project2_OSEMN_plus_mvp_final

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#

Increase Your Property Value and Stretch Your House Buying Budget Further

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0.1 Table of Contents

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1 Introduction

1.1 Business Problem

This project is the Inference Analysis project of King County, WA house prices, and various factors that might affect the sales price. This study aims to build a model(s) of house sale prices depending on the features of the property in the dataset provided. This information can be helpful for house owners, house buyers, and real estate agents in the county.

2 Obtain

2.1 Data Understanding

The dataset used in this project has been downloaded from KAGGLE site. The dataset includes the information about properties sold in King County of Washington State between May 2014 and May 2015. The area consists of Seattle city area but does not include the inner city. The dataset consists of 21 dependent and independent variables and 21597 records.

2.1.1 Importing Python tools and utilities

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
import json

import plotly.express as px

import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms
import sklearn.metrics as metrics
#import plotly.graph_objects as go

import scipy.stats as stats

import math
#import pickle
import scipy.stats

from matplotlib import style

from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor

#from pandasql import sqldf
```

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
#from sklearn.preprocessing import OneHotEncoder, PolynomialFeatures,␣
↪StandardScaler, RobustScaler, MinMaxScaler
from sklearn.preprocessing import OneHotEncoder, PolynomialFeatures,␣
↪RobustScaler, MinMaxScaler

from sklearn.feature_selection import RFE
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

from scipy.stats import pearsonr
from IPython.display import display, Math, Latex
from folium import plugins
from plotly.subplots import make_subplots

#from mlxtend.evaluate import bias_variance_decomp

from warnings import filterwarnings
filterwarnings('ignore')

%matplotlib inline
```

2.1.2 Functions used

[2]:
```python
def count_unique_records(df):
    unique_records=[]
    for column in df.columns:
        n = df[column].nunique()
        unique_records.append((column,n))
    print(unique_records)
    return None

def count_dups_field(field1):
    dups = df.pivot_table(index = [field1], aggfunc ='size')
    return dups

def count_dups_fields(field1, field2):
    dups = df.pivot_table(index = [field1, field2], aggfunc ='size')
    return dups

def remove_columns(df, y_columns=['price'], x_columns=[], exclude_columns=[],␣
↪add_constant=True):
```

```
    if x_columns==[]:
        x_columns=list(df.drop(columns=y_columns, axis=1))

    [x_columns.remove(columns) for columns in exclude_columns]

    df_x=df[x_columns]
    df_y=df[y_columns]

    return df_x, df_y

# Function to convert geo coordinates to distance from center. I am using␣
↪coordinates
def distance_from_center(lat_coord,lon_coord):
    R = 3959.999

# I am using geo coordinates of Seattle 47.6062° N, 122.3321° W, from Wikipedia

    lat1 = math.radians(47.6062)
    lon1 = math.radians(122.3321)
    lat2 = math.radians(lat_coord)
    lon2 = math.radians(lon_coord)

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = math.sin(dlat / 2)**2 + math.cos(lat1) * math.cos(lat2) * math.sin(dlon␣
↪/ 2)**2
    c = 2 * math.atan2(math.sqrt(a), math.sqrt(1 - a))
    d=R*c
    return round(d,1)

def jointplot(df):
    sns.set_style('white')
    for col in df.columns:
        g=sns.jointplot(x=col, y='price', data=df, size=5, kind='reg',␣
↪marginal_ticks=True,
                        joint_kws={'line_kws':{'color':'green'}}, height=15,␣
↪space=0.7)
        name=col
        R2,p= scipy.stats.pearsonr(x=df[col], y=df.price)
        g.fig.suptitle('For {}: R2 coefficient is {}, p-value is {}'.
↪format(name, round(R2,4),p))
        g.fig.tight_layout()
        g.fig.subplots_adjust(top=0.85)

    return None
```

```
def r2_p(df):
    for col in df.columns:
        name=col
        R2,p= scipy.stats.pearsonr(x=df[col], y=df.price)
        print('For {}: R2 coefficient is {}, p-value is {}'.format(name,␣
 ↪round(R2,4),p))
    return None

# This is a snippet from https://www.analyticsvidhya.com/blog/2020/03/
 ↪what-is-multicollinearity/
def calc_vif(X):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]

    return(vif)

# This is a snippet from https://atmamani.github.io/cheatsheets/seaborn/
 ↪seaborn_cheat_sheet_1/
def distribution(column):
    col_mean = column.mean()
    col_sd = column.std()
    skew_val = stats.skew(column, bias=False)
    kurt_val = stats.kurtosis(column,bias=False)

    ax = sns.distplot(column, kde_kws={"color": "r", "lw": 2, "label": "KDE",␣
 ↪"bw_adjust": 3})

    ax.axvline(x=col_mean, color='black', linestyle='dashed')

    ax.axvline(x=col_mean + col_sd, color='red', linestyle='dotted')
    ax.axvline(x=col_mean - col_sd, color='red', linestyle='dotted')

    ax.set_title('$\mu = {}$ | $\sigma = {}$ | Skew = {} | Kurtosis = {}'.
                 format(round(col_mean, 2), round(col_sd, 2),␣
 ↪round(skew_val,2), round(kurt_val,2)))

    plt.subplots_adjust(top=0.5)
    plt.tight_layout()

    return None

def boxen_plot(df,colname):
```

```python
    ax = sns.catplot(x=df[colname], y=df.price/1000000, kind="boxen",
                 data=df.sort_values(colname), height=7, aspect=8/5)
    ax.set_xticklabels(fontsize=12)
    ax.set_yticklabels(fontsize=12)
    plt.ylabel('Price in millions', fontsize=15)
    plt.xlabel(colname,fontsize=15)
    plt.grid()
    plt.show()
    return None

#Zipcode choropleth maps with average values per a zipcode (King County)
def map_choropleth_zip(df, column, title, column_name):
    fig=px.choropleth_mapbox(data_frame=df, locations='zipcode',␣
 ↪geojson=KC_zip_json, color=column,
                         mapbox_style='open-street-map', zoom=8.5, height=900,␣
 ↪featureidkey='properties.ZCTA5CE10',
                        center={'lat': 47.403768, 'lon': -122.005863},␣
 ↪opacity=0.4,
                        color_continuous_scale=px.colors.sequential.YlOrRd,
                        title=title,
                        template = "plotly_dark",
                        labels={
                            column: column_name})
    fig.update_layout(
    font_family="Arial",
    font_size=16,
    font_color="white",
    title_font_family="Arial",
    title_font_color="white",
    title_font_size=20)

    fig.update_layout(
    title={
        'y':0.98,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
    })

    fig.show()
    return None
```

2.1.3 Importing data

[3]:
```
# Importing raw data
df=pd.read_csv('data/kc_house_data.csv')
pd.set_option('display.width', 1000)
df.head()
```

[3]:
```
            id        date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  waterfront  view  …  grade  sqft_above  sqft_basement yr_built
yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0  7129300520  10/13/2014  221900.0         3       1.00         1180      5650
1.0         NaN   0.0  …      7        1180            0.0     1955
0.0    98178  47.5112 -122.257           1340         5650
1  6414100192   12/9/2014  538000.0         3       2.25         2570      7242
2.0         0.0   0.0  …      7        2170          400.0     1951
1991.0    98125  47.7210 -122.319           1690         7639
2  5631500400   2/25/2015  180000.0         2       1.00          770     10000
1.0         0.0   0.0  …      6         770            0.0     1933
NaN    98028  47.7379 -122.233           2720         8062
3  2487200875   12/9/2014  604000.0         4       3.00         1960      5000
1.0         0.0   0.0  …      7        1050          910.0     1965
0.0    98136  47.5208 -122.393           1360         5000
4  1954400510   2/18/2015  510000.0         3       2.00         1680      8080
1.0         0.0   0.0  …      8        1680            0.0     1987
0.0    98074  47.6168 -122.045           1800         7503

[5 rows x 21 columns]
```

[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  float64
 9   view            21534 non-null  float64
 10  condition       21597 non-null  int64
 11  grade           21597 non-null  int64
 12  sqft_above      21597 non-null  int64
```

 13 sqft_basement 21597 non-null object
 14 yr_built   21597 non-null int64
 15 yr_renovated   17755 non-null float64
 16 zipcode   21597 non-null int64
 17 lat   21597 non-null float64
 18 long   21597 non-null float64
 19 sqft_living15 21597 non-null int64
 20 sqft_lot15   21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB

[5]:
```
# Displaying tuples of fields and unique records in them
count_unique_records(df)
```

```
[('id', 21420), ('date', 372), ('price', 3622), ('bedrooms', 12), ('bathrooms',
29), ('sqft_living', 1034), ('sqft_lot', 9776), ('floors', 6), ('waterfront',
2), ('view', 5), ('condition', 5), ('grade', 11), ('sqft_above', 942),
('sqft_basement', 304), ('yr_built', 116), ('yr_renovated', 70), ('zipcode',
70), ('lat', 5033), ('long', 751), ('sqft_living15', 777), ('sqft_lot15', 8682)]
```

[6]:
```
# Finding all duplicate IDs

df_a=pd.DataFrame(count_dups_field('id'))
df_a.columns=['count']
df_a = df_a[df_a['count'] > 1].sort_values('count', ascending=False)
df_a.reset_index(level=0, inplace=True)
df_a
```

[6]:

	id	count
0	795000620	3
1	1000102	2
2	5430300171	2
3	6021500970	2
4	6021501535	2
..	…	…
171	2726049071	2
172	2767602141	2
173	2767603612	2
174	2787460720	2
175	9834200885	2

[176 rows x 2 columns]

[7]:
```
# Listing duplicate IDs and associated dataset records to find out the reason␣
↪they are in the file twice

df_dup=pd.DataFrame()
for i in range(len(df_a)):
```

```
    df_dup=df_dup.append(df[df.id==df_a.id[i]], ignore_index=True)
df_dup
```

[7]:

```
             id        date     price  bedrooms  bathrooms  sqft_living
sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement
yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0     795000620   9/24/2014  115000.0         3       1.00         1080
6250     1.0         0.0   0.0  …      5       1080            0.0     1950
0.0    98168  47.5045 -122.330          1070         6250
1     795000620  12/15/2014  124000.0         3       1.00         1080
6250     1.0         0.0   0.0  …      5       1080            0.0     1950
0.0    98168  47.5045 -122.330          1070         6250
2     795000620   3/11/2015  157000.0         3       1.00         1080
6250     1.0         NaN   0.0  …      5       1080            0.0     1950
NaN    98168  47.5045 -122.330          1070         6250
3       1000102   9/16/2014  280000.0         6       3.00         2400
9373     2.0         NaN   0.0  …      7       2400            0.0     1991
0.0    98002  47.3262 -122.214          2060         7316
4       1000102   4/22/2015  300000.0         6       3.00         2400
9373     2.0         0.0   0.0  …      7       2400            0.0     1991
0.0    98002  47.3262 -122.214          2060         7316
..          …         …       …       …        …          …
…     …          …   …  …     …        …            …      …
…      …      …       …             …        …
348  2767603612   1/13/2015  489000.0         2       2.25         1290
1334     3.0         0.0   0.0  …      8       1290            0.0     2007
NaN    98107  47.6719 -122.382          1350         1334
349  2787460720   2/27/2015  200000.0         3       2.00         1010
7896     1.0         0.0   0.0  …      7       1010            0.0     1984
0.0    98031  47.4046 -122.181          1540         7896
350  2787460720    5/6/2015  259950.0         3       2.00         1010
7896     1.0         0.0   0.0  …      7       1010            0.0     1984
0.0    98031  47.4046 -122.181          1540         7896
351  9834200885   7/17/2014  360000.0         4       2.50         2080
4080     1.0         0.0   0.0  …      7       1040         1040.0     1962
0.0    98144  47.5720 -122.290          1340         4080
352  9834200885   4/20/2015  550000.0         4       2.50         2080
4080     1.0         0.0   0.0  …      7       1040         1040.0     1962
0.0    98144  47.5720 -122.290          1340         4080

[353 rows x 21 columns]
```

The inspection of the records shows that the records with duplicate IDs have different sale dates and sale prices. However, all other features remain the same. Records with the same set of predictors but different prices would introduce additional “noise” to the data. Because there are only 353 records with that problem, I decided to drop them from the dataset.

[8]:
```
#listing datatype, number of null values, min and max values in the fields of␣
↪the dataset

fields1=['bedrooms','bathrooms','floors','waterfront',␣
↪'view','condition','grade']
fields2=['sqft_lot15',␣
↪'sqft_living15','yr_renovated','yr_built','sqft_above','sqft_living','sqft_lot']
for column in df.columns:
    type_=df[column].dtypes
    num_nulls=df[column].isna().sum()
    min_=0
    max_=0
    unique_=[0]
    if column in fields1:
        unique_=df[column].unique()
        unique_.sort()
    else:
        if column in fields2:
            min_=df[column].min()
            max_=df[column].max()
        else:
            continue
    print('Column name:', column)
    print('Type:', type_)
    print('Number of null values', num_nulls)
    print('Unique values:',unique_)
    print('Min value: ', min_, 'Max value:', max_)
    print('***********************************')
```

```
Column name: bedrooms
Type: int64
Number of null values 0
Unique values: [ 1  2  3  4  5  6  7  8  9 10 11 33]
Min value:  0 Max value: 0
***********************************
Column name: bathrooms
Type: float64
Number of null values 0
Unique values: [0.5  0.75 1.   1.25 1.5  1.75 2.   2.25 2.5  2.75 3.   3.25 3.5
3.75
 4.   4.25 4.5  4.75 5.   5.25 5.5  5.75 6.   6.25 6.5  6.75 7.5  7.75
 8.  ]
Min value:  0 Max value: 0
***********************************
Column name: sqft_living
Type: int64
Number of null values 0
```

```
Unique values: [0]
Min value:  370 Max value: 13540
**********************************
Column name: sqft_lot
Type: int64
Number of null values 0
Unique values: [0]
Min value:  520 Max value: 1651359
**********************************
Column name: floors
Type: float64
Number of null values 0
Unique values: [1.  1.5 2.  2.5 3.  3.5]
Min value:  0 Max value: 0
**********************************
Column name: waterfront
Type: float64
Number of null values 2376
Unique values: [ 0.  1. nan]
Min value:  0 Max value: 0
**********************************
Column name: view
Type: float64
Number of null values 63
Unique values: [ 0.  1.  2.  3.  4. nan]
Min value:  0 Max value: 0
**********************************
Column name: condition
Type: int64
Number of null values 0
Unique values: [1 2 3 4 5]
Min value:  0 Max value: 0
**********************************
Column name: grade
Type: int64
Number of null values 0
Unique values: [ 3  4  5  6  7  8  9 10 11 12 13]
Min value:  0 Max value: 0
**********************************
Column name: sqft_above
Type: int64
Number of null values 0
Unique values: [0]
Min value:  370 Max value: 9410
**********************************
Column name: yr_built
Type: int64
Number of null values 0
```

```
Unique values: [0]
Min value:  1900 Max value: 2015
**********************************
Column name: yr_renovated
Type: float64
Number of null values 3842
Unique values: [0]
Min value:  0.0 Max value: 2015.0
**********************************
Column name: sqft_living15
Type: int64
Number of null values 0
Unique values: [0]
Min value:  399 Max value: 6210
**********************************
Column name: sqft_lot15
Type: int64
Number of null values 0
Unique values: [0]
Min value:  651 Max value: 871200
**********************************
```

2.1.4 Description of the fields

The file has 21597 records with 21 columns, out of which 11 columns have integer values, 8 are real numbers, and 2 are strings. The annotation to the fields and associated data (link to the definitions here) * id: Unique ID for each home sold

```
1. no NULL values<br>
2.integer numbers<br>
3.176 duplicate records
```

353 rows to be dropped

- **date:** Date of the sale >no NULL values string

  Convert to DateTime type

- **price** - Price of each home sold >no NULL values Real numbers Minimum price: 78000 Maximum price: 7700000
- **bedrooms** - Number of bedrooms >no NULL values >Integer numbers, between 1 and 33
- **bathrooms** - Number of bathrooms, where .5 accounts for a room with a toilet but no shower >no NULL values >Real numbers, between 0.5 and 8.0
- **sqft_living** - Square footage of the house interior living space >No NULL values Integer numbers Minimum value: 370 Maximum value: 13540
- **sqft_lot** - Square footage of the land lot >No NULL values Integer numbers Minimum value: 520 Maximum value: 1651359
- **floors** - Number of floors >no NULL values >Real numbers, between 1.0 and 3.5

- **waterfront** - A categorical variable for whether the house was overlooking the waterfront or not >**2376** NULL values >Real numbers, only two values 1.0 and 0.0

  Convert to a categorical variable Waterfront, not Waterfront Replace NULL values with "Missing" category

- **view** - A categorical variable describing how good the view of the property was >**63** NULL values >Real numbers: 1.0, 2.0, 3.0, 4.0

  Convert to a categorical variable Poor, Fair, Good Excellent

  Replace NULL values with "Missing" category

- **condition** - A categorical variable describing the condition of the house >no NULL values >Integer numbers, between 1 and 5

  Convert to a categorical variable Poor, Fair, Good, Very Good, Excellent

- **grade** - A categorical variable describing the quality of construction, from 1 to 13; 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 have a high quality level of construction and design. >no NULL values >Integer numbers, between 3 and 13

- **sqft_above** - The square footage of the interior housing space that is above ground level >No NULL values Integer numbers Minimum value: 370 Maximum value: 9410

- **sqft_basement** - The square footage of the interior housing space that is below ground level >No NULL values String

  Convert to integer

- **yr_built** - The year the house was initially built >No NULL values Integer numbers Minimum value: 1900 Maximum value: 2015

- **yr_renovated** - The year of the last house renovation >**3842** NULL values >Real numbers, between 0.0 and 2015.0

  Convert to integer

- **zipcode** - What zipcode area the house is in >no NULL values Integer numbers, 70 unique values

  Convert to categorical variable or drop

- **lat** - Lattitude >no NULL values >Real numbers

- **long** - Longitude >no NULL values >Real numbers

- **sqft_living15** - The square footage of interior housing living space for the nearest 15 neighbors >No NULL values Integer numbers Minimum value: 399 Maximum value: 6210

- **sqft_lot15** - The square footage of the land lots of the nearest 15 neighbors >No NULL values Integer numbers Minimum value: 651 Maximum value: 871200

2.1.5 Initial cleaning of the data

[9]:
```
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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64
 11  grade          21597 non-null  int64
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

1. Dropping duplicate rows for houses sold twice in the timeframe of the dataset

[10]:
```
#Dropping duplicate rows for houses sold twice in the timeframe of the dataset
df = df.drop_duplicates(subset='id', keep="first")
df
```

[10]:
```
               id        date     price  bedrooms  bathrooms  sqft_living
sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement
yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0      7129300520  10/13/2014  221900.0         3       1.00         1180
5650     1.0          NaN    0.0  …      7         1180            0.0     1955
0.0    98178  47.5112 -122.257           1340         5650
1      6414100192   12/9/2014  538000.0         3       2.25         2570
7242     2.0          0.0    0.0  …      7         2170          400.0     1951
1991.0    98125  47.7210 -122.319           1690         7639
2      5631500400   2/25/2015  180000.0         2       1.00          770
```

```
10000     1.0          0.0   0.0  …      6         770            0.0     1933
NaN     98028  47.7379 -122.233          2720        8062
3       2487200875   12/9/2014  604000.0         4       3.00           1960
5000     1.0          0.0   0.0  …      7         1050          910.0     1965
0.0     98136  47.5208 -122.393          1360        5000
4       1954400510   2/18/2015  510000.0         3       2.00           1680
8080     1.0          0.0   0.0  …      8         1680            0.0     1987
0.0     98074  47.6168 -122.045          1800        7503
…          …         …        …        …        …          …
…      …          …    …  …     …        …           …       …
…       …       …       …           …          …
21592   263000018   5/21/2014  360000.0          3       2.50           1530
1131     3.0          0.0   0.0  …      8         1530            0.0     2009
0.0     98103  47.6993 -122.346          1530        1509
21593  6600060120   2/23/2015  400000.0          4       2.50           2310
5813     2.0          0.0   0.0  …      8         2310            0.0     2014
0.0     98146  47.5107 -122.362          1830        7200
21594  1523300141   6/23/2014  402101.0          2       0.75           1020
1350     2.0          0.0   0.0  …      7         1020            0.0     2009
0.0     98144  47.5944 -122.299          1020        2007
21595   291310100   1/16/2015  400000.0          3       2.50           1600
2388     2.0          NaN   0.0  …      8         1600            0.0     2004
0.0     98027  47.5345 -122.069          1410        1287
21596  1523300157  10/15/2014  325000.0          2       0.75           1020
1076     2.0          0.0   0.0  …      7         1020            0.0     2008
0.0     98144  47.5941 -122.299          1020        1357

[21420 rows x 21 columns]
```

2. Converting the 'date' field to DateTime formate and making sure it worked

[11]:
```python
# date string to datetime type
df['date'] = pd.to_datetime(df['date'])
```

[12]:
```python
#Checking if the conversion went OK
mask = (df['date'] > '9/24/2014') & (df['date'] <= '4/22/2015')
df.loc[mask]
```

[12]:
```
               id       date     price  bedrooms  bathrooms  sqft_living
sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement
yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0       7129300520 2014-10-13   221900.0         3       1.00           1180
5650     1.0          NaN   0.0  …      7         1180            0.0     1955
0.0     98178  47.5112 -122.257          1340        5650
1       6414100192 2014-12-09   538000.0         3       2.25           2570
7242     2.0          0.0   0.0  …      7         2170          400.0     1951
1991.0     98125  47.7210 -122.319          1690        7639
2       5631500400 2015-02-25   180000.0         2       1.00            770
```

```
10000      1.0          0.0    0.0   …       6         770             0.0      1933
NaN     98028  47.7379 -122.233            2720        8062
3       2487200875 2014-12-09   604000.0         4       3.00          1960
5000     1.0          0.0    0.0   …       7         1050          910.0      1965
0.0     98136  47.5208 -122.393            1360        5000
4       1954400510 2015-02-18   510000.0         3       2.00          1680
8080     1.0          0.0    0.0   …       8         1680            0.0      1987
0.0     98074  47.6168 -122.045            1800        7503
…          …        …        …       …        …         …
…      …         …    …   …     …          …          …       …
…       …       …       …           …        …
21590  7936000429 2015-03-26  1010000.0         4       3.50          3510
7200     2.0          0.0    0.0   …       9         2600          910.0      2009
0.0     98136  47.5537 -122.398            2050        6200
21591  2997800021 2015-02-19   475000.0         3       2.50          1310
1294     2.0          0.0    0.0   …       8         1180          130.0      2008
0.0     98116  47.5773 -122.409            1330        1265
21593  6600060120 2015-02-23   400000.0         4       2.50          2310
5813     2.0          0.0    0.0   …       8         2310            0.0      2014
0.0     98146  47.5107 -122.362            1830        7200
21595   291310100 2015-01-16   400000.0         3       2.50          1600
2388     2.0          NaN    0.0   …       8         1600            0.0      2004
0.0     98027  47.5345 -122.069            1410        1287
21596  1523300157 2014-10-15   325000.0         2       0.75          1020
1076     2.0          0.0    0.0   …       7         1020            0.0      2008
0.0     98144  47.5941 -122.299            1020        1357

[10574 rows x 21 columns]
```

3. Locations of the houses with missing 'waterfront' values

[13]:
```python
# Possible strategies:
# 1. Check if there are waterfront properties among neighbors within a certain␣
↪distance range
# 2. Make a map and place properties with missing values on it visually
# 3. What is the longitude of the bay shore? Any house with a missing value too␣
↪far away from it
#    should have their waterfront value set to 0. Hopefully, it will eliminate␣
↪most of the missing values in this field
```

[14]:
```python
# Leaving just coordinates of the waterfront NaN properties
mask = (df['waterfront'].isna())
df_wf_na_coord=df.loc[mask]
df_wf_na_coord.drop(df_wf_na_coord.
↪columns[[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,19,20]], axis=1,␣
↪inplace=True)

df_wf_na_coord
```

[14]:
```
           lat     long
0      47.5112 -122.257
10     47.6007 -122.145
23     47.3533 -122.166
40     47.6145 -122.027
55     47.6597 -122.290
…          …        …
21578  47.3749 -122.107
21582  47.2931 -122.264
21586  47.3095 -122.002
21587  47.5389 -121.881
21595  47.5345 -122.069

[2353 rows x 2 columns]
```

3.1 Visual assesment of the houses with Null value in the 'waterfront column

[15]:
```
# Initializing the map based on the Wikipedia location of Seattle
KCMap = folium.Map(location=[47.6171,-122.3249],  tiles='Stamen Terrain',␣
↪zoom_start=9)

# for each row in the KC_house dataset with missing waterfront value,
# plot the corresponding latitude and longitude on the map
for index, row in df_wf_na_coord.iterrows():
    folium.CircleMarker((row['lat'], row['long']), radius=1, weight=2,
                        color='red', fill_color='red', fill_opacity=.5).
↪add_to(KCMap)

display(KCMap)
# adding the heatmap
KCMap.add_child(plugins.HeatMap(data=df_wf_na_coord[['lat', 'long']],␣
↪radius=20, blur=10))
```

```
<folium.folium.Map at 0x21a69232fd0>
```

[15]:
```
<folium.folium.Map at 0x21a69232fd0>
```

[16]:
```
# Displaying
# the percentage of waterfront properties in the dataset with missing␣
↪waterfront values,
# the percentage of waterfront properties in the full dataset
# The systemic error introduced to the full dataset if missing waterfront␣
↪values would be replaced with 0

a=round((20/len(df_wf_na_coord))*100,3)

b=round((len(df[df['waterfront'] == 1])/len(df)*100),2)
```

```
c=round(round(((len(df[df['waterfront'] == 1])+20)/
↪len(df)*100),3)-round((len(df[df['waterfront'] == 1])/len(df)*100),3),3)

print('{}%, {}%, {}%'.format(a, b, c))
```

```
0.85%, 0.68%, 0.093%
```

It is self-evident from the visuals above that the vast majority of the houses are located inland. Simple zooming in the maps allows a rough counting of alleged waterfront properties. The estimate is approximately 20 waterfront houses. It is 0.85% of all properties with no value in 'waterfront column (2353). In the primary dataset, the percentage of waterfront properties out of the total number of properties is 0.68%. The numbers above indicate that replacing the NaN values with 0 would introduce a systemic error of 0.01% to the whole system. Conclusion: The NULL values in the 'waterfront' column will be replaced with 0.

3.2 Replacing NULL values in 'waterfront' column and converting the column to the integer datatype to make it categorical

[17]:
```
#Replacing NaN values in 'waterfront' column

df.loc[df.waterfront.isna(),'waterfront']=0
df.waterfront=df.waterfront.astype('int64')


subset_df = df[df['waterfront'] == 1]
count = len(subset_df)
print(count)
#df.info()
```

```
146
```

[18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  datetime64[ns]
 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           21357 non-null  float64
 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  object
 14  yr_built       21420 non-null  int64
 15  yr_renovated   17616 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: datetime64[ns](1), float64(7), int64(12), object(1)
memory usage: 3.6+ MB
```

3.3 Replacing NULL values in waterfront and view field using IterativeImputer

[19]:

```python
# Dropping columns with str datatypes to use IterativeImputer on the rest

df_to_II=df.drop(['date','id','zipcode','sqft_basement'],axis=1)
df_to_II.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21420 non-null  float64
 1   bedrooms       21420 non-null  int64
 2   bathrooms      21420 non-null  float64
 3   sqft_living    21420 non-null  int64
 4   sqft_lot       21420 non-null  int64
 5   floors         21420 non-null  float64
 6   waterfront     21420 non-null  int64
 7   view           21357 non-null  float64
 8   condition      21420 non-null  int64
 9   grade          21420 non-null  int64
 10  sqft_above     21420 non-null  int64
 11  yr_built       21420 non-null  int64
 12  yr_renovated   17616 non-null  float64
 13  lat            21420 non-null  float64
 14  long           21420 non-null  float64
 15  sqft_living15  21420 non-null  int64
 16  sqft_lot15     21420 non-null  int64
dtypes: float64(7), int64(10)
memory usage: 2.9 MB
```

[20]:

```python
# Using IterativeImputer to fill in Nan cells

imp = IterativeImputer(max_iter=10,random_state=0)
imp.fit(df_to_II)
```

```
imputed_df_to_II = imp.transform(df_to_II)
imputed_df = pd.DataFrame(imputed_df_to_II, columns=df_to_II.columns)
imputed_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21420 entries, 0 to 21419
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21420 non-null  float64
 1   bedrooms       21420 non-null  float64
 2   bathrooms      21420 non-null  float64
 3   sqft_living    21420 non-null  float64
 4   sqft_lot       21420 non-null  float64
 5   floors         21420 non-null  float64
 6   waterfront     21420 non-null  float64
 7   view           21420 non-null  float64
 8   condition      21420 non-null  float64
 9   grade          21420 non-null  float64
 10  sqft_above     21420 non-null  float64
 11  yr_built       21420 non-null  float64
 12  yr_renovated   21420 non-null  float64
 13  lat            21420 non-null  float64
 14  long           21420 non-null  float64
 15  sqft_living15  21420 non-null  float64
 16  sqft_lot15     21420 non-null  float64
dtypes: float64(17)
memory usage: 2.8 MB
```

[21]:
```
df.head(20)
```

[21]:
```
            id        date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  waterfront  view  …  grade  sqft_above  sqft_basement yr_built
yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
0   7129300520 2014-10-13   221900.0         3       1.00         1180      5650
1.0           0    0.0  …      7        1180           0.0     1955
0.0    98178  47.5112 -122.257          1340         5650
1   6414100192 2014-12-09   538000.0         3       2.25         2570      7242
2.0           0    0.0  …      7        2170         400.0     1951
1991.0     98125  47.7210 -122.319          1690         7639
2   5631500400 2015-02-25   180000.0         2       1.00          770     10000
1.0           0    0.0  …      6         770           0.0     1933
NaN    98028  47.7379 -122.233          2720         8062
3   2487200875 2014-12-09   604000.0         4       3.00         1960      5000
1.0           0    0.0  …      7        1050         910.0     1965
0.0    98136  47.5208 -122.393          1360         5000
4   1954400510 2015-02-18   510000.0         3       2.00         1680      8080
1.0           0    0.0  …      8        1680           0.0     1987
```

```
0.0    98074  47.6168 -122.045           1800        7503
5  7237550310 2014-05-12  1230000.0         4        4.50          5420    101930
1.0          0   0.0  …      11        3890        1530.0     2001
0.0    98053  47.6561 -122.005           4760      101930
6  1321400060 2014-06-27   257500.0         3        2.25          1715      6819
2.0          0   0.0  …       7        1715             ?     1995
0.0    98003  47.3097 -122.327           2238        6819
7  2008000270 2015-01-15   291850.0         3        1.50          1060      9711
1.0          0   NaN  …       7        1060           0.0     1963
0.0    98198  47.4095 -122.315           1650        9711
8  2414600126 2015-04-15   229500.0         3        1.00          1780      7470
1.0          0   0.0  …       7        1050         730.0     1960
0.0    98146  47.5123 -122.337           1780        8113
9  3793500160 2015-03-12   323000.0         3        2.50          1890      6560
2.0          0   0.0  …       7        1890           0.0     2003
0.0    98038  47.3684 -122.031           2390        7570
10  1736800520 2015-04-03   662500.0         3        2.50          3560      9796
1.0          0   0.0  …       8        1860        1700.0     1965
0.0    98007  47.6007 -122.145           2210        8925
11  9212900260 2014-05-27   468000.0         2        1.00          1160      6000
1.0          0   0.0  …       7         860         300.0     1942
0.0    98115  47.6900 -122.292           1330        6000
12   114101516 2014-05-28   310000.0         3        1.00          1430     19901
1.5          0   0.0  …       7        1430           0.0     1927
NaN    98028  47.7558 -122.229           1780       12697
13  6054650070 2014-10-07   400000.0         3        1.75          1370      9680
1.0          0   0.0  …       7        1370           0.0     1977
0.0    98074  47.6127 -122.045           1370       10208
14  1175000570 2015-03-12   530000.0         5        2.00          1810      4850
1.5          0   0.0  …       7        1810           0.0     1900
0.0    98107  47.6700 -122.394           1360        4850
15  9297300055 2015-01-24   650000.0         4        3.00          2950      5000
2.0          0   3.0  …       9        1980         970.0     1979
0.0    98126  47.5714 -122.375           2140        4000
16  1875500060 2014-07-31   395000.0         3        2.00          1890     14040
2.0          0   0.0  …       7        1890           0.0     1994
0.0    98019  47.7277 -121.962           1890       14018
17  6865200140 2014-05-29   485000.0         4        1.00          1600      4300
1.5          0   0.0  …       7        1600           0.0     1916
0.0    98103  47.6648 -122.343           1610        4300
18    16000397 2014-12-05   189000.0         2        1.00          1200      9850
1.0          0   0.0  …       7        1200             ?     1921
0.0    98002  47.3089 -122.210           1060        5095
19  7983200060 2015-04-24   230000.0         3        1.00          1250      9774
1.0          0   0.0  …       7        1250           0.0     1969
0.0    98003  47.3343 -122.306           1280        8850
```

```
[20 rows x 21 columns]
```

[22]:
```
imputed_df.head(20)
```

[22]:
```
        price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
view  condition  grade  sqft_above  yr_built  yr_renovated      lat     long  \
sqft_living15  sqft_lot15
0    221900.0       3.0       1.00       1180.0    5650.0     1.0         0.0
0.000000         3.0    7.0      1180.0    1955.0       0.00000  47.5112 -122.257
1340.0      5650.0
1    538000.0       3.0       2.25       2570.0    7242.0     2.0         0.0
0.000000         3.0    7.0      2170.0    1951.0    1991.00000  47.7210 -122.319
1690.0      7639.0
2    180000.0       2.0       1.00        770.0   10000.0     1.0         0.0
0.000000         3.0    6.0       770.0    1933.0     120.63025  47.7379 -122.233
2720.0      8062.0
3    604000.0       4.0       3.00       1960.0    5000.0     1.0         0.0
0.000000         5.0    7.0      1050.0    1965.0       0.00000  47.5208 -122.393
1360.0      5000.0
4    510000.0       3.0       2.00       1680.0    8080.0     1.0         0.0
0.000000         3.0    8.0      1680.0    1987.0       0.00000  47.6168 -122.045
1800.0      7503.0
5   1230000.0       4.0       4.50       5420.0  101930.0     1.0         0.0
0.000000         3.0   11.0      3890.0    2001.0       0.00000  47.6561 -122.005
4760.0    101930.0
6    257500.0       3.0       2.25       1715.0    6819.0     2.0         0.0
0.000000         3.0    7.0      1715.0    1995.0       0.00000  47.3097 -122.327
2238.0      6819.0
7    291850.0       3.0       1.50       1060.0    9711.0     1.0         0.0
0.153019         3.0    7.0      1060.0    1963.0       0.00000  47.4095 -122.315
1650.0      9711.0
8    229500.0       3.0       1.00       1780.0    7470.0     1.0         0.0
0.000000         3.0    7.0      1050.0    1960.0       0.00000  47.5123 -122.337
1780.0      8113.0
9    323000.0       3.0       2.50       1890.0    6560.0     2.0         0.0
0.000000         3.0    7.0      1890.0    2003.0       0.00000  47.3684 -122.031
2390.0      7570.0
10   662500.0       3.0       2.50       3560.0    9796.0     1.0         0.0
0.000000         3.0    8.0      1860.0    1965.0       0.00000  47.6007 -122.145
2210.0      8925.0
11   468000.0       2.0       1.00       1160.0    6000.0     1.0         0.0
0.000000         4.0    7.0       860.0    1942.0       0.00000  47.6900 -122.292
1330.0      6000.0
12   310000.0       3.0       1.00       1430.0   19901.0     1.5         0.0
0.000000         4.0    7.0      1430.0    1927.0     106.23238  47.7558 -122.229
1780.0     12697.0
13   400000.0       3.0       1.75       1370.0    9680.0     1.0         0.0
```

```
0.000000         4.0    7.0       1370.0    1977.0        0.00000  47.6127 -122.045
1370.0     10208.0
14   530000.0        5.0        2.00       1810.0    4850.0     1.5          0.0
0.000000         3.0    7.0       1810.0    1900.0        0.00000  47.6700 -122.394
1360.0      4850.0
15   650000.0        4.0        3.00       2950.0    5000.0     2.0          0.0
3.000000         3.0    9.0       1980.0    1979.0        0.00000  47.5714 -122.375
2140.0      4000.0
16   395000.0        3.0        2.00       1890.0   14040.0     2.0          0.0
0.000000         3.0    7.0       1890.0    1994.0        0.00000  47.7277 -121.962
1890.0     14018.0
17   485000.0        4.0        1.00       1600.0    4300.0     1.5          0.0
0.000000         4.0    7.0       1600.0    1916.0        0.00000  47.6648 -122.343
1610.0      4300.0
18   189000.0        2.0        1.00       1200.0    9850.0     1.0          0.0
0.000000         4.0    7.0       1200.0    1921.0        0.00000  47.3089 -122.210
1060.0      5095.0
19   230000.0        3.0        1.00       1250.0    9774.0     1.0          0.0
0.000000         4.0    7.0       1250.0    1969.0        0.00000  47.3343 -122.306
1280.0      8850.0
```

[23]:
```python
# Creating a subset of records with imputed NaN values

subset_df = imputed_df[(imputed_df['yr_renovated'] < 1934) &␣
 ↪(imputed_df['yr_renovated'] != 0)]
count = len(subset_df)
print(count)
```

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[24]:
```python
# Listing Imputed NaN values in yr_renovated column
list_unique=list(df.yr_renovated.unique())

inverse_boolean_series = ~imputed_df.yr_renovated.isin(list_unique)
inverse_filtered_df = imputed_df[inverse_boolean_series]
inverse_filtered_df.yr_renovated.sort_values()
```

[24]:
```
9787     -275.837124
2661     -245.605029
19729    -238.322030
4500     -237.754900
15831    -232.222954
            …
3986      730.910013
14413     739.149439
7278      778.387115
8206      779.072447
10163     786.483270
```

```
Name: yr_renovated, Length: 3804, dtype: float64
```

[25]:
```python
# Listing Imputed NaN values in waterfront column
inverse_boolean_series = ~imputed_df.waterfront.isin([0,1])
inverse_filtered_df = imputed_df[inverse_boolean_series]
inverse_filtered_df.waterfront.sort_values()
```

[25]:
```
Series([], Name: waterfront, dtype: float64)
```

[26]:
```python
# Listing Imputed NaN values in view column
inverse_boolean_series = ~imputed_df.view.isin([0,1,2,3,4])
inverse_filtered_df = imputed_df[inverse_boolean_series]
inverse_filtered_df.view.sort_values()
```

[26]:
```
128     -0.186803
6341    -0.162364
17069   -0.116911
11207   -0.110384
19976   -0.099051
           …
3124     1.100092
18447    1.108053
19818    1.125893
9326     1.669403
1301     5.984964
Name: view, Length: 63, dtype: float64
```

```
<b>Conclusion:</b>  Based on the results of IterativeImputer the original approach of replacin
```

4. Replacing NULL values in yr_renovated column with 0. value and changing the type to integer

[27]:
```python
df.loc[df.yr_renovated.isna(),'yr_renovated']=0.0
df.yr_renovated=df.yr_renovated.astype('int64')
```

5. Replacing '?' values in 'sqft_basement' column with 0. value and changing the type to integer

[28]:
```python
df.loc[(df.sqft_basement == '?')]
```

[28]:
```
               id       date     price  bedrooms  bathrooms  sqft_living
sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement
yr_built  yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15
6      1321400060 2014-06-27   257500.0         3       2.25         1715
6819      2.0             0    0.0  …       7         1715               ?     1995
0     98003   47.3097 -122.327           2238         6819
18       16000397 2014-12-05   189000.0         2       1.00         1200
9850      1.0             0    0.0  …       7         1200               ?     1921
0     98002   47.3089 -122.210           1060         5095
```

```
42     7203220400  2014-07-07   861990.0         5       2.75         3595
5639      2.0            0    0.0  …       9        3595              ?     2014
0     98053  47.6848 -122.016           3625       5639
79     1531000030  2015-03-23   720000.0         4       2.50         3450
39683      2.0            0    0.0  …       10        3450              ?     2002
0     98010  47.3420 -122.025           3350       39750
112     2525310310  2014-09-16   272500.0         3       1.75         1540
12600      1.0            0    0.0  …       7        1160              ?     1980
0     98038  47.3624 -122.031           1540       11656
…           …          …          …         …         …         …
…      …          …    …   …      …          …           …       …
…       …        …        …              …          …
21442  3226049565  2014-07-11   504600.0         5       3.00         2360
5000      1.0            0    0.0  …       7        1390              ?     2008
0     98103  47.6931 -122.330           2180       5009
21447  1760650900  2014-07-21   337500.0         4       2.50         2330
4907      2.0            0    0.0  …       7        2330              ?     2013
0     98042  47.3590 -122.081           2300       3836
21473  6021503707  2015-01-20   352500.0         2       2.50          980
1010      3.0            0    0.0  …       8         980              ?     2008
0     98117  47.6844 -122.387            980       1023
21519  2909310100  2014-10-15   332000.0         4       2.50         2380
5737      2.0            0    0.0  …       7        2380              ?     2010
0     98023  47.2815 -122.356           2380       5396
21581   191100405  2015-04-21  1580000.0         4       3.25         3410
10125      2.0            0    0.0  …       10        3410              ?     2007
0     98040  47.5653 -122.223           2290       10125

[452 rows x 21 columns]
```

[29]:

```python
# Converting '?' sqft_basement values to 0 and listing unique values
df.loc[(df.sqft_basement == '?'),'sqft_basement']='0.0'

df.sqft_basement=df.sqft_basement.astype('float64')

df.sqft_basement=df.sqft_basement.astype('int64')

#Checking the result
df_temp=df.sqft_basement.unique()
list1 = df_temp.tolist()
list1.sort()
print(list1)
```

