Final Project Submission

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House Price Prediction in King County

Introduction

The real estate industry is complex and involves many factors that can greatly influence the prices. Predicting house prices accurately can help all parties involved to make profits incase they are sellers or to get good deals for the real estate if they are buyers. In this project, we will be using the King County House data which contains information about prices of real estate in King County, Washington. We'll build a regression model that will predict the selling price of a house based on the features. We'll use regression analysis techniques to analyze the data and come up with a model that can provide estimations of house prices. This will aim to provide insight to the factors that are influencing house prices and also help buyers and sellers to make well infromed decisions

Challenges

- Lack of affordable housing due to the rapid growth in population due to more people moving to the area. Demand for houses is going higher.
- Property owners or developers might give false information about the house grade to drive the prices up. The rating may also not be accurate due to other factors.
- Scarcity of available units for residence within Kings County has driven up the cost of house units between the various grades ie: average, good, excellent and luxurious.

- The disparities in the housing market play out on a sub regional basis within King County Properties located in desirable areas, such as waterfront or downtown areas are limited and highly valued.
- Limited supply of land in the region, particularly in desirable areas close to job centers and transportation. The scarcity of land can limit the number of available units and drive up prices

Proposed Solution

- Increase the affordable housing by researching on house features that are essential and that will not make house expensive.
- Implement tougher standards for house grading that are not dependent on developers. They can used things like building codes
- Construct high rises to counter the land scarcity.

Conclusion

Using KC House Data to predict house prices is a challenging and exciting task. By using data on diffret features and characteristics of a house, we will develop a regression model that can accurately predict house prices. This will be a systematic process that entails steps such as preprocessing, model training and model tuning. The insights that will be gaioned from the model can help buyers and sellers to make well informed decisions to their advantage.

Problem Statement

Our goal in this project is to analyze the relationship between various home features and the sale price of the houses in a northwestern county.Our aim is to provide insights and advice to stakeholders in the real estate industry about how they can improve their returns on investments by focusing on the features that have the most significant impact on the sale price of the houses.

Objectives

1:

To determine the relationship between the square footage of the house and the sale price of the houses in a northwestern county.

2:

To examine the relationship between the overall grade of the house and the sale price of the houses in a northwestern county.

3:

To explore the relationship between the year built and the sale price of the houses in a northwestern county.

4:

To investigate the relationship between the number of bedrooms and the sale price of the houses in a northwestern county.

Data

We have been provided with a dataset with house sale prices in King County, Washington State, USA from 2014 to 2015 to use for this project.

A dataset has been provided and can be found in the `kc_house_data.csv` file in this repository.

The column names and descriptions as provided can be found in the `column_names.md` file in this repository. We have explained them here for convenience.

Column Names and descriptions for Kings County Data Set

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
- `view` - Quality of view from house
- `condition` - How good the overall condition of the house is.
- `grade` - Overall grade of the house. Related to the construction and design of the house.
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated

- `zipcode` - ZIP Code used by the United States Postal Service
- `lat` - Latitude coordinate
- `long` - Longitude coordinate
- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors
- `sqft_lot15` - The square footage of the land lots of the nearest 15 neighbors

In [1]:
```
# import the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as sfm
import statsmodels.api as sm
import scipy.stats as stats
%matplotlib inline

plt.style.use('seaborn')
import warnings
warnings.filterwarnings('ignore')
```

Obtaining data

In [2]:
```
# reading in the data and previewing the dataframe
df = pd.read_csv('data/kc_house_data.csv')
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basem
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	40
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	91
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	

5 rows × 21 columns

Data Preparation

In this section, we shall be preparing the data for further processing and modelling

Investigate data types

In [3]:
```
# summary of the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

We conclude that

- `date` column should be changed to `DateTime` .
- `sqft_basement` column should be changed to `float`
- `waterfront` , `view` , `condition` , and `grade` will remain unchanged for now because they contain text

