normality_homoscadescacity(model);
```



[139]:
```python
multicollinearity(X).head()
# All variables are below 5, so multicollinearity is not an issue:
```

[139]:

	0
const	128.4061
sqft_living	4.2551
bathrooms	2.8644
grade	2.7441
floors	1.8117

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

0.11.6 MODEL #6

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

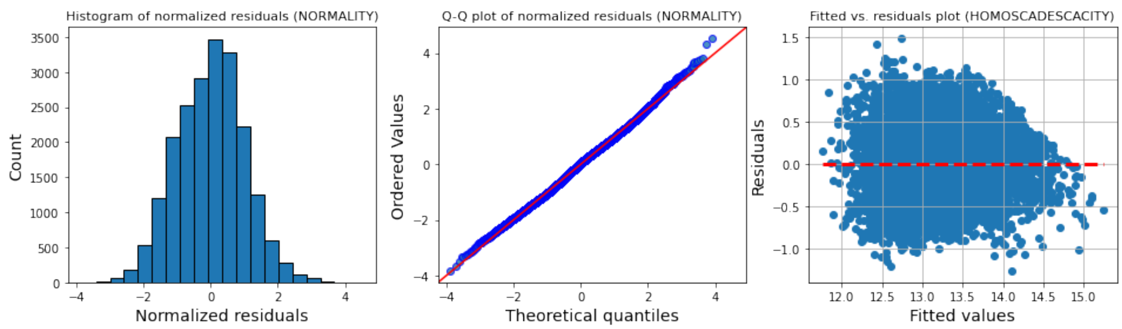
[140]:
```python
variables = ['sqft_living', 'sqft_lot', 'condition', 'grade', 'has_view',
 ↪'waterfront',
             'bedrooms', 'bathrooms', 'has_basement', 'floors',
             'april', 'august', 'december', 'february', 'july', 'june', 'march',
               'may', 'november', 'october', 'september']
```

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

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

[140]:
```
<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:                     1401.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:49:40   Log-Likelihood:                -6397.6
No. Observations:               20795   AIC:                         1.284e+04
Df Residuals:                   20773   BIC:                         1.301e+04
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          10.7876      0.028    388.561      0.000      10.733      10.842
sqft_living     0.0002   5.45e-06     38.704      0.000       0.000       0.000
sqft_lot    -2.006e-06   2.28e-07     -8.792      0.000   -2.45e-06   -1.56e-06
condition       0.0967      0.004     26.228      0.000       0.090       0.104
grade           0.1914      0.003     57.684      0.000       0.185       0.198
has_view        0.1817      0.008     21.422      0.000       0.165       0.198
waterfront      0.4368      0.031     13.926      0.000       0.375       0.498
bedrooms       -0.0222      0.003     -6.551      0.000      -0.029      -0.016
bathrooms      -0.0296      0.005     -5.706      0.000      -0.040      -0.019
has_basement    0.1150      0.005     21.493      0.000       0.105       0.125
floors          0.0621      0.006     10.928      0.000       0.051       0.073
april           0.0823      0.013      6.405      0.000       0.057       0.108
august          0.0157      0.013      1.191      0.234      -0.010       0.042
december       -0.0026      0.014     -0.185      0.853      -0.030       0.025
february        0.0069      0.014      0.484      0.629      -0.021       0.035
july            0.0192      0.013      1.485      0.137      -0.006       0.044
june            0.0282      0.013      2.179      0.029       0.003       0.054
march           0.0587      0.013      4.442      0.000       0.033       0.085
may             0.0409      0.013      3.210      0.001       0.016       0.066
november        0.0046      0.014      0.330      0.742      -0.023       0.032
october         0.0179      0.013      1.352      0.176      -0.008       0.044
september       0.0171      0.013      1.281      0.200      -0.009       0.043
==============================================================================
```

```
Omnibus:                        8.768   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.012   Jarque-Bera (JB):                8.761
Skew:                           0.050   Prob(JB):                       0.0125
Kurtosis:                       3.008   Cond. No.                     2.54e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.54e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[141]:
```
normality_homoscadescacity(model);
```



[142]:
```
multicollinearity(X).head()
```

[142]:

	0
const	147.8026
sqft_living	4.2570
may	3.0664
april	2.9603
july	2.9327

- R2 increased very slightly from 0.584 to .586 - normality and homoscadescacity are intact, and multicollinearity is not an issue.
- It seems like it is the months of spring that have an impact on price, and there are 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 our sample to conclude that a correlation exists).