```
[0, 10, 20, 40, 50, 60, 65, 70, 80, 90, 100, 110, 120, 130, 140, 143, 145, 150,
160, 170, 172, 176, 180, 190, 200, 207, 210, 220, 225, 230, 235, 240, 243, 248,
250, 260, 265, 266, 270, 274, 276, 280, 283, 290, 295, 300, 310, 320, 330, 340,
350, 360, 370, 374, 380, 390, 400, 410, 414, 415, 417, 420, 430, 435, 440, 450,
460, 470, 475, 480, 490, 500, 506, 508, 510, 515, 516, 518, 520, 530, 540, 550,
```

```
556, 560, 570, 580, 588, 590, 600, 602, 610, 620, 630, 640, 650, 652, 660, 666,
670, 680, 690, 700, 704, 710, 720, 730, 740, 750, 760, 768, 770, 780, 784, 790,
792, 800, 810, 820, 830, 840, 850, 860, 861, 862, 870, 875, 880, 890, 900, 906,
910, 915, 920, 930, 935, 940, 946, 950, 960, 970, 980, 990, 1000, 1008, 1010,
1020, 1024, 1030, 1040, 1050, 1060, 1070, 1080, 1090, 1100, 1110, 1120, 1130,
1135, 1140, 1150, 1160, 1170, 1180, 1190, 1200, 1210, 1220, 1230, 1240, 1245,
1248, 1250, 1260, 1270, 1275, 1280, 1281, 1284, 1290, 1300, 1310, 1320, 1330,
1340, 1350, 1360, 1370, 1380, 1390, 1400, 1410, 1420, 1430, 1440, 1450, 1460,
1470, 1480, 1481, 1490, 1500, 1510, 1520, 1525, 1530, 1540, 1548, 1550, 1560,
1570, 1580, 1590, 1600, 1610, 1620, 1630, 1640, 1650, 1660, 1670, 1680, 1690,
1700, 1710, 1720, 1730, 1740, 1750, 1760, 1770, 1780, 1790, 1798, 1800, 1810,
1816, 1820, 1830, 1840, 1850, 1852, 1860, 1870, 1880, 1890, 1900, 1910, 1913,
1920, 1930, 1940, 1950, 1960, 1990, 2000, 2010, 2020, 2030, 2040, 2050, 2060,
2070, 2080, 2090, 2100, 2110, 2120, 2130, 2150, 2160, 2170, 2180, 2190, 2196,
2200, 2220, 2240, 2250, 2300, 2310, 2330, 2350, 2360, 2390, 2400, 2490, 2500,
2550, 2570, 2580, 2600, 2610, 2720, 2730, 2810, 2850, 3000, 3260, 3480, 3500,
4130, 4820]
```

6. Replacing NULL values in 'view' column with 0.0 and making it integer

[30]:
```
df.loc[df.view.isna(),'view']=0
df.view=df.view.astype('int64')

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  datetime64[ns]
 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  int64
 14  yr_built       21420 non-null  int64
 15  yr_renovated   21420 non-null  int64
 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: datetime64[ns](1), float64(5), int64(15)
memory usage: 3.6 MB
```

3 Scrub and Explore

3.1 Additional data cleaning

3.1.1 Dropping non-needed fields

[31]:
```
# Dropping 'zipcode' variable because I think there are better indicators of a␣
↪location.
# Zipcodes boundaries are usually drawn out of convenience for postal services␣
↪or
# other more formal reasons than geographic location

# Dropping 'id' field
# Resettingh index because of the removal of the duplicates

df_1=df
df_1=df_1.drop(['id','zipcode'], axis=1)
#df_1.tail()


df_1.reset_index()
```

[31]:
```
       index       date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  waterfront  view  condition  grade  sqft_above  sqft_basement  yr_built
yr_renovated      lat     long  sqft_living15  sqft_lot15
0          0 2014-10-13  221900.0         3       1.00         1180      5650
1.0          0      0          3      7        1180              0      1955
0  47.5112 -122.257          1340        5650
1          1 2014-12-09  538000.0         3       2.25         2570      7242
2.0          0      0          3      7        2170            400      1951
1991  47.7210 -122.319          1690        7639
2          2 2015-02-25  180000.0         2       1.00          770     10000
1.0          0      0          3      6         770              0      1933
0  47.7379 -122.233          2720        8062
3          3 2014-12-09  604000.0         4       3.00         1960      5000
1.0          0      0          5      7        1050            910      1965
0  47.5208 -122.393          1360        5000
4          4 2015-02-18  510000.0         3       2.00         1680      8080
1.0          0      0          3      8        1680              0      1987
0  47.6168 -122.045          1800        7503
…       …          …        …        …         …           …        …
…          …    …          …     …          …             …        …
```

```
…      …      …           …          …
21415  21592 2014-05-21  360000.0          3       2.50          1530      1131
3.0           0      0          3      8        1530            0      2009
0  47.6993 -122.346            1530        1509
21416  21593 2015-02-23  400000.0          4       2.50          2310      5813
2.0           0      0          3      8        2310            0      2014
0  47.5107 -122.362            1830        7200
21417  21594 2014-06-23  402101.0          2       0.75          1020      1350
2.0           0      0          3      7        1020            0      2009
0  47.5944 -122.299            1020        2007
21418  21595 2015-01-16  400000.0          3       2.50          1600      2388
2.0           0      0          3      8        1600            0      2004
0  47.5345 -122.069            1410        1287
21419  21596 2014-10-15  325000.0          2       0.75          1020      1076
2.0           0      0          3      7        1020            0      2008
0  47.5941 -122.299            1020        1357

[21420 rows x 20 columns]

<b>21420</b> records out of the original <b>21597</b> left
</div>
```

3.2 Exploring distributions and correlation of original variables

3.2.1 Numerical variables: Investigating distributions and correlations between the original, minimally processed predictors and the target (price)

Histograms and pair correlations of the original predictor variables

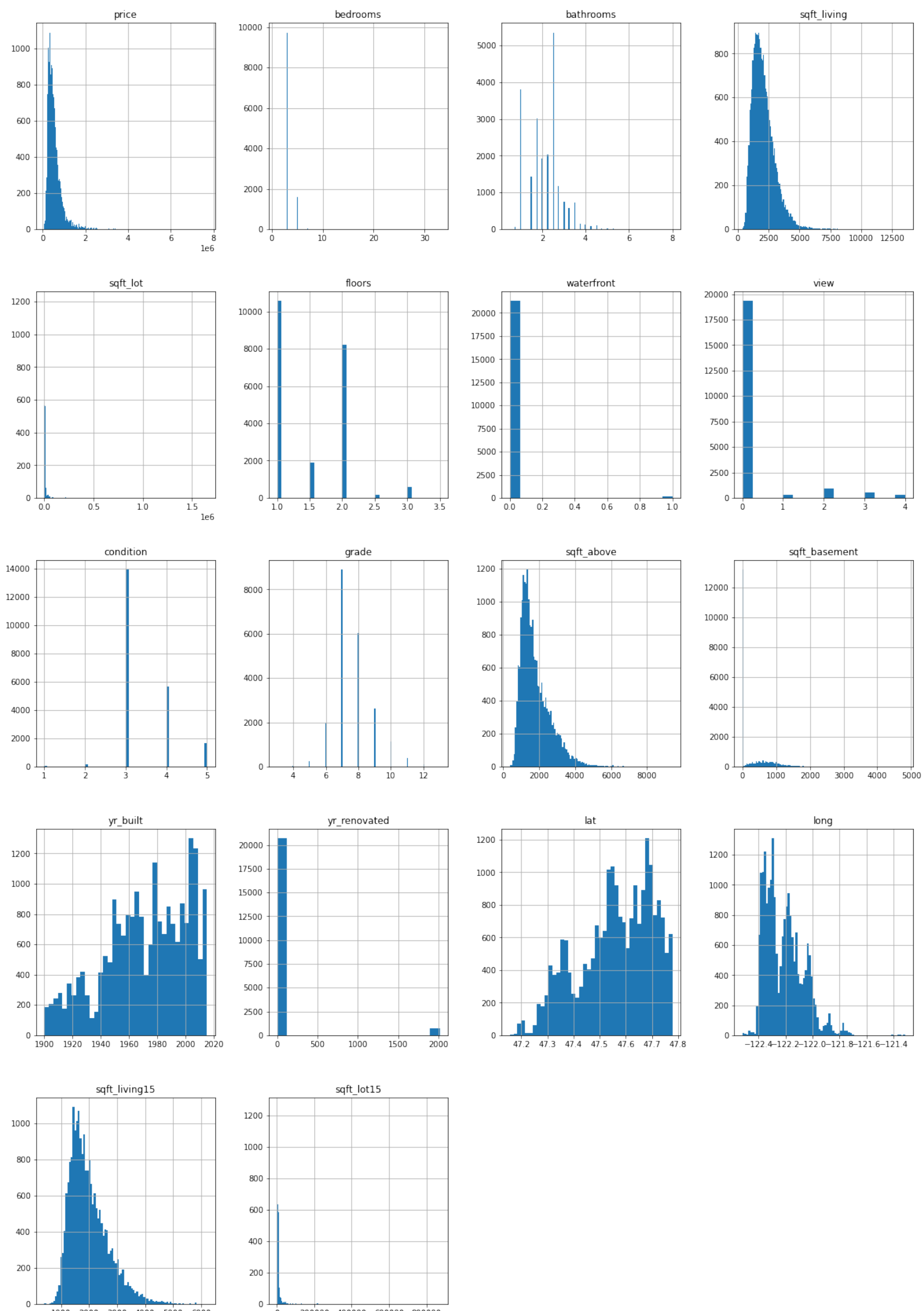
[32]:
```python
df_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21420 non-null  datetime64[ns]
 1   price          21420 non-null  float64
 2   bedrooms       21420 non-null  int64
 3   bathrooms      21420 non-null  float64
 4   sqft_living    21420 non-null  int64
 5   sqft_lot       21420 non-null  int64
 6   floors         21420 non-null  float64
 7   waterfront     21420 non-null  int64
 8   view           21420 non-null  int64
 9   condition      21420 non-null  int64
 10  grade          21420 non-null  int64
 11  sqft_above     21420 non-null  int64
 12  sqft_basement  21420 non-null  int64
 13  yr_built       21420 non-null  int64
```

```
 14  yr_renovated   21420 non-null  int64
 15  lat            21420 non-null  float64
 16  long           21420 non-null  float64
 17  sqft_living15  21420 non-null  int64
 18  sqft_lot15     21420 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(13)
memory usage: 3.3 MB
```

[33]:
```python
# Investigating histograms

df_1.hist(figsize=(20, 30), bins='auto')
```

[33]:
```
array([[<AxesSubplot:title={'center':'price'}>,
        <AxesSubplot:title={'center':'bedrooms'}>,
        <AxesSubplot:title={'center':'bathrooms'}>,
        <AxesSubplot:title={'center':'sqft_living'}>],
       [<AxesSubplot:title={'center':'sqft_lot'}>,
        <AxesSubplot:title={'center':'floors'}>,
        <AxesSubplot:title={'center':'waterfront'}>,
        <AxesSubplot:title={'center':'view'}>],
       [<AxesSubplot:title={'center':'condition'}>,
        <AxesSubplot:title={'center':'grade'}>,
        <AxesSubplot:title={'center':'sqft_above'}>,
        <AxesSubplot:title={'center':'sqft_basement'}>],
       [<AxesSubplot:title={'center':'yr_built'}>,
        <AxesSubplot:title={'center':'yr_renovated'}>,
        <AxesSubplot:title={'center':'lat'}>,
        <AxesSubplot:title={'center':'long'}>],
       [<AxesSubplot:title={'center':'sqft_living15'}>,
        <AxesSubplot:title={'center':'sqft_lot15'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```


price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
grade
sqft_above
sqft_basement
yr_built
yr_renovated
lat
long
sqft_living15
sqft_lot15

Based on the histograms above > 1. The following variables should be considered categorical: »Waterfront Condition View > 2. sqft_basement, sqft_lot, sqft_lot15, and yr_renovated have a large number of zeros and are strong candidates for removal of outliers and/or engineered variables > 3. Latitudes and Longitudes can be used as descriptors of a geographic location of a property. However, I think there is a better variable to describe the location of a property, a distance from the center of the city, which can be calculated from geocoordinates. >4. The target variable, the price of the property, has a strong positive skew attributed to outliers in the higher price bracket. The strategy is to **remove the outliers and to transform the variable** to make it more normally distributed

[34]:
```
# Checking for correlations between the variables with Pearson coefficient␣
↪between 1 and 0.3
# I am using the same approach and reusing the code from Lesson 19

df_coeff=df_1.corr().abs().stack().reset_index().sort_values(0, ascending=False)
df_coeff['pairs'] = list(zip(df_coeff.level_0, df_coeff.level_1))
df_coeff.set_index(['pairs'], inplace = True)
df_coeff.drop(columns=['level_1', 'level_0'], inplace = True)
df_coeff.columns = ['cc']
df_coeff.drop_duplicates(inplace=True)
df_coeff[((df_coeff.cc>.3) & (df_coeff.cc <1))]
```

[34]:

	cc
pairs	
(sqft_above, sqft_living)	0.876533
(sqft_living, grade)	0.762477
(grade, sqft_above)	0.756221
(sqft_living, sqft_living15)	0.756186
(bathrooms, sqft_living)	0.755522
(sqft_above, sqft_living15)	0.731887
(sqft_lot, sqft_lot15)	0.717743
(grade, sqft_living15)	0.713178
(sqft_living, price)	0.701875
(sqft_above, bathrooms)	0.686328
(price, grade)	0.668020
(bathrooms, grade)	0.665587
(price, sqft_above)	0.605294
(sqft_living15, price)	0.584549
(bedrooms, sqft_living)	0.579069
(sqft_living15, bathrooms)	0.569453
(price, bathrooms)	0.526229
(sqft_above, floors)	0.522751
(bathrooms, bedrooms)	0.515383
(bathrooms, yr_built)	0.506252
(floors, bathrooms)	0.501803
(yr_built, floors)	0.488935
(sqft_above, bedrooms)	0.480242

```
(floors, grade)                0.458091
(grade, yr_built)              0.446235
(sqft_living, sqft_basement)   0.428026
(yr_built, sqft_above)         0.422977
(yr_built, long)               0.409173
(sqft_living15, bedrooms)      0.394949
(view, price)                  0.393113
(view, waterfront)             0.381654
(condition, yr_built)          0.365129
(bedrooms, grade)              0.357988
(floors, sqft_living)          0.352868
(long, sqft_above)             0.344161
(long, sqft_living15)          0.334679
(yr_built, sqft_living15)      0.324715
(price, sqft_basement)         0.320842
(yr_built, sqft_living)        0.316646
(price, bedrooms)              0.309453
(price, lat)                   0.305744
```

The variables which have the strongest correlations with the price are * sqft_living * grade * sqft_above * sqft_living15 * bathrooms * view * bedrooms *lat

Establishing an intermediate dataframe and removing some outliers from it

[35]:
```
# Removing extreme values from sqft_lot, sqft_lot15, bathrooms, and price
# On one hand, it can be left to the step of outlier removal, on the other␣
 ↪doing it now
# will help a visual investigation of the distributions of the variables␣
 ↪mentioned above

df_2=df_1[(df_1.sqft_lot >100) & (df_1.sqft_lot<40000)]

df_2=df_2[(df_2.sqft_lot15 >100) & (df_2.sqft_lot15<40000)]

df_2=df_2[df_2.price < 2500000]

df_2=df_2[df_2.bedrooms < 30]

df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20015 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           20015 non-null  datetime64[ns]
 1   price          20015 non-null  float64
 2   bedrooms       20015 non-null  int64
 3   bathrooms      20015 non-null  float64
```

```
 4   sqft_living    20015 non-null  int64
 5   sqft_lot       20015 non-null  int64
 6   floors         20015 non-null  float64
 7   waterfront     20015 non-null  int64
 8   view           20015 non-null  int64
 9   condition      20015 non-null  int64
 10  grade          20015 non-null  int64
 11  sqft_above     20015 non-null  int64
 12  sqft_basement  20015 non-null  int64
 13  yr_built       20015 non-null  int64
 14  yr_renovated   20015 non-null  int64
 15  lat            20015 non-null  float64
 16  long           20015 non-null  float64
 17  sqft_living15  20015 non-null  int64
 18  sqft_lot15     20015 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(13)
memory usage: 3.1 MB
```

[36]:
```
# Creating a new categorical variable: month
df_2['month'] = pd.to_datetime(df_2['date']).dt.month

# Creating a new numerical variable: distance (distance from center)
df_2['distance'] = df_2.apply(lambda row: distance_from_center(row.lat,abs(row.
 ↪long)), axis=1)

# Creating a new categorical variable: basement_exists (1/0), integer datatype
df_2.loc[(df_2['sqft_basement'] > 50), 'basement_exists'] = 1
df_2.loc[(df_2['sqft_basement'] <= 50), 'basement_exists'] = 0
df_2.basement_exists=df_2.basement_exists.astype('int64')
```

[37]:
```
# Creating a new categorical variable (integer datatype) renovation_done with␣
 ↪values [0,1,2,3,4]

# 0 representing renovation never done on houses more than 9 years old␣
 ↪(yr_built between 2015 and 2006)
# 1 representing renovation done more than or equal 50 years ago
# 2 representing renovation done between 30 and 49 years ago
# 3 representing renovation done between 29 and 10 years ago
# 4 representing renovation done between 9 and 1 year ago OR houses built less␣
 ↪or equal 9 years ago
#   (yr_built between 2015 and 2006)

df_2.loc[((df_2['yr_renovated'] == 0) & (df_2['yr_built'] < 2006)),␣
 ↪'renovation_done'] = 0
df_2.loc[((2015-df_2['yr_renovated'] >= 50) & (df_2['yr_renovated'] != 0)),␣
 ↪'renovation_done'] = 1
```

```
df_2.loc[((2015-df_2['yr_renovated'] < 50) & (2015-df_2['yr_renovated'] >=␣
↪30)), 'renovation_done'] = 2
df_2.loc[((2015-df_2['yr_renovated'] < 30) & (2015-df_2['yr_renovated'] >=␣
↪10)), 'renovation_done'] = 3
df_2.loc[((2015-df_2['yr_renovated'] < 10) | (df_2['yr_built'] >= 2006)),␣
↪'renovation_done'] = 4

df_2.renovation_done=df_2.renovation_done.astype('int64')
```

[38]:

```
# Dropping sqft_basement variable
# Dropping latitude & longtitude variable
# Dropping date variable# Resetting index due to removal of records with␣
↪extreme values in
# sqft_lot, sqft_lot15, bathrooms and price

df_2=df_2.drop(['sqft_basement','date', 'lat','long','yr_renovated'], axis=1)

df_2=df_2.reset_index(drop=True)

df_2
```

[38]:

```
          price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront
view  condition  grade  sqft_above  yr_built  sqft_living15  sqft_lot15  month
distance  basement_exists  renovation_done
0      221900.0         3       1.00         1180      5650     1.0           0
0          3      7        1180      1955           1340       5650      10
7.4                 0                 0
1      538000.0         3       2.25         2570      7242     2.0           0
0          3      7        2170      1951           1690       7639      12
8.0                 1                 3
2      180000.0         2       1.00          770     10000     1.0           0
0          3      6         770      1933           2720       8062       2
10.2                0                 0
3      604000.0         4       3.00         1960      5000     1.0           0
0          5      7        1050      1965           1360       5000      12
6.6                 1                 0
4      510000.0         3       2.00         1680      8080     1.0           0
0          3      8        1680      1987           1800       7503       2
13.4                0                 0
…          …       …        …          …       …      …        …
…        …    …         …       …           …         …     …
…                …                 …
20010  360000.0         3       2.50         1530      1131     3.0           0
0          3      8        1530      2009           1530       1509       5
6.5                 0                 4
20011  400000.0         4       2.50         2310      5813     2.0           0
0          3      8        2310      2014           1830       7200       2
```

```
6.7                0                4
20012  402101.0        2      0.75          1020       1350      2.0           0
0         3      7         1020       2009            1020      2007       6
1.7                0                4
20013  400000.0        3      2.50          1600       2388      2.0           0
0         3      8         1600       2004            1410      1287       1
13.2                0                0
20014  325000.0        2      0.75          1020       1076      2.0           0
0         3      7         1020       2008            1020      1357      10
1.8                0                4

[20015 rows x 18 columns]
```

```
<b>df_2</b> DataFrame<br><br><b>20015</b> records out of the original <b>21597</b> left
</div><br>

<b>Index reset</b>
</div><br>
```

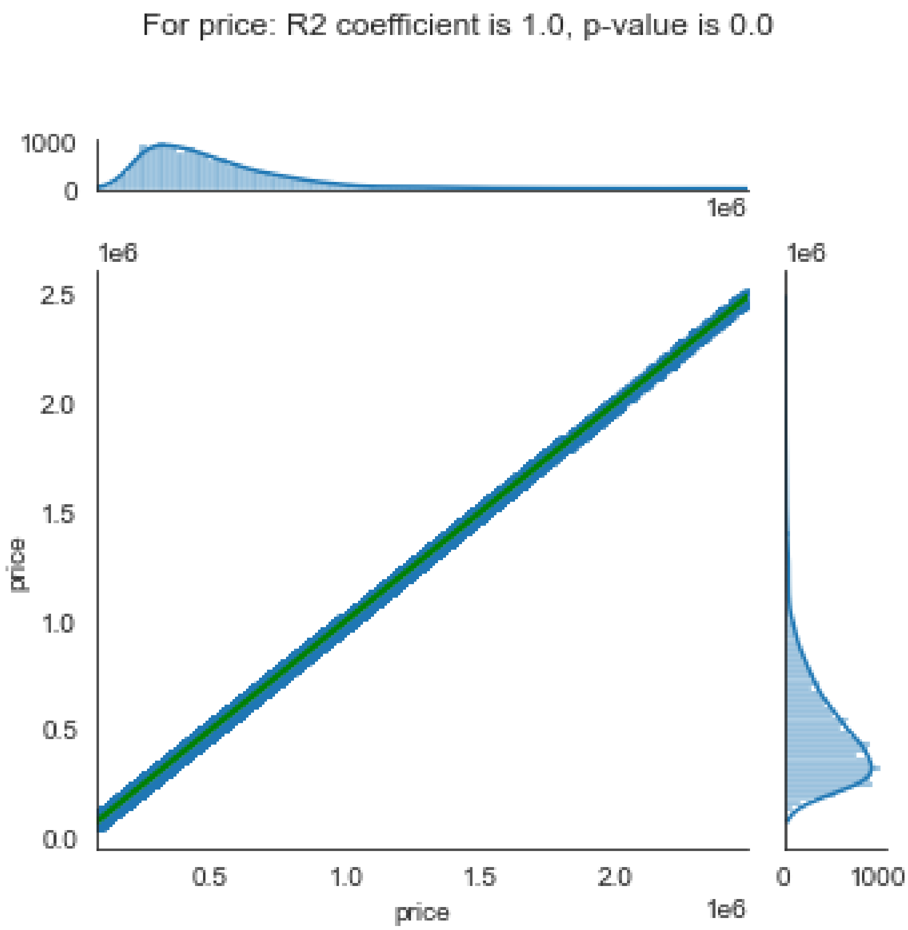
Plotting numerical variables against the target variable

[39]:
```
# Dropping categorical variables to simplify the analysis of the numerical ones

df_num1=df_2.
 ↪drop(['waterfront','view','condition','basement_exists','renovation_done','month'],␣
 ↪axis=1)
```

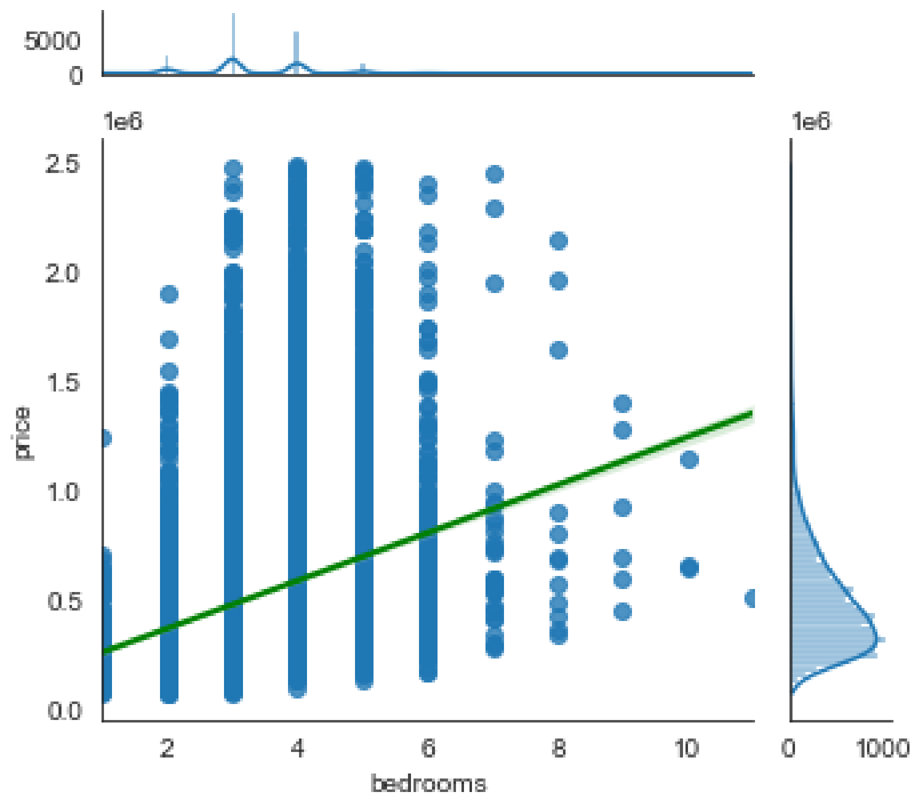
[40]:
```
# Displaying the Coefficients of Determination and p-values for the remaining␣
 ↪variables
r2_p(df_num1)
```

```
For price: R2 coefficient is 1.0, p-value is 0.0
For bedrooms: R2 coefficient is 0.3195, p-value is 0.0
For bathrooms: R2 coefficient is 0.4999, p-value is 0.0
For sqft_living: R2 coefficient is 0.6795, p-value is 0.0
For sqft_lot: R2 coefficient is 0.1565, p-value is 7.279024950162686e-110
For floors: R2 coefficient is 0.2657, p-value is 1.2233e-320
For grade: R2 coefficient is 0.6726, p-value is 0.0
For sqft_above: R2 coefficient is 0.5746, p-value is 0.0
For yr_built: R2 coefficient is 0.0348, p-value is 8.471205832359682e-07
For sqft_living15: R2 coefficient is 0.5951, p-value is 0.0
For sqft_lot15: R2 coefficient is 0.1512, p-value is 1.1950868785722046e-102
For distance: R2 coefficient is -0.3432, p-value is 0.0
```

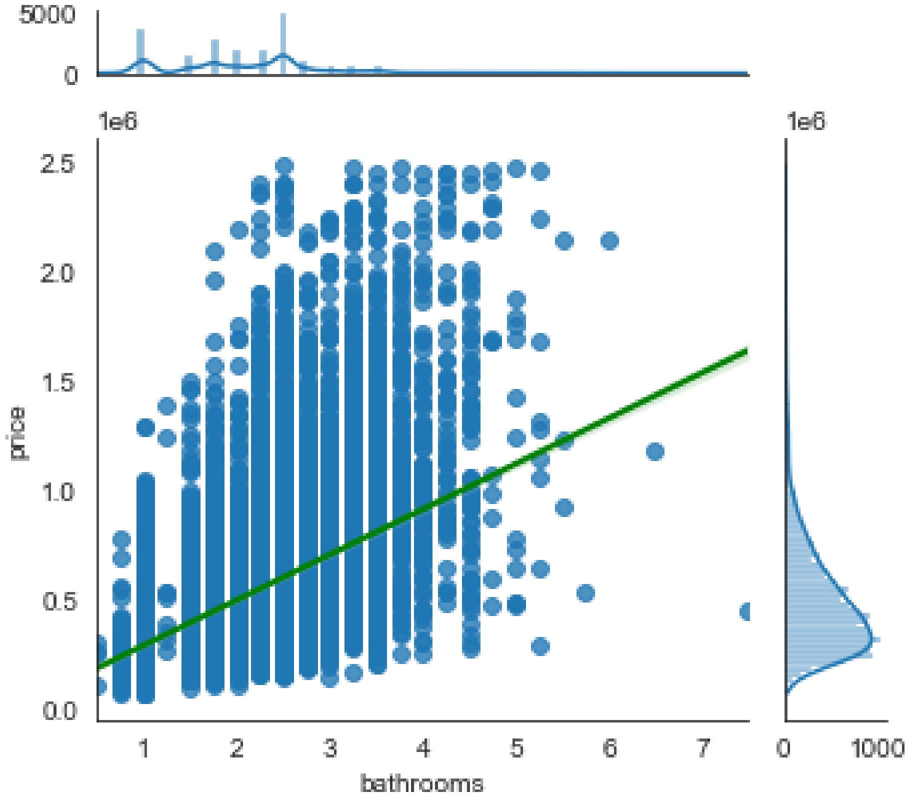
[41]:
```
# Joint plot of the original (not altered) numerical variables
jointplot(df_num1)
```


For price: R2 coefficient is 1.0, p-value is 0.0
1000
0
1e6
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
0.5
1.0
1.5
2.0
price
1e6
1e6
0
1000

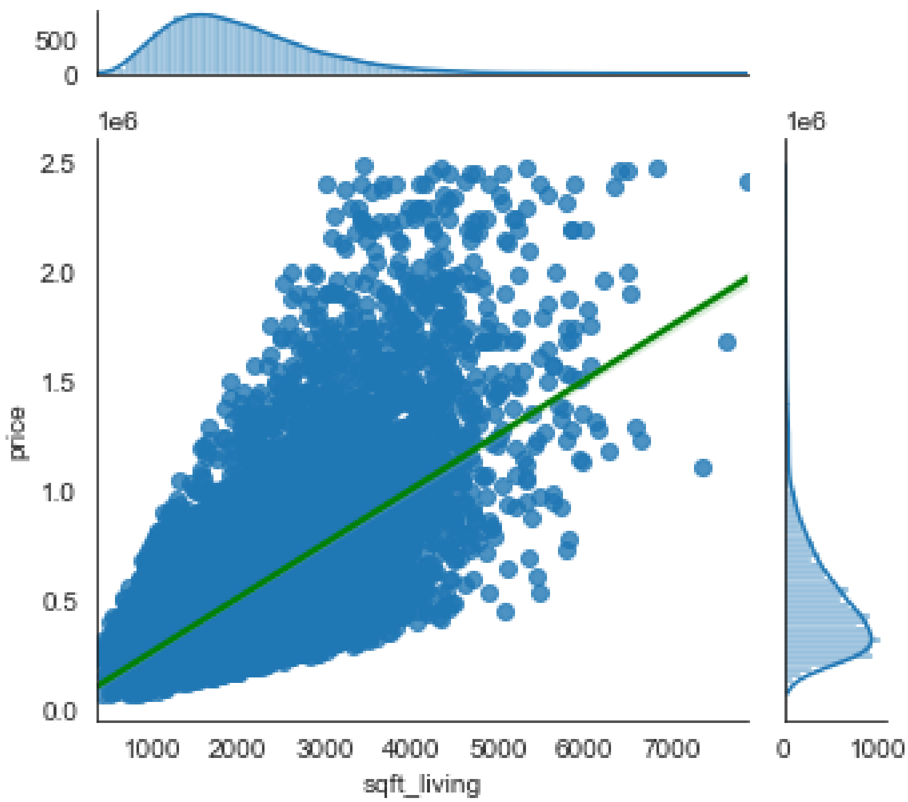
For bedrooms: R2 coefficient is 0.3195, p-value is 0.0



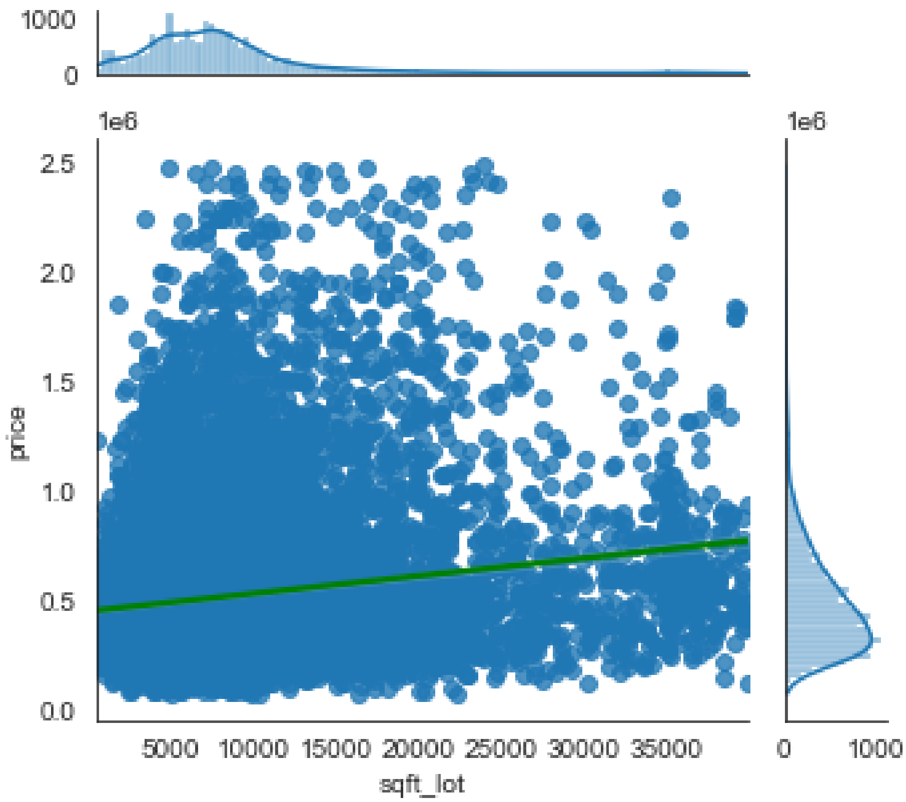
For bathrooms: R2 coefficient is 0.4999, p-value is 0.0

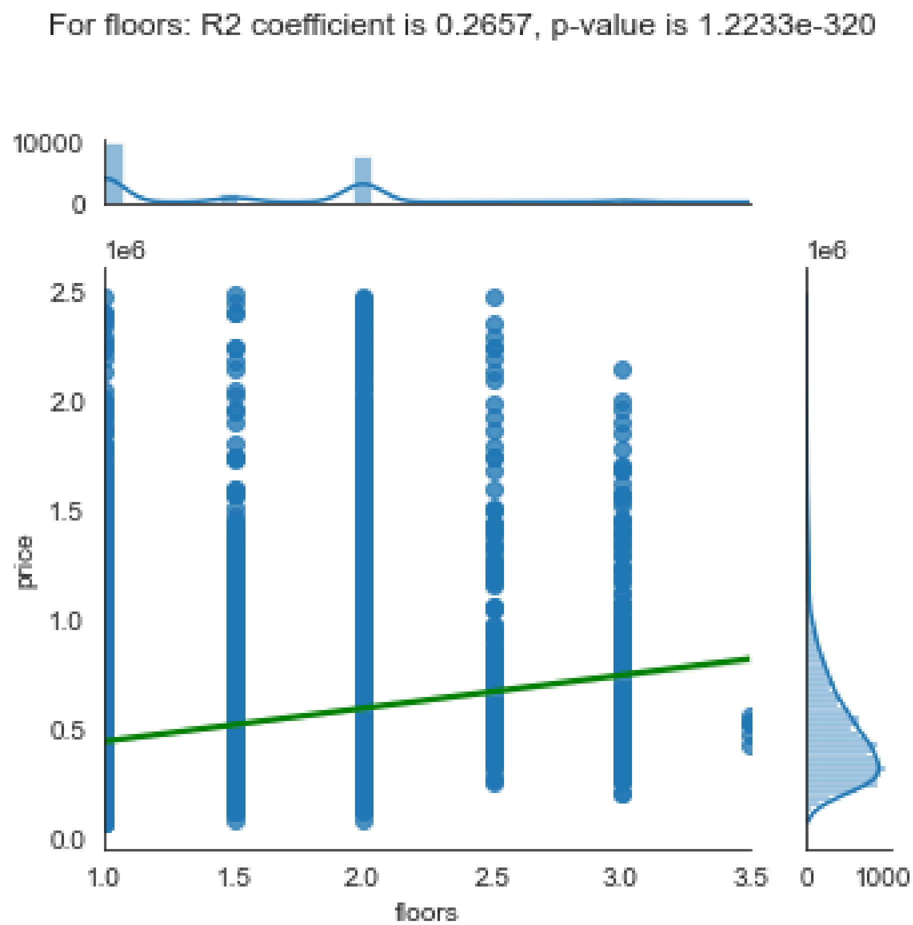


For sqft_living: R2 coefficient is 0.6795, p-value is 0.0

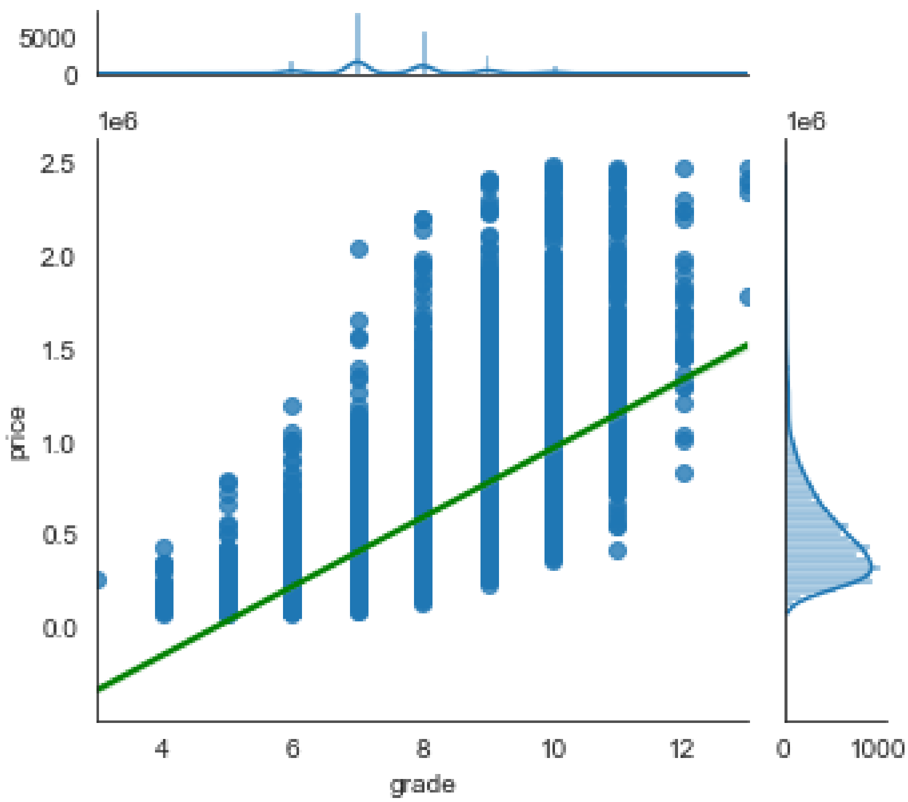


For sqft_lot: R2 coefficient is 0.1565, p-value is 7.279024950162686e-110

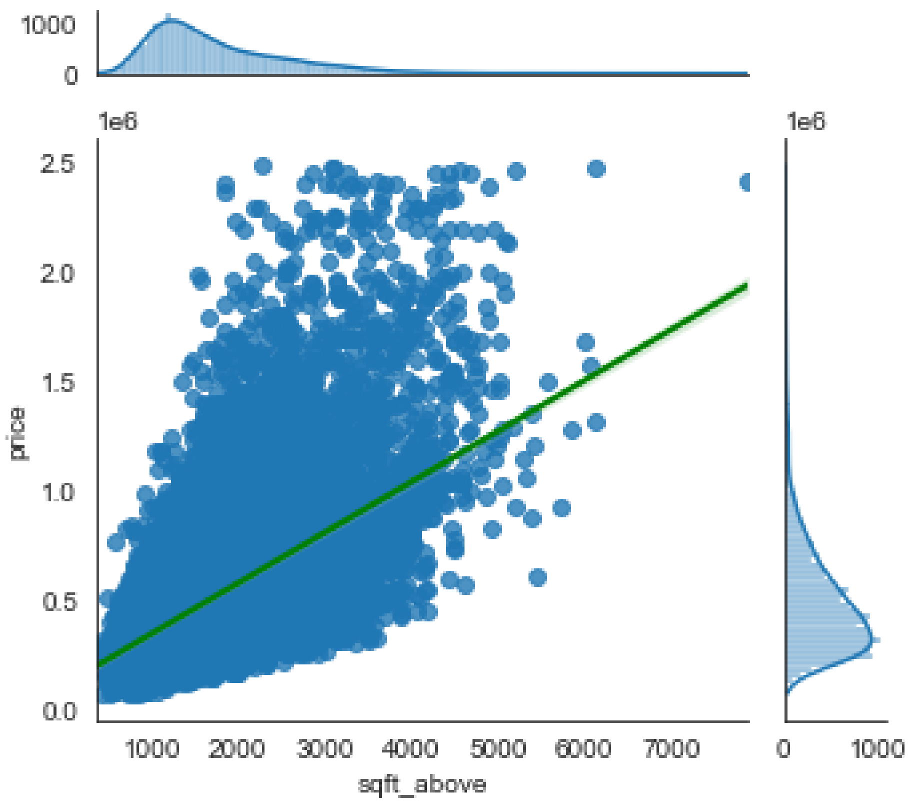



For floors: R2 coefficient is 0.2657, p-value is 1.2233e-320
10000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1.0
1.5
2.0
2.5
3.0
3.5
floors
1e6
0
1000

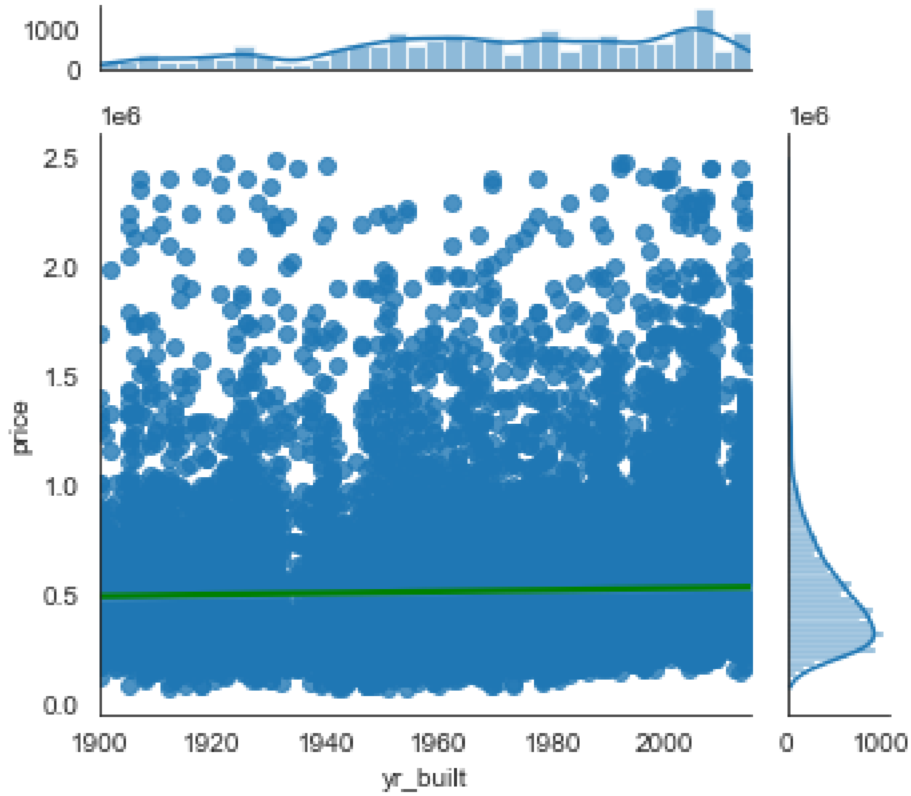
For grade: R2 coefficient is 0.6726, p-value is 0.0

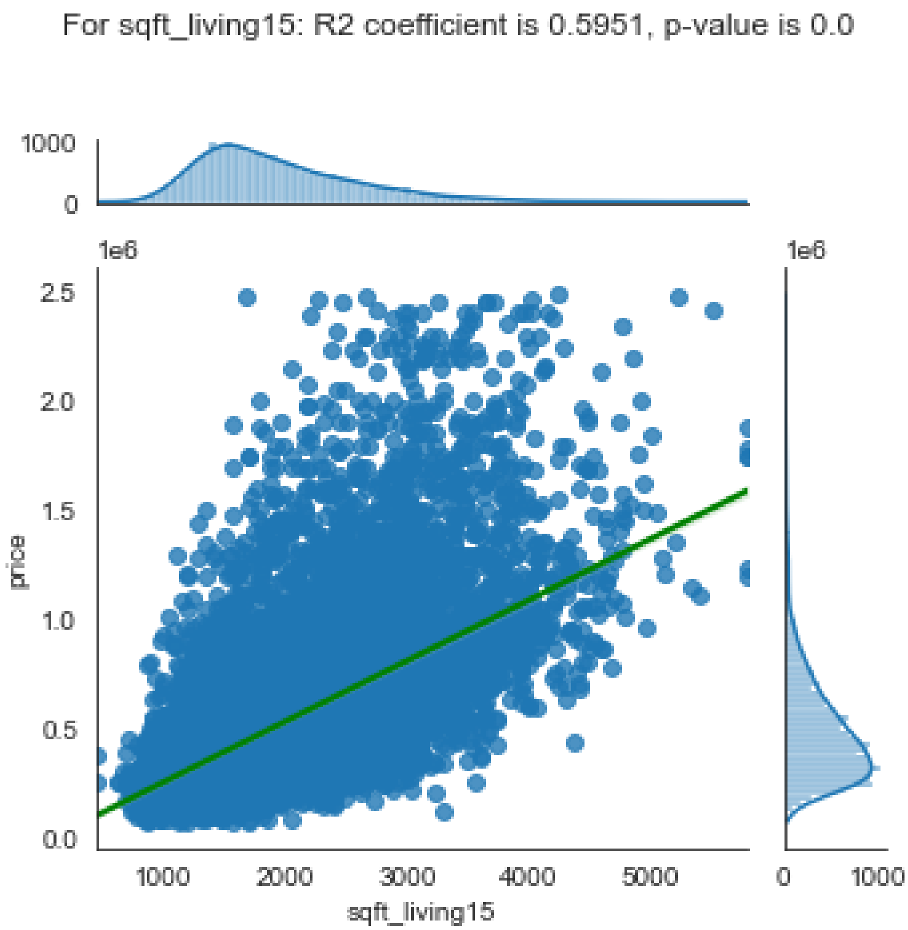


For sqft_above: R2 coefficient is 0.5746, p-value is 0.0

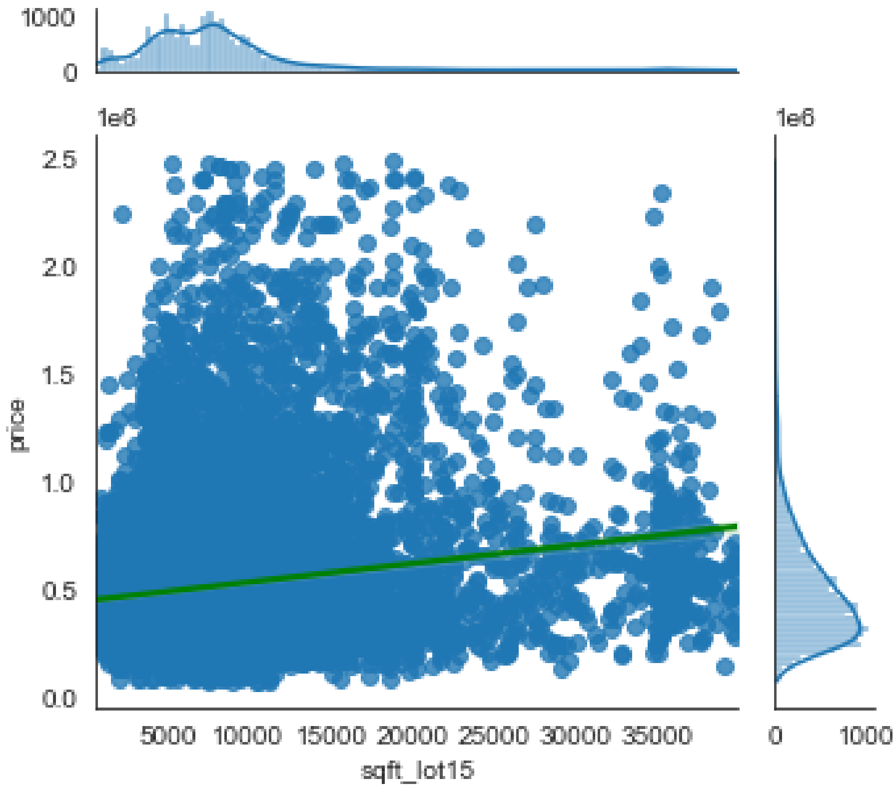


For yr_built: R2 coefficient is 0.0348, p-value is 8.471205832359682e-07

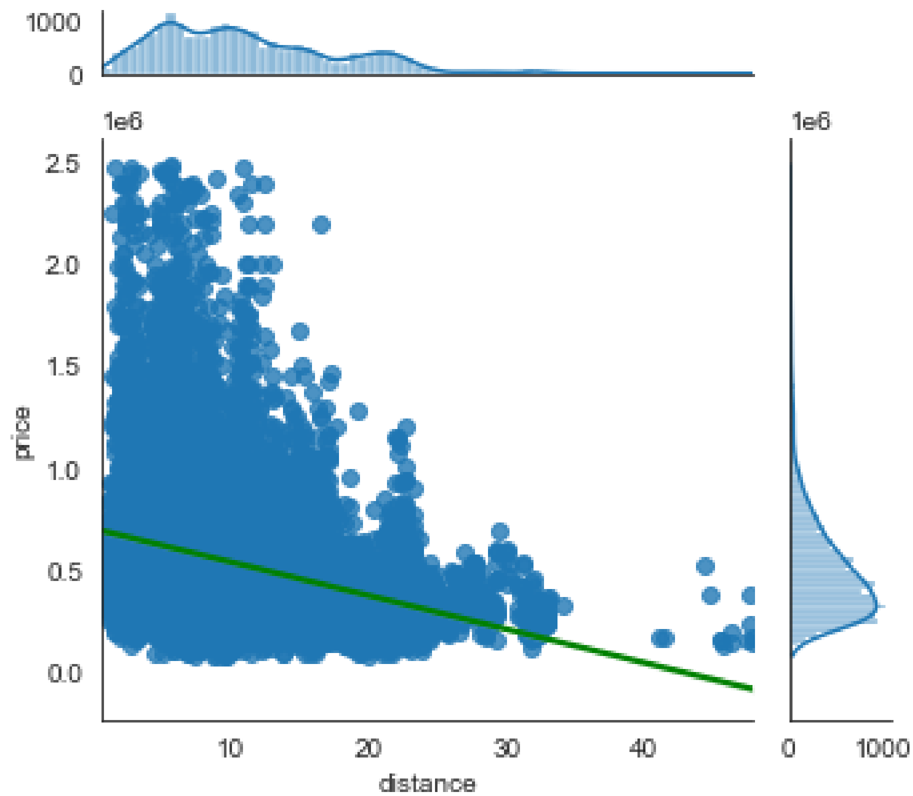



For sqft_living15: R2 coefficient is 0.5951, p-value is 0.0
1000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1000
2000
3000
4000
5000
sqft_living15
1e6
0
1000

For sqft_lot15: R2 coefficient is 0.1512, p-value is 1.1950868785722046e-102



For distance: R2 coefficient is -0.3432, p-value is 0.0



[42]:
```
df_num1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20015 entries, 0 to 20014
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          20015 non-null  float64
 1   bedrooms       20015 non-null  int64
 2   bathrooms      20015 non-null  float64
 3   sqft_living    20015 non-null  int64
 4   sqft_lot       20015 non-null  int64
 5   floors         20015 non-null  float64
 6   grade          20015 non-null  int64
 7   sqft_above     20015 non-null  int64
 8   yr_built       20015 non-null  int64
 9   sqft_living15  20015 non-null  int64
 10  sqft_lot15     20015 non-null  int64
```

```
 11  distance       20015 non-null  float64
dtypes: float64(4), int64(8)
memory usage: 1.8 MB
```

[43]:
```
# Removing extreme values from bedrooms, bathrooms, floors, and distance
# The observations with the extreme values of these variables are visually␣
↪identifiable

df_num2=df_num1[(df_num1.bedrooms < 9) & (df_num1.bathrooms < 5.5) &(df_num1.
↪distance < 30)
               & (df_num1.floors<3.5)]
df_num2.drop(['yr_built'], axis=1, inplace=True)
df_num2.reset_index(drop=True, inplace=True)
```

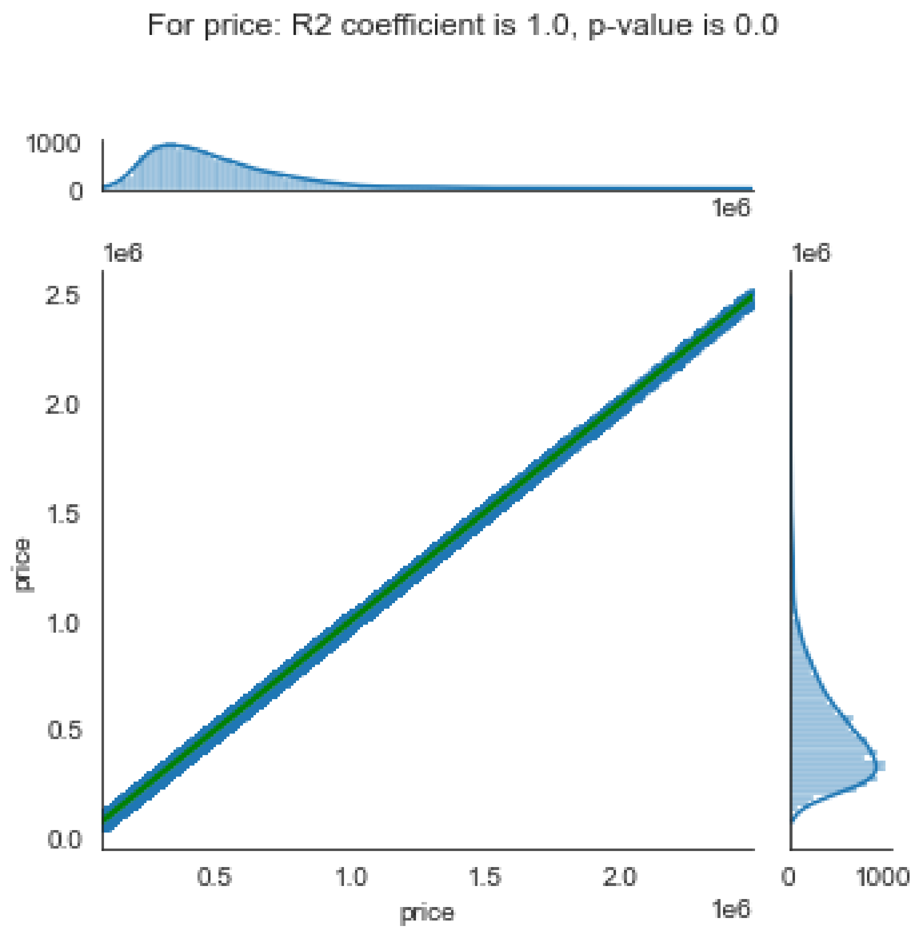
[44]:
```
df_num2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19811 entries, 0 to 19810
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          19811 non-null  float64
 1   bedrooms       19811 non-null  int64
 2   bathrooms      19811 non-null  float64
 3   sqft_living    19811 non-null  int64
 4   sqft_lot       19811 non-null  int64
 5   floors         19811 non-null  float64
 6   grade          19811 non-null  int64
 7   sqft_above     19811 non-null  int64
 8   sqft_living15  19811 non-null  int64
 9   sqft_lot15     19811 non-null  int64
 10  distance       19811 non-null  float64
dtypes: float64(4), int64(7)
memory usage: 1.7 MB
```

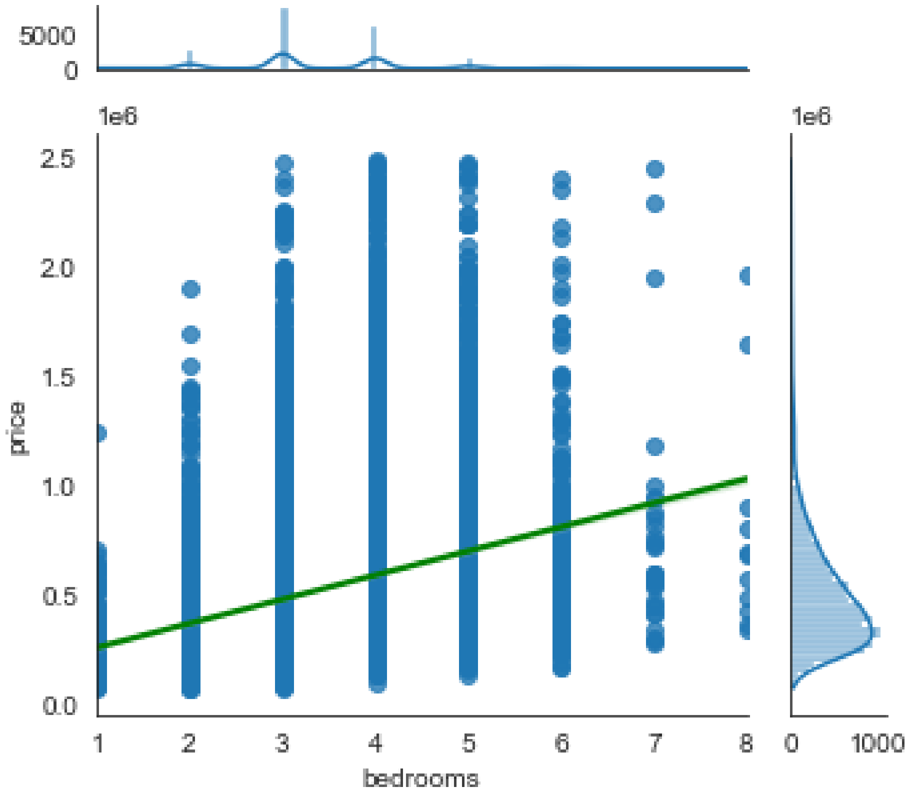
```
<b>df_num2</b> DataFrame<br><br><b>19811</b> records out of original <b>21597</b> left
</div><br>
```

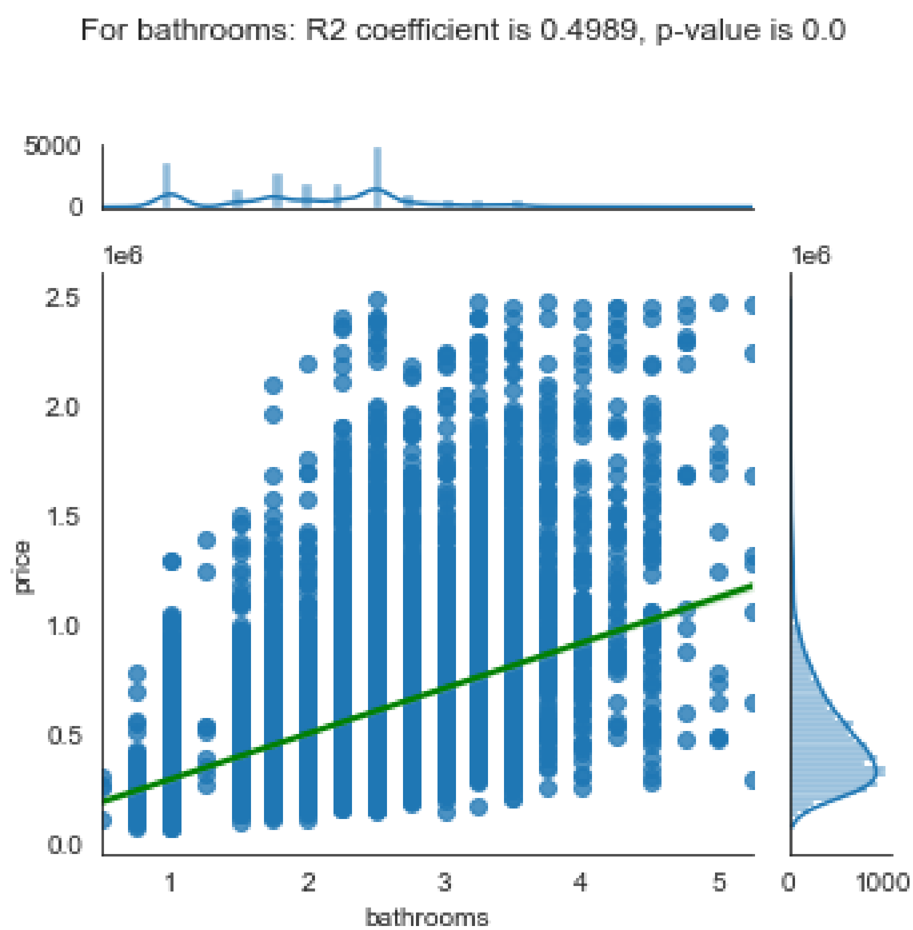
```
<b>Index reset</b>
</div><br>
```

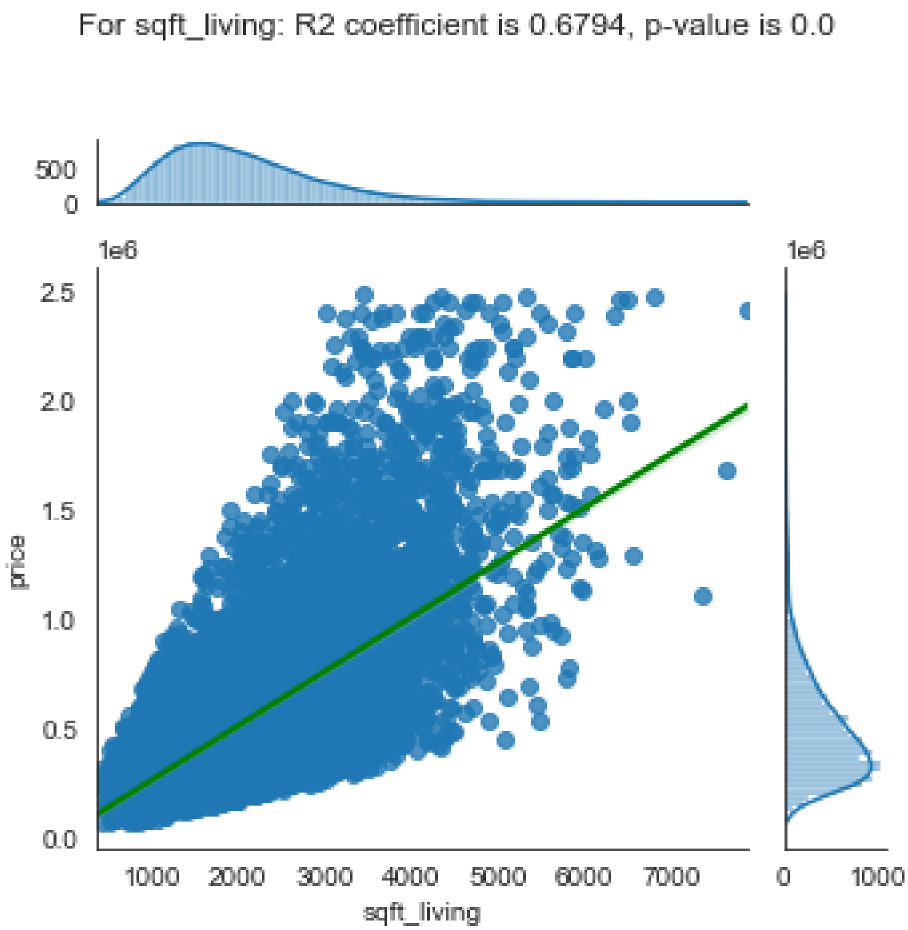
[45]:
```
# Joint plot of numerical variables after adjustments
jointplot(df_num2)
```


For price: R2 coefficient is 1.0, p-value is 0.0
1000
0
1e6
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
0.5
1.0
1.5
2.0
price
1e6
1e6
0
1000

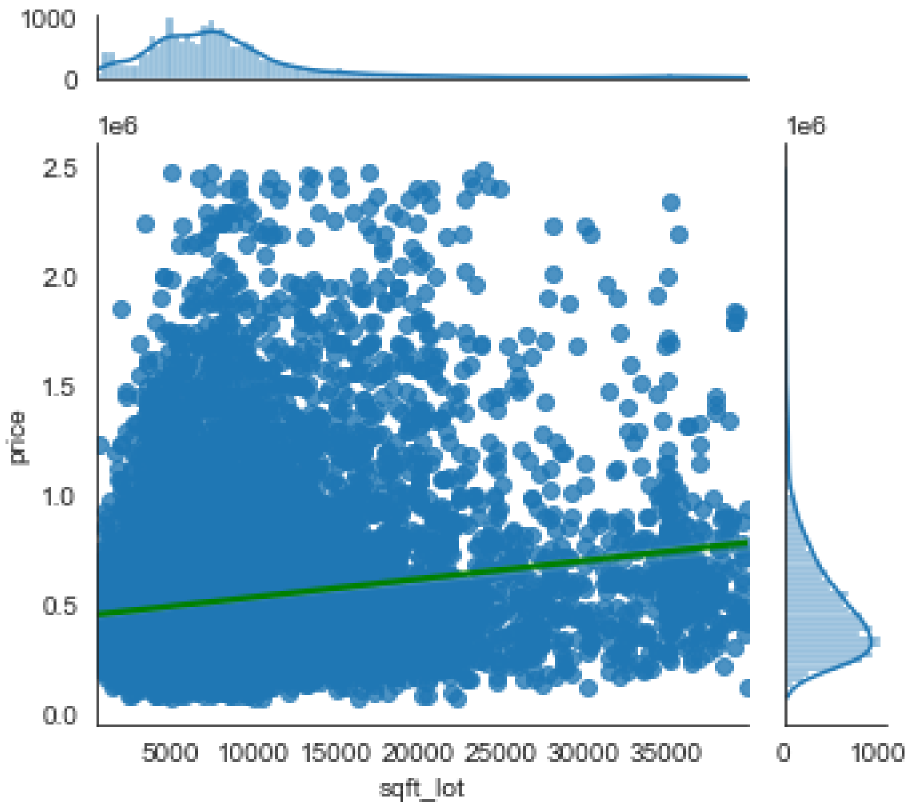
For bedrooms: R2 coefficient is 0.3179, p-value is 0.0

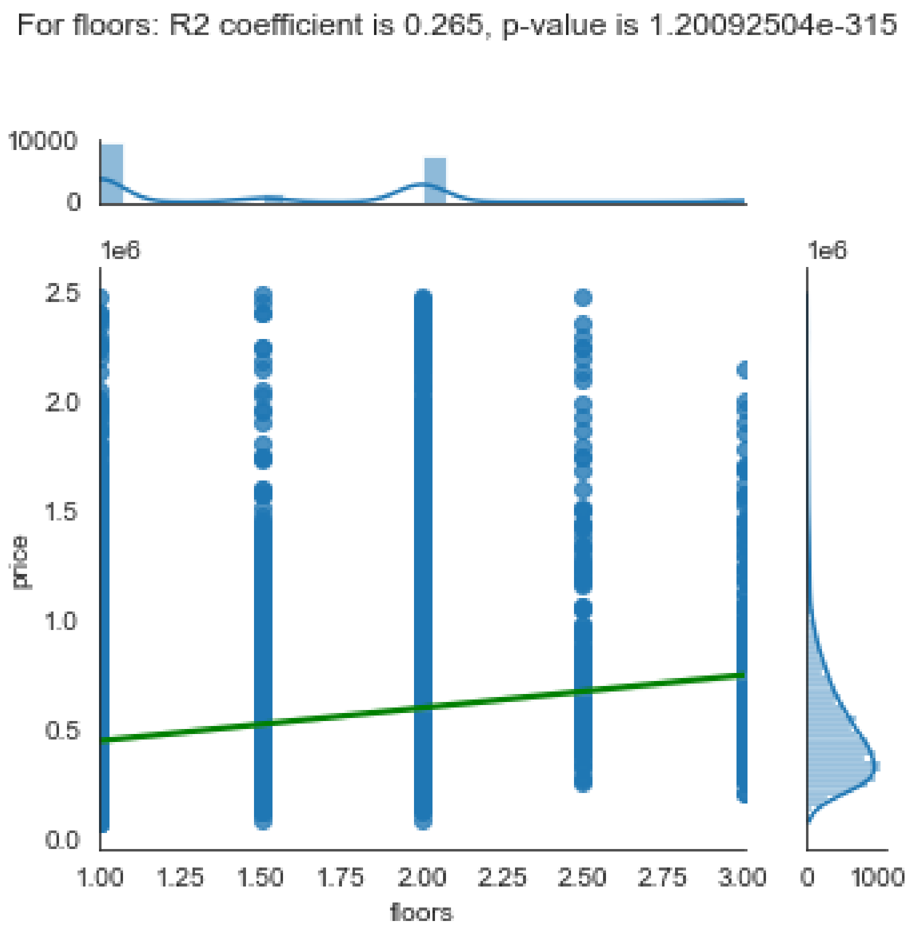


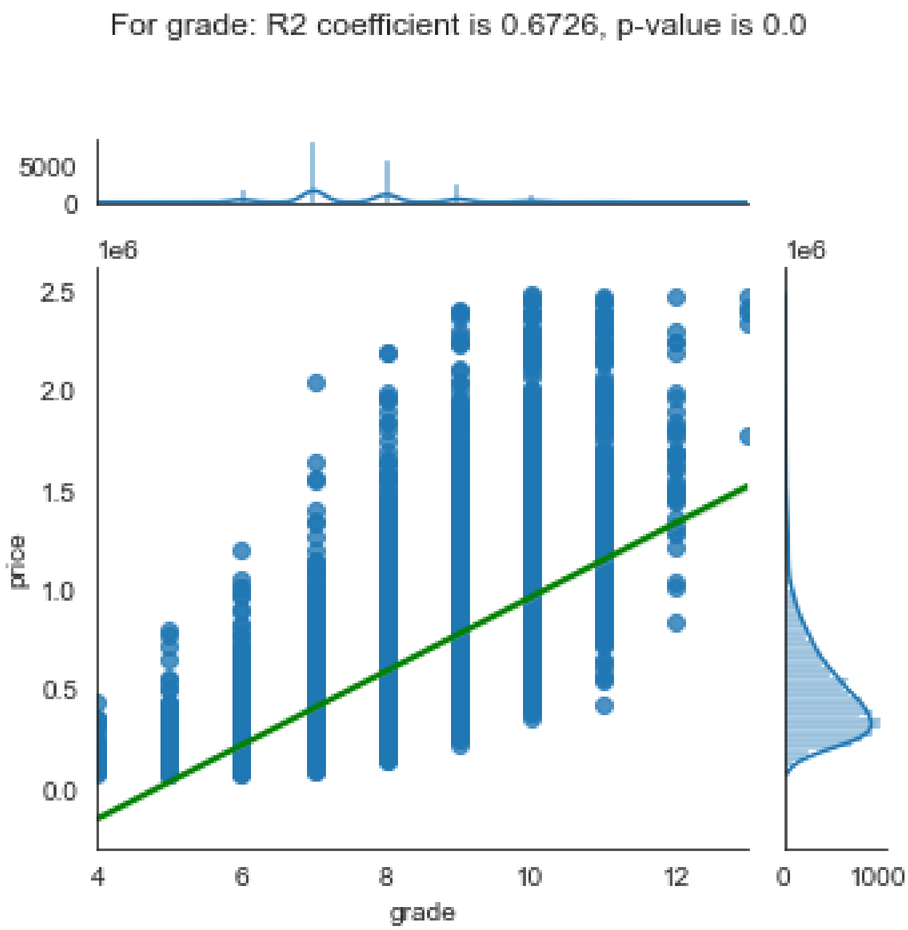

For bathrooms: R2 coefficient is 0.4989, p-value is 0.0
5000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1
2
3
4
5
bathrooms
1e6
0
1000


For sqft_living: R2 coefficient is 0.6794, p-value is 0.0
500
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1000 2000 3000 4000 5000 6000 7000
sqft_living
1e6
0 1000

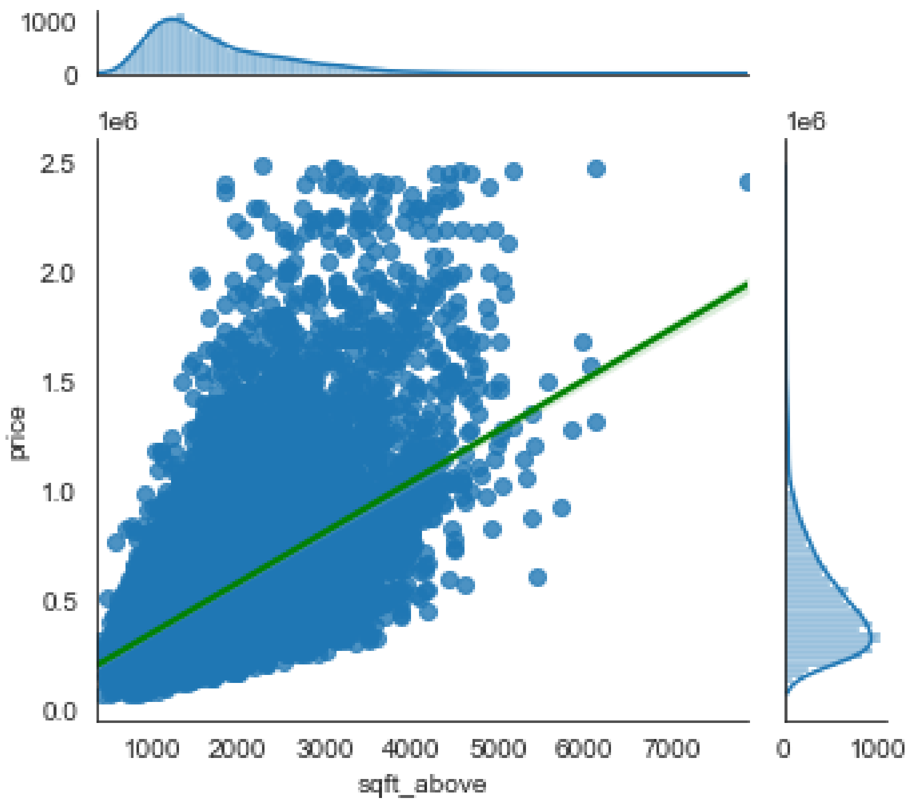
For sqft_lot: R2 coefficient is 0.1606, p-value is 1.3229570300257684e-114



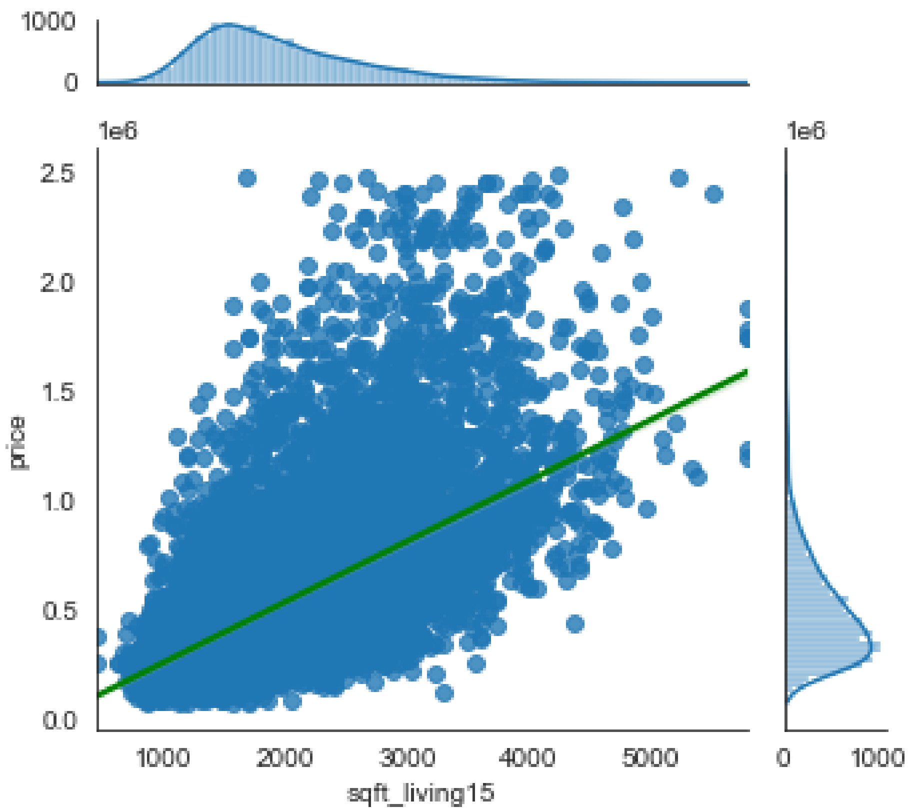

For floors: R2 coefficient is 0.265, p-value is 1.20092504e-315
10000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
floors
1e6
0
1000


For grade: R2 coefficient is 0.6726, p-value is 0.0
5000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
4
6
8
10
12
grade
1e6
0
1000

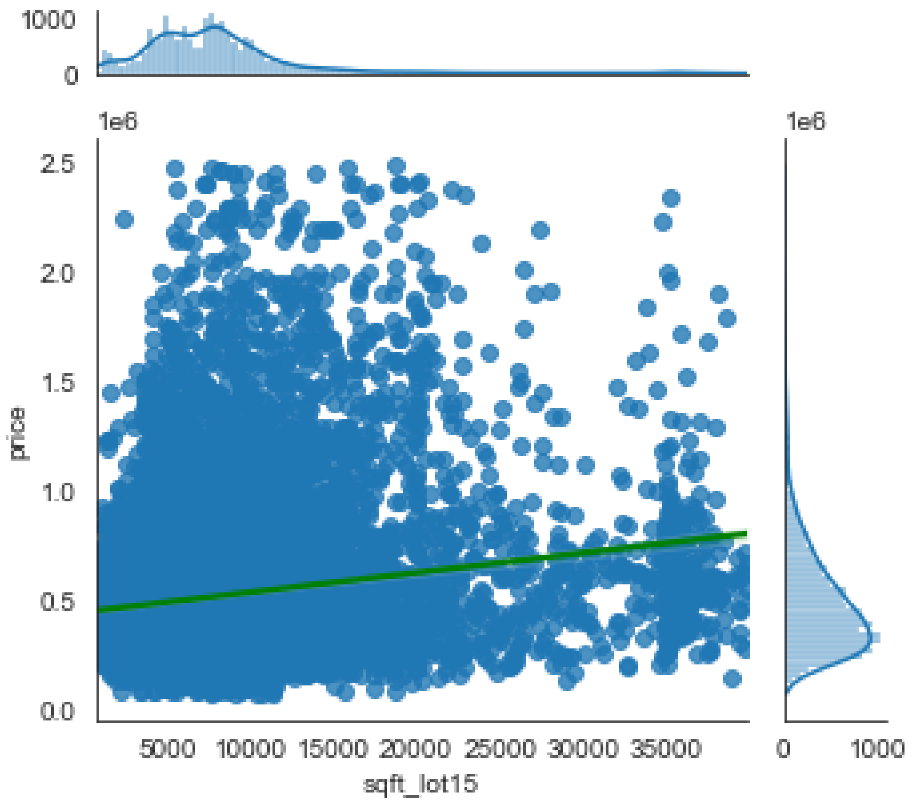
For sqft_above: R2 coefficient is 0.5746, p-value is 0.0

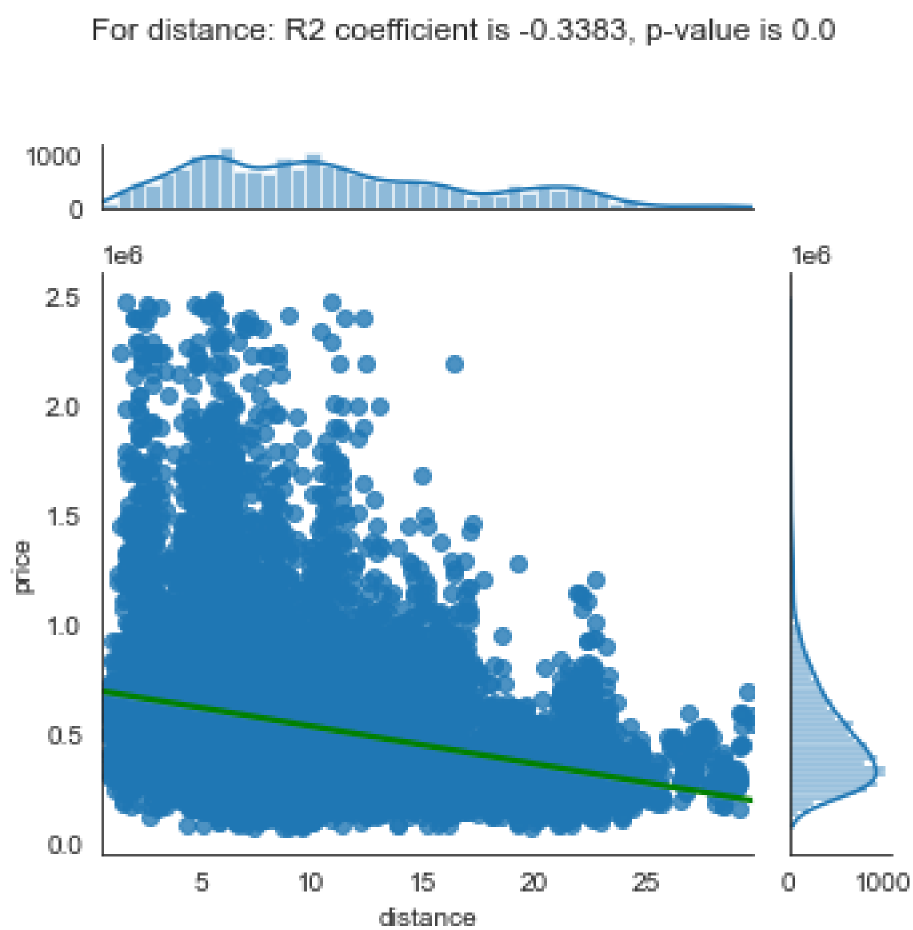


For sqft_living15: R2 coefficient is 0.5946, p-value is 0.0



For sqft_lot15: R2 coefficient is 0.1557, p-value is 8.785298244418031e-108





[46]:
```
r2_p(df_num2)
```

```
For price: R2 coefficient is 1.0, p-value is 0.0
For bedrooms: R2 coefficient is 0.3179, p-value is 0.0
For bathrooms: R2 coefficient is 0.4989, p-value is 0.0
For sqft_living: R2 coefficient is 0.6794, p-value is 0.0
For sqft_lot: R2 coefficient is 0.1606, p-value is 1.3229570300257684e-114
For floors: R2 coefficient is 0.265, p-value is 1.20092504e-315
For grade: R2 coefficient is 0.6726, p-value is 0.0
For sqft_above: R2 coefficient is 0.5746, p-value is 0.0
For sqft_living15: R2 coefficient is 0.5946, p-value is 0.0
For sqft_lot15: R2 coefficient is 0.1557, p-value is 8.785298244418031e-108
For distance: R2 coefficient is -0.3383, p-value is 0.0
```