Removing nonsignificant months:

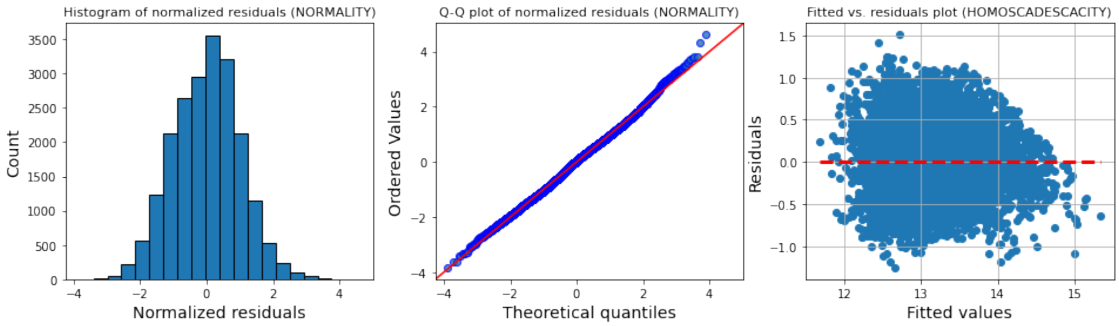
[143]:
```
variables = ['sqft_living', 'log_sqft_lot', 'condition', 'grade', 'has_view',␣
↪'waterfront',
```

```
             '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()
```

[143]:
```
<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:                     2145.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:49:49   Log-Likelihood:                -6273.9
No. Observations:               20795   AIC:                         1.258e+04
Df Residuals:                   20780   BIC:                         1.270e+04
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.4261      0.044    261.341      0.000      11.340      11.512
sqft_living      0.0002    5.7e-06     42.046      0.000       0.000       0.000
log_sqft_lot    -0.0708      0.004    -18.282      0.000      -0.078      -0.063
condition        0.0982      0.004     26.811      0.000       0.091       0.105
grade            0.1907      0.003     57.871      0.000       0.184       0.197
has_view         0.1831      0.008     21.726      0.000       0.167       0.200
waterfront       0.4626      0.031     14.825      0.000       0.401       0.524
bedrooms        -0.0182      0.003     -5.400      0.000      -0.025      -0.012
bathrooms       -0.0348      0.005     -6.741      0.000      -0.045      -0.025
has_basement     0.0884      0.006     15.869      0.000       0.077       0.099
floors           0.0170      0.006      2.695      0.007       0.005       0.029
april            0.0703      0.008      9.231      0.000       0.055       0.085
march            0.0469      0.008      5.709      0.000       0.031       0.063
may              0.0277      0.007      3.734      0.000       0.013       0.042
june             0.0182      0.008      2.357      0.018       0.003       0.033
==============================================================================
Omnibus:                        8.474   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.014   Jarque-Bera (JB):                8.472
Skew:                           0.045   Prob(JB):                       0.0145
Kurtosis:                       3.041   Cond. No.                     4.32e+04
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.32e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

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



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

[145]:

	0
const	371.0576
sqft_living	4.7046
bathrooms	2.8766
grade	2.7426
floors	2.2618

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

0.11.7 MODEL #7

- adding `age<30`

[146]:
```
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]
```