[47]:
```
df_num2.info()
```

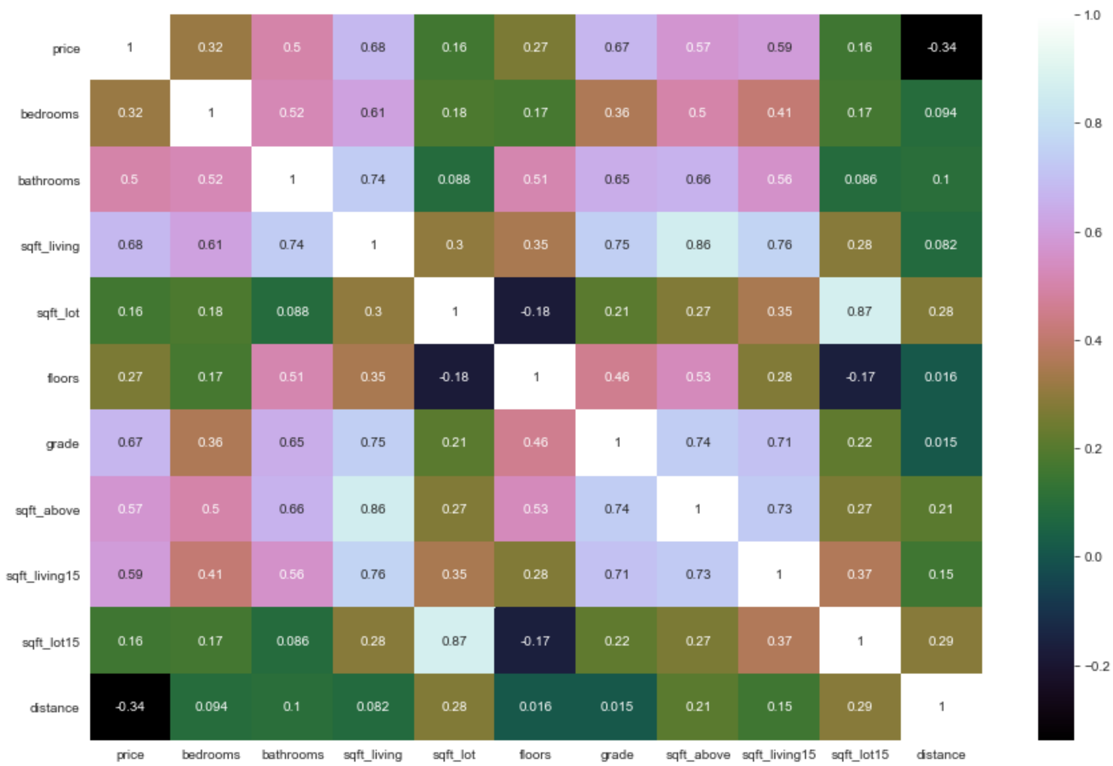
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19811 entries, 0 to 19810
Data columns (total 11 columns):
```

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          19811 non-null  float64
 1   bedrooms       19811 non-null  int64
 2   bathrooms      19811 non-null  float64
 3   sqft_living    19811 non-null  int64
 4   sqft_lot       19811 non-null  int64
 5   floors         19811 non-null  float64
 6   grade          19811 non-null  int64
 7   sqft_above     19811 non-null  int64
 8   sqft_living15  19811 non-null  int64
 9   sqft_lot15     19811 non-null  int64
 10  distance       19811 non-null  float64
dtypes: float64(4), int64(7)
memory usage: 1.7 MB
```

Visualizing numerical predictors correlation with the price and with each other using heat map

[48]:
```python
fig, ax = plt.subplots(figsize=(15,10))
sns.heatmap(df_num2.corr(), cmap="cubehelix", annot=True)
```

[48]: <AxesSubplot:>

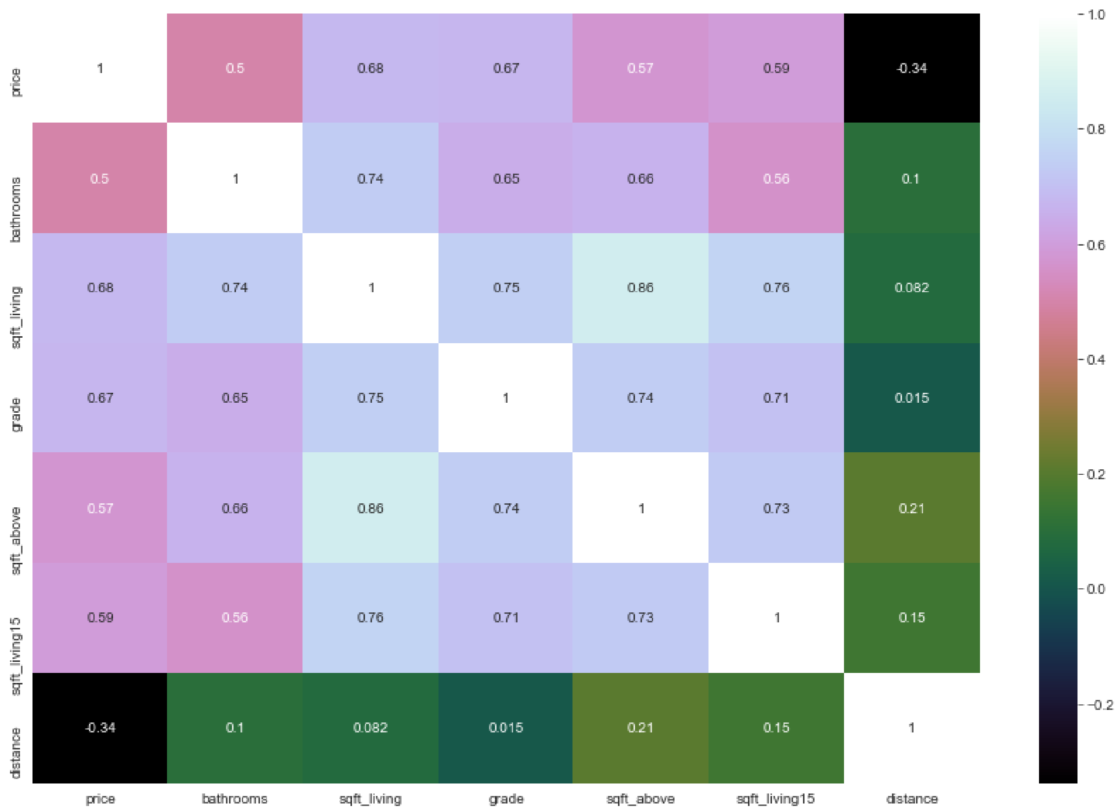


	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	grade	sqft_above	sqft_living15	sqft_lot15	distance
price	1	0.32	0.5	0.68	0.16	0.27	0.67	0.57	0.59	0.16	-0.34
bedrooms	0.32	1	0.52	0.61	0.18	0.17	0.36	0.5	0.41	0.17	0.094
bathrooms	0.5	0.52	1	0.74	0.088	0.51	0.65	0.66	0.56	0.086	0.1
sqft_living	0.68	0.61	0.74	1	0.3	0.35	0.75	0.86	0.76	0.28	0.082
sqft_lot	0.16	0.18	0.088	0.3	1	-0.18	0.21	0.27	0.35	0.87	0.28
floors	0.27	0.17	0.51	0.35	-0.18	1	0.46	0.53	0.28	-0.17	0.016
grade	0.67	0.36	0.65	0.75	0.21	0.46	1	0.74	0.71	0.22	0.015
sqft_above	0.57	0.5	0.66	0.86	0.27	0.53	0.74	1	0.73	0.27	0.21
sqft_living15	0.59	0.41	0.56	0.76	0.35	0.28	0.71	0.73	1	0.37	0.15
sqft_lot15	0.16	0.17	0.086	0.28	0.87	-0.17	0.22	0.27	0.37	1	0.29
distance	-0.34	0.094	0.1	0.082	0.28	0.016	0.015	0.21	0.15	0.29	1

[49]:
```
# Bedrooms is relatively highly correlated with bathrooms and sqft_living;␣
↪correlations of floors, sqft_lot and sqft_lot15
# with prices are low. Dropping these variables

df_num3=df_num2.drop(['bedrooms','sqft_lot','sqft_lot15','floors'], axis=1)
```

[50]:
```
fig, ax = plt.subplots(figsize=(15,10))
sns.heatmap(df_num3.corr(), cmap="cubehelix", annot=True)
```

[50]:
```
<AxesSubplot:>
```



[51]:
```
r2_p(df_num3)
```

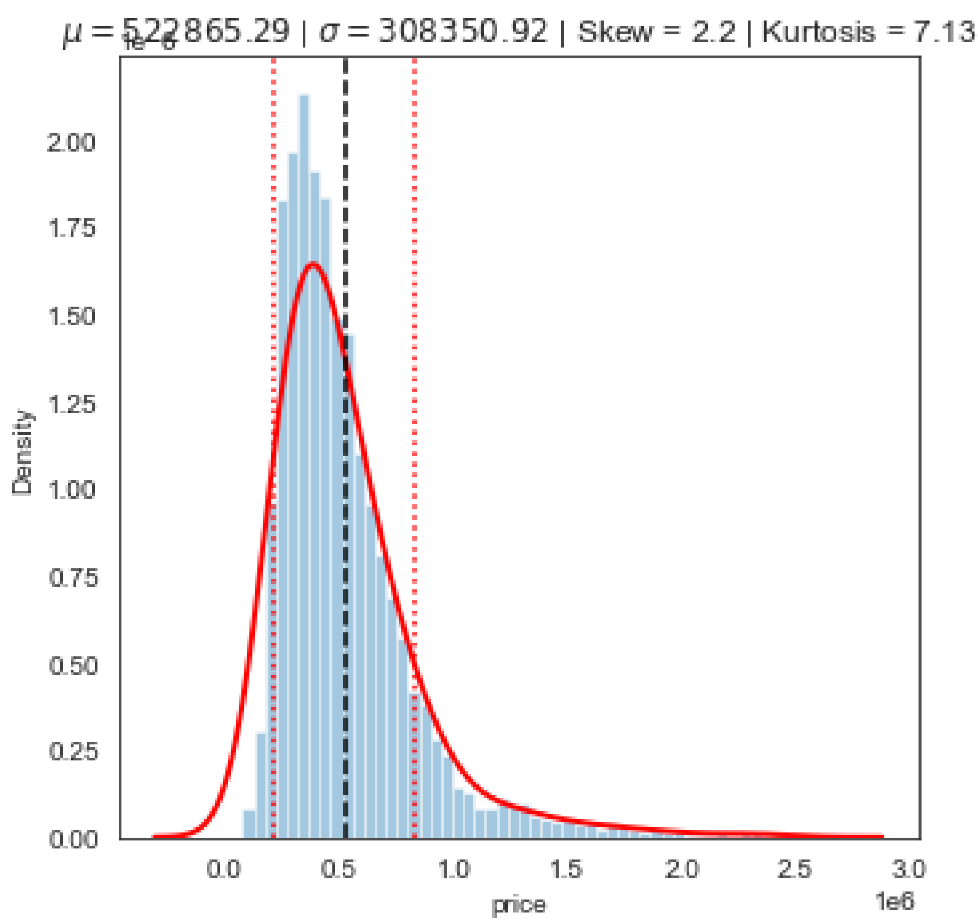
```
For price: R2 coefficient is 1.0, p-value is 0.0
For bathrooms: R2 coefficient is 0.4989, p-value is 0.0
For sqft_living: R2 coefficient is 0.6794, p-value is 0.0
For grade: R2 coefficient is 0.6726, p-value is 0.0
For sqft_above: R2 coefficient is 0.5746, p-value is 0.0
For sqft_living15: R2 coefficient is 0.5946, p-value is 0.0
For distance: R2 coefficient is -0.3383, p-value is 0.0
```

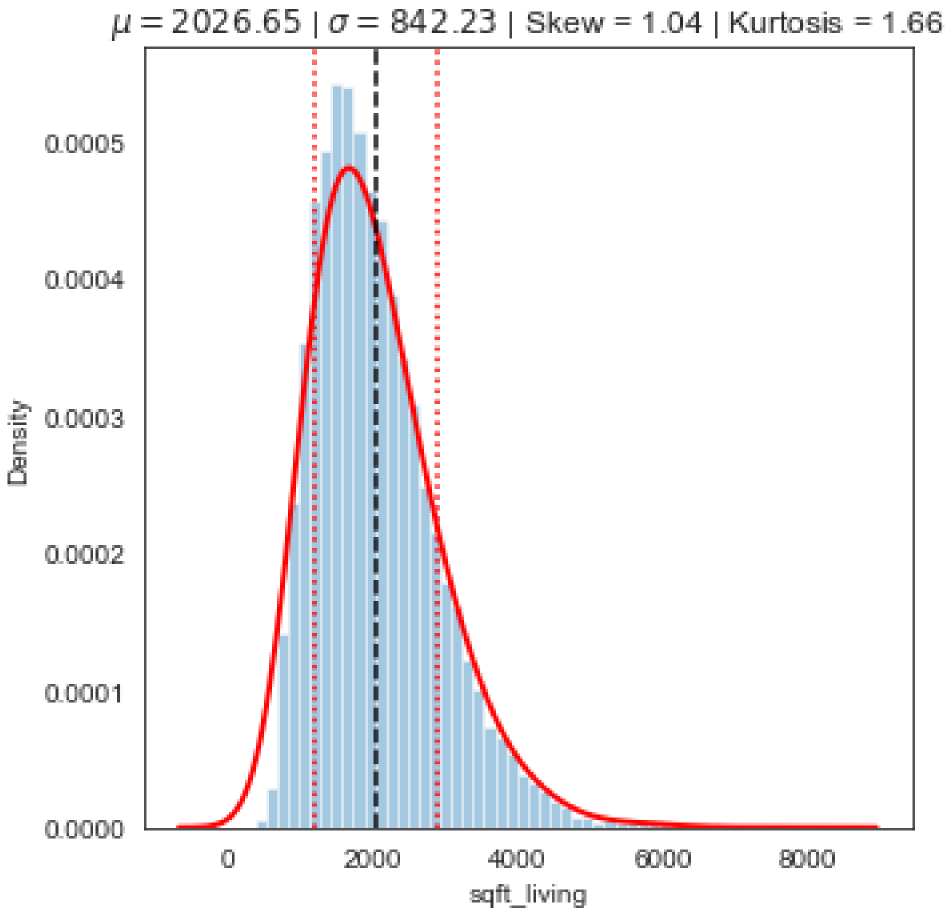
Exploring the distribution of the remaining numerical predictors

[52]:

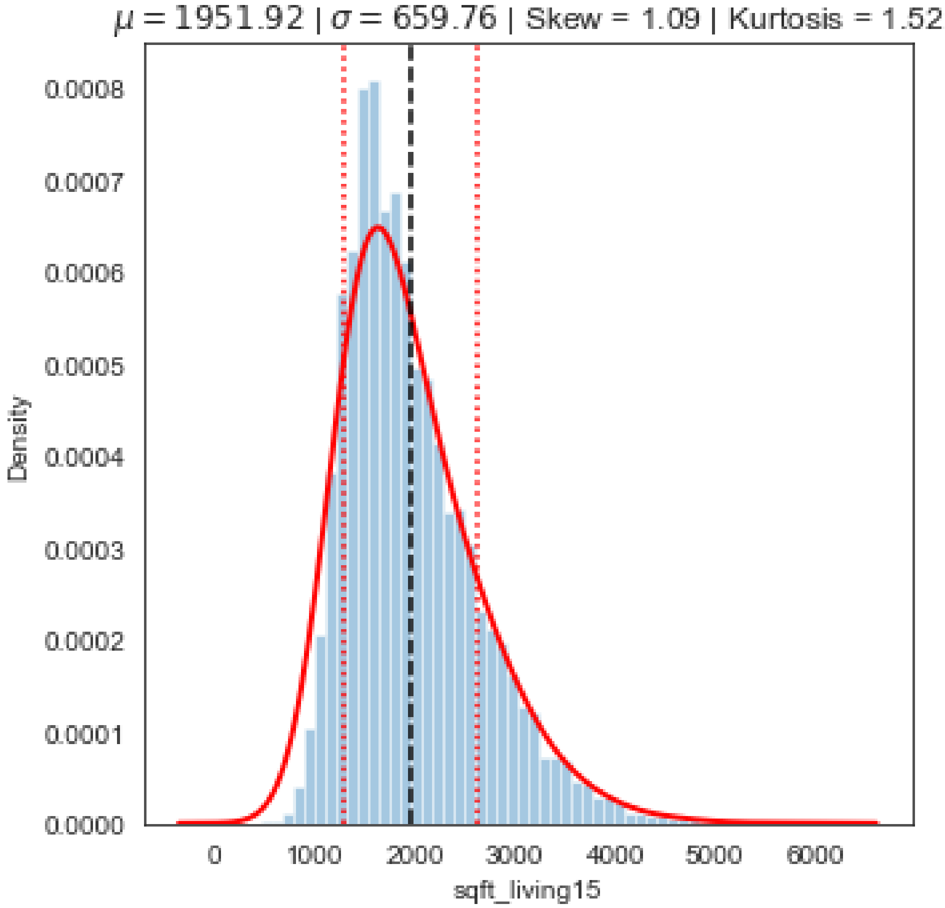
```
# Plotting KDE and distribution plots of the remaining variables

continuous=['price','sqft_living','sqft_living15','sqft_above','distance']
for col in continuous:
    fig, ax =plt.subplots(figsize=(5, 5))
    distribution(df_num3[col])

discrete=['bathrooms','grade']
for col in discrete:
    fig, ax =plt.subplots(figsize=(5, 5))
    ax = sns.distplot(df_num3[col], bins=10, kde_kws={"color": "r", "lw": 2,␣
 ↪"label": "KDE", "bw_adjust": 4})
    skew_val = stats.skew(df_num3[col], bias=False)
    kurt_val = stats.kurtosis(df_num3[col],bias=False)
    print('Column: {} | Skewness = {} | Kurtosis = {}'.
                format(col, round(skew_val,2), round(kurt_val,2)))
```

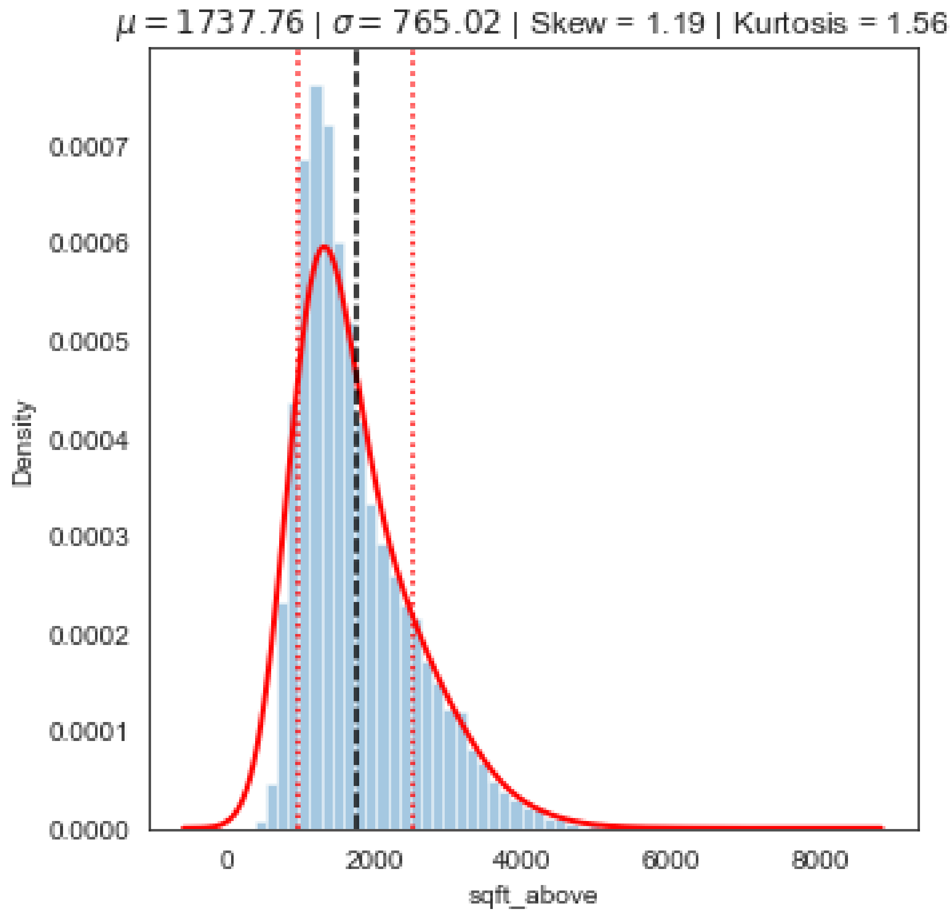
```
Column: bathrooms | Skewness = 0.28 | Kurtosis = 0.09
Column: grade | Skewness = 0.73 | Kurtosis = 1.02
```



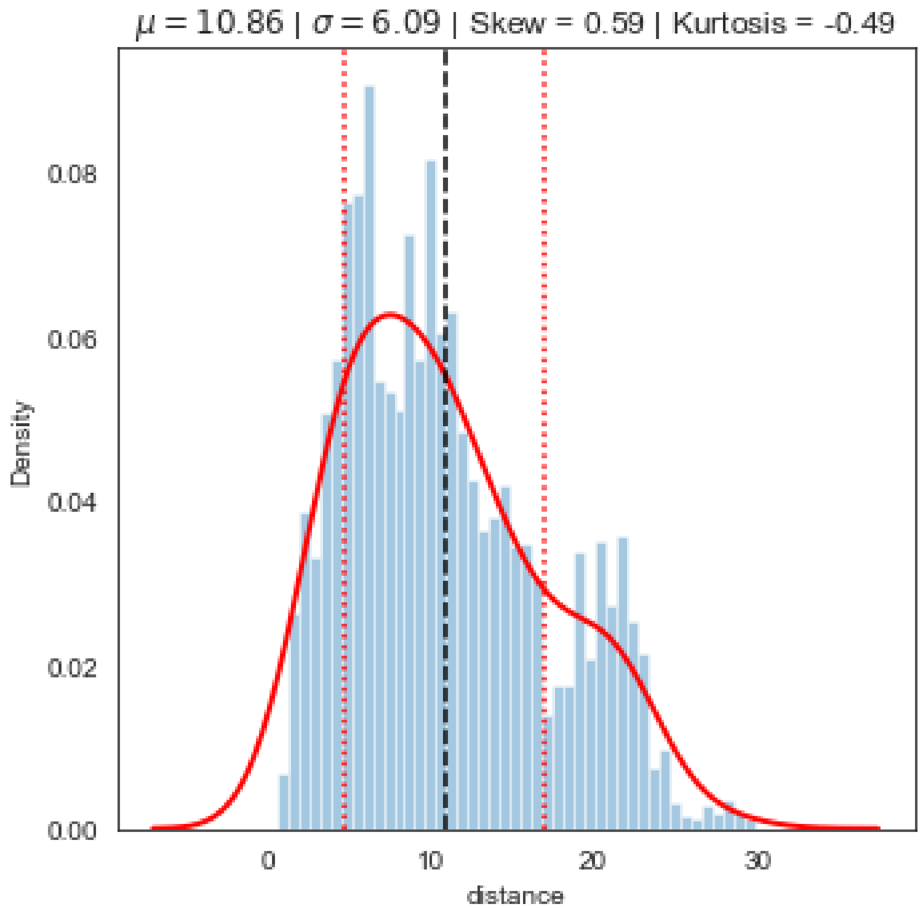


$\mu = 2026.65$ | $\sigma = 842.23$ | Skew = 1.04 | Kurtosis = 1.66
Density
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
0
2000
4000
6000
8000
sqft_living

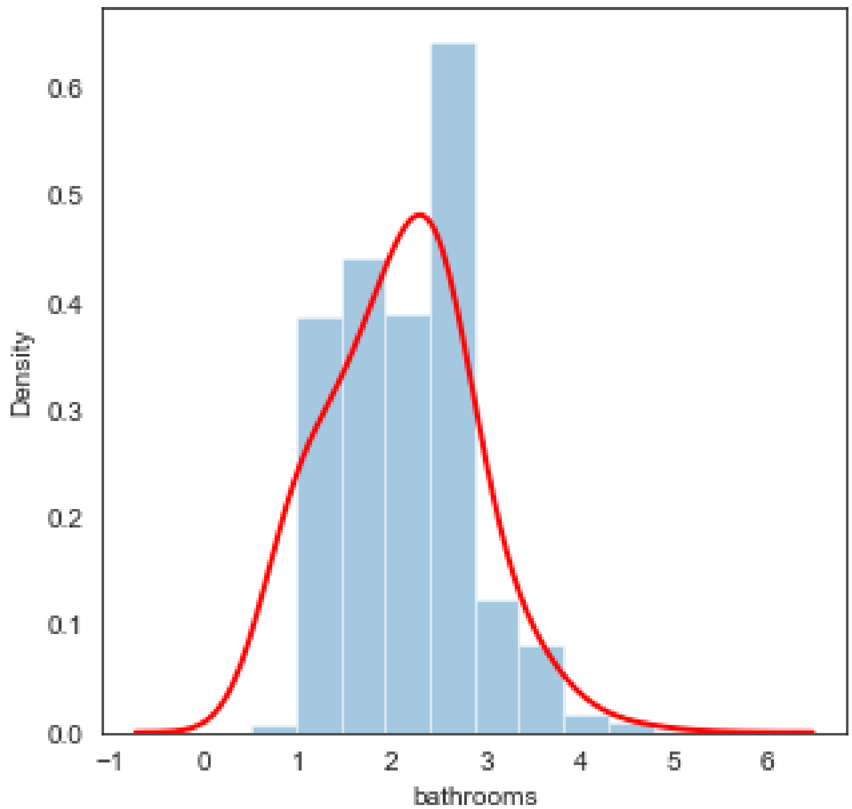

$\mu = 1951.92$ | $\sigma = 659.76$ | Skew = 1.09 | Kurtosis = 1.52
Density
0.0000
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0
1000
2000
3000
4000
5000
6000
sqft_living15



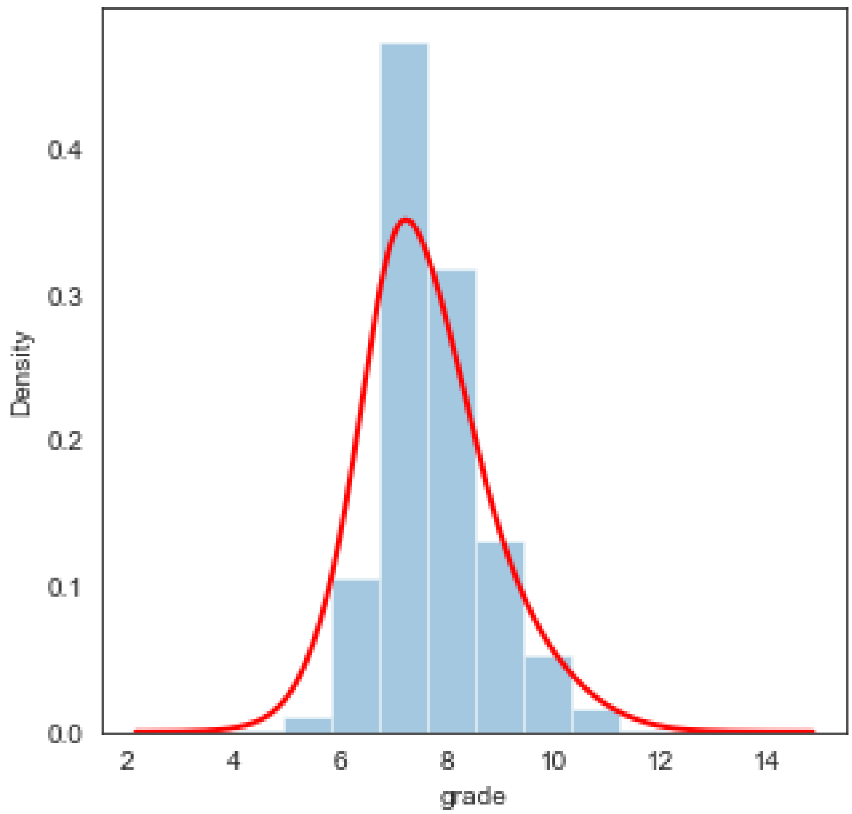
$\mu = 1737.76$ | $\sigma = 765.02$ | Skew = 1.19 | Kurtosis = 1.56
Density
0.0000
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0
2000
4000
6000
8000
sqft_above



$\mu = 10.86$ | $\sigma = 6.09$ | Skew = 0.59 | Kurtosis = -0.49
Density
0.00
0.02
0.04
0.06
0.08
0
10
20
30
distance

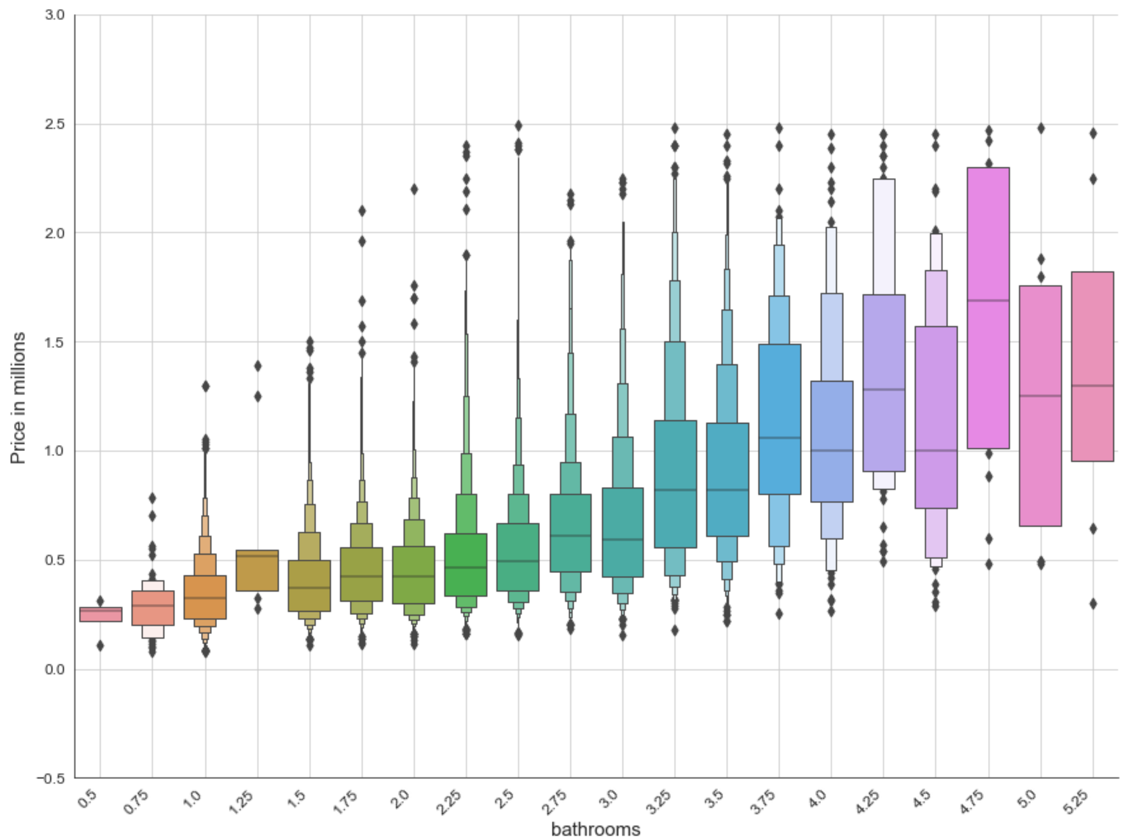


0.6
0.5
0.4
0.3
0.2
0.1
0.0
Density
−1
0
1
2
3
4
5
6
bathrooms

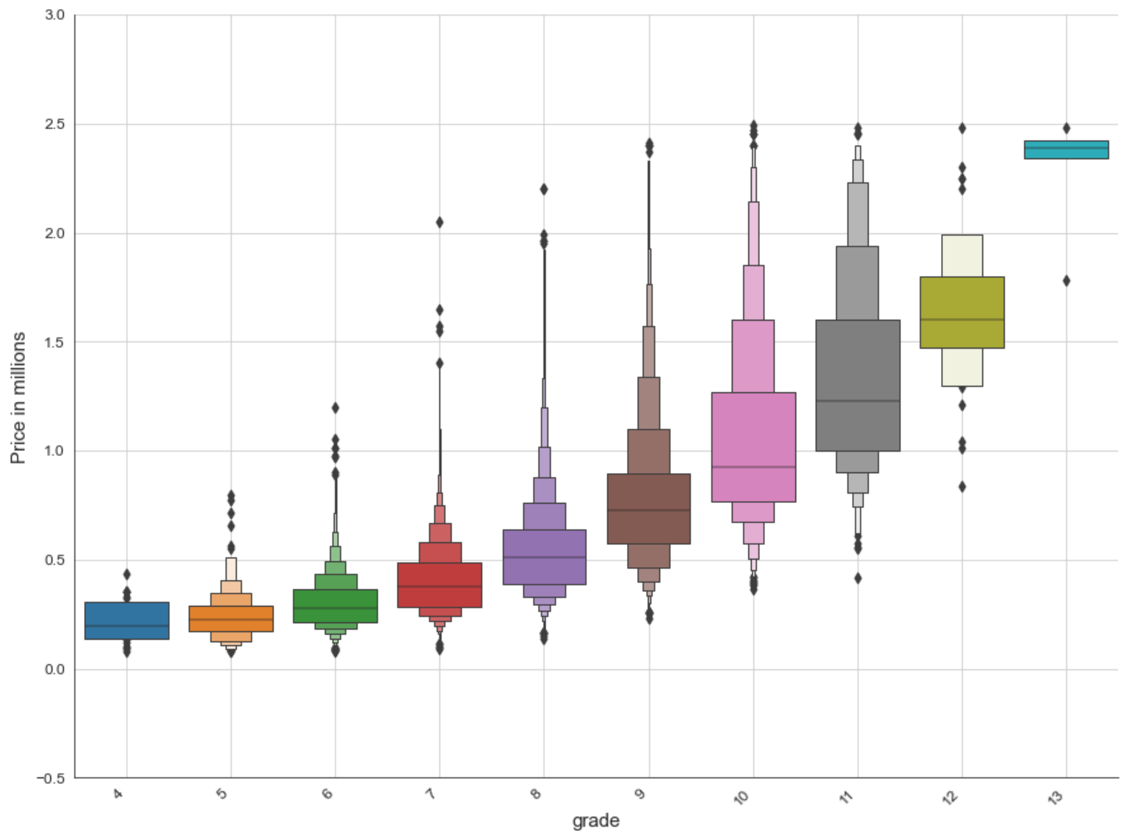


All but one variable (distance) are left shifted, which is indicated by the skewness values >1, with price has the most skewed distribution. Because the skewness it to the left (positive values), the log transformation might be needed to normalize the variables. Kurtosis values for all variables are different from 0 (Pearson's definition of kurtosis of a normal distribution). Price distribution is highly Leptokurtic, other variables are slightly Leptokurtic (sqft_living, sqft_above, sqft_living15, grade), slightly Platykurtic (distance) or almost Mesokurtic (bathrooms)

[53]:
```
# Diamond box plots for descrete numerical variables

discrete=['bathrooms','grade']
for col in discrete:

    ax = sns.catplot(x=col, y='price', kind="boxen",
            data=df_num3.sort_values(col), height=9, aspect=12/9)
    ax.set_xticklabels(rotation=45, ha='right', fontsize=12)
    ax.set_yticklabels(fontsize=12)
    plt.ylabel('Price in millions', fontsize=15)
    plt.xlabel(col, fontsize=15);
    plt.grid()
    plt.show()
```



Price in millions
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0.5
0.75
1.0
1.25
1.5
1.75
2.0
2.25
2.5
2.75
3.0
3.25
3.5
3.75
4.0
4.25
4.5
4.75
5.0
5.25
bathrooms



Based on the distribution plots, variable 'bathroom' has a symmetrical distribution (Skewness is 0.28), with a very low kurtosis (0.09) indicative of a Mesokurtic curve (Gaussian distribution has a kurtosis of 0 by Pearson's definition used by scipy.stats.kurtosis method) Variable 'grade' is slightly skewed to the right (0.73) and relatively low kurtosis, slightly above 1. The pronounced correlation of these variables with the price is identifiable in the box plots above. The plots show that the numbers of outliers in the distribution of the variables are reasonable. Both variables have a wider range of values in the higher price brackets.

3.2.2 Numerical variables: Exploring Mutual Correlation Coefficients and Variance Inflation Factor

Using VIF as an indicator of collinearity between independent variables

[54]:
```
calc_vif(df_num3)
```

[54]:

	variables	VIF
0	price	11.713924
1	bathrooms	21.024526
2	sqft_living	42.036909
3	grade	27.796857
4	sqft_above	26.850680
5	sqft_living15	28.037076

```
6       distance   6.670397
```

[55]:
```
# Dropping fields that have high VIF. I decided to leave in sqft_living versus␣
↪sqft_living15 due to the fact that it is
# easier to interpret in a model and it is a feature under control of a␣
↪property owner (versus sqft_living15 which is
# a charecteristic of a neighborhood)

df_num4=df_num3.drop(['price','sqft_above','sqft_living15'],axis=1)

calc_vif(df_num4)
```

[55]:

	variables	VIF
0	bathrooms	20.829518
1	sqft_living	16.749281
2	grade	18.971120
3	distance	3.971751

Pearson coefficients analysis of the remaining independent variables

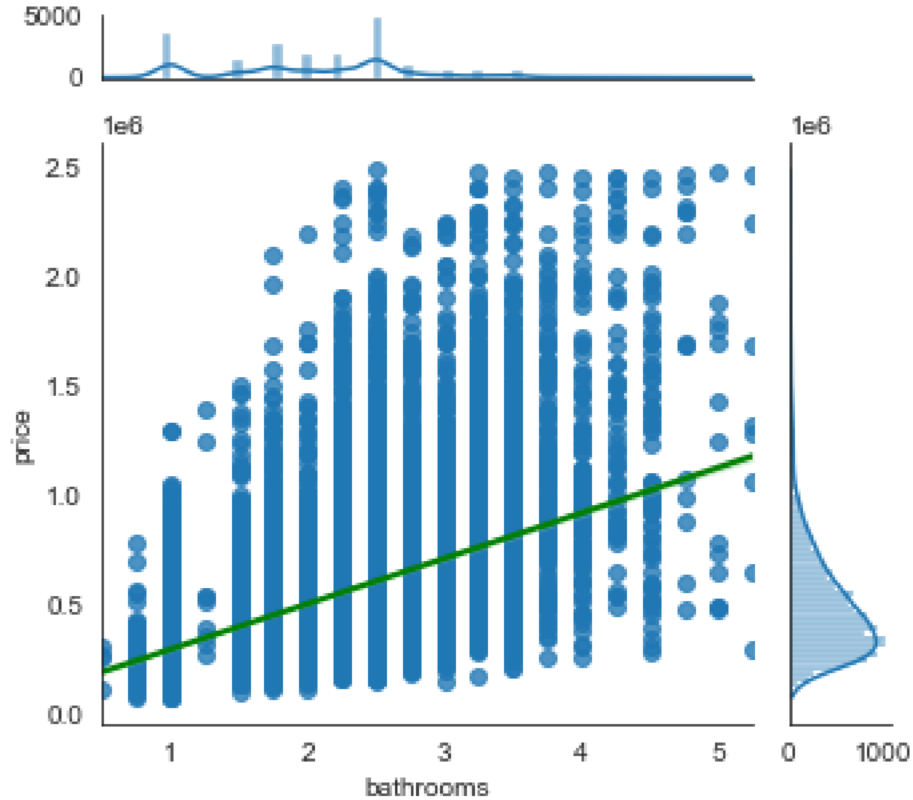
[56]:
```
df_num4['price']=df_num3['price']
```

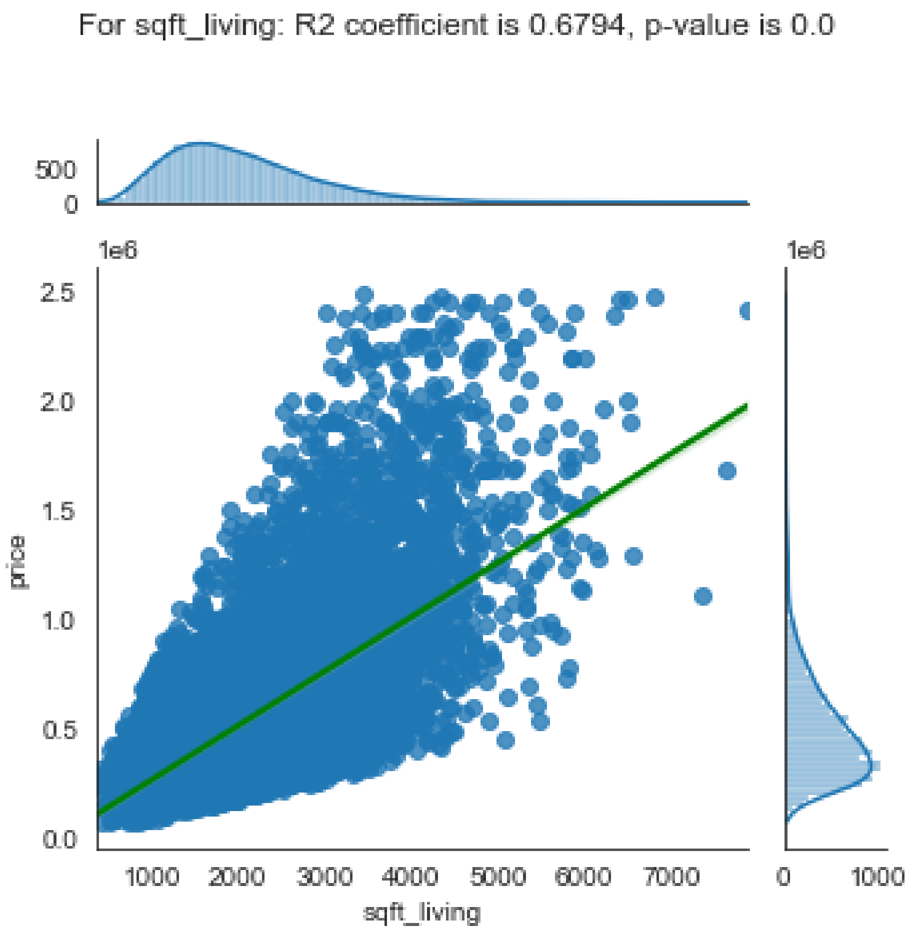
[57]:
```
# Displaying R2s for the remaining variables
r2_p(df_num4)
```

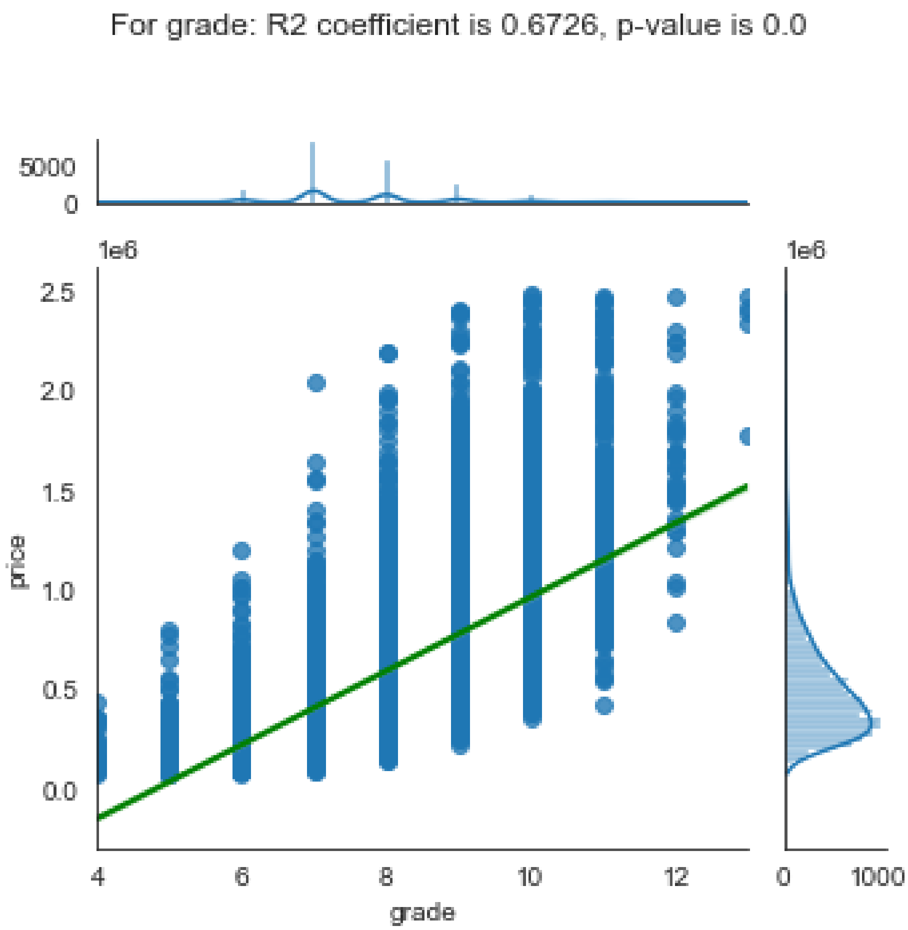
```
For bathrooms: R2 coefficient is 0.4989, p-value is 0.0
For sqft_living: R2 coefficient is 0.6794, p-value is 0.0
For grade: R2 coefficient is 0.6726, p-value is 0.0
For distance: R2 coefficient is -0.3383, p-value is 0.0
For price: R2 coefficient is 1.0, p-value is 0.0
```

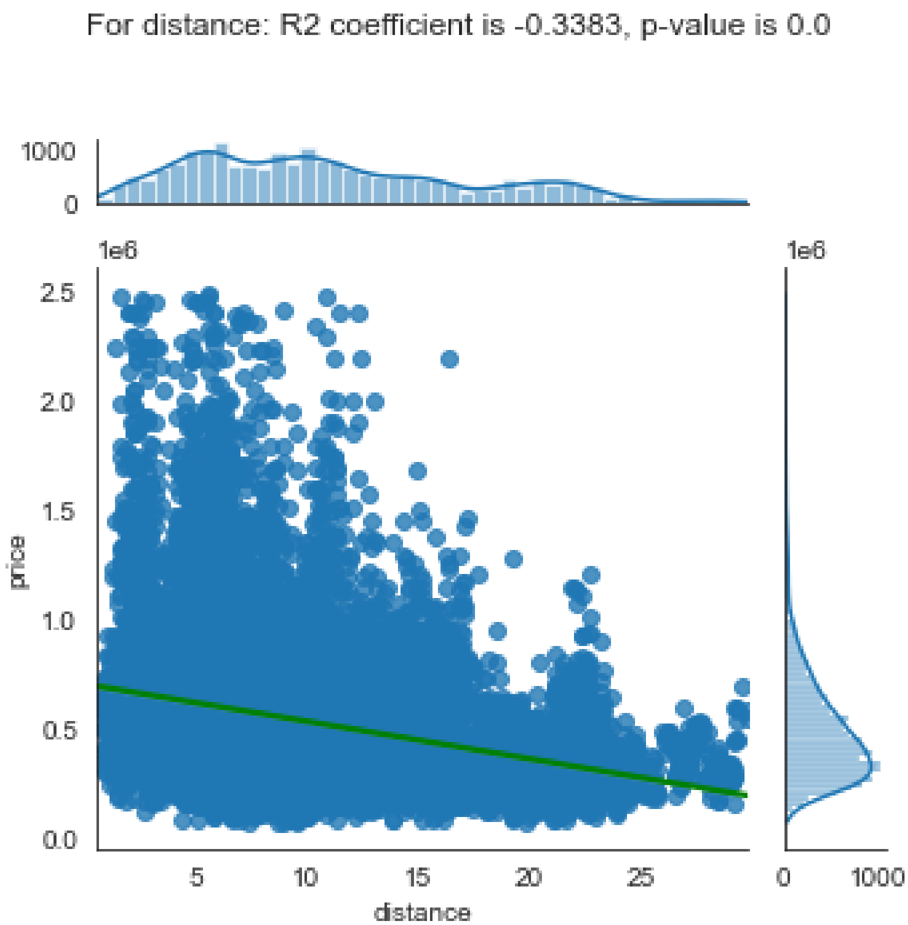
[58]:
```
# Displaying correlations between predictors and the target
jointplot(df_num4)
```

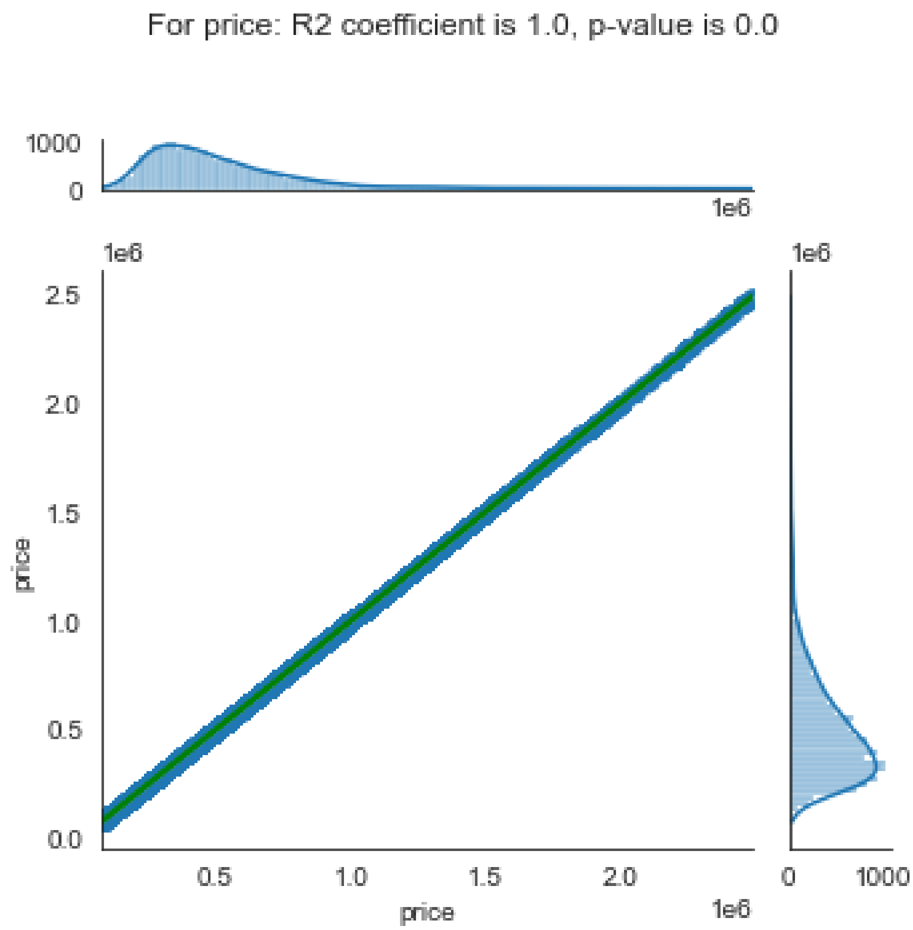
For bathrooms: R2 coefficient is 0.4989, p-value is 0.0




For sqft_living: R2 coefficient is 0.6794, p-value is 0.0
500
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
1000
2000
3000
4000
5000
6000
7000
sqft_living
1e6
0
1000

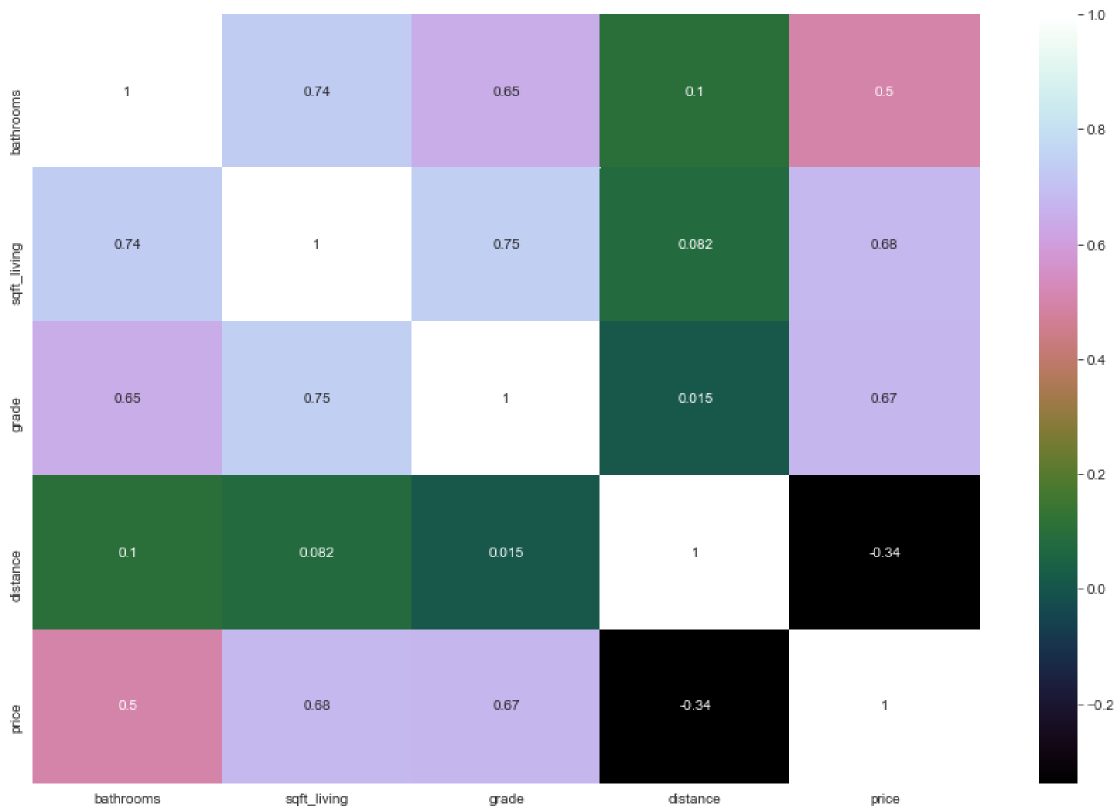

For grade: R2 coefficient is 0.6726, p-value is 0.0
5000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
4
6
8
10
12
grade
1e6
0
1000


For distance: R2 coefficient is -0.3383, p-value is 0.0
1000
0
1e6
2.5
2.0
1.5
1.0
0.5
0.0
price
5
10
15
20
25
distance
1e6
0
1000



[59]:
```
# Using heatmap to visualize mutual relationships between predictors and their␣
↪correlations with the target
fig, ax = plt.subplots(figsize=(15,10))
sns.heatmap(df_num4.corr(), cmap="cubehelix", annot=True)
```

[59]: <AxesSubplot:>



[60]:
```
# Checking for correlations between the variables with pearson coefficient␣
↪between 1 and 0.3


df_coeff=df_num4.corr().abs().stack().reset_index().sort_values(0,␣
↪ascending=False)
df_coeff['pairs'] = list(zip(df_coeff.level_0, df_coeff.level_1))
df_coeff.set_index(['pairs'], inplace = True)
df_coeff.drop(columns=['level_1', 'level_0'], inplace = True)
df_coeff.columns = ['cc']
df_coeff.drop_duplicates(inplace=True)
df_coeff[((df_coeff.cc>.3) & (df_coeff.cc <1))]
```

[60]:

pairs	cc
(sqft_living, grade)	0.746576
(bathrooms, sqft_living)	0.737962
(price, sqft_living)	0.679411
(price, grade)	0.672609
(grade, bathrooms)	0.647588
(price, bathrooms)	0.498869

```
(distance, price)         0.338264
```

Mutual correlation coefficients between the remaining independent variables are slightly higher or below 0.7. I am leaving sqft_living, grade, and bathroom variables in because of their logical connection with a property price despite their multicollinearity (0.74 & 0.73 are above the 0.7 threshold).

Therefore the remaining numerical variables for modeling are 1. grade 2. bathrooms 3. sqft_living 4. distance

[61]:
```
df_num4.describe()
```

[61]:

	bathrooms	sqft_living	grade	distance	price
count	19811.000000	19811.000000	19811.000000	19811.000000	1.981100e+04
mean	2.091338	2026.647670	7.615264	10.861961	5.228653e+05
std	0.739792	842.234389	1.116205	6.093693	3.083509e+05
min	0.500000	370.000000	4.000000	0.600000	7.800000e+04
25%	1.500000	1410.000000	7.000000	5.900000	3.200000e+05
50%	2.250000	1880.000000	7.000000	9.900000	4.450000e+05
75%	2.500000	2500.000000	8.000000	14.800000	6.338170e+05
max	5.250000	7880.000000	13.000000	29.800000	2.490000e+06

3.2.3 Categorical variables: Investigating distributions and the raw correlations between the original, minimally processed predictor and the target (price)

Original categorical variables: waterfront, view, condition, basement_exists, renovation_done, month

[62]:
```
#Creating a DataFrame with categorical variables

df_cat1 = df_2.
 ↪filter(['price','waterfront','view','condition','basement_exists','renovation_done','month'],
 ↪axis=1)
```

Visual investigation of the box plots

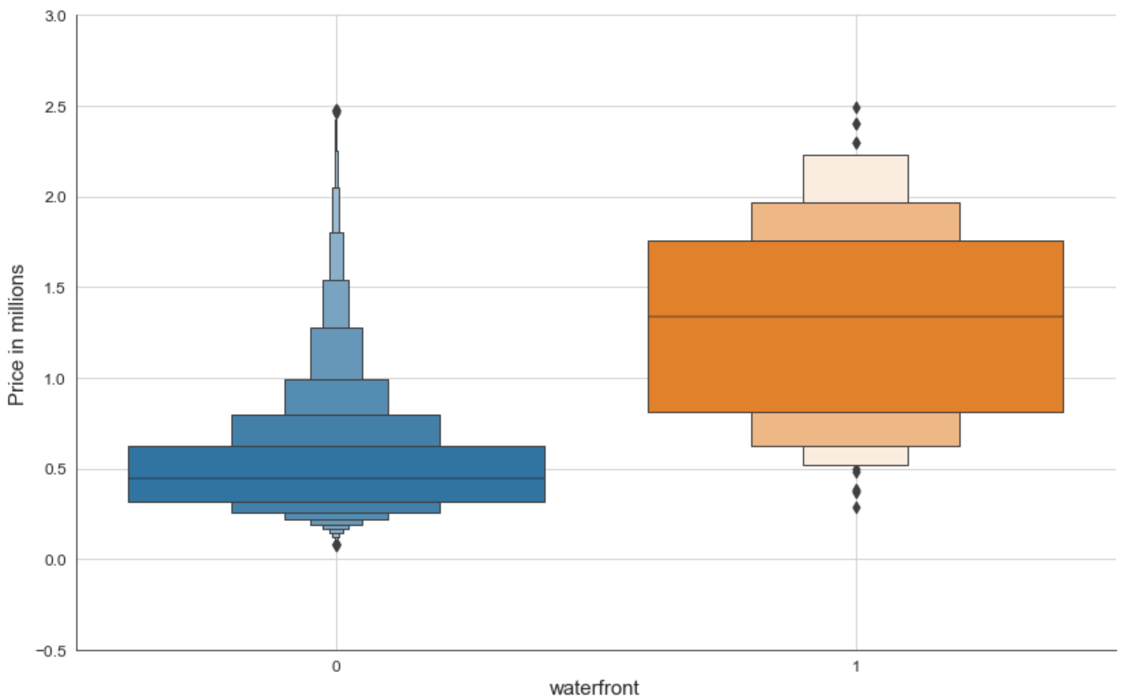
[63]:
```
df_cat1
```

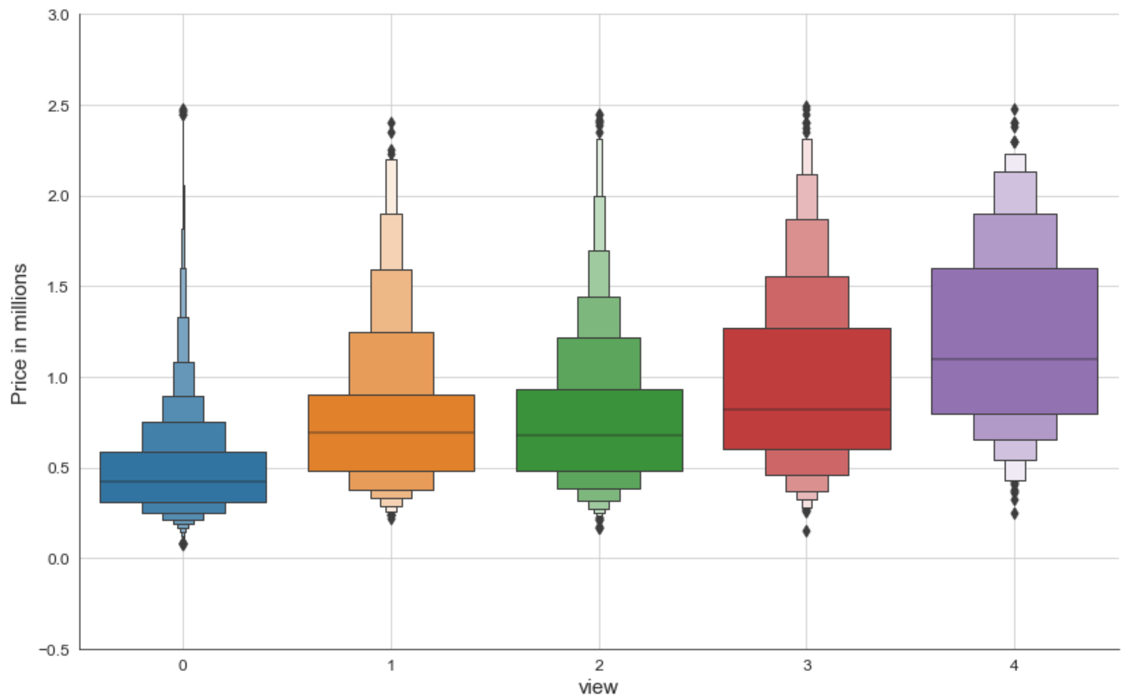
[63]:

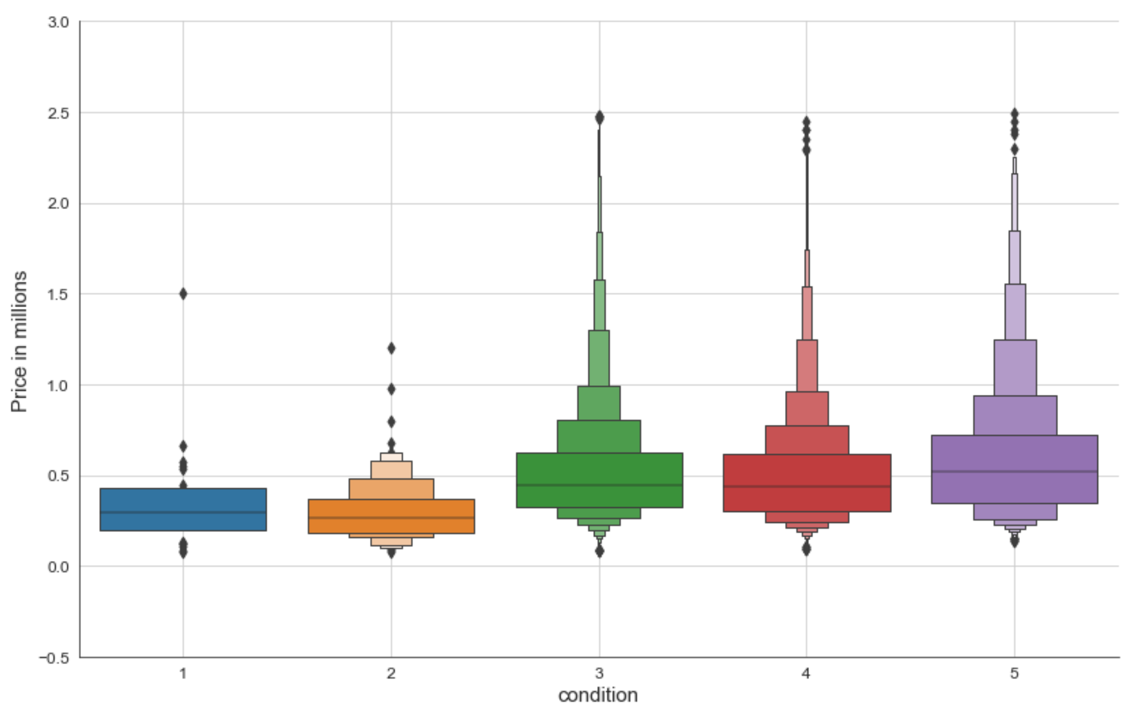
	price	waterfront	view	condition	basement_exists	renovation_done	month
0	221900.0	0	0	3	0	0	10
1	538000.0	0	0	3	1	3	12
2	180000.0	0	0	3	0	0	2
3	604000.0	0	0	5	1	0	12
4	510000.0	0	0	3	0	0	2

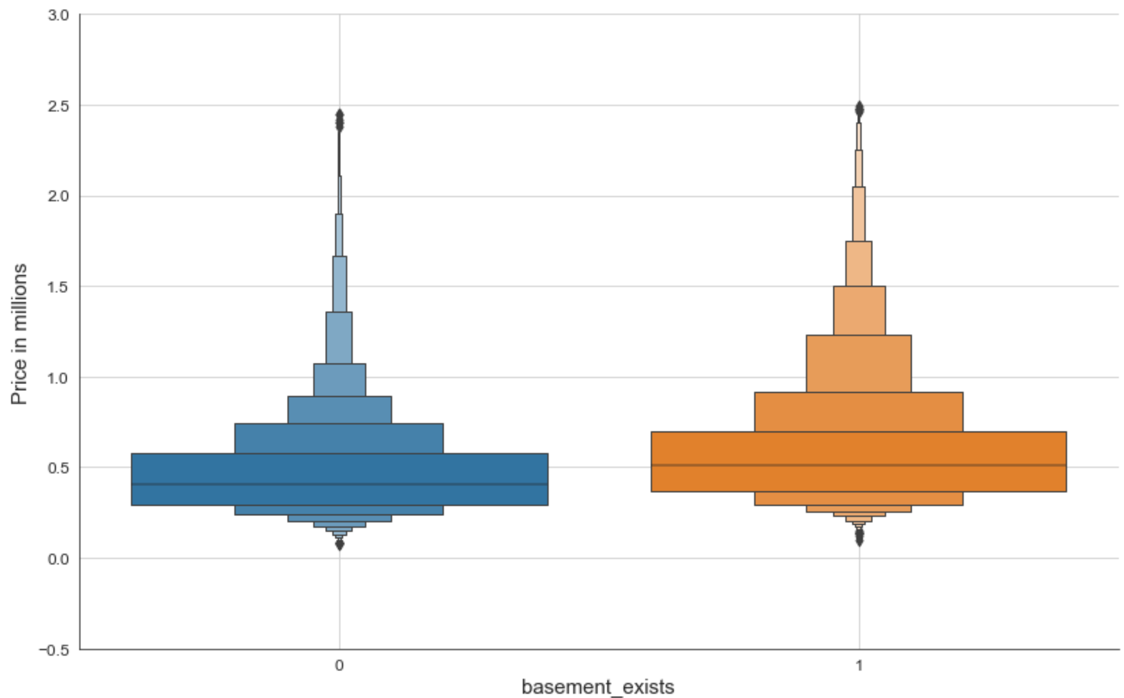
```
…        …         …   …      …           …           …
…
20010   360000.0       0     0          3           0           4
5
20011   400000.0       0     0          3           0           4
2
20012   402101.0       0     0          3           0           4
6
20013   400000.0       0     0          3           0           0
1
20014   325000.0       0     0          3           0           4
10

[20015 rows x 7 columns]
```

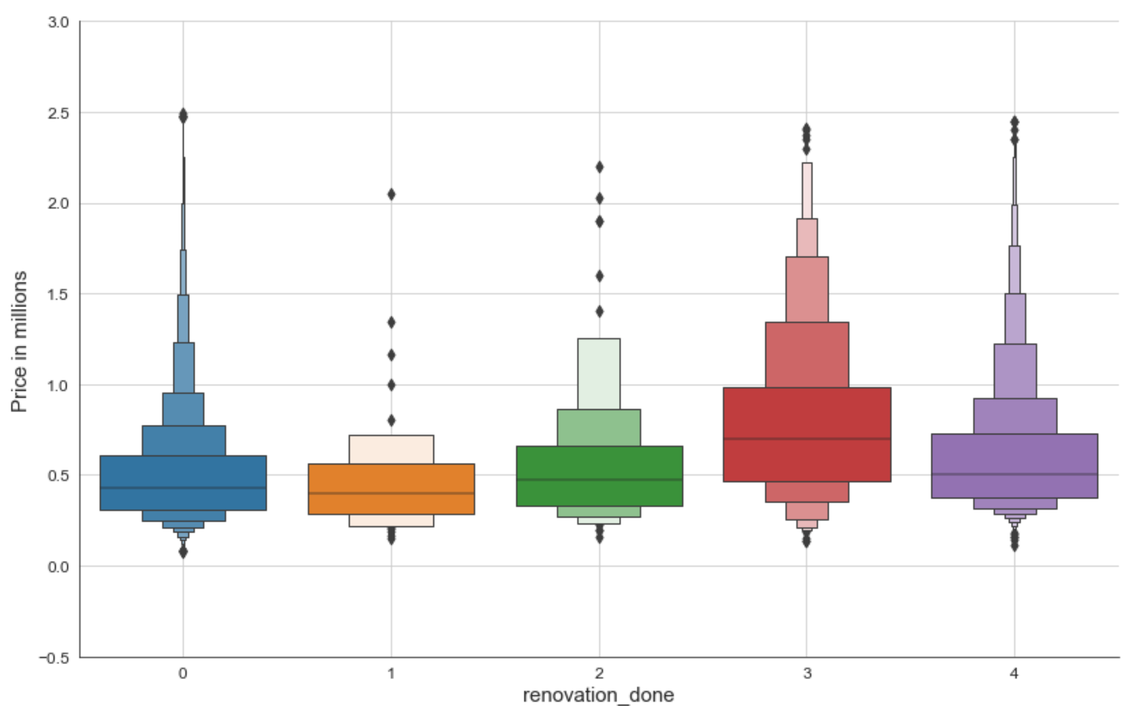
[64]:
```python
names=['waterfront','view','condition','basement_exists','renovation_done','month']
for col in names:
    boxen_plot(df_cat1,col)
```

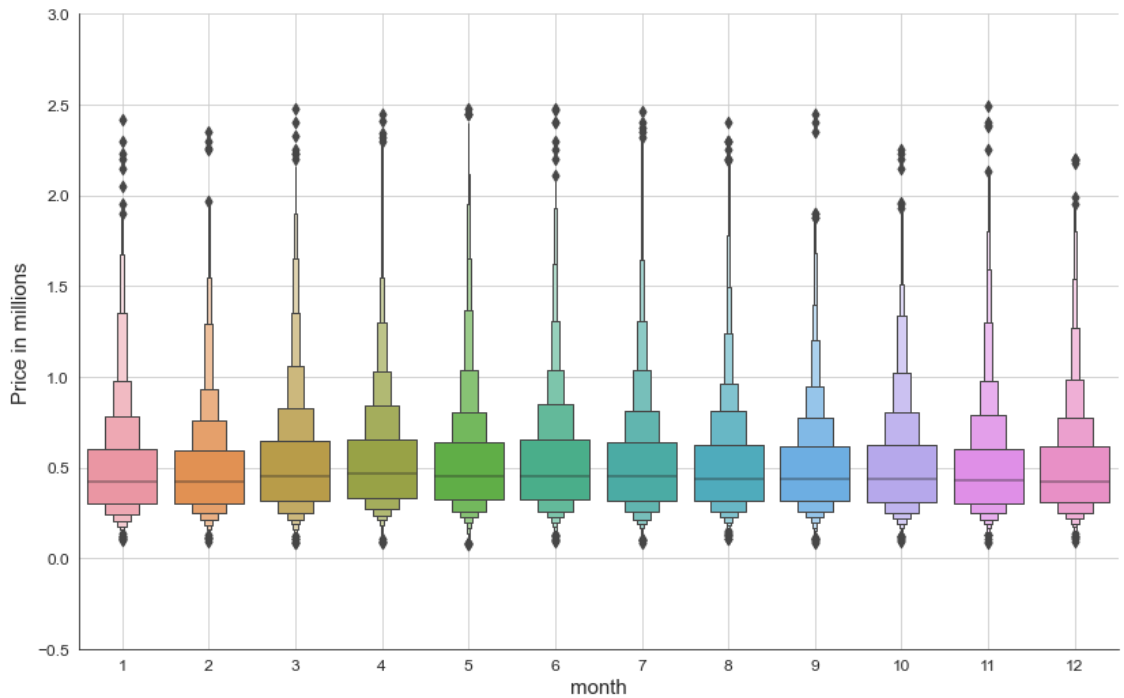



Price in millions
view
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0
1
2
3
4


Price in millions
condition
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
1
2
3
4
5


3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
Price in millions
0
1
basement_exists


3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
Price in millions
0
1
2
3
4
renovation_done



Based on the plots, it is quite clear that 'month', 'condition' and 'basement_exists' variables do not affect the price of the properties and can be dropped from the categorical variables

Dumming out variables in the categorical DataFrame

[65]:
```
# Using OheHotEncoder to dummy categorical out. Based on the boxplots above, I␣
↪am leaving
# 'month','basement_exists','condition' variables out, they seem not to have␣
↪too much effect on the target.
# The reason for removing 'waterfront' variable is a tiny porting of all␣
↪properties in the dataset.

ohe=OneHotEncoder(drop='first')
df_cat_transform=ohe.fit_transform(df_cat1.
↪drop(['price','month','basement_exists','condition','waterfront'], axis=1))
df_cat1_trsfm=pd.DataFrame(df_cat_transform.todense(),
                           columns=ohe.
↪get_feature_names(['view','renovation_done']))
df_cat1_trsfm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20015 entries, 0 to 20014
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   view_1             20015 non-null  float64
```

```
 1   view_2             20015 non-null  float64
 2   view_3             20015 non-null  float64
 3   view_4             20015 non-null  float64
 4   renovation_done_1  20015 non-null  float64
 5   renovation_done_2  20015 non-null  float64
 6   renovation_done_3  20015 non-null  float64
 7   renovation_done_4  20015 non-null  float64
dtypes: float64(8)
memory usage: 1.2 MB
```

[66]:

```
# Adding a price column and resetting the index
# Due to the removal of the extreme values in numerical values, some rows have
↪Nan price values; these rows are dropped

df_cat1_trsfm['price']=df_num4['price']

df_cat1_trsfm=df_cat1_trsfm[df_cat1_trsfm.price.notna()]

df_cat1_trsfm=df_cat1_trsfm.reset_index()

df_cat1_trsfm=df_cat1_trsfm.drop('index', axis=1)

df_cat1_trsfm
```

[66]:

```
       view_1  view_2  view_3  view_4  renovation_done_1  renovation_done_2
renovation_done_3  renovation_done_4     price
0         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  221900.0
1         0.0     0.0     0.0     0.0                0.0                0.0
1.0                  0.0  538000.0
2         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  180000.0
3         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  604000.0
4         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  510000.0
…        …      …      …      …                 …                 …
…                  …         …
19806     0.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  360000.0
19807     0.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  400000.0
19808     1.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  402101.0
19809     0.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  400000.0
19810     0.0     0.0     0.0     0.0                0.0                0.0
```

```
 0.0                1.0  325000.0

 [19811 rows x 9 columns]
```

df_cat1_trsfm DataFrame

19811 records out of original 21597 left
</div>

Index reset
</div>

[67]:
```
df_cat1_trsfm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19811 entries, 0 to 19810
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   view_1              19811 non-null  float64
 1   view_2              19811 non-null  float64
 2   view_3              19811 non-null  float64
 3   view_4              19811 non-null  float64
 4   renovation_done_1   19811 non-null  float64
 5   renovation_done_2   19811 non-null  float64
 6   renovation_done_3   19811 non-null  float64
 7   renovation_done_4   19811 non-null  float64
 8   price               19811 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

4 Model

4.1 Data Modeling

4.1.1 Baseline model

> "Everything should be made as simple as possible, but no simpler."
>
> Albert Einstein

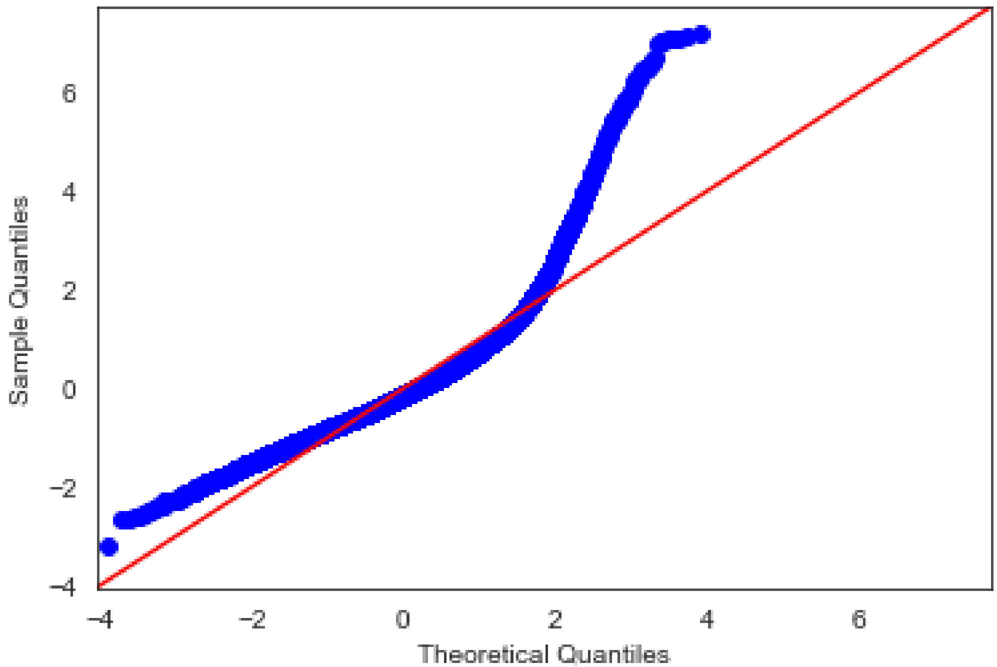
The chosen baseline model is a model with only one numerical variable, grade.

Creating a model

[68]:
```
## Create the formula and  the model

f  = 'price~grade'

model_baseline = smf.ols(f, df_num4).fit()
model_baseline.summary()
```

[68]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.452
Model:                            OLS   Adj. R-squared:                  0.452
Method:                 Least Squares   F-statistic:                 1.637e+04
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:25   Log-Likelihood:            -2.7254e+05
No. Observations:               19811   AIC:                         5.451e+05
Df Residuals:                   19809   BIC:                         5.451e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept  -8.921e+05   1.12e+04    -79.803      0.000   -9.14e+05    -8.7e+05
grade       1.858e+05   1452.448    127.927      0.000    1.83e+05    1.89e+05
==============================================================================
Omnibus:                     7709.438   Durbin-Watson:                   1.964
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            46187.116
Skew:                           1.765   Prob(JB):                         0.00
Kurtosis:                       9.595   Cond. No.                         53.9
==============================================================================

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

[69]:
```
fig = sm.graphics.qqplot(model_baseline.resid,dist=stats.
 ↪norm,fit=True,line='45')
```



The baseline model has a coefficient of determination of 0.452, indicating that roughly 45% of the observations fit the model. F-statistics is very high that indicates that the baseline model is a significant improvement of the "intercept only model" The Skewness and the Kurtosis values indicate non-normal distribution of the target variable QQ plot is also indicative of the abnormal distribution of the residuals, especially in the upper Quantile

4.1.2 Model 1 (all numerical variables considered significant, see Explore section)

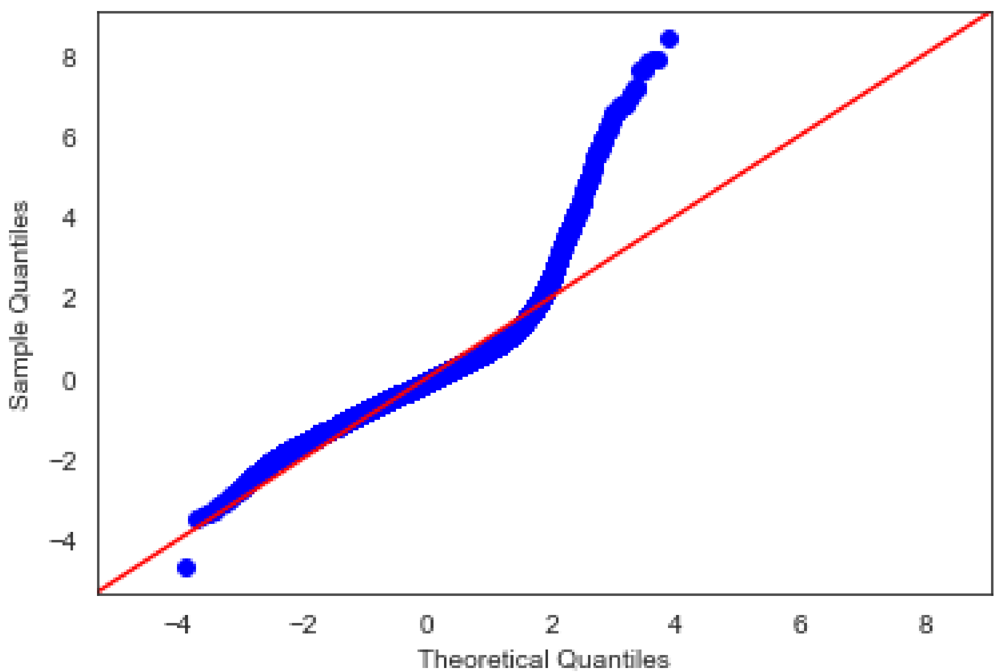
[70]:
```
## Create a formula including the remaining numerical variables

variables_to_include = ' + '.join(df_num4.drop('price',axis=1).columns)