```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:                       0.602
Model:                            OLS   Adj. R-squared:                  0.602
Method:                 Least Squares   F-statistic:                     2094.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:49:56   Log-Likelihood:                -5994.7
No. Observations:               20795   AIC:                         1.202e+04
Df Residuals:                   20779   BIC:                         1.215e+04
Df Model:                          15
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.5175      0.043    265.933      0.000      11.433      11.602
sqft_living      0.0002   5.62e-06     42.609      0.000       0.000       0.000
log_sqft_lot    -0.0812      0.004    -21.121      0.000      -0.089      -0.074
condition        0.0685      0.004     17.912      0.000       0.061       0.076
grade            0.1993      0.003     60.904      0.000       0.193       0.206
has_view         0.1628      0.008     19.480      0.000       0.146       0.179
waterfront       0.4575      0.031     14.861      0.000       0.397       0.518
bedrooms        -0.0293      0.003     -8.735      0.000      -0.036      -0.023
bathrooms        0.0052      0.005      0.975      0.330      -0.005       0.016
has_basement     0.0646      0.006     11.570      0.000       0.054       0.076
floors           0.0631      0.007      9.667      0.000       0.050       0.076
april            0.0695      0.008      9.237      0.000       0.055       0.084
march            0.0461      0.008      5.688      0.000       0.030       0.062
may              0.0310      0.007      4.226      0.000       0.017       0.045
june             0.0179      0.008      2.348      0.019       0.003       0.033
age<30          -0.1677      0.007    -23.782      0.000      -0.182      -0.154
==============================================================================
Omnibus:                       16.922   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.241
Skew:                          -0.002   Prob(JB):                     6.64e-05
Kurtosis:                       3.149   Cond. No.                     4.34e+04
==============================================================================

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

```
[2] The condition number is large, 4.34e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Remove bathrooms as it is not significant any more:

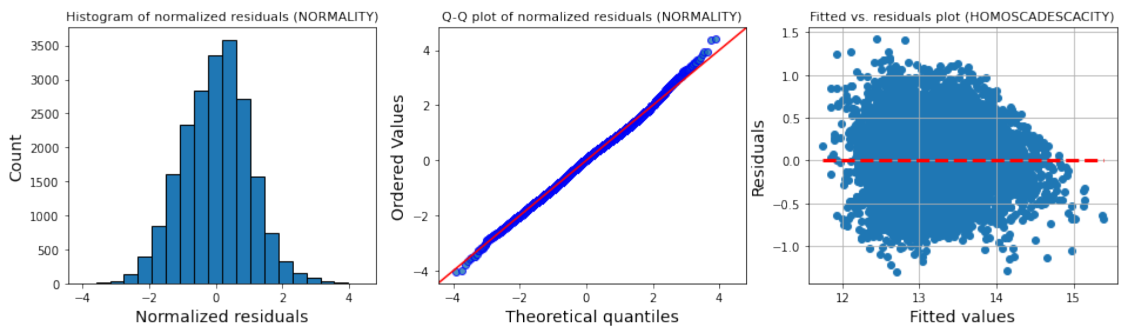
- It also correlates highly with `sqft_living`.

[147]:
```
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()
```

[147]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.602
Model:                            OLS   Adj. R-squared:                  0.602
Method:                 Least Squares   F-statistic:                     2244.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:49:57   Log-Likelihood:                -5995.2
No. Observations:               20795   AIC:                         1.202e+04
Df Residuals:                   20780   BIC:                         1.214e+04
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.5173      0.043    265.932      0.000      11.432      11.602
sqft_living      0.0002   5.29e-06     45.655      0.000       0.000       0.000
log_sqft_lot    -0.0814      0.004    -21.177      0.000      -0.089      -0.074
condition        0.0688      0.004     18.024      0.000       0.061       0.076
grade            0.1996      0.003     61.326      0.000       0.193       0.206
has_view         0.1629      0.008     19.489      0.000       0.146       0.179
waterfront       0.4577      0.031     14.868      0.000       0.397       0.518
bedrooms        -0.0286      0.003     -8.739      0.000      -0.035      -0.022
has_basement     0.0657      0.005     11.985      0.000       0.055       0.076
floors           0.0641      0.006      9.975      0.000       0.052       0.077
```

```
april            0.0694      0.008      9.236      0.000       0.055       0.084
march            0.0461      0.008      5.682      0.000       0.030       0.062
may              0.0309      0.007      4.218      0.000       0.017       0.045
june             0.0180      0.008      2.360      0.018       0.003       0.033
age<30          -0.1656      0.007    -24.725      0.000      -0.179      -0.152
==============================================================================
Omnibus:                       16.948   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.270
Skew:                          -0.002   Prob(JB):                     6.54e-05
Kurtosis:                       3.149   Cond. No.                     4.34e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.34e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

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



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

[149]:

	0
const	373.9967
sqft_living	4.1618
grade	2.7467
floors	2.4096
age<30	2.1403

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

0.11.8 FINAL MODEL #8

- adding location variables

[150]:
```python
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]