## Create the formula and  the model
f  = "price~" + variables_to_include

model_1 = smf.ols(f, df_num4).fit()
model_1.summary()
```

[70]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.668
Model:                            OLS   Adj. R-squared:                  0.668
Method:                 Least Squares   F-statistic:                     9947.
```

```
Date:                Mon, 26 Apr 2021   Prob (F-statistic):                 0.00
Time:                        16:58:25   Log-Likelihood:              -2.6759e+05
No. Observations:               19811   AIC:                           5.352e+05
Df Residuals:                   19806   BIC:                           5.352e+05
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept   -3.142e+05   1.04e+04    -30.071      0.000   -3.35e+05   -2.94e+05
bathrooms   -1.725e+04   2599.797     -6.634      0.000   -2.23e+04   -1.22e+04
sqft_living   177.5465      2.610     68.031      0.000     172.431     182.662
grade        9.475e+04   1748.262     54.195      0.000    9.13e+04    9.82e+04
distance    -1.917e+04    209.218    -91.613      0.000   -1.96e+04   -1.88e+04
==============================================================================
Omnibus:                     8098.307   Durbin-Watson:                   1.981
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            65266.147
Skew:                           1.762   Prob(JB):                         0.00
Kurtosis:                      11.163   Cond. No.                     1.84e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.84e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

QQ plot: to access normality of the target variable

[71]:
```python
fig = sm.graphics.qqplot(model_1.resid,dist=stats.norm,fit=True,line='45')
```



The summary of the model above indicates that 1. All the independent variables coefficients and the intercept value are significant (p-values< 0.05) 2. The coefficient of determination (R2) is not very high, but it is significantly higher than R2 of the baseline model. It indicates that about 66.8 percent of the observations fall within the regression line 3. The skew and the Kurtosis values indicate the highly non-normal distribution of the target variable 4. The high value of JB coefficient also indicates that the data is highly non-normal

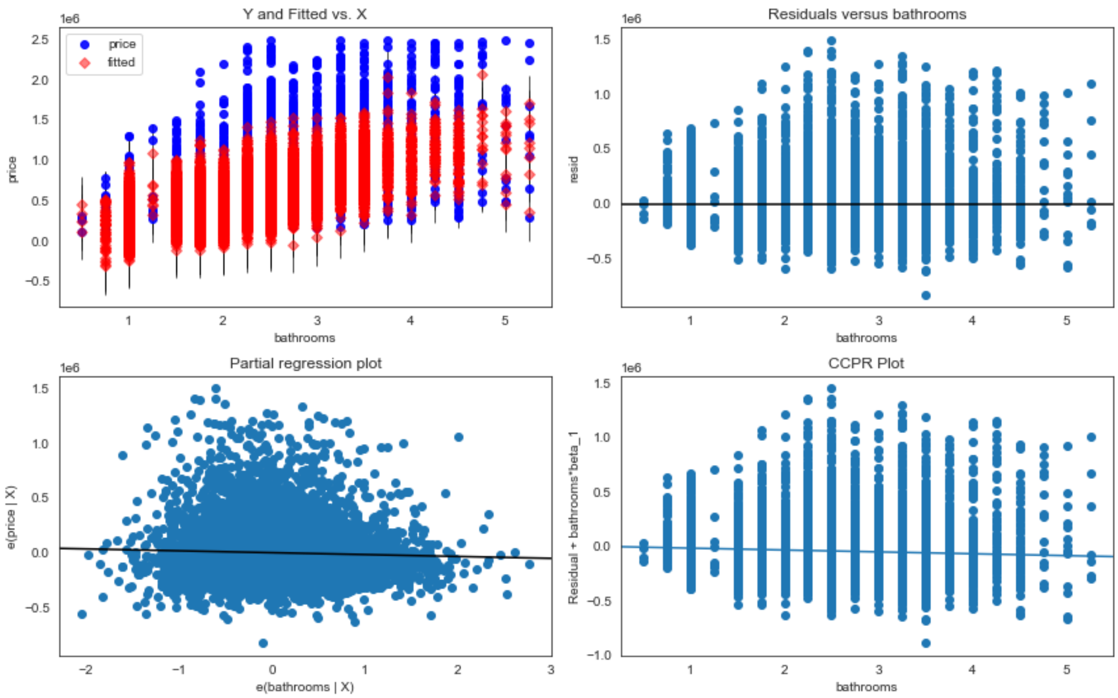
From the model's QQ plot, it is also quite obvious that the 'price' target variable is not normally distributed. A steep swing up indicates that the higher-priced houses are less likely to fit the baseline model and are more spread out. One possible reason might be an unusually large number of outliers in the dataset

There are two potential approaches that can be taken 1. Normalization by either log or square root transformation 2. Removal of outliers

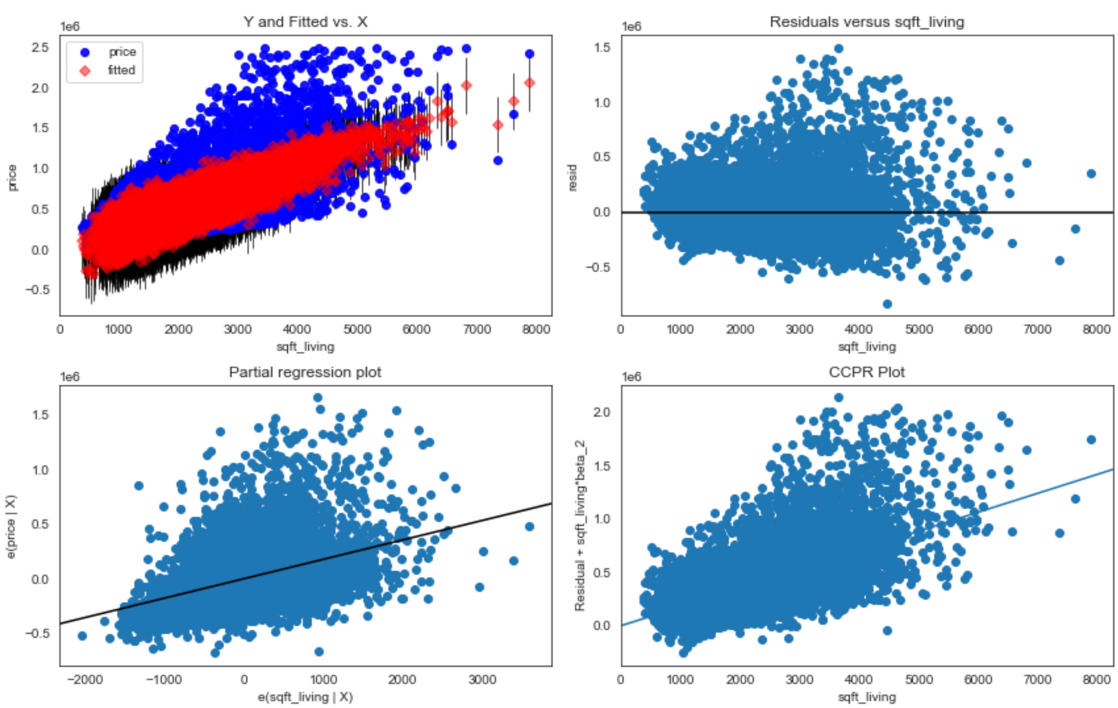
Plot regression results against each regressor: accessing linearity of there relationship with the target and their homoscedasticity

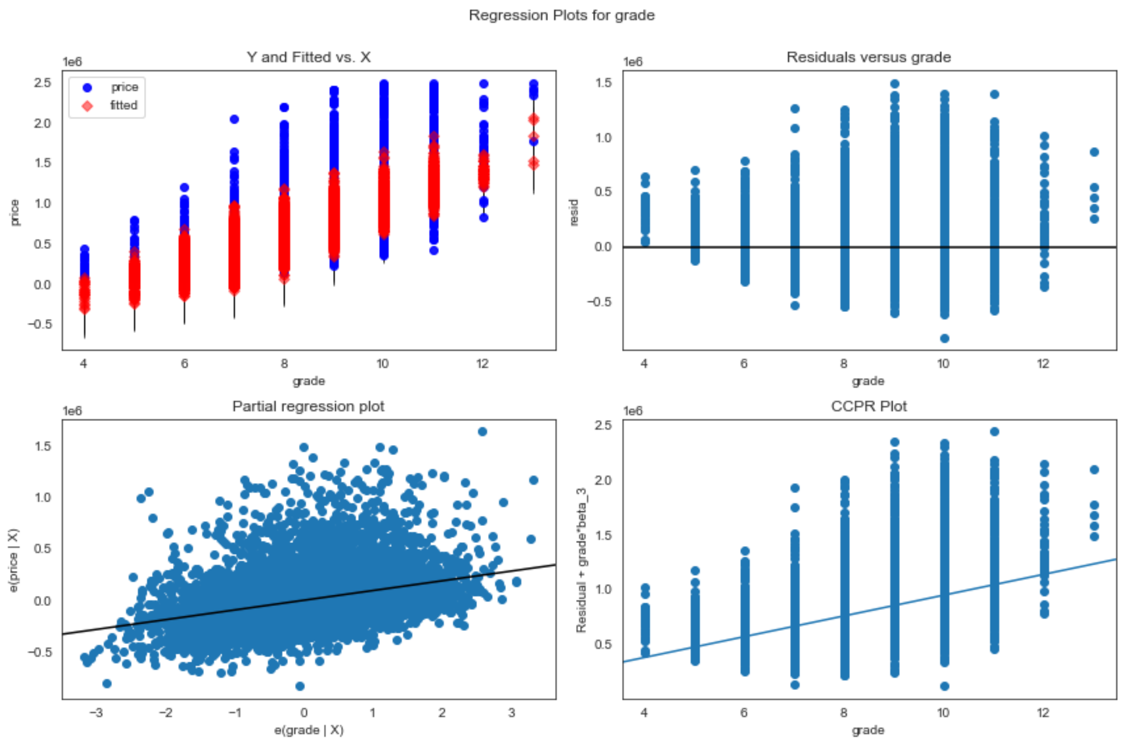
[72]:
```
for col in (df_num4.drop('price',axis=1).columns):
    fig = sm.graphics.plot_regress_exog(model_1, col, fig=plt.
↪figure(figsize=(12,8)))
```

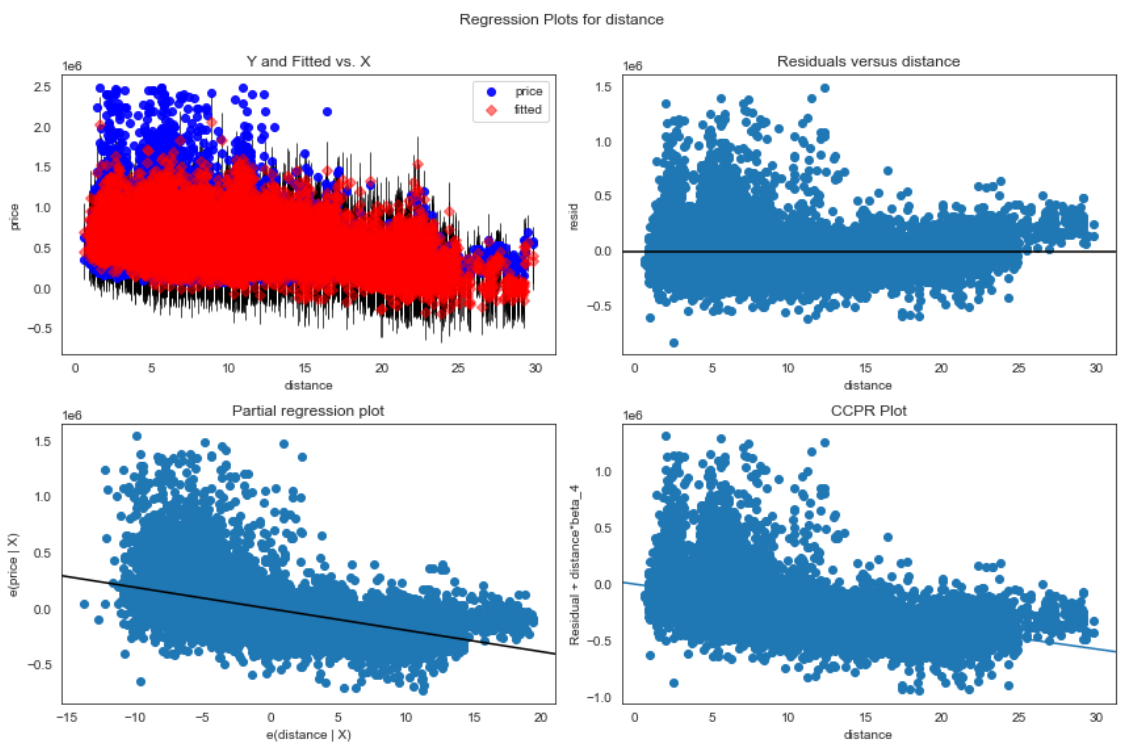
Regression Plots for bathrooms



Regression Plots for sqft_living




Regression Plots for grade
Y and Fitted vs. X
price
fitted
grade
Residuals versus grade
resid
Partial regression plot
e(price | X)
e(grade | X)
CCPR Plot
Residual + grade*beta_3


Regression Plots for distance
Y and Fitted vs. X
price
fitted
distance
Residuals versus distance
resid
Partial regression plot
e(price | X)
e(distance | X)
CCPR Plot
Residual + distance*beta_4

The results indicate that all of the predictors display linear relationship with the target. The distance, sqft_living and bathrooms variables display less heteroscedasticity than the grade variable does.

There might be several appropriate ways to address this issue 1. Log transformation of the target and/or independent variables 2. Using either Generalized Least Squares or Weighted Least squares 3. Bootstrapping

4.1.3 Model 2 (adding categorical variables)

Creating a model with all numerical variables and all categorical variables

[73]:
```
df_num4
```

[73]:
```
       bathrooms  sqft_living  grade  distance     price
0           1.00         1180      7       7.4  221900.0
1           2.25         2570      7       8.0  538000.0
2           1.00          770      6      10.2  180000.0
3           3.00         1960      7       6.6  604000.0
4           2.00         1680      8      13.4  510000.0
…              …          …    …      …       …
19806       2.50         1530      8       6.5  360000.0
19807       2.50         2310      8       6.7  400000.0
19808       0.75         1020      7       1.7  402101.0
19809       2.50         1600      8      13.2  400000.0
19810       0.75         1020      7       1.8  325000.0

[19811 rows x 5 columns]
```

[74]:
```
df_cat1_trsfm
```

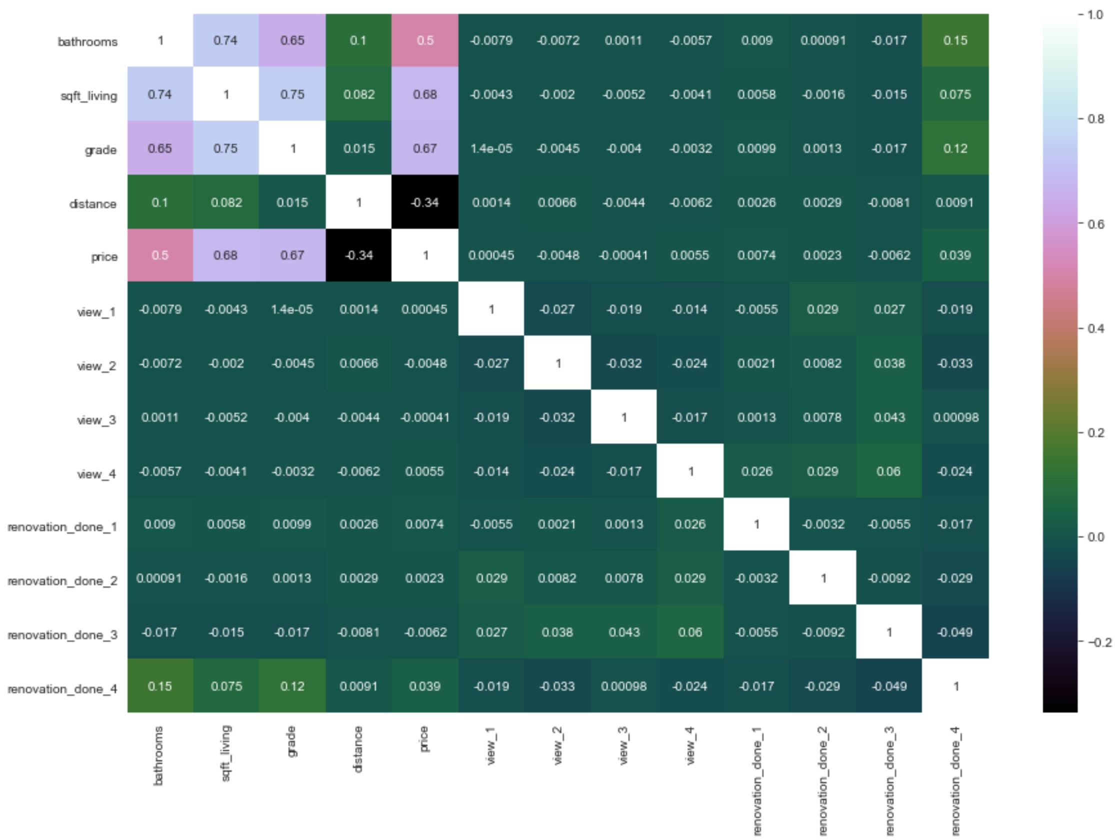
[74]:
```
       view_1  view_2  view_3  view_4  renovation_done_1  renovation_done_2
renovation_done_3  renovation_done_4     price
0         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  221900.0
1         0.0     0.0     0.0     0.0                0.0                0.0
1.0                  0.0  538000.0
2         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  180000.0
3         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  604000.0
4         0.0     0.0     0.0     0.0                0.0                0.0
0.0                  0.0  510000.0
…         …     …     …     …                …                …
…                  …       …
19806     0.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  360000.0
19807     0.0     0.0     0.0     0.0                0.0                0.0
0.0                  1.0  400000.0
```

```
19808      1.0      0.0      0.0      0.0                 0.0                 0.0
0.0                  1.0   402101.0
19809      0.0      0.0      0.0      0.0                 0.0                 0.0
0.0                  1.0   400000.0
19810      0.0      0.0      0.0      0.0                 0.0                 0.0
0.0                  1.0   325000.0

[19811 rows x 9 columns]
```

[75]:
```python
# DatyaFrames to concatinate: df_cat1_trsfm AND df_num4
df_num_cat_1 = pd.concat([df_num4, df_cat1_trsfm.drop('price',axis=1)],axis=1)
```

[76]:
```python
# Visualizing multicollinearity in the new dataset
fig, ax = plt.subplots(figsize=(15,10))
sns.heatmap(df_num_cat_1.corr(), cmap="cubehelix", annot=True)
```

[76]: <AxesSubplot:>



The matrix indicates no strong correlation between the price and any of the categorical variables. However, renovation_done_4 correlation is slightly higher than the rest of the categorical variables. Conceptually this variables indicative of a recent renovation or a newer property.

There is no high expectations that adding the categorical variables to the mix will significantly improve the model

[77]:
```
df_num_cat_1
```

[77]:
```
       bathrooms  sqft_living  grade  distance     price  view_1  view_2  view_3
view_4  renovation_done_1  renovation_done_2  renovation_done_3
renovation_done_4
0           1.00         1180      7       7.4  221900.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
1           2.25         2570      7       8.0  538000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  1.0                  0.0
2           1.00          770      6      10.2  180000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
3           3.00         1960      7       6.6  604000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
4           2.00         1680      8      13.4  510000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
…          …          …    …       …        …      …      …      …
…           …                 …                 …                 …
19806       2.50         1530      8       6.5  360000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19807       2.50         2310      8       6.7  400000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19808       0.75         1020      7       1.7  402101.0     1.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19809       2.50         1600      8      13.2  400000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19810       0.75         1020      7       1.8  325000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0

[19811 rows x 13 columns]
```

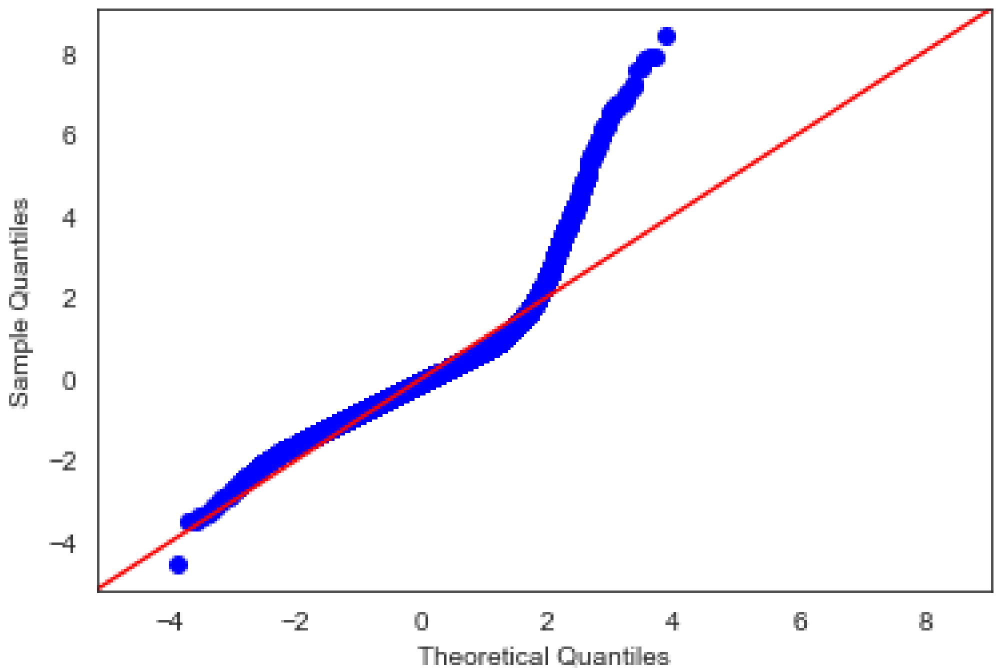
[78]:
```
# Create a formula for the numerical variables from the basemodel
# AND the categorical variables from the previous section

variables_to_include = ' + '.join(df_num_cat_1.drop('price',axis=1).columns)

## Create the formula and the model
f  = "price~" + variables_to_include


model_2 = smf.ols(f, df_num_cat_1).fit()
model_2.summary()
```

[78]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:                  price   R-squared:                       0.669
Model:                            OLS   Adj. R-squared:                  0.668
Method:                 Least Squares   F-statistic:                     3328.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:33   Log-Likelihood:            -2.6756e+05
No. Observations:               19811   AIC:                         5.352e+05
Df Residuals:                   19798   BIC:                         5.353e+05
Df Model:                          12
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept         -3.189e+05   1.05e+04    -30.473      0.000   -3.39e+05
-2.98e+05
bathrooms         -1.502e+04   2616.457     -5.740      0.000   -2.01e+04
-9888.816
sqft_living         176.1368      2.615     67.355      0.000     171.011
181.263
grade              9.553e+04   1750.159     54.586      0.000    9.21e+04
9.9e+04
distance          -1.917e+04    208.998    -91.705      0.000   -1.96e+04
-1.88e+04
view_1             5556.1173   1.02e+04      0.547      0.584   -1.43e+04
2.55e+04
view_2            -1185.4496   6242.542     -0.190      0.849   -1.34e+04
1.11e+04
view_3             4061.7300   8636.371      0.470      0.638   -1.29e+04
2.1e+04
view_4             1.425e+04   1.14e+04      1.249      0.212   -8114.035
3.66e+04
renovation_done_1  1.333e+04   2.89e+04      0.462      0.644   -4.32e+04
6.99e+04
renovation_done_2   1.11e+04   1.72e+04      0.644      0.520   -2.27e+04
4.49e+04
renovation_done_3  3143.7672   1.03e+04      0.305      0.761   -1.71e+04
2.34e+04
renovation_done_4 -2.634e+04   3771.177     -6.985      0.000   -3.37e+04
-1.9e+04
==============================================================================
Omnibus:                     8082.328   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            64840.177
Skew:                           1.760   Prob(JB):                         0.00
Kurtosis:                      11.134   Cond. No.                     5.02e+04
```

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.02e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[79]:
```
fig = sm.graphics.qqplot(model_2.resid,dist=stats.norm,fit=True,line='45')
```



The summary indicates a very slight improvement over the previous model, 66.9% versus 66.8% of all of the observations fall within the results of the line formed by the regression equation. It is also evident that p-values of most of the categorical values are very high, indicating their insignificance in the model. However, because they describe the same feature, I am leaving them in for now The residuals normality did not improve

4.1.4 Model 3 (preprocessing and removal of outliers)

Scaling with Robust Scaler I ruled out the scaling of the data in this step of the process because it would not change the statistics of the mode, though the correlation coefficients would become more compatible with each other. I am leaving the snippets in the notebook in case I reconsider.

The next step is a removal of ourliers

[80]:
```
# Using RobustScaler to scale the data
"""# Using RobustScaler, which transforms the feature vector by subtracting the␣
↪median and then dividing by the
# interquartile range (%25-75%). It is the most robust to the ourliers

df_for_scalers=df_num_cat_2.copy()

cols=['bathrooms','grade','sqft_living15','distance','waterfront_1','renovation_done_4']
scaler = RobustScaler()
robust_df = scaler.fit_transform(df_for_scalers.drop('price',axis=1))
robust_df = pd.DataFrame(robust_df, columns=cols)

df_num_cat_2.describe()"""

"""robust_df.describe()"""

"""fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize =(20, 5))
ax1.set_title('Before Scaling')

sns.kdeplot(df_for_scalers['distance'], ax = ax1, color ='blue')

ax2.set_title('After Robust Scaling')

sns.kdeplot(robust_df['distance'], ax = ax2, color ='red')


plt.show()"""
```

[80]:
```
"fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize =(20,
5))\nax1.set_title('Before Scaling')\n
\nsns.kdeplot(df_for_scalers['distance'], ax = ax1, color
='blue')\n\nax2.set_title('After Robust Scaling')\n
\nsns.kdeplot(robust_df['distance'], ax = ax2, color ='red')\n\n\nplt.show()"
```

[81]:
```
# Building and summary of the model with scaled data
"""robust_df['price']=df_for_scalers['price']
robust_df.info()


num_cat_var2_robust = ' + '.join(robust_df.drop('price',axis=1).columns)

## Create the formula and the model
f  = "price~" + num_cat_var2_robust


model_num_cat_2_robust = smf.ols(f, robust_df).fit()
model_num_cat_2_robust.summary()
```

```
coeffs=model_num_cat_2.params
coeffs.sort_values().round(2)

coeffs=model_num_cat_2_robust.params
coeffs.sort_values().round(2)"""
```

[81]:
```
'robust_df[\'price\']=df_for_scalers[\'price\']\nrobust_df.info()\n\n\nnum_cat_v
ar2_robust = \' + \'.join(robust_df.drop(\'price\',axis=1).columns)\n\n## Create
the formula and the model\nf  = "price~" +
num_cat_var2_robust\n\n\nmodel_num_cat_2_robust = smf.ols(f, robust_df).fit()\nm
odel_num_cat_2_robust.summary()\n\ncoeffs=model_num_cat_2.params\ncoeffs.sort_va
lues().round(2)\n\ncoeffs=model_num_cat_2_robust.params\ncoeffs.sort_values().ro
und(2)'
```

Removal of outliers

IQR method
Using IQR

[82]:
```
df_num_cat_1
```

[82]:
```
       bathrooms  sqft_living  grade  distance     price  view_1  view_2  view_3
view_4  renovation_done_1  renovation_done_2  renovation_done_3
renovation_done_4
0           1.00         1180      7       7.4  221900.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
1           2.25         2570      7       8.0  538000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  1.0                  0.0
2           1.00          770      6      10.2  180000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
3           3.00         1960      7       6.6  604000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
4           2.00         1680      8      13.4  510000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  0.0
…            …            …      …         …         …       …       …       …
…                    …                    …                    …                    …
19806       2.50         1530      8       6.5  360000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19807       2.50         2310      8       6.7  400000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19808       0.75         1020      7       1.7  402101.0     1.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19809       2.50         1600      8      13.2  400000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
19810       0.75         1020      7       1.8  325000.0     0.0     0.0     0.0
0.0                  0.0                  0.0                  0.0                  1.0
```

```
[19811 rows x 13 columns]
```

[83]:
```
df_num_cat_2=df_num_cat_1.copy()

# Due to the fact that discrete variables are not suitable for IQR method␣
↪outlier removal, they are being dropped
# from the DataFrame. They will be added back to the Dataframe for modeling

df_num_cat_2=df_num_cat_2.drop(['view_1','view_2','view_3','view_4',
                              ␣
↪'renovation_done_1','renovation_done_2','renovation_done_3','renovation_done_4',
                              'grade','bathrooms'], axis=1)

Q1 = df_num_cat_2.quantile(q=.25)
Q3 = df_num_cat_2.quantile(q=.75)
IQR = df_num_cat_2.apply(stats.iqr)

df_num_cat_3 = df_num_cat_2[~((df_num_cat_2 < (Q1-1.5*IQR)) | (df_num_cat_2 >␣
↪(Q3+1.5*IQR))).any(axis=1)]

df_num_cat_3
```

[83]:

	sqft_living	distance	price
0	1180	7.4	221900.0
1	2570	8.0	538000.0
2	770	10.2	180000.0
3	1960	6.6	604000.0
4	1680	13.4	510000.0
…	…	…	…
19806	1530	6.5	360000.0
19807	2310	6.7	400000.0
19808	1020	1.7	402101.0
19809	1600	13.2	400000.0
19810	1020	1.8	325000.0

```
[18619 rows x 3 columns]
```

[84]:
```
df_num_cat_3['grade']=df_num_cat_1['grade']
df_num_cat_3['bathrooms']=df_num_cat_1['bathrooms']
df_num_cat_3['view_1']=df_num_cat_1['view_1']
df_num_cat_3['view_2']=df_num_cat_1['view_2']
df_num_cat_3['view_3']=df_num_cat_1['view_3']
df_num_cat_3['view_4']=df_num_cat_1['view_4']
df_num_cat_3['renovation_done_1']=df_num_cat_1['renovation_done_1']
df_num_cat_3['renovation_done_2']=df_num_cat_1['renovation_done_2']
df_num_cat_3['renovation_done_3']=df_num_cat_1['renovation_done_3']
df_num_cat_3['renovation_done_4']=df_num_cat_1['renovation_done_4']
```

[85]:
```
df_num_cat_3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18619 entries, 0 to 19810
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   sqft_living         18619 non-null  int64
 1   distance            18619 non-null  float64
 2   price               18619 non-null  float64
 3   grade               18619 non-null  int64
 4   bathrooms           18619 non-null  float64
 5   view_1              18619 non-null  float64
 6   view_2              18619 non-null  float64
 7   view_3              18619 non-null  float64
 8   view_4              18619 non-null  float64
 9   renovation_done_1   18619 non-null  float64
 10  renovation_done_2   18619 non-null  float64
 11  renovation_done_3   18619 non-null  float64
 12  renovation_done_4   18619 non-null  float64
dtypes: float64(11), int64(2)
memory usage: 2.0 MB
```

[86]:
```
df_num_cat_3=df_num_cat_3.reset_index()

df_num_cat_3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18619 entries, 0 to 18618
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   index               18619 non-null  int64
 1   sqft_living         18619 non-null  int64
 2   distance            18619 non-null  float64
 3   price               18619 non-null  float64
 4   grade               18619 non-null  int64
 5   bathrooms           18619 non-null  float64
 6   view_1              18619 non-null  float64
 7   view_2              18619 non-null  float64
 8   view_3              18619 non-null  float64
 9   view_4              18619 non-null  float64
 10  renovation_done_1   18619 non-null  float64
 11  renovation_done_2   18619 non-null  float64
 12  renovation_done_3   18619 non-null  float64
 13  renovation_done_4   18619 non-null  float64
dtypes: float64(11), int64(3)
memory usage: 2.0 MB
```

[87]:
```
df_num_cat_3=df_num_cat_3.drop('index', axis=1)
df_num_cat_3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18619 entries, 0 to 18618
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   sqft_living         18619 non-null  int64
 1   distance            18619 non-null  float64
 2   price               18619 non-null  float64
 3   grade               18619 non-null  int64
 4   bathrooms           18619 non-null  float64
 5   view_1              18619 non-null  float64
 6   view_2              18619 non-null  float64
 7   view_3              18619 non-null  float64
 8   view_4              18619 non-null  float64
 9   renovation_done_1   18619 non-null  float64
 10  renovation_done_2   18619 non-null  float64
 11  renovation_done_3   18619 non-null  float64
 12  renovation_done_4   18619 non-null  float64
dtypes: float64(11), int64(2)
memory usage: 1.8 MB
```

```
<b>df_num_cat_3</b> DataFrame<br><br><b>18619</b> records out of the original <b>21597</b> lef
</div><br>
```

```
<b>Index reset</b>
</div><br>
```

Building the model

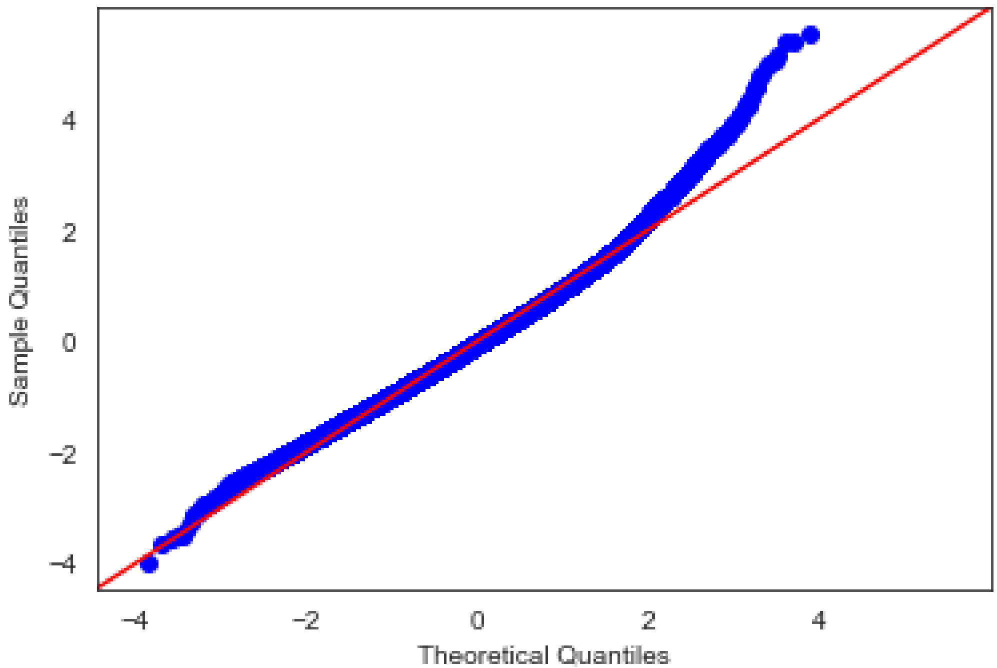
[88]:
```
## Formula is the same, model is for the cleaned DF

variables_to_include_3_1 = ' + '.join(df_num_cat_3.drop('price',axis=1).columns)
f  = "price~" + variables_to_include_3_1


model_3_1 = smf.ols(f, df_num_cat_3).fit()
model_3_1.summary()
```

[88]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.633
Model:                            OLS   Adj. R-squared:                  0.633
Method:                 Least Squares   F-statistic:                     2672.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
```

```
Time:                        16:58:33   Log-Likelihood:            -2.4463e+05
No. Observations:               18619   AIC:                         4.893e+05
Df Residuals:                   18606   BIC:                         4.894e+05
Df Model:                          12
Covariance Type:            nonrobust
===============================================================================
=====
                      coef    std err          t      P>|t|      [0.025
0.975]
-------------------------------------------------------------------------------
-----
Intercept        -1.397e+05   7752.045    -18.019      0.000   -1.55e+05
-1.24e+05
sqft_living        129.1653      2.028     63.697      0.000     125.191
133.140
distance         -1.527e+04    152.634   -100.023      0.000   -1.56e+04
-1.5e+04
grade             7.293e+04   1291.290     56.478      0.000    7.04e+04
7.55e+04
bathrooms        -7626.9730   1901.298     -4.011      0.000   -1.14e+04
-3900.255
view_1            1295.3996   7317.902      0.177      0.859    -1.3e+04
1.56e+04
view_2           -1419.9738   4457.993     -0.319      0.750   -1.02e+04
7318.099
view_3             454.9216   6141.592      0.074      0.941   -1.16e+04
1.25e+04
view_4            1.163e+04   8208.818      1.417      0.156   -4457.709
2.77e+04
renovation_done_1  3.485e+04   2.08e+04      1.673      0.094   -5972.705
7.57e+04
renovation_done_2  1.589e+04   1.22e+04      1.299      0.194   -8087.988
3.99e+04
renovation_done_3  -907.0686   7331.656     -0.124      0.902   -1.53e+04
1.35e+04
renovation_done_4 -1.562e+04   2714.396     -5.753      0.000   -2.09e+04
-1.03e+04
==============================================================================
Omnibus:                      849.136   Durbin-Watson:                   1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1199.719
Skew:                           0.438   Prob(JB):                    3.05e-261
Kurtosis:                       3.882   Cond. No.                     4.74e+04
==============================================================================

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

```
[2] The condition number is large, 4.74e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[89]:
```python
fig = sm.graphics.qqplot(model_3_1.resid,dist=stats.norm,fit=True,line='45')
```



While the IQR removal of outliers decreased the R squared of the model, it made the distribution more normal (Skew and Kurtosis values are almost within the normality ranges). This fact is also reflected by the QQ plot of the model residuals. Unfortunately, the Coefficient of determination dropped

Z-score method Using Z scores

[90]:
```python
df_num_cat_1
```

[90]:
```
       bathrooms  sqft_living  grade  distance     price  view_1  view_2  view_3
view_4  renovation_done_1  renovation_done_2  renovation_done_3
renovation_done_4
0           1.00         1180      7       7.4  221900.0     0.0     0.0     0.0
0.0                   0.0                 0.0                 0.0                 0.0
1           2.25         2570      7       8.0  538000.0     0.0     0.0     0.0
0.0                   0.0                 0.0                 1.0                 0.0
2           1.00          770      6      10.2  180000.0     0.0     0.0     0.0
0.0                   0.0                 0.0                 0.0                 0.0
3           3.00         1960      7       6.6  604000.0     0.0     0.0     0.0
```

```
0.0                 0.0                 0.0                 0.0                 0.0
4            2.00         1680       8       13.4  510000.0      0.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 0.0
…           …           …     …       …       …       …      …      …
…                 …                 …                 …                 …
19806        2.50         1530       8        6.5  360000.0      0.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
19807        2.50         2310       8        6.7  400000.0      0.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
19808        0.75         1020       7        1.7  402101.0      1.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
19809        2.50         1600       8       13.2  400000.0      0.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
19810        0.75         1020       7        1.8  325000.0      0.0       0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0

[19811 rows x 13 columns]
```

[91]:

```
df_num_cat_4=df_num_cat_1.copy()

df_num_cat_4=df_num_cat_4.drop(['view_1','view_2','view_3','view_4',
 ↪'renovation_done_1','renovation_done_2','renovation_done_3','renovation_done_4',
                              'grade','bathrooms'], axis=1)

df_num_cat_4['z_sqft_living']=stats.zscore(df_num_cat_4['sqft_living'])
df_num_cat_4['z_distance']=stats.zscore(df_num_cat_4['distance'])
df_num_cat_4['z_price']=stats.zscore(df_num_cat_4['price'])

df_num_cat_4
```

[91]:

	sqft_living	distance	price	z_sqft_living	z_distance	z_price
0	1180	7.4	221900.0	-1.005265	-0.568136	-0.976073
1	2570	8.0	538000.0	0.645148	-0.469671	0.049084
2	770	10.2	180000.0	-1.492078	-0.108633	-1.111960
3	1960	6.6	604000.0	-0.079134	-0.699423	0.263131
4	1680	13.4	510000.0	-0.411591	0.416513	-0.041724
…	…	…	…	…	…	…
19806	1530	6.5	360000.0	-0.589694	-0.715834	-0.528195
19807	2310	6.7	400000.0	0.336438	-0.683012	-0.398469
19808	1020	1.7	402101.0	-1.195241	-1.503553	-0.391656
19809	1600	13.2	400000.0	-0.506579	0.383692	-0.398469
19810	1020	1.8	325000.0	-1.195241	-1.487142	-0.641705

[19811 rows x 6 columns]

[92]:
```
df_num_cat_5=df_num_cat_4[(abs(df_num_cat_4.z_price) < 3)]

df_num_cat_5=df_num_cat_5[(abs(df_num_cat_5.z_distance) < 3)]

df_num_cat_5=df_num_cat_5[(abs(df_num_cat_5.z_sqft_living) < 3)]
df_num_cat_5
```

[92]:

	sqft_living	distance	price	z_sqft_living	z_distance	z_price
0	1180	7.4	221900.0	-1.005265	-0.568136	-0.976073
1	2570	8.0	538000.0	0.645148	-0.469671	0.049084
2	770	10.2	180000.0	-1.492078	-0.108633	-1.111960
3	1960	6.6	604000.0	-0.079134	-0.699423	0.263131
4	1680	13.4	510000.0	-0.411591	0.416513	-0.041724
…	…	…	…	…	…	…
19806	1530	6.5	360000.0	-0.589694	-0.715834	-0.528195
19807	2310	6.7	400000.0	0.336438	-0.683012	-0.398469
19808	1020	1.7	402101.0	-1.195241	-1.503553	-0.391656
19809	1600	13.2	400000.0	-0.506579	0.383692	-0.398469
19810	1020	1.8	325000.0	-1.195241	-1.487142	-0.641705

[19261 rows x 6 columns]

[93]:
```
df_num_cat_5['grade']=df_num_cat_1['grade']
df_num_cat_5['bathrooms']=df_num_cat_1['bathrooms']
df_num_cat_5['view_1']=df_num_cat_1['view_1']
df_num_cat_5['view_2']=df_num_cat_1['view_2']
df_num_cat_5['view_3']=df_num_cat_1['view_3']
df_num_cat_5['view_4']=df_num_cat_1['view_4']
df_num_cat_5['renovation_done_1']=df_num_cat_1['renovation_done_1']
df_num_cat_5['renovation_done_2']=df_num_cat_1['renovation_done_2']
df_num_cat_5['renovation_done_3']=df_num_cat_1['renovation_done_3']
df_num_cat_5['renovation_done_4']=df_num_cat_1['renovation_done_4']
```

[94]:
```
df_num_cat_5=df_num_cat_5.drop(['z_sqft_living','z_distance','z_price'], axis=1)
```

[95]:
```
df_num_cat_5=df_num_cat_5.reset_index()
df_num_cat_5=df_num_cat_5.drop('index', axis=1)
df_num_cat_5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19261 entries, 0 to 19260
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   sqft_living        19261 non-null  int64
 1   distance           19261 non-null  float64
 2   price              19261 non-null  float64
 3   grade              19261 non-null  int64
```

```
 4   bathrooms          19261 non-null  float64
 5   view_1             19261 non-null  float64
 6   view_2             19261 non-null  float64
 7   view_3             19261 non-null  float64
 8   view_4             19261 non-null  float64
 9   renovation_done_1  19261 non-null  float64
 10  renovation_done_2  19261 non-null  float64
 11  renovation_done_3  19261 non-null  float64
 12  renovation_done_4  19261 non-null  float64
dtypes: float64(11), int64(2)
memory usage: 1.9 MB
```

```
<b>df_num_cat_5</b> DataFrame<br><br><b>19261</b> records out of the original <b>21597</b> lef
</div><br>
```