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:                       0.753
Model:                            OLS   Adj. R-squared:                  0.753
Method:                 Least Squares   F-statistic:                     3518.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:50:03   Log-Likelihood:                -1032.0
No. Observations:               20795   AIC:                             2102.
Df Residuals:                   20776   BIC:                             2253.
Df Model:                          18
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           10.6465      0.020    526.759      0.000      10.607      10.686
sqft_living      0.0002      4e-06     54.856      0.000       0.000       0.000
sqft_lot      1.424e-06   1.83e-07      7.793      0.000    1.07e-06    1.78e-06
condition        0.0833      0.003     27.626      0.000       0.077       0.089
grade            0.1608      0.003     61.928      0.000       0.156       0.166
has_view         0.1427      0.007     21.555      0.000       0.130       0.156
waterfront       0.5185      0.024     21.383      0.000       0.471       0.566
bedrooms        -0.0039      0.003     -1.500      0.134      -0.009       0.001
has_basement     0.0171      0.004      3.983      0.000       0.009       0.025
floors           0.0293      0.005      6.093      0.000       0.020       0.039
april            0.0679      0.006     11.458      0.000       0.056       0.079
march            0.0562      0.006      8.798      0.000       0.044       0.069
may              0.0182      0.006      3.145      0.002       0.007       0.029
june             0.0089      0.006      1.477      0.140      -0.003       0.021
age<30          -0.0247      0.005     -4.518      0.000      -0.035      -0.014
east             0.4873      0.005     90.539      0.000       0.477       0.498
fareast          0.4034      0.006     62.691      0.000       0.391       0.416
```

```
north              0.3322      0.008     40.510      0.000       0.316       0.348
west               0.5316      0.005    104.020      0.000       0.522       0.542
==============================================================================
Omnibus:                      560.606   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1339.083
Skew:                          -0.088   Prob(JB):                    1.67e-291
Kurtosis:                       4.231   Cond. No.                     2.06e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.06e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

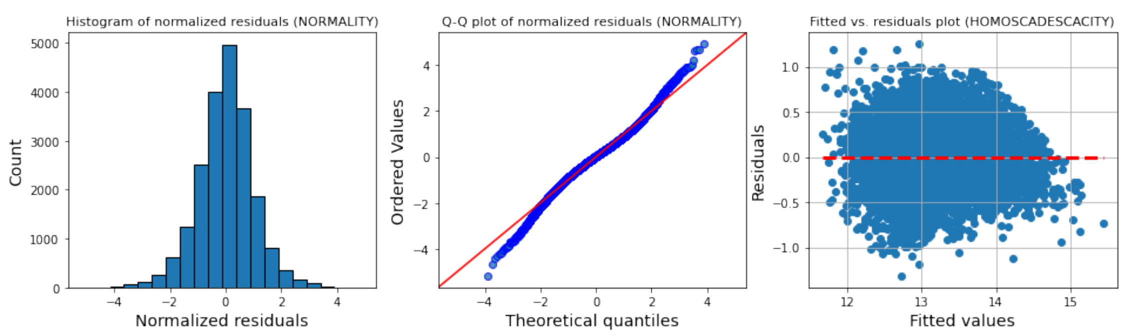
Remove bedrooms and june from the model:

[151]:
```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()
```

[151]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.753
Method:                 Least Squares   F-statistic:                     3958.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:50:05   Log-Likelihood:                -1034.2
No. Observations:               20795   AIC:                             2102.
Df Residuals:                   20778   BIC:                             2237.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
```

```
==============================================================================
const           10.6363      0.019    561.915      0.000      10.599      10.673
sqft_living      0.0002   3.45e-06     62.591      0.000       0.000       0.000
sqft_lot      1.448e-06   1.82e-07      7.951      0.000    1.09e-06     1.8e-06
condition        0.0833      0.003     27.644      0.000       0.077       0.089
grade            0.1614      0.003     62.643      0.000       0.156       0.166
has_view         0.1435      0.007     21.760      0.000       0.131       0.156
waterfront       0.5201      0.024     21.473      0.000       0.473       0.568
has_basement     0.0169      0.004      3.943      0.000       0.009       0.025
floors           0.0288      0.005      6.010      0.000       0.019       0.038
april            0.0665      0.006     11.351      0.000       0.055       0.078
march            0.0548      0.006      8.661      0.000       0.042       0.067
may              0.0168      0.006      2.950      0.003       0.006       0.028
age<30          -0.0239      0.005     -4.392      0.000      -0.035      -0.013
east             0.4875      0.005     90.567      0.000       0.477       0.498
fareast          0.4042      0.006     62.973      0.000       0.392       0.417
north            0.3325      0.008     40.548      0.000       0.316       0.349
west             0.5326      0.005    104.948      0.000       0.523       0.543
==============================================================================
Omnibus:                      559.114   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1337.377
Skew:                          -0.086   Prob(JB):                    3.91e-291
Kurtosis:                       4.231   Cond. No.                     2.05e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.05e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

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



[153]:
```
multicollinearity(X).head()
```

[153]:

```
                    0
const        115.1126
sqft_living    2.8640
grade          2.7727
age<30         2.2686
floors         2.1632
```

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

[154]:

```python
# Print the coefficients using a better format:
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
```

[154]:

	var	coef
0	const	10.636341
1	sqft_living	0.000216
2	sqft_lot	0.000001
3	condition	0.083309
4	grade	0.161366
5	has_view	0.143503
6	waterfront	0.520139
7	has_basement	0.016903
8	floors	0.028842
9	april	0.066522
10	march	0.054830
11	may	0.016844
12	age<30	-0.023856
13	east	0.487455
14	fareast	0.404172
15	north	0.332521
16	west	0.532614

[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	10.636341	4161920.394068

1	sqft_living	0.000216	0.021602
2	sqft_lot	0.000001	0.000100
3	condition	0.083309	8.687760
4	grade	0.161366	17.511498
5	has_view	0.143503	15.431027
6	waterfront	0.520139	68.226147
7	has_basement	0.016903	1.704666
8	floors	0.028842	2.926196
9	april	0.066522	6.878448
10	march	0.054830	5.636102
11	may	0.016844	1.698666
12	age<30	-0.023856	-2.357369
13	east	0.487455	62.816726
14	fareast	0.404172	49.806159
15	north	0.332521	39.447918
16	west	0.532614	70.337913

Model summary (from the model with UNSCALED coefficients):

- 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, Homoscadescacity is preserved, no presence of multicollinearity,
- Durbin-Watson score is between 1.5 and 2.5, meaning: no first-order autocorrelation - independence of residuals. Autocorrelation refers to the degree of correlation of the same variable between two successive time intervals. Autocorrelation would ential that here is a pattern such that values in the series can be predicted based on preceding values in the series.
- 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 % (given all other variables are kept constant).
- For every 100 sqft increase of 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 of 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 2.9%.
- Houses sold in `April` are 6.9% 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 1.7% 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 63% more expensive than those in South.