```
<b>Index reset</b>
</div><br>
```

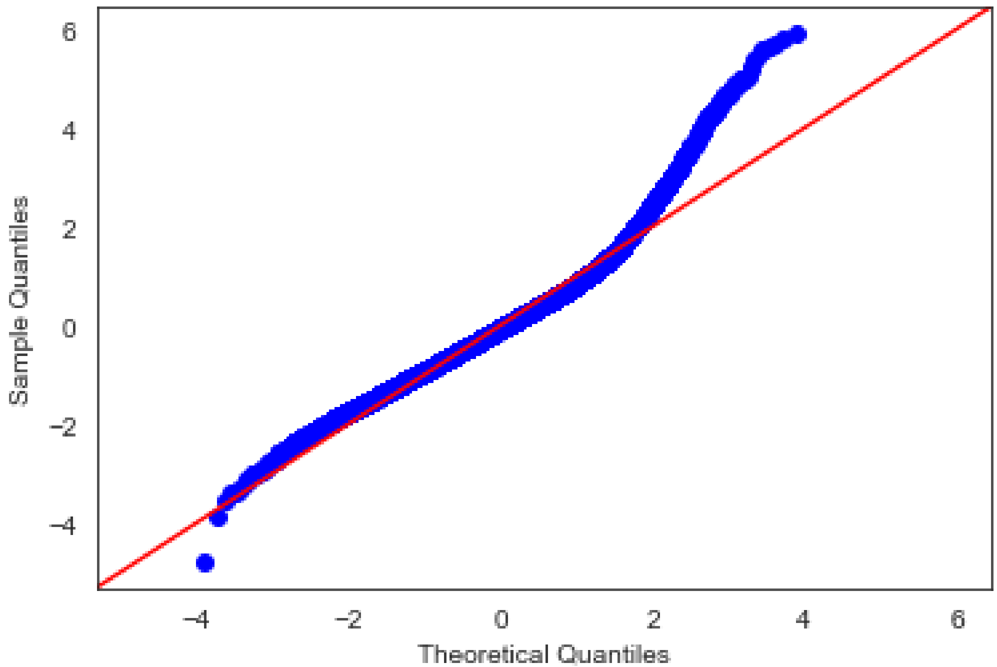
Building the model

[96]:
```python
## Formula is the same, model is for the cleaned DF

variables_to_include_3_2 = ' + '.join(df_num_cat_5.drop('price',axis=1).columns)
f  = "price~" + variables_to_include_3_2


model_3_2 = smf.ols(f, df_num_cat_5).fit()
model_3_2.summary()
```

[96]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.654
Model:                            OLS   Adj. R-squared:                  0.653
Method:                 Least Squares   F-statistic:                     3027.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:34   Log-Likelihood:            -2.5551e+05
No. Observations:               19261   AIC:                         5.110e+05
Df Residuals:                   19248   BIC:                         5.111e+05
Df Model:                          12
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept         -2.074e+05   8498.928    -24.399      0.000   -2.24e+05
```

```
-1.91e+05
sqft_living         141.6977      2.203     64.311      0.000     137.379
146.016
distance          -1.666e+04    167.636    -99.371      0.000     -1.7e+04
-1.63e+04
grade              8.286e+04   1416.839     58.485      0.000     8.01e+04
8.56e+04
bathrooms         -1.001e+04   2109.297     -4.746      0.000    -1.41e+04
-5875.419
view_1             1.247e+04   8077.275      1.544      0.123    -3357.516
2.83e+04
view_2            -1948.1291   4983.950     -0.391      0.696    -1.17e+04
7820.847
view_3            -3331.9562   6896.935     -0.483      0.629    -1.69e+04
1.02e+04
view_4             1.641e+04   9104.994      1.802      0.072    -1441.323
3.43e+04
renovation_done_1  3.577e+04    2.27e+04     1.576      0.115    -8719.452
8.03e+04
renovation_done_2  1.284e+04    1.37e+04     0.938      0.348     -1.4e+04
3.97e+04
renovation_done_3 -4898.3754   8252.665     -0.594      0.553    -2.11e+04
1.13e+04
renovation_done_4  -2.12e+04   3022.668     -7.014      0.000    -2.71e+04
-1.53e+04
==============================================================================
Omnibus:                     2690.071   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6382.550
Skew:                           0.811   Prob(JB):                         0.00
Kurtosis:                       5.307   Cond. No.                     4.75e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.75e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[97]:
```
fig = sm.graphics.qqplot(model_3_2.resid,dist=stats.norm,fit=True,line='45')
```



The R squared of the model is 0.654 and F-statistics is higher than for the previous model The IQR method of outliers removal made the residual distribution more normal than Z-score method due to the former having more strict criteria. The decision is to use the dataset compiled after Z-score outlier removal.

The next step is Log transformation of the target variable

4.1.5 Model 4 (Using log and square root transformations on the target variable)

Log Transformation

[98]:
```
df_num_cat_5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19261 entries, 0 to 19260
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   sqft_living       19261 non-null  int64
 1   distance          19261 non-null  float64
 2   price             19261 non-null  float64
 3   grade             19261 non-null  int64
 4   bathrooms         19261 non-null  float64
 5   view_1            19261 non-null  float64
 6   view_2            19261 non-null  float64
 7   view_3            19261 non-null  float64
 8   view_4            19261 non-null  float64
```

```
 9   renovation_done_1  19261 non-null  float64
 10  renovation_done_2  19261 non-null  float64
 11  renovation_done_3  19261 non-null  float64
 12  renovation_done_4  19261 non-null  float64
dtypes: float64(11), int64(2)
memory usage: 1.9 MB
```

[99]:
```
# Log transform
df_num_cat_5_log=df_num_cat_5.copy()

df_num_cat_5_log['log_price'] = df_num_cat_5['price'].map(lambda x: np.log(x))
df_num_cat_5_log
```

[99]:
```
       sqft_living  distance     price  grade  bathrooms  view_1  view_2  view_3
view_4  renovation_done_1  renovation_done_2  renovation_done_3
renovation_done_4  log_price
0             1180       7.4  221900.0      7       1.00     0.0     0.0     0.0
0.0                0.0                0.0                0.0                0.0
12.309982
1             2570       8.0  538000.0      7       2.25     0.0     0.0     0.0
0.0                0.0                0.0                1.0                0.0
13.195614
2              770      10.2  180000.0      6       1.00     0.0     0.0     0.0
0.0                0.0                0.0                0.0                0.0
12.100712
3             1960       6.6  604000.0      7       3.00     0.0     0.0     0.0
0.0                0.0                0.0                0.0                0.0
13.311329
4             1680      13.4  510000.0      8       2.00     0.0     0.0     0.0
0.0                0.0                0.0                0.0                0.0
13.142166
…             …        …        …     …          …       …       …       …
…                 …                 …                 …                 …
…
19256         1530       6.5  360000.0      8       2.50     0.0     0.0     0.0
0.0                0.0                0.0                0.0                1.0
12.793859
19257         2310       6.7  400000.0      8       2.50     0.0     0.0     0.0
0.0                0.0                0.0                0.0                1.0
12.899220
19258         1020       1.7  402101.0      7       0.75     1.0     0.0     0.0
0.0                0.0                0.0                0.0                1.0
12.904459
19259         1600      13.2  400000.0      8       2.50     0.0     0.0     0.0
0.0                0.0                0.0                0.0                1.0
12.899220
19260         1020       1.8  325000.0      7       0.75     0.0     0.0     0.0
```

```
 0.0                 0.0                 0.0                 0.0                 1.0
 12.691580

 [19261 rows x 14 columns]
```

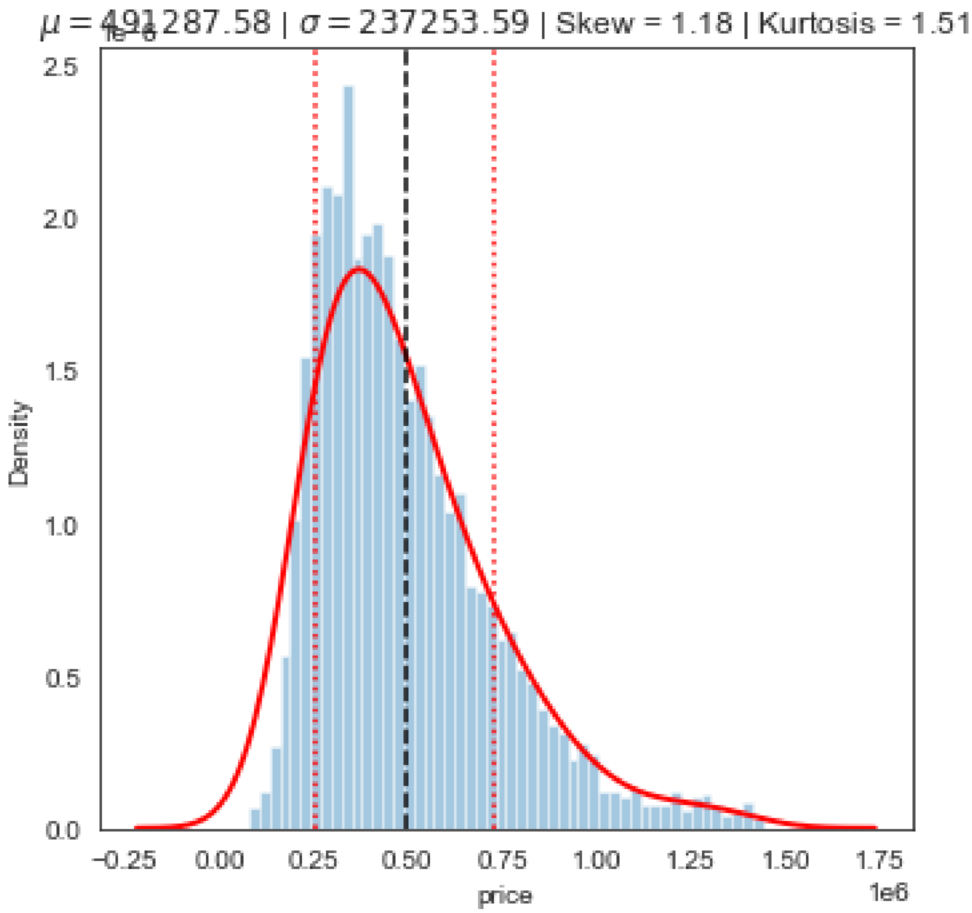
[100]:

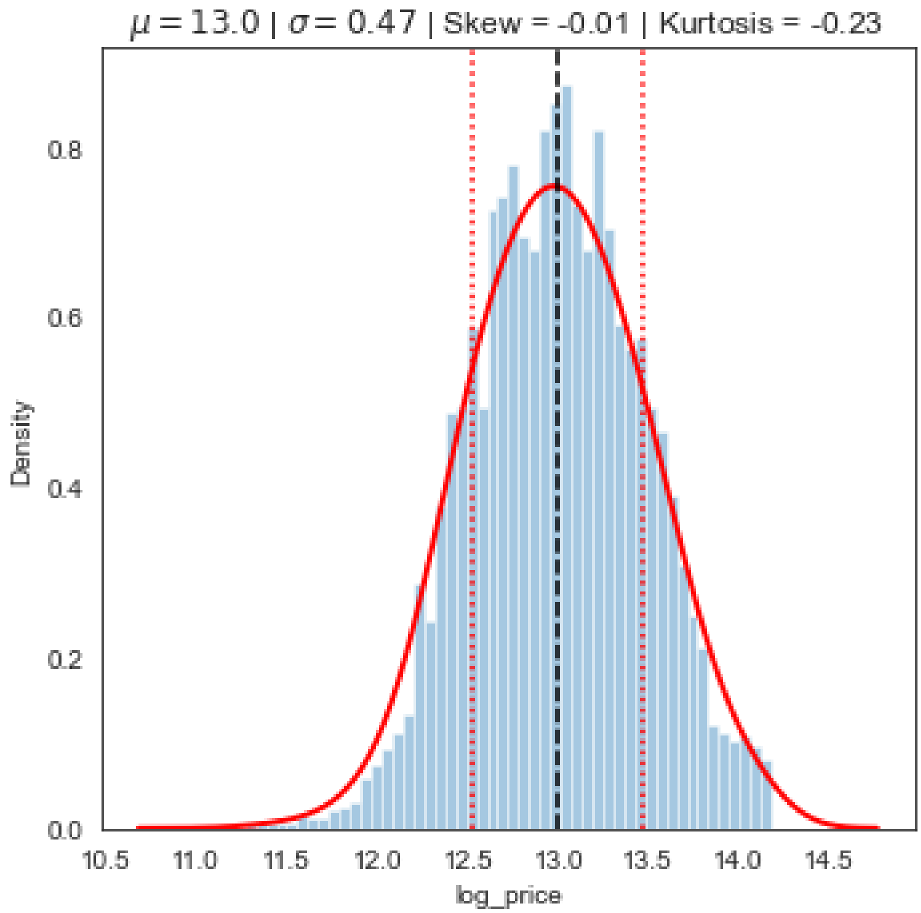
```python
df_num_cat_5_log.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19261 entries, 0 to 19260
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   sqft_living         19261 non-null  int64
 1   distance            19261 non-null  float64
 2   price               19261 non-null  float64
 3   grade               19261 non-null  int64
 4   bathrooms           19261 non-null  float64
 5   view_1              19261 non-null  float64
 6   view_2              19261 non-null  float64
 7   view_3              19261 non-null  float64
 8   view_4              19261 non-null  float64
 9   renovation_done_1   19261 non-null  float64
 10  renovation_done_2   19261 non-null  float64
 11  renovation_done_3   19261 non-null  float64
 12  renovation_done_4   19261 non-null  float64
 13  log_price           19261 non-null  float64
dtypes: float64(12), int64(2)
memory usage: 2.1 MB
```

[101]:

```python
# Histogram of log_price and price
continuous=['price','log_price']
for col in continuous:
    fig, ax =plt.subplots(figsize=(5, 5))
    distribution(df_num_cat_5_log[col])
```


$\mu = 491287.58$ | $\sigma = 237253.59$ | Skew = 1.18 | Kurtosis = 1.51
1e-6
2.5
2.0
1.5
1.0
0.5
0.0
Density
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
price
1e6



The transformation worked well, improving the normality of the 'price' variable. Log_price distribution looks more symmetrical. Skewness improved dramatically (from 1.18 to -0.01, 0 being perfectly symmetrical) Kurtosis value decreased, making the curve more Mesokurtic (close to a Gaussian curve). It is an expected effect of log transform.

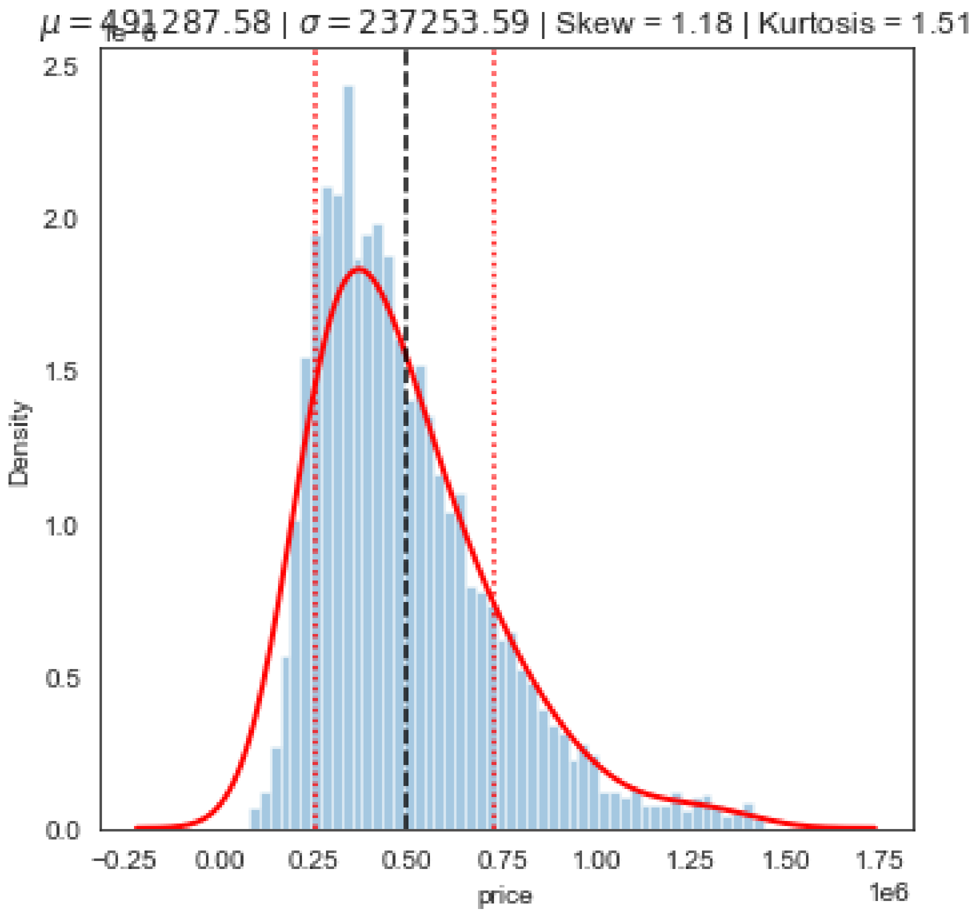
The next step is test a square root transformation.

[102]:
```
# Square transform
df_num_cat_5_sqrt=df_num_cat_5.copy()

df_num_cat_5_sqrt['sqrt_price'] = df_num_cat_5['price'].map(lambda x: np.
→sqrt(x))
df_num_cat_5_sqrt
```

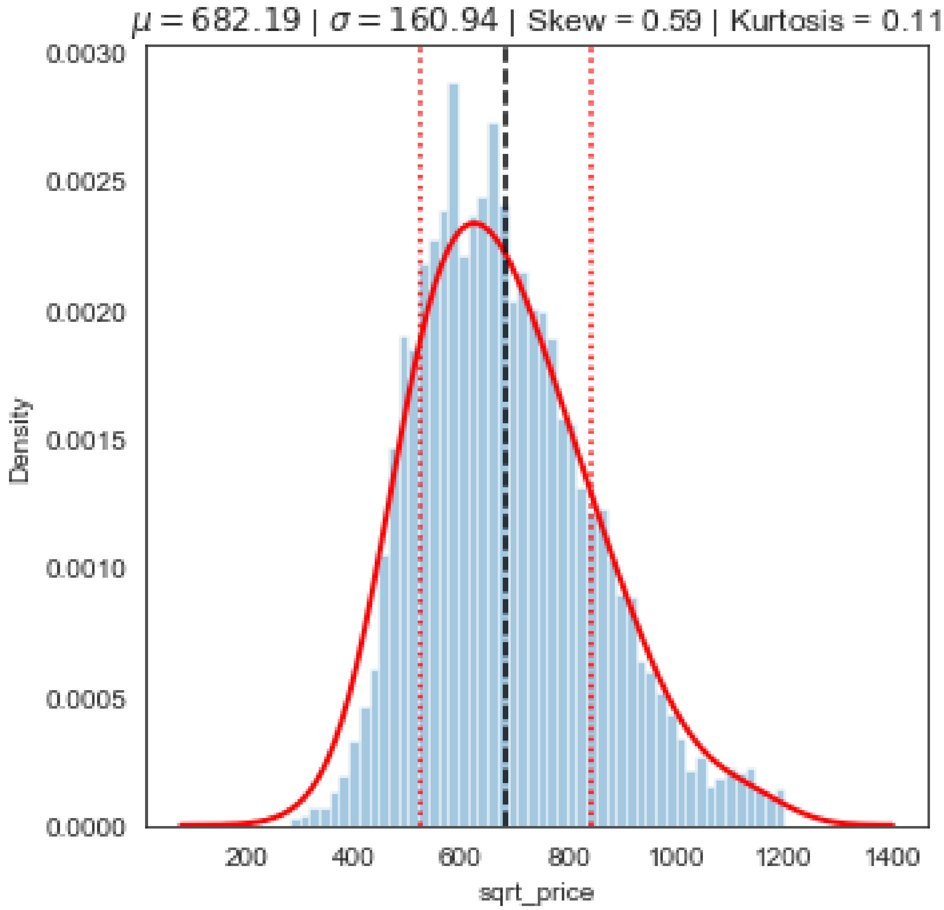
[102]:
```
       sqft_living  distance     price  grade  bathrooms  view_1  view_2  view_3
view_4  renovation_done_1  renovation_done_2  renovation_done_3
renovation_done_4  sqrt_price
0             1180       7.4  221900.0      7       1.00     0.0     0.0     0.0
0.0                 0.0                 0.0                 0.0                 0.0
```

```
471.062629
1               2570      8.0  538000.0      7        2.25     0.0      0.0      0.0
0.0                 0.0                 0.0                 1.0                 0.0
733.484833
2                770     10.2  180000.0      6        1.00     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 0.0
424.264069
3               1960      6.6  604000.0      7        3.00     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 0.0
777.174369
4               1680     13.4  510000.0      8        2.00     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 0.0
714.142843
…             …       …       …    …         …      …      …      …
…                 …                 …                 …                 …
…
19256           1530      6.5  360000.0      8        2.50     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
600.000000
19257           2310      6.7  400000.0      8        2.50     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
632.455532
19258           1020      1.7  402101.0      7        0.75     1.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
634.114343
19259           1600     13.2  400000.0      8        2.50     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
632.455532
19260           1020      1.8  325000.0      7        0.75     0.0      0.0      0.0
0.0                 0.0                 0.0                 0.0                 1.0
570.087713

[19261 rows x 14 columns]
```

[103]:
```
# Histogram of log_price and price
continuous=['price','sqrt_price']
for col in continuous:
    fig, ax =plt.subplots(figsize=(5, 5))
    distribution(df_num_cat_5_sqrt[col])
```



$\mu = 491287.58$ | $\sigma = 237253.59$ | Skew = 1.18 | Kurtosis = 1.51
1e−6
2.5
2.0
1.5
1.0
0.5
0.0
Density
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
price
1e6



The square root transformation also worked well in improving the normality of the 'price' variable. sqrt_price distribution looks more symmetrical. Skewness improved dramatically (from 1.18 to -0.59, 0 being perfectly symmetrical) However, both of the parameters are worse that the parameters of log_price distribution.

The next step is create two separate models and to see if the transformations made a difference

Model using log transformed target variable

[104]:
```
## Formula is the same, model is for the cleaned DF

variables_to_include_4_1 = ' + '.join(df_num_cat_5_log.
 ↪drop(['price','log_price'],axis=1).columns)
f  = "log_price~" + variables_to_include_4_1


model_4_1 = smf.ols(f, df_num_cat_5_log).fit()
model_4_1.summary()
```

[104]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.664
Model:                            OLS   Adj. R-squared:                  0.663
Method:                 Least Squares   F-statistic:                     3164.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:36   Log-Likelihood:                -2224.4
No. Observations:               19261   AIC:                             4475.
Df Residuals:                   19248   BIC:                             4577.
Df Model:                          12
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept            11.6414      0.017    704.222      0.000      11.609
11.674
sqft_living           0.0003   4.29e-06     60.161      0.000       0.000
0.000
distance             -0.0348      0.000   -106.862      0.000      -0.035
-0.034
grade                 0.1599      0.003     58.035      0.000       0.155
0.165
bathrooms             0.0125      0.004      3.052      0.002       0.004
0.021
view_1                0.0120      0.016      0.764      0.445      -0.019
0.043
view_2               -0.0027      0.010     -0.281      0.779      -0.022
0.016
view_3                0.0017      0.013      0.128      0.898      -0.025
0.028
view_4                0.0253      0.018      1.427      0.154      -0.009
0.060
renovation_done_1     0.0788      0.044      1.785      0.074      -0.008
0.165
renovation_done_2     0.0449      0.027      1.688      0.091      -0.007
0.097
renovation_done_3    -0.0161      0.016     -1.002      0.316      -0.048
0.015
renovation_done_4    -0.0340      0.006     -5.782      0.000      -0.046
-0.022
==============================================================================
Omnibus:                      310.255   Durbin-Watson:                   2.003
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              482.347
Skew:                          -0.167   Prob(JB):                    1.82e-105
Kurtosis:                       3.700   Cond. No.                     4.75e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.75e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

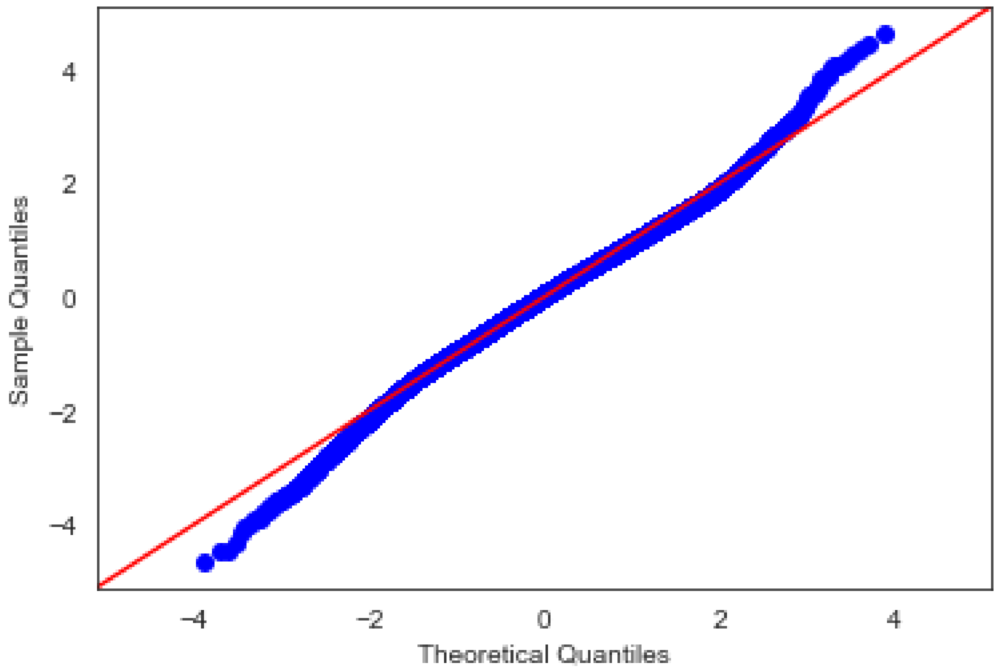
Model using square root transformed target variable

[105]:
```
## Formula is the same, model is for the cleaned DF

variables_to_include_4_2 = ' + '.join(df_num_cat_5_sqrt.
 ↪drop(['price','sqrt_price'],axis=1).columns)
f  = "sqrt_price~" + variables_to_include_4_2


model_4_2= smf.ols(f, df_num_cat_5_sqrt).fit()
model_4_2.summary()
```

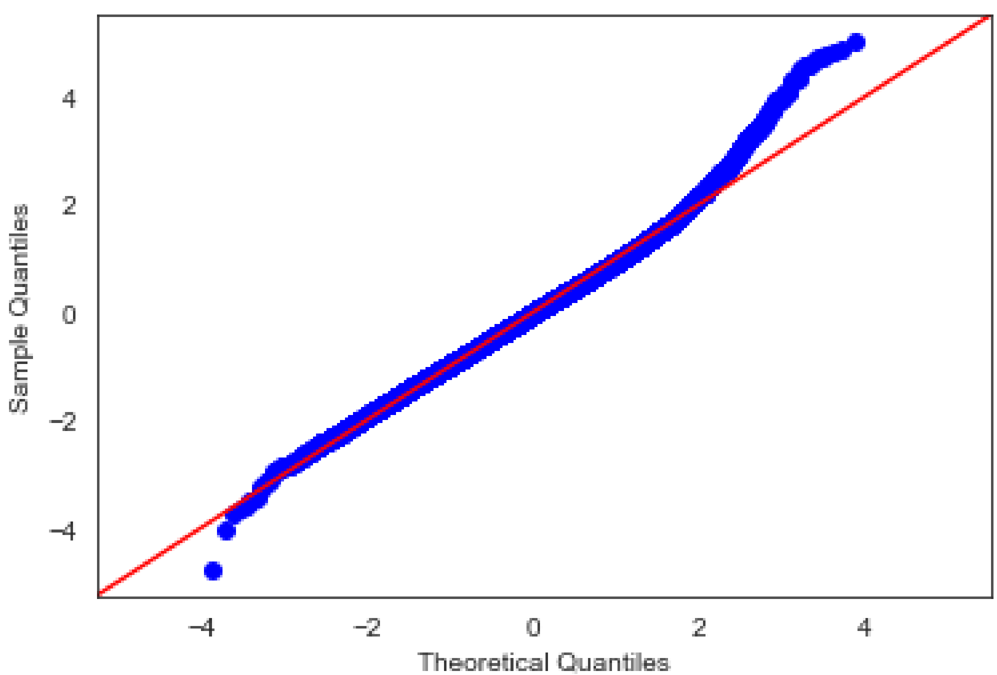
[105]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:             sqrt_price   R-squared:                       0.673
Model:                            OLS   Adj. R-squared:                  0.673
Method:                 Least Squares   F-statistic:                     3307.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:36   Log-Likelihood:            -1.1442e+05
No. Observations:               19261   AIC:                         2.289e+05
Df Residuals:                   19248   BIC:                         2.290e+05
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
Intercept           207.9501      5.598     37.145      0.000     196.977
218.923
sqft_living           0.0938      0.001     64.625      0.000       0.091
0.097
distance            -11.7839      0.110   -106.715      0.000     -12.000
```

```
-11.567
grade                56.1638      0.933     60.178      0.000      54.334
57.993
bathrooms            -1.7413      1.389     -1.253      0.210      -4.465
0.982
view_1                6.2009      5.321      1.165      0.244      -4.228
16.630
view_2               -1.1299      3.283     -0.344      0.731      -7.565
5.305
view_3               -0.9735      4.543     -0.214      0.830      -9.878
7.931
view_4                9.9751      5.998      1.663      0.096      -1.781
21.731
renovation_done_1    25.8342     14.951      1.728      0.084      -3.471
55.140
renovation_done_2    12.2778      9.018      1.362      0.173      -5.397
29.953
renovation_done_3    -4.3359      5.436     -0.798      0.425     -14.991
6.319
renovation_done_4   -13.1475      1.991     -6.603      0.000     -17.050
-9.245
==============================================================================
Omnibus:                      571.397   Durbin-Watson:                   1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              863.310
Skew:                           0.300   Prob(JB):                    3.42e-188
Kurtosis:                       3.846   Cond. No.                     4.75e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.75e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[106]:
```python
fig = sm.graphics.qqplot(model_4_1.resid,dist=stats.norm,fit=True,line='45')
```



[107]:
```
fig = sm.graphics.qqplot(model_4_2.resid,dist=stats.norm,fit=True,line='45')
```



Both models have improved the R squared and the F-statistics of the previous models. The residuals of both models display a close-to-normal distribution. Log transformation helped improve the upper part of the distribution, while square root transformation worked better in the lower part of the distribution. R squared of the square root transformation-based model is slightly higher, while its kurtosis value is slightly worse than the kurtosis value of the log-transformed price model. The decision is to use the log-transformed target variable.

The next step is to remove unnecessary categorical variables, scale the remaining variables, and built the last model with coefficients in the regression model, which are easy to compare and interpret

[108]:
```
# Removing all categorical values with high p-values and renaming the␣
↪renovation_done_4
# to a more prominent name, reflective of the definition of the field (see␣
↪Categorical variables subsection
# in Exploring distributions and correlations section)

df_num_cat_5_log_cropped=df_num_cat_5_log.copy()
df_num_cat_5_log_cropped=df_num_cat_5_log_cropped.
↪drop(['view_1','view_2','view_3','view_4','renovation_done_1',
                                                       ␣
↪'renovation_done_2','renovation_done_3'], axis=1)
df_num_cat_5_log_cropped.rename(columns={'renovation_done_4':␣
↪'recent_renovation_new'}, inplace=True)
```

[109]:
```
df_num_cat_5_log_cropped
```

[109]:
```
       sqft_living  distance     price  grade  bathrooms  recent_renovation_new  \
0             1180       7.4  221900.0      7       1.00                    0.0
1             2570       8.0  538000.0      7       2.25                    0.0
2              770      10.2  180000.0      6       1.00                    0.0
3             1960       6.6  604000.0      7       3.00                    0.0
4             1680      13.4  510000.0      8       2.00                    0.0
…              …         …         …      …         …                      …
19256         1530       6.5  360000.0      8       2.50                    1.0
19257         2310       6.7  400000.0      8       2.50                    1.0
19258         1020       1.7  402101.0      7       0.75                    1.0
19259         1600      13.2  400000.0      8       2.50                    1.0
19260         1020       1.8  325000.0      7       0.75                    1.0

       log_price
0      12.309982
1      13.195614
2      12.100712
3      13.311329
4      13.142166
…            …
19256  12.793859
19257  12.899220
19258  12.904459
19259  12.899220
```

```
12.691580

[19261 rows x 7 columns]
```

[110]:

```
# Standardizing the independent variables. I decided to do it manually due to a␣
↪better control of the utput


df_num_cat_5_log_cropped_st=df_num_cat_5_log_cropped.copy()


lv_min=df_num_cat_5_log_cropped_st.sqft_living.min()
lv_range=df_num_cat_5_log_cropped_st.sqft_living.
↪max()-df_num_cat_5_log_cropped_st.sqft_living.min()
distance_range=df_num_cat_5_log_cropped_st.distance.
↪max()-df_num_cat_5_log_cropped_st.distance.min()
distance_min=df_num_cat_5_log_cropped_st.distance.min()
bathroom_range=df_num_cat_5_log_cropped_st.bathrooms.
↪max()-df_num_cat_5_log_cropped_st.bathrooms.min()
bathroom_min=df_num_cat_5_log_cropped_st.bathrooms.min()
grade_range=df_num_cat_5_log_cropped_st.grade.max()-df_num_cat_5_log_cropped_st.
↪grade.min()
grade_min=df_num_cat_5_log_cropped_st.grade.min()


df_num_cat_5_log_cropped_st['sqft_living_st']=df_num_cat_5_log_cropped_st.
↪apply(lambda row: round((row.sqft_living-lv_min)/lv_range,3), axis=1)
df_num_cat_5_log_cropped_st['distance_st']=df_num_cat_5_log_cropped_st.
↪apply(lambda row: round((row.distance-distance_min)/distance_range,3),␣
↪axis=1)
df_num_cat_5_log_cropped_st['bathrooms_st']=df_num_cat_5_log_cropped_st.
↪apply(lambda row: round((row.bathrooms-bathroom_min)/bathroom_range,3),␣
↪axis=1)
df_num_cat_5_log_cropped_st['grade_st']=df_num_cat_5_log_cropped_st.
↪apply(lambda row: (row.grade-grade_min)/grade_range, axis=1)
#df_num_cat_5_sqrt_cropped_st['recent_renovation_new_str']=df_num_cat_5_sqrt_cropped_st['recen
↪astype('str')

df_num_cat_5_log_cropped_st
```

[110]:

```
     sqft_living  distance     price  grade  bathrooms  recent_renovation_new
log_price  sqft_living_st  distance_st  bathrooms_st  grade_st
0             1180       7.4  221900.0      7       1.00                    0.0
12.309982          0.194        0.239        0.105     0.375
1             2570       8.0  538000.0      7       2.25                    0.0
13.195614          0.528        0.260        0.368     0.375
```

```
2              770      10.2  180000.0      6       1.00                   0.0
12.100712           0.096        0.337        0.105     0.250
3             1960       6.6  604000.0      7       3.00                   0.0
13.311329           0.381        0.211        0.526     0.375
4             1680      13.4  510000.0      8       2.00                   0.0
13.142166           0.314        0.449        0.316     0.500
…            …       …       …     …        …                   …
…             …         …            …       …
19256         1530       6.5  360000.0      8       2.50                   1.0
12.793859           0.278        0.207        0.421     0.500
19257         2310       6.7  400000.0      8       2.50                   1.0
12.899220           0.465        0.214        0.421     0.500
19258         1020       1.7  402101.0      7       0.75                   1.0
12.904459           0.156        0.039        0.053     0.375
19259         1600      13.2  400000.0      8       2.50                   1.0
12.899220           0.295        0.442        0.421     0.500
19260         1020       1.8  325000.0      7       0.75                   1.0
12.691580           0.156        0.042        0.053     0.375

[19261 rows x 11 columns]
```

[111]:
```
## Formula is the same, model is for the cleaned DF

variables_to_include_4_3 = ' + '.join(df_num_cat_5_log_cropped_st.drop(
    ['price','log_price','sqft_living','distance','grade','bathrooms'],axis=1).
 ↪columns)
f  = "log_price~" + variables_to_include_4_3
print(f)
model_4_3= smf.ols(f, df_num_cat_5_log_cropped_st).fit()
model_4_3.summary()
```

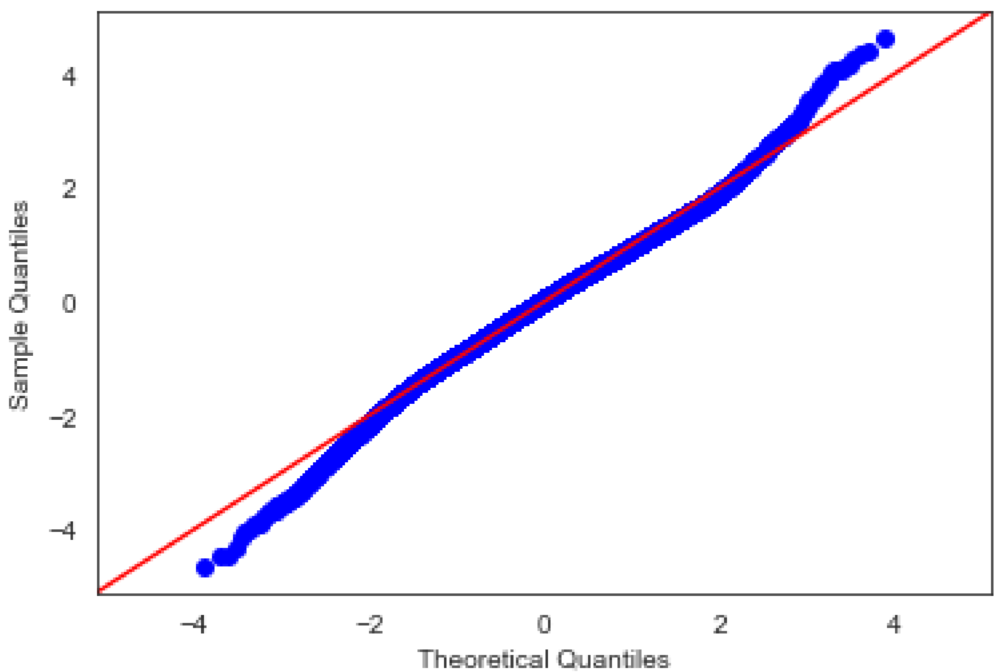
```
log_price~recent_renovation_new + sqft_living_st + distance_st + bathrooms_st +
grade_st
```

[111]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.663
Model:                            OLS   Adj. R-squared:                  0.663
Method:                 Least Squares   F-statistic:                     7593.
Date:                Mon, 26 Apr 2021   Prob (F-statistic):               0.00
Time:                        16:58:37   Log-Likelihood:                -2228.2
No. Observations:               19261   AIC:                             4468.
Df Residuals:                   19255   BIC:                             4516.
Df Model:                           5
Covariance Type:            nonrobust
================================================================================
```

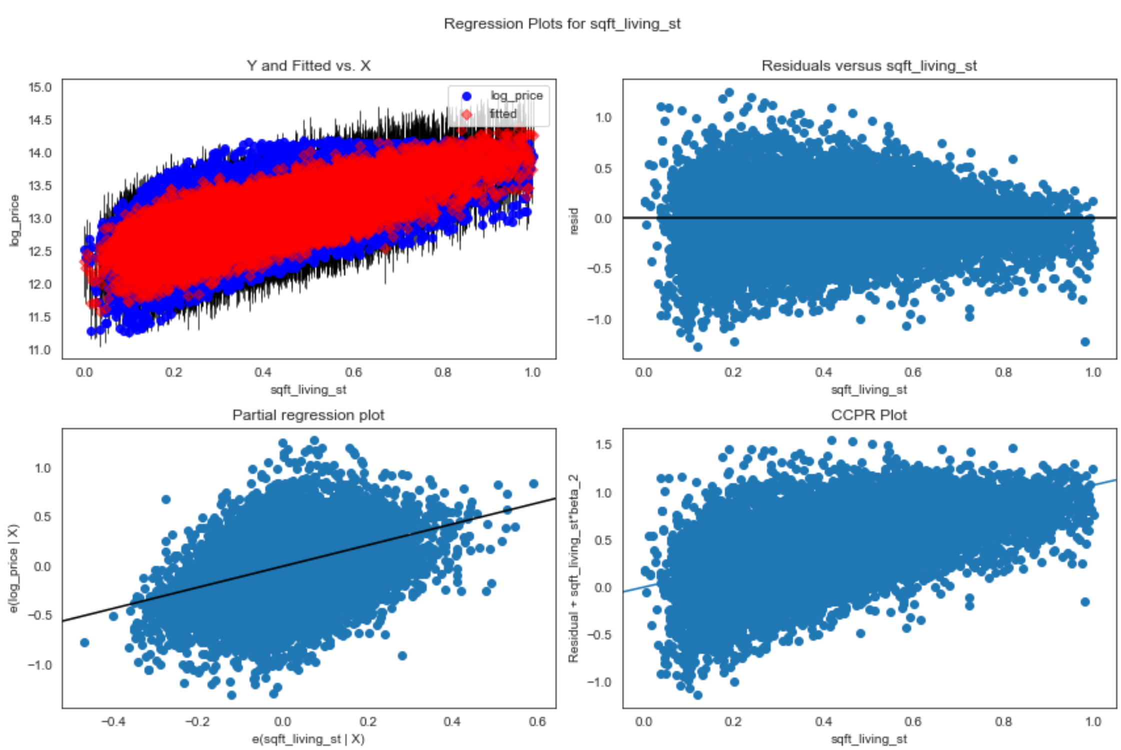
```
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
Intercept              12.3621      0.008   1602.897      0.000      12.347
12.377
recent_renovation_new  -0.0345      0.006     -5.875      0.000      -0.046
-0.023
sqft_living_st          1.0747      0.018     60.141      0.000       1.040
1.110
distance_st            -0.9931      0.009   -106.878      0.000      -1.011
-0.975
bathrooms_st            0.0598      0.019      3.072      0.002       0.022
0.098
grade_st                1.2805      0.022     58.089      0.000       1.237
1.324
==============================================================================
Omnibus:                      310.179   Durbin-Watson:                   2.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              482.427
Skew:                          -0.166   Prob(JB):                    1.75e-105
Kurtosis:                       3.700   Cond. No.                         16.5
==============================================================================

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

[112]:

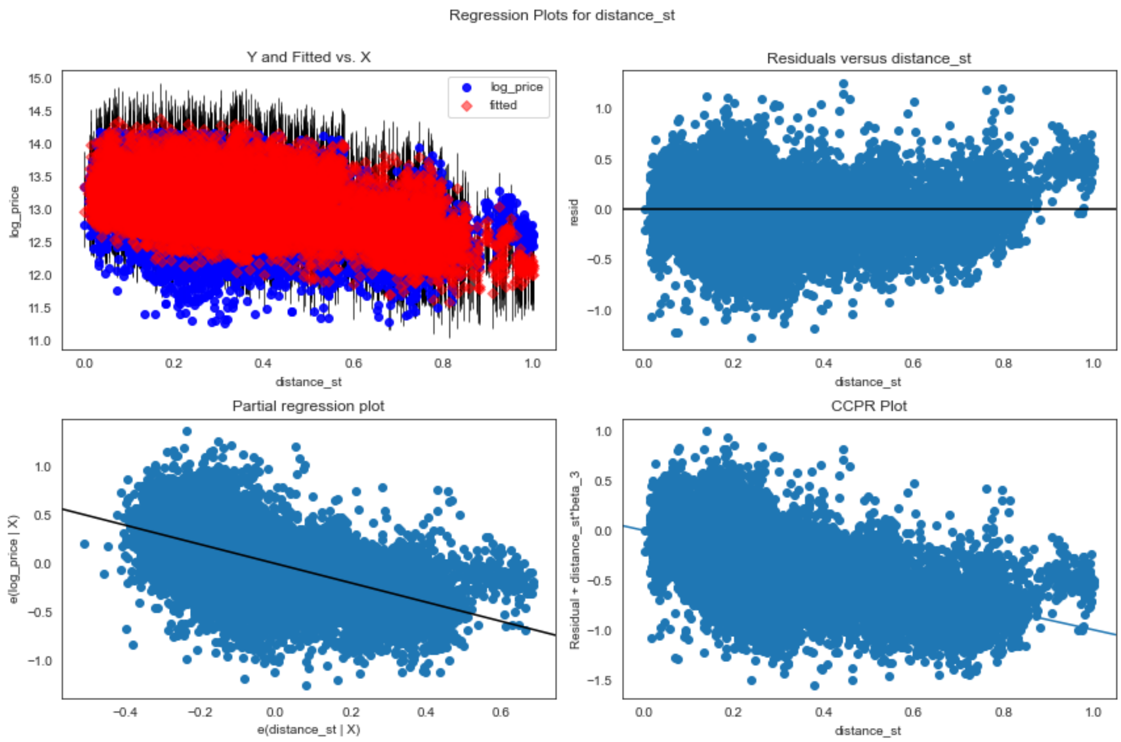
```python
fig = sm.graphics.qqplot(model_4_3.resid,dist=stats.norm,fit=True,line='45')

# Removing variable to simplify the display (categorical variable with only 2␣
↪values does not have
# much use when plotted by regress_exog)
# print(df_num_cat_5_log_cropped_st.
↪drop(['price','log_price','recent_renovation_new',
#                                         'sqft_living', 'distance', 'grade',␣
↪'bathrooms'],axis=1).columns)


for col in (df_num_cat_5_log_cropped_st.
↪drop(['price','log_price','recent_renovation_new',
                                        'sqft_living', 'distance', 'grade',␣
↪'bathrooms'],axis=1).columns):
    fig = sm.graphics.plot_regress_exog(model_4_3, col, fig=plt.
↪figure(figsize=(12,8)))
```

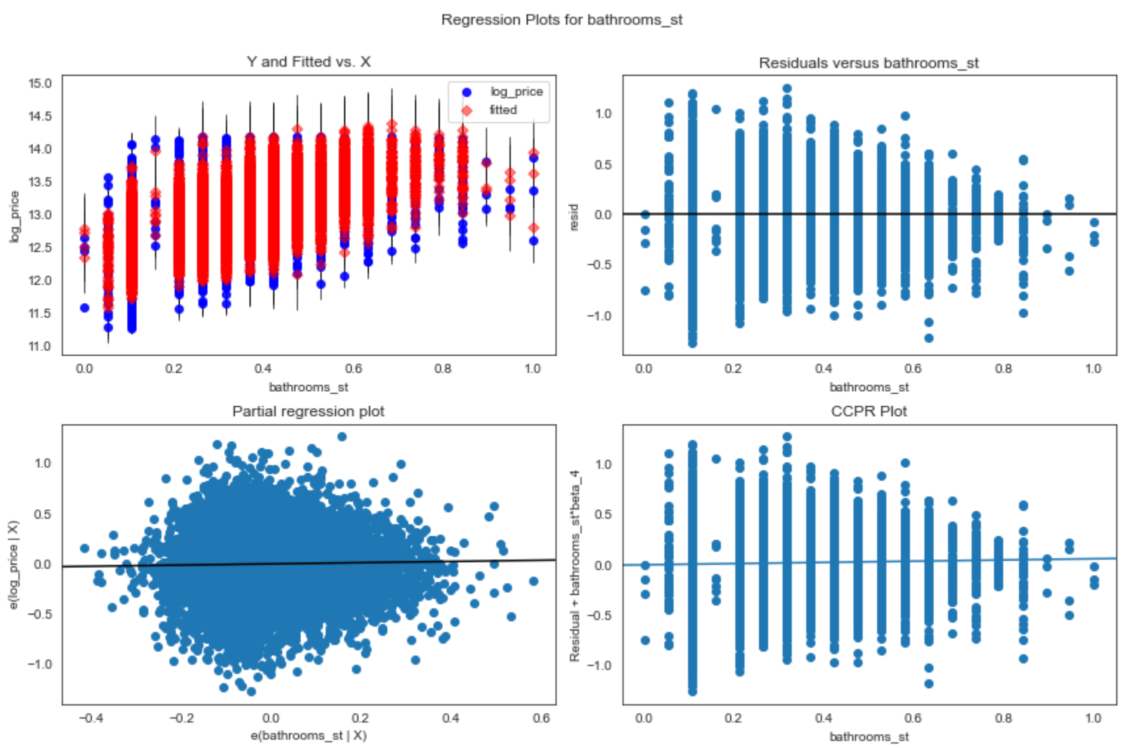


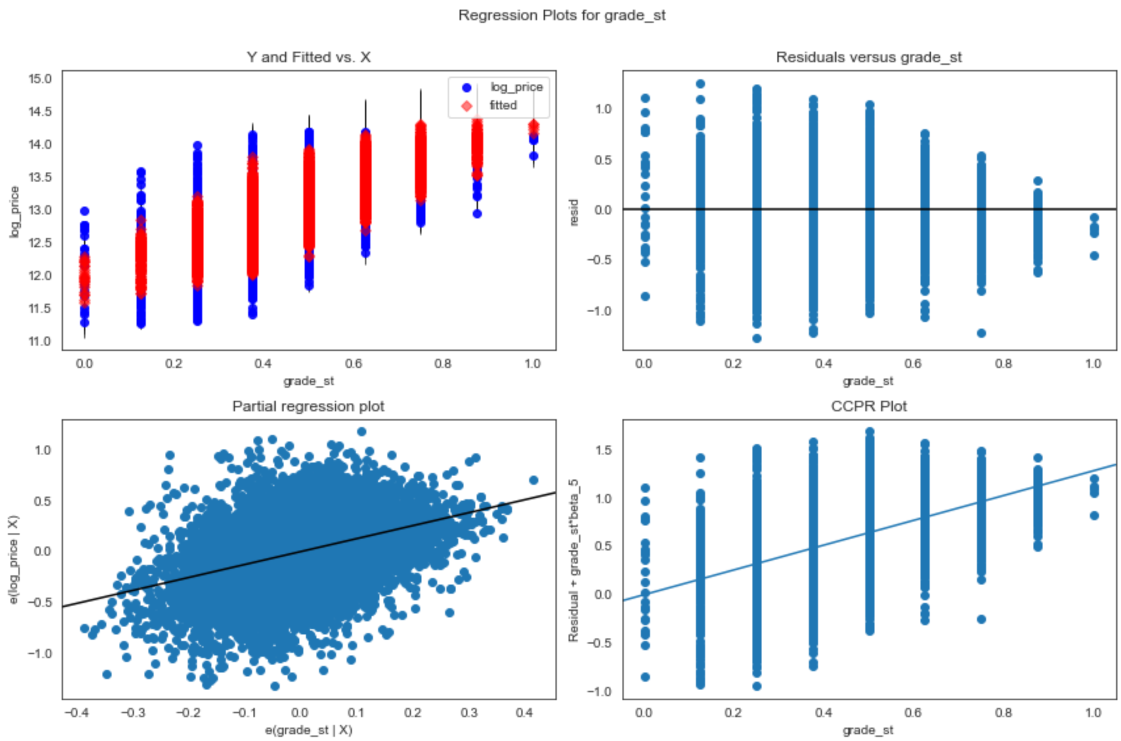
Sample Quantiles
Theoretical Quantiles



Regression Plots for sqft_living_st
Y and Fitted vs. X
log_price
fitted
sqft_living_st
Residuals versus sqft_living_st
resid
Partial regression plot
e(log_price | X)
e(sqft_living_st | X)
CCPR Plot
Residual + sqft_living_st*beta_2


Regression Plots for distance_st
Y and Fitted vs. X
log_price
fitted
distance_st
Residuals versus distance_st
resid
Partial regression plot
e(log_price | X)
e(distance_st | X)
CCPR Plot
Residual + distance_st*beta_3


Regression Plots for bathrooms_st
Y and Fitted vs. X
log_price
fitted
bathrooms_st
Residuals versus bathrooms_st
resid
Partial regression plot
e(log_price | X)
e(bathrooms_st | X)
CCPR Plot
Residual + bathrooms_st*beta_4



The final linear regression model of a log of the price variable versus grade, bathrooms, distance from the center of the city, sqft_living space, and the indicator if a house has been renovated recently or a newer house has a Coefficient of Determination of 0.663. It is indicative of the fact that 66.3% of the sold properties fall within the results of the line formed by the regression equation. F-statistics displays the high value and the overall p-value much lower than the confidence interval The independent variables used in the equation display a clear linear relationship with the target and homoscedasticity.

The next step is to validate the model by using training and test datasets

4.1.6 Train the model

[113]:
```
# Define X and y
y=df_num_cat_5_log_cropped_st[['log_price']]
X=df_num_cat_5_log_cropped_st.drop(['price','log_price','recent_renovation_new',
                                    'sqft_living', 'distance', 'grade',␣
 ↪'bathrooms'], axis=1)
```

[114]:
```
y
```

[114]:
```
       log_price
0      12.309982
1      13.195614
2      12.100712
```

```
3      13.311329
4      13.142166
…          …
19256  12.793859
19257  12.899220
19258  12.904459
19259  12.899220
19260  12.691580

[19261 rows x 1 columns]
```

[115]:
```python
X
```

[115]:
```
        sqft_living_st  distance_st  bathrooms_st  grade_st
0                0.194        0.239         0.105     0.375
1                0.528        0.260         0.368     0.375
2                0.096        0.337         0.105     0.250
3                0.381        0.211         0.526     0.375
4                0.314        0.449         0.316     0.500
…                  …          …             …         …
19256            0.278        0.207         0.421     0.500
19257            0.465        0.214         0.421     0.500
19258            0.156        0.039         0.053     0.375
19259            0.295        0.442         0.421     0.500
19260            0.156        0.042         0.053     0.375

[19261 rows x 4 columns]
```

[116]:
```python
# Split the data into training and test sets. Use the default split size
# X_train, X_test, y_train, y_test = train_test_split(X, y)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=100)

print(len(X_train), len(X_test), len(y_train), len(y_test))
```

```
13482 5779 13482 5779
```

[117]:
```python
# Fit the model to train data
linreg = LinearRegression()
model=linreg.fit(X_train, y_train)

# Calculate predictions on training and test sets for y_hat
y_hat_train=linreg.predict(X_train)
y_hat_test=linreg.predict(X_test)

# Calculate residuals
train_residuals=y_hat_train-y_train
```

```
test_residuals=y_hat_test-y_test

# Calculate training and test RMSE
train_mse = mean_squared_error(y_train, y_hat_train, squared=False)
test_mse = mean_squared_error(y_test, y_hat_test, squared=False)
print('Train MSE:', round(train_mse,3))
print('Test MSE:', round(test_mse,3))
```

```
Train MSE: 0.272
Test MSE: 0.272
```

[118]:
```
print(model.coef_, model.intercept_, model.score(X_test, y_test))
```

```
[[ 1.07971047 -0.9891889   0.04547509  1.26484854]] [12.36601493]
0.6718738822346366
```

4.1.7 Validation

[119]:
```
price_target=df_num_cat_5_log_cropped_st[['log_price']]
price_predictors= df_num_cat_5_log_cropped_st.
 ↪drop(['price','log_price','recent_renovation_new',
                                        'sqft_living', 'distance', 'grade',␣
 ↪'bathrooms'], axis=1)
```

[120]:
```
metrics.r2_score(price_target, linreg.predict(price_predictors))
```

[120]: 0.6628669814917774

[121]:
```
metrics.mean_absolute_error(price_target, linreg.predict(price_predictors))
```

[121]: 0.21292952976823826

[122]:
```
mean_squared_error(price_target, linreg.predict(price_predictors))
```

[122]: 0.07392658991485863

Train MSE: 0.272 Test MSE: 0.272 Are equal down to the third decimal digit indicating a good agreement between the training and the test sets R squared for for the prediction on the full dataset is the same as in model_4_3: 0.663 Mean Absolute Error for the prediction on the full dataset is 0.213 which is not great but acceptable. The best possible theoretical value is 0. Mean Squared Error for the prediction on the full dataset is 0.074. The best possible theoretical value is 0.

[123]:
```
# Not sure if the results of this function are indicative of anything, but␣
 ↪leaving it here for a possible future use
"""mse, bias, var = bias_variance_decomp(model, X_train.values, y_train.values.
 ↪flatten(),
                                        X_test.values, y_test.values,␣
 ↪num_rounds=200, random_seed=1, loss='mse')
```

```
# summarize results
print('MSE: %.3f' % mse)
print('Bias: %.3f' % bias)
print('Variance: %.3f' % var)"""
```

[123]:
```
"mse, bias, var = bias_variance_decomp(model, X_train.values,
y_train.values.flatten(), \n                                                X_test.values,
y_test.values, num_rounds=200, random_seed=1, loss='mse')\n# summarize
results\nprint('MSE: %.3f' % mse)\nprint('Bias: %.3f' % bias)\nprint('Variance:
%.3f' % var)"
```

5 iNterpret

[124]:
```
%%latex

\begin{align}\ln\left( {Price} \right) = 12.366 + 1.265 \cdot \left( grade␣
↪\right) +
1.080 \cdot \left( sqft\_living \right) - 0.989 \cdot \left( distance \right)
+ 0.060 \cdot \left( bathrooms \right) - 0.035 \cdot \left(␣
↪recent\_renovation\_new \right) \end{align}
```

$$\ln\left({Price} \right) = 12.366 + 1.265 \cdot \left(grade \right) + 1.080 \cdot \left(sqft\_living \right) - 0.989 \cdot \left(distance \right) + 0.060 \cdot \left(bathrooms \right) - 0.035 \cdot \left(r \tag{1}$$

The final model has a reasonable predictive ability tested in the final step of the model validation. MSE, MAE, and R2 score along with the model p-values for all predictors indicate a good fit. The most influential predictor is a **building grade**, following by a **living space footage**. Both factors are **positively correlated** with the price of the property. Both factors are within property owners' control when they are renovating their houses.A **distance** from the center of the city is **negatively correlated** with the price of property, meaning the further away a property is, the lower is the price. It is not a controllable variable but is helpful for home buyers if the living space and the number of bedrooms/bathrooms are important. A **number of bathrooms** has a **positive effect** on the price of a property, but it is not as strong as the first two factors. This fact indicates that the convenience of having multiple bathrooms is essential for potential buyers and should be taken into account when owners are planning a renovation. The last predictor in the model is an indicator of whether a property **has been renovated recently or a new construction**. It is very **weakly negatively correlated** with the price variable. The negative correlation (reduction of the price) might be related to the following factors: newer properties, on the average, are of less building quality. **The intercept** of the model is a **bias** of the model and can be interpreted as an offset of the model due to other factors not taken into account for various reasons.

6 Conclusions and Recommendation

Recommendations to property owners planning a renovation to their properties: * Increase the living space of your property * Do the renovation with higher building quality *

Consider adding a bathroom

Recommendations to potential buyers: * Look for properties further away from the city center to make the best out of your property buying budget * Properties in some zipcodes of the city are more affordable than others at the same distance from the city center * Properties in some zipcodes of the city are more affordable than others with a better view, more considerable property lots, and with older houses of better quality construction if these factors are essential to a buyer

Limitations of the model: * The original dataset does not include other important factors, and therefore the model is biased * Multiple linear regression models, while easily interpretable, are limited in their predictive ability * Some variables in the dataset are strongly correlated with each other, and that affect the predictive power of the model

Suggestion for future improvements: * Add variables to the original dataset like kitchen renovation, average commute time, crime index, average nearby public school quality, etc. * Update the dataset with more current data

7 Appendix

7.0.1 Visualization

[125]:
```
df_test=X_test.copy()
df_test['log_price']=y_test['log_price']
df_test['recent_renovation_new']=df_num_cat_5_log_cropped_st['recent_renovation_new']
df_test['sqft_living']=df_num_cat_5_log_cropped_st['sqft_living']
df_test['distance']=df_num_cat_5_log_cropped_st['distance']
df_test['grade']=df_num_cat_5_log_cropped_st['grade']
df_test['bathrooms']=df_num_cat_5_log_cropped_st['bathrooms']
df_test['price']=df_test.apply(lambda row: math.exp(row.log_price), axis=1)
df_test['recent_renovation_new_str']=df_test['recent_renovation_new'].
 ↪astype('str')
#df_test=df_test.reset_index(drop='index')
df_test
```

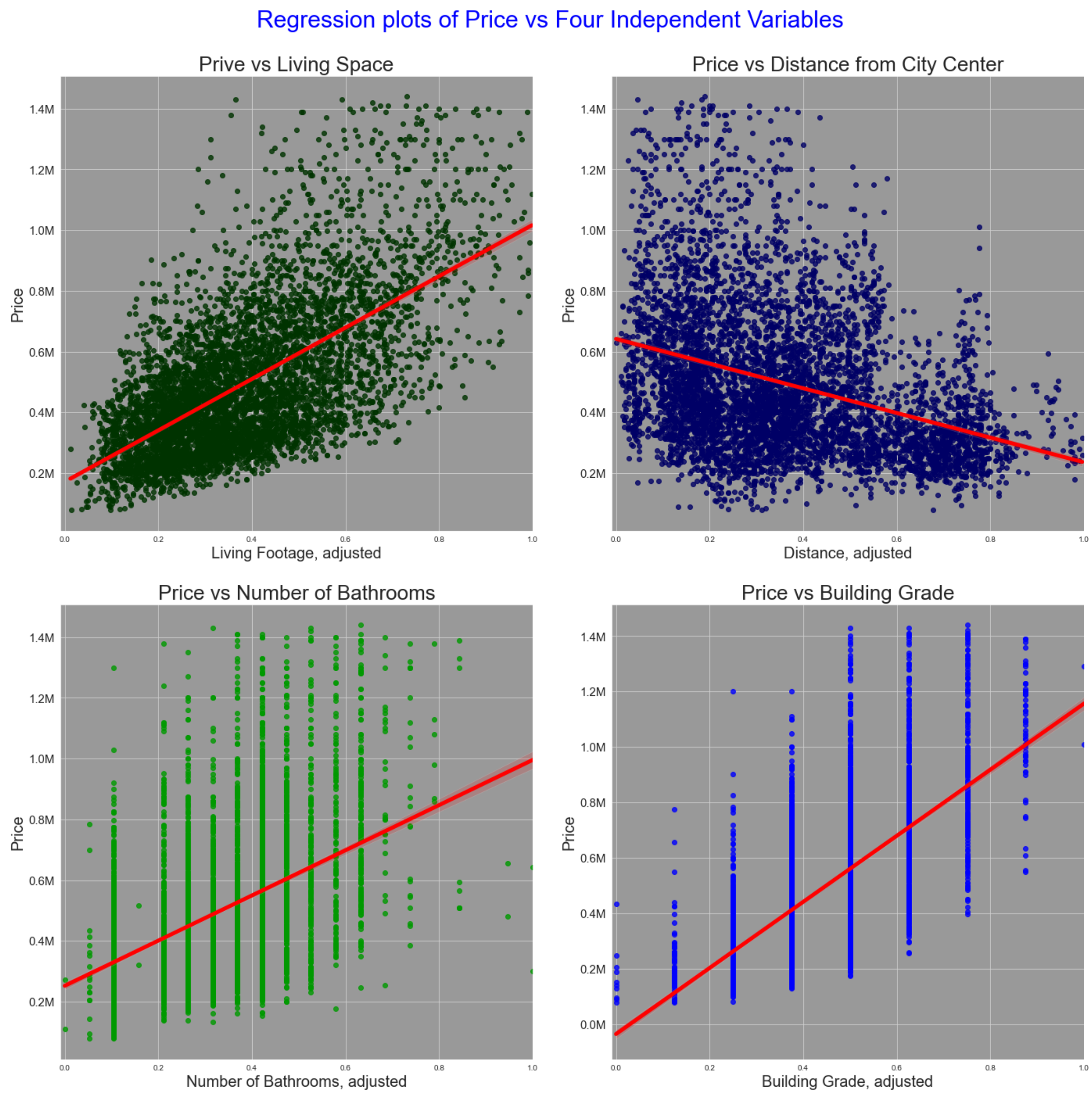
[125]:
```
       sqft_living_st  distance_st  bathrooms_st  grade_st  log_price
recent_renovation_new  sqft_living  distance  grade  bathrooms      price
recent_renovation_new_str
4977            0.317        0.088         0.263     0.375  12.860999
0.0         1690        3.1       7       1.75   385000.0
0.0
8676            0.233        0.646         0.105     0.375  12.415523
0.0         1340       19.0       7       1.00   246600.0
0.0
9682            0.451        0.246         0.526     0.375  13.507626
0.0         2250        7.6       7       3.00   735000.0
0.0
2046            0.129        0.351         0.105     0.375  12.631340
0.0          910       10.6       7       1.00   306000.0
0.0
```

```
18744           0.511         0.740         0.421     0.625  13.262125
1.0         2500      21.7      9       2.50   575000.0
1.0
…                …          …           …       …        …
…           …       …    …        …        …
…
12600           0.528         0.126         0.421     0.500  13.825461
0.0         2570       4.2      8       2.50  1010000.0
0.0
8951            0.621         0.232         0.368     0.750  14.100690
0.0         2960       7.2     10       2.25  1330000.0
0.0
14452           0.137         0.179         0.105     0.375  12.739638
0.0          940       5.7      7       1.00   341000.0
0.0
10710           0.336         0.779         0.421     0.375  12.767116
0.0         1770      22.8      7       2.50   350500.0
0.0
8312            0.252         0.270         0.263     0.125  12.345835
0.0         1420       8.3      5       1.75   230000.0
0.0

[5779 rows x 12 columns]
```

[126]:

```
# Regplots for all four variables

sns.set_style("darkgrid", {"axes.facecolor": ".6"})
fig, axes = plt.subplots(figsize=(20,20), ncols=2, nrows=2)

g1=sns.regplot(data=df_test, x="sqft_living_st", y="price", color="#003300",␣
 ↪fit_reg=True,
               ax=axes[0,0], line_kws={"color": "red", "lw":5});
g2=sns.regplot(data=df_test, x="distance_st", y="price", color="#000066",
               ax=axes[0,1], line_kws={"color": "red", "lw":5});
g3=sns.regplot(data=df_test, x="bathrooms_st", y="price", color="#009900",
               ax=axes[1,0], line_kws={"color": "red", "lw":5});
g4=sns.regplot(data=df_test, x="grade_st", y="price", color="#0000ff",
               ax=axes[1,1], line_kws={"color": "red", "lw":5});

axes[0,0].set_title("Prive vs Living Space", fontsize=26);
axes[0,0].set_ylabel('Price', fontsize=20)
axes[0,0].set_xlabel('Living Footage, adjusted', fontsize=20)
axes[0,0].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) + 'M' for x in g1.get_yticks()/1000000]
axes[0,0].set_yticklabels(ylabels, size=15)
axes[0,0].grid(color='lightgrey')
```

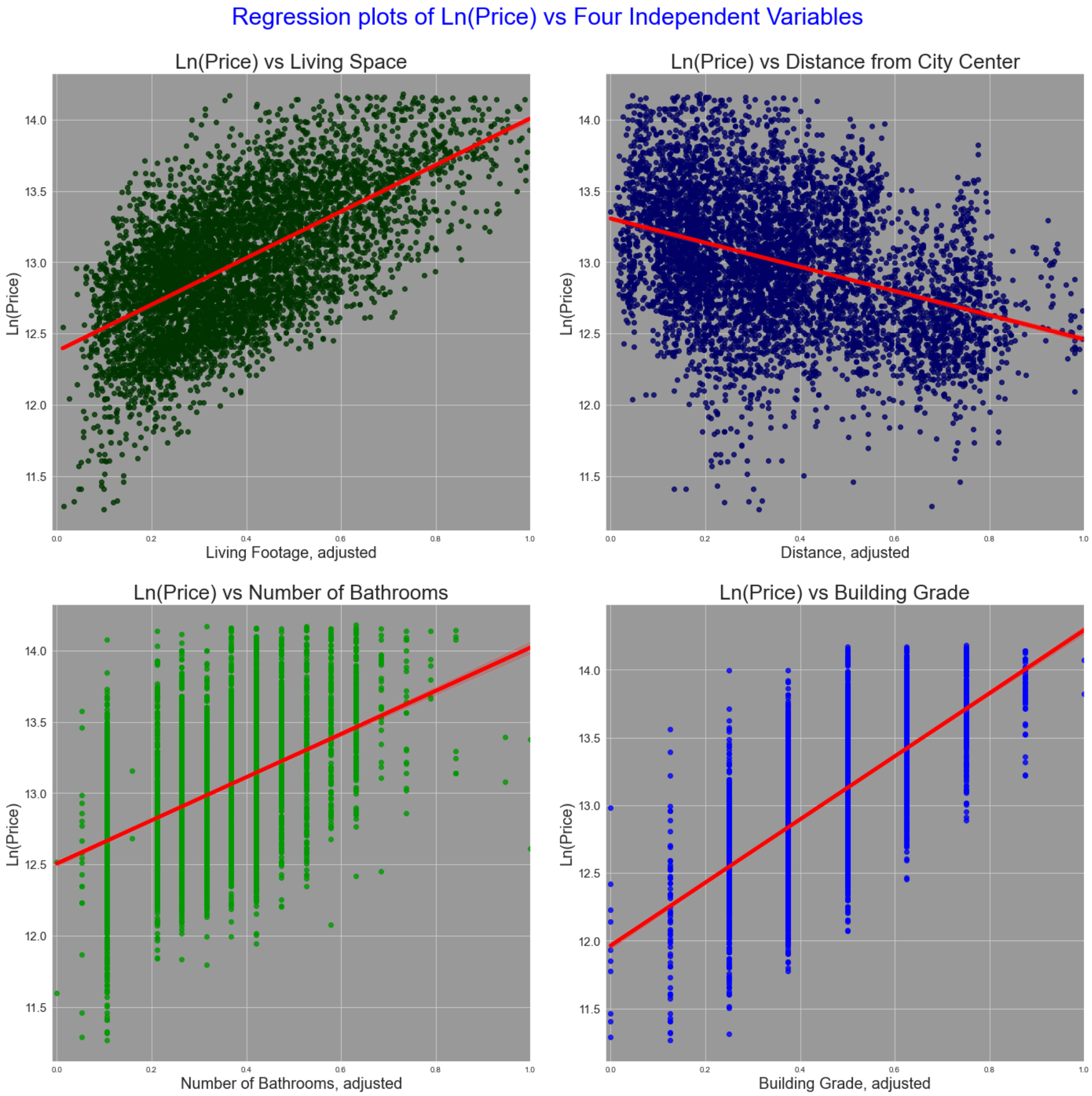
```
axes[0,1].set_title("Price vs Distance from City Center", fontsize=26);
axes[0,1].set_ylabel('Price', fontsize=20)
axes[0,1].set_xlabel('Distance, adjusted', fontsize=20)
axes[0,1].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) + 'M' for x in g2.get_yticks()/1000000]
axes[0,1].set_yticklabels(ylabels, size=15)
axes[0,1].grid(color='lightgrey')

axes[1,0].set_title("Price vs Number of Bathrooms", fontsize=26);
axes[1,0].set_ylabel('Price', fontsize=20)
axes[1,0].set_xlabel('Number of Bathrooms, adjusted', fontsize=20)
axes[1,0].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) + 'M' for x in g3.get_yticks()/1000000]
axes[1,0].set_yticklabels(ylabels, size=15)
axes[1,0].grid(color='lightgrey')

axes[1,1].set_title("Price vs Building Grade", fontsize=26);
axes[1,1].set_ylabel('Price', fontsize=20)
axes[1,1].set_xlabel('Building Grade, adjusted', fontsize=20)
axes[1,1].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) + 'M' for x in g4.get_yticks()/1000000]
axes[1,1].set_yticklabels(ylabels, size=15)
axes[1,1].grid(color='lightgrey')


plt.suptitle("Regression plots of Price vs Four Independent Variables",
 ↪size=30, c="Blue")
plt.tight_layout(pad=3)
```



[127]:

```
# Regplots for all four variables

sns.set_style("darkgrid", {"axes.facecolor": ".6"})
fig, axes = plt.subplots(figsize=(20,20), ncols=2, nrows=2)

g1=sns.regplot(data=df_test, x="sqft_living_st", y="log_price",␣
↪color="#003300", fit_reg=True,
                ax=axes[0,0], line_kws={"color": "red", "lw":5});
g2=sns.regplot(data=df_test, x="distance_st", y="log_price", color="#000066",
                ax=axes[0,1], line_kws={"color": "red", "lw":5});
g3=sns.regplot(data=df_test, x="bathrooms_st", y="log_price", color="#009900",
                ax=axes[1,0], line_kws={"color": "red", "lw":5});
```

```
g4=sns.regplot(data=df_test, x="grade_st", y="log_price", color="#0000ff",
               ax=axes[1,1], line_kws={"color": "red", "lw":5});

axes[0,0].set_title("Ln(Price) vs Living Space", fontsize=26);
axes[0,0].set_ylabel('Ln(Price)', fontsize=20)
axes[0,0].set_xlabel('Living Footage, adjusted', fontsize=20)
axes[0,0].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) for x in g1.get_yticks()]
axes[0,0].set_yticklabels(ylabels, size=15)
axes[0,0].grid(color='lightgrey')

axes[0,1].set_title("Ln(Price) vs Distance from City Center", fontsize=26);
axes[0,1].set_ylabel('Ln(Price)', fontsize=20)
axes[0,1].set_xlabel('Distance, adjusted', fontsize=20)
axes[0,1].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) for x in g2.get_yticks()]
axes[0,1].set_yticklabels(ylabels, size=15)
axes[0,1].grid(color='lightgrey')

axes[1,0].set_title("Ln(Price) vs Number of Bathrooms", fontsize=26);
axes[1,0].set_ylabel('Ln(Price)', fontsize=20)
axes[1,0].set_xlabel('Number of Bathrooms, adjusted', fontsize=20)
axes[1,0].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) for x in g3.get_yticks()]
axes[1,0].set_yticklabels(ylabels, size=15)
axes[1,0].grid(color='lightgrey')

axes[1,1].set_title("Ln(Price) vs Building Grade", fontsize=26);
axes[1,1].set_ylabel('Ln(Price)', fontsize=20)
axes[1,1].set_xlabel('Building Grade, adjusted', fontsize=20)
axes[1,1].set_xlim(-0.01, 1.0)
ylabels = ['{:,.1f}'.format(x) for x in g4.get_yticks()]
axes[1,1].set_yticklabels(ylabels, size=15)
axes[1,1].grid(color='lightgrey')

plt.suptitle("Regression plots of Ln(Price) vs Four Independent Variables",␣
 ↪size=30, c="Blue")
plt.tight_layout(pad=3)
```



[128]:
```
fig = px.scatter(df_test, x='sqft_living', y='price',  trendline='lowess', trendline_color_override='blue',
                 color='grade', size='distance',width=1000, height=800, size_max=20,
                 color_continuous_scale=px.colors.sequential.Blackbody_r,
                 labels={
                     "price": "Price",
                     "sqft_living": "Living Space (sq ft)",
                     "grade": "Building Grade"
                  },
                title="Correlation: Property Price vs Living Space Footage", template = "plotly_dark")
```

```
fig.update_traces(marker=dict(
            line=dict(
                color='coral',
                width=0.5
            )))
fig.update_layout(
    font_family="Arial",
    font_size=18,
    font_color="white",
    title_font_family="Arial",
    title_font_color="white",

)
fig.update_layout(
    title={
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[129]:
```
fig = px.scatter(df_test, x='bathrooms', y='price', color_continuous_scale=px.
 ↪colors.sequential.Blackbody_r,
                 size='sqft_living',size_max=20,
                 trendline='lowess', trendline_color_override='blue',␣
 ↪color='grade',
                 width=1000, height=800, labels={
                     "price": "Price",
                     "bathrooms": "Number of bathrooms",
                     "grade": "Building Grade"
                 },
                title="Correlation: Property Price vs Number of Bathrooms",
                 template = "plotly_dark")


fig.update_traces(marker=dict(
            line=dict(
                color='coral',
                width=0.5
            )))
fig.update_layout(
    font_family="Arial",
    font_size=18,
```

```
    font_color="white",
    title_font_family="Arial",
    title_font_color="white",

)

fig.update_layout(
    title={
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[130]:
```
fig = px.scatter(df_test, x='distance', y='price',  trendline='lowess',␣
 ↪trendline_color_override='blue',
                 color='grade', size='bathrooms',width=1000, height=800,␣
 ↪size_max=20,
                 color_continuous_scale=px.colors.sequential.Blackbody_r,
                 labels={
                     "price": "Price",
                     "distance": "Distance",
                     "grade": "Building Grade"
                  },
                title="Correlation: Property Price vs Distance from the City␣
 ↪Center",  template = "plotly_dark")

fig.update_traces(marker=dict(
            line=dict(
                color='coral',
                width=0.5
            )))
fig.update_layout(
    font_family="Arial",
    font_size=18,
    font_color="white",
    title_font_family="Arial",
    title_font_color="white",

)
fig.update_layout(
    title={
        'y':0.95,
        'x':0.5,
```

```
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[131]:
```
fig = px.scatter(df_test, x='sqft_living', y='price',  trendline='ols',␣
↪trendline_color_override='yellow',
                 color='recent_renovation_new_str', width=1000, height=800,␣
↪size_max=20,
                 labels={
                     "price": "Price",
                     "sqft_living": "Living Space (sq ft)",
                     "recent_renovation_new_str": "Newer(1)/Older(0)"
                  },
                title="Correlation: Property Price vs Living Space Footage of␣
↪newer vs older properties",
                 template = "plotly_dark")

fig.update_traces(marker=dict(
            line=dict(
                color='coral',
                width=0.5
            )))
fig.update_layout(
    font_family="Arial",
    font_size=18,
    font_color="white",
    title_font_family="Arial",
    title_font_color="white",

)
fig.update_layout(
    title={
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[132]:
```
fig = px.scatter_3d(df_test, x='bathrooms', z='grade', y='sqft_living',
              color='price', size='distance', size_max=50, opacity=1,␣
↪width=1000, height=800,
```

```
                    color_continuous_scale=px.colors.sequential.Blackbody_r,
                    labels={
                      "bathrooms": "Number of Bathrooms",
                      "sqft_living": "Living Space (sq ft)",
                      "grade": "Grade",
                        "price": "Price"
                   },
                title="3D plot: Living Space Footage, Number of Bathrooms and␣
↪Grade of Sold Properties",
                    template = "plotly_dark")

fig.update_traces(marker=dict(
            line=dict(
                color='coral',
                width=0.5
            )))
fig.update_layout(
    font_family="Arial",
    font_size=16,
    font_color="white",
    title_font_family="Arial",
    title_font_color="white"
)
fig.update_layout(
    title={
        'y':0.9,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[133]:
```
df_cut_off=df.copy()
df_cut_off=df_cut_off[(df_cut_off['price']<1500000)]

fig = px.scatter_mapbox(df_cut_off, lat="lat", lon="long", color="price",
                  color_continuous_scale=px.colors.sequential.Plasma, zoom=10,
                        mapbox_style='open-street-map', width=900, height=900,
                        title="Properties Sold in King County in 2014-2015",
                   template = "plotly_dark")

fig.update_layout(
    font_family="Arial",
    font_size=20,
    font_color="white",
```

```
    title_font_family="Arial",
    title_font_color="white"
)
fig.update_layout(
    title={
        'y':0.98,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top',
})


fig.show()
```

[134]:

```
df_zipcode_viz=df.groupby('zipcode').mean()

df_zipcode_viz=df_zipcode_viz.reset_index()

df_zipcode_viz=df_zipcode_viz.
↪drop(['id','sqft_above','sqft_basement','yr_renovated','lat','long'], axis=1)
df_zipcode_viz
```

[134]:

```
    zipcode         price  bedrooms  bathrooms  sqft_living      sqft_lot
floors  waterfront      view  condition     grade     yr_built  sqft_living15
sqft_lot15
0     98001  2.813837e+05  3.402235   2.012570  1908.256983  14966.393855
1.432961    0.000000  0.094972   3.329609  7.296089  1981.047486    1832.279330
11200.337989
1     98002  2.340839e+05  3.314721   1.837563  1627.416244   7509.248731
1.332487    0.000000  0.010152   3.751269  6.695431  1967.695431    1478.461929
7587.690355
2     98003  2.942254e+05  3.358696   2.053442  1931.438406  10625.137681
1.309783    0.000000  0.217391   3.373188  7.550725  1976.873188    1880.416667
9771.572464
3     98004  1.355200e+06  3.853968   2.530159  2910.730159  13084.374603
1.431746    0.003175  0.307937   3.495238  8.688889  1971.542857    2672.634921
12798.577778
4     98005  8.102897e+05  3.851190   2.424107  2656.803571  19928.785714
1.279762    0.000000  0.095238   3.696429  8.488095  1969.744048    2567.863095
18367.773810
..      …            …        …         …           …            …
…         …        …         …        …          …             …
…
65    98177  6.770352e+05  3.397638   2.099409  2325.511811  11921.086614
1.277559    0.003937  0.814961   3.496063  7.976378  1960.822835    2186.220472
11704.362205
66    98178  3.106226e+05  3.306202   1.738372  1736.744186   8308.457364
```

```
1.186047    0.034884   0.542636   3.325581   6.829457   1955.325581    1650.503876
8132.344961
67    98188   2.893271e+05   3.437037   1.870370   1806.125926   10136.644444
1.225926    0.000000   0.148148   3.333333   7.044444   1965.681481    1638.770370
9760.600000
68    98198   3.029441e+05   3.178182   1.792727   1749.530909   10553.425455
1.225455    0.032727   0.603636   3.450909   7.109091   1966.865455    1715.927273
9502.130909
69    98199   7.919480e+05   3.208861   2.166930   2162.246835    5439.721519
1.466772    0.003165   0.553797   3.503165   8.009494   1956.569620    1992.341772
5282.101266

[70 rows x 14 columns]
```

[135]:
```
KC_zip_json=json.load(open('data/wa_washington_zip_codes_geo.min.json', 'r'))
```

[136]:
```
map_choropleth_zip(df_zipcode_viz, 'price', "Average Prices of Sold Properties␣
↪per Zipcode (King County, 2014-2015)",
                   "Price")
```

[137]:
```
map_choropleth_zip(df_zipcode_viz, 'sqft_lot', "Average Lot Size of Sold␣
↪Properties per Zipcode (King County, 2014-2015)",
                   "Lot size (sq ft)")
```

[138]:
```
map_choropleth_zip(df_zipcode_viz, 'sqft_living', "Average Living Space of Sold␣
↪Properties per Zipcode (King County, 2014-2015)",
                   "Living Space (sq ft) ")
```

[139]:
```
map_choropleth_zip(df_zipcode_viz, 'view', "Average View Category of Sold␣
↪Properties per Zipcode (King County, 2014-2015)",
                   "View Category")
```

[140]:
```
map_choropleth_zip(df_zipcode_viz, 'yr_built', "Average Year Built of Sold␣
↪Properties per Zipcode (King County, 2014-2015)",
                   "Year Built")
```

[141]:
```
!conda info
```

```
     active environment : learn-env
    active env location : C:\Users\elena\anaconda3\envs\learn-env
            shell level : 2
       user config file : C:\Users\elena\.condarc
 populated config files : C:\Users\elena\.condarc
          conda version : 4.9.2
    conda-build version : 3.20.5
         python version : 3.8.5.final.0
       virtual packages : __cuda=11.1=0
```

```
                          __win=0=0
                          __archspec=1=x86_64
       base environment : C:\Users\elena\anaconda3  (writable)
           channel URLs : https://repo.anaconda.com/pkgs/main/win-64
                          https://repo.anaconda.com/pkgs/main/noarch
                          https://repo.anaconda.com/pkgs/r/win-64
                          https://repo.anaconda.com/pkgs/r/noarch
                          https://repo.anaconda.com/pkgs/msys2/win-64
                          https://repo.anaconda.com/pkgs/msys2/noarch
          package cache : C:\Users\elena\anaconda3\pkgs
                          C:\Users\elena\.conda\pkgs
                          C:\Users\elena\AppData\Local\conda\conda\pkgs
       envs directories : C:\Users\elena\anaconda3\envs
                          C:\Users\elena\.conda\envs
                          C:\Users\elena\AppData\Local\conda\conda\envs
               platform : win-64
             user-agent : conda/4.9.2 requests/2.24.0 CPython/3.8.5 Windows/10
Windows/10.0.19041
          administrator : False
             netrc file : None
           offline mode : False
```