Scaling the variables to see the most impactful variables in order:

[156]:
```
# Perform a min-max scaling on the continuous variables:
for var in ['sqft_living','sqft_lot','condition' , 'grade', 'floors']:
    data[f"scaled_"+var] = (data[var] - min(data[var])) / (max(data[var]) -␣
 ↪min(data[var]))
```

[157]:
```
# Run the model on scaled variables:
variables = variables = ['scaled_sqft_living', 'scaled_sqft_lot',␣
 ↪'scaled_condition', 'scaled_grade', 'has_view' ,'waterfront',
             'has_basement', 'scaled_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()
```

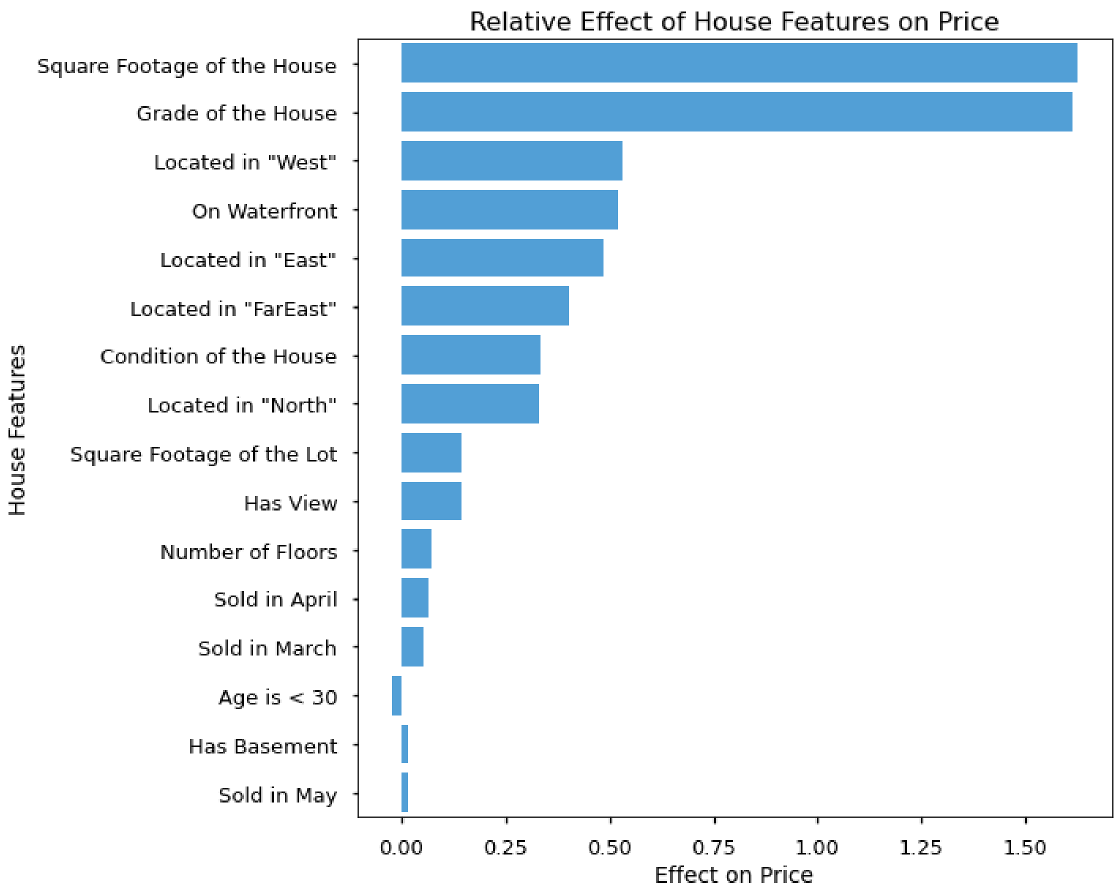
[157]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.753
Method:                 Least Squares   F-statistic:                     3958.
Date:                Fri, 26 Aug 2022   Prob (F-statistic):               0.00
Time:                        13:50:13   Log-Likelihood:                -1034.2
No. Observations:               20795   AIC:                             2102.
Df Residuals:                   20778   BIC:                             2237.
Df Model:                          16
Covariance Type:            nonrobust
```

```
==============================================================================
======
                        coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const                11.3133      0.012    943.542      0.000      11.290
11.337
scaled_sqft_living    1.6236      0.026     62.591      0.000       1.573
1.674
scaled_sqft_lot       0.1439      0.018      7.951      0.000       0.108
0.179
scaled_condition      0.3332      0.012     27.644      0.000       0.310
0.357
scaled_grade          1.6137      0.026     62.643      0.000       1.563
1.664
has_view              0.1435      0.007     21.760      0.000       0.131
0.156
waterfront            0.5201      0.024     21.473      0.000       0.473
0.568
has_basement          0.0169      0.004      3.943      0.000       0.009
0.025
scaled_floors         0.0721      0.012      6.010      0.000       0.049
0.096
april                 0.0665      0.006     11.351      0.000       0.055
0.078
march                 0.0548      0.006      8.661      0.000       0.042
0.067
may                   0.0168      0.006      2.950      0.003       0.006
0.028
age<30               -0.0239      0.005     -4.392      0.000      -0.035
-0.013
east                  0.4875      0.005     90.567      0.000       0.477
0.498
fareast               0.4042      0.006     62.973      0.000       0.392
0.417
north                 0.3325      0.008     40.548      0.000       0.316
0.349
west                  0.5326      0.005    104.948      0.000       0.523
0.543
==============================================================================
Omnibus:                      559.114   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1337.377
Skew:                          -0.086   Prob(JB):                    3.91e-291
Kurtosis:                       4.231   Cond. No.                         28.6
==============================================================================
```

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

[158]:

```
# Drop the model coefficient for graphing purposes:
coeff = model.params.drop('const')

# Sort the coefficients:
coeff = coeff.iloc[(coeff.abs()*-1.0).argsort()]

# Plot the coefficients using a TORNADO PLOT:
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ax  = plt.subplots(figsize=(10, 8))
    sns.barplot(x=coeff.values, y=coeff.index, color = base_color, ax=ax,␣
 ↪orient='h')
    ax.set_title('Relative Effect of House Features on Price', fontsize=16)
    ax.set_xlabel("Effect on Price", fontsize=14)
    ax.set_ylabel("House Features", fontsize=14)
    ax.set_yticklabels(labels=['Square Footage of the House', 'Grade of the␣
 ↪House', 'Located in "West"', 'On Waterfront', 'Located in "East"',
                               'Located in "FarEast"', 'Condition of the House',␣
 ↪'Located in "North"', 'Square Footage of the Lot', 'Has View',
                               'Number of Floors', 'Sold in April', 'Sold in␣
 ↪March','Age is < 30' , 'Has Basement' , 'Sold in May'])
    fig.tight_layout();

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



Tornado Plot Summary:

- `Square footage of the house` is the most impactful variable as expected.
- `Grade` of the house is also very impactful (however this is not a very useful variable for our stakeholder since they rebuild the houses).
- Other impactful variables in order are:
  - `Being on Waterfront`
  - `Not being located in the south`
  - `Condition of the house`
  - `square footage of the lot`
  - `Having a view`
  - `number of Floors`
  - `Going on the Market in April or March`
  - `young age`
  - `having a basement`

0.11.9 Specific 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). This is the most important feature to invest on. For every 1000

sqft increase in the house price increases by about 22%.

2. Being on waterfront increases the house price by 68%, so invest on houses on waterfront.
3. Put the house on the market in April which increases the price by 6.9% compared to selling it in other seasons. 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 63% increase compared to the South.

0.11.10 Limitations

- Skewed data required outlier removal or data transformation.
- Zipcodes could not be used in regression due to the huge number of levels (70).
- City to zipcode mapping did not work due to the zipcode and city boundaries overlapping.

0.11.11 Improvements

- Clustering zipcodes into meaningful groups would be helpful.
- Gathering more detailed location info using API calls would enrich the modeling process.

Exporting to PDF using nbconvert:

1. install nbconvert: `! pip install nbconvert`
2. install MacTeX from tps://tug.org/mactex/
3. `! export PATH=/Library/TeX/texbin:$PATH`
4. `! jupyter nbconvert --to PDF NOTEBOOKNAME.ipynb`