In [4]:
```
# function to change data type to datetime
def change_to_datetime(df, col):
    ''' Changes column to DateTime object'''
    df[col] = pd.to_datetime(df[col])
    return df.info()
```

In [5]:
```
# changing date column type to DateTime
change_to_datetime(df, 'date')
```

```
<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  datetime64[ns]
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: datetime64[ns](1), float64(6), int64(9), object(5)
memory usage: 3.5+ MB
```

In [6]:
```
# checking column names
df.columns
```

Out[6]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [7]:
```
# function to check null values
def check_null(df):
    return df.isna().sum()
```

In [8]:
```
# checking for null values in the data
check_null(df)
```

Out[8]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

There are missing values in three columns.
Depending on the ratio of missing values, we will decide on what approach to take in dealing with them

In [9]:
```
# function to calculate percentage of null values
def miss_percent(df,col):
    miss = ((df[col].isna().sum()) / len(df[col])) * 100
    return print(f'There is {miss} percent of values missing in {col}.')
```

In [10]:
```
# checking percentage of missing values in waterfront
miss_percent(df,'waterfront')
miss_percent(df, 'view')
miss_percent(df, 'yr_renovated')
```

```
There is 11.00152798999861 percent of values missing in waterfront.
There is 0.29170718155299347 percent of values missing in view.
There is 17.78950780200954 percent of values missing in yr_renovated.
```

Dealing with `yr_renovated`

In [11]:
```
# investigating yr_renovated
df['yr_renovated'].value_counts()
```

Out[11]:
```
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

We replace `nan` and `0` with values from the column `yr_built` based on the assumption that houses with `0` and `nan` have never had any renovation.

In [12]:
```
# function to replace null with a specificied value
def replace_nan(df,col, replace_value):
    return df[col].fillna(replace_value, inplace=True)
```

In [13]:
```
# replacing the null
df['yr_renovated'].replace(0.0, np.nan, inplace=True)
df['yr_renovated'].fillna(df['yr_built'], inplace=True)
```

In [14]:
```
df
```

Out[14]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_baseme
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	(
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	40(
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	(
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	91(
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	(
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	263000018	2014-05-21	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	8 Good	1530	(
21593	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	8 Good	2310	(
21594	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	7 Average	1020	(
21595	291310100	2015-01-16	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	8 Good	1600	(
21596	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	7 Average	1020	(

21597 rows × 21 columns

In [15]:
```
# confirming null values are removed
miss_percent(df, 'yr_renovated')
```

```
There is 0.0 percent of values missing in yr_renovated.
```

Dealing with `waterfront`

In [16]:
```
# investigating the column
print(f'Unique values:{df.waterfront.unique()}')
print(f'Count:{df.waterfront.value_counts()}')
```

```
Unique values:[nan 'NO' 'YES']
Count:NO     19075
YES      146
Name: waterfront, dtype: int64
```

`NO` occurs the highest number of times hence we change the `null` to `NO`

In [17]:
```
#replacing the null values with zero
replace_nan(df,'waterfront', 'NO')
```

In [18]:
```
# function to replace a value with another
def substitute(df,col,original_value, sub_value):
    return df[col].replace(original_value, sub_value, inplace=True)
```

In [19]:
```
# changing YES to  1
substitute(df,'waterfront','YES',1)

# changing NO to  0
substitute(df, 'waterfront', 'NO', 0)
```

In [20]:
```
# confirming null values are out
miss_percent(df, 'waterfront')
```

```
There is 0.0 percent of values missing in waterfront.
```

Dealing with `view`

In [21]:
```
# investigating the column
print(f'Unique values:{df.view.unique()}')
print(f'Count:{df.view.value_counts()}')
```

```
Unique values:['NONE' nan 'GOOD' 'EXCELLENT' 'AVERAGE' 'FAIR']
Count:NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In `view` , we have five types of rating.

`NONE` has the most entries and we decide to replace `null` with it.

In [22]:
```
#replacing the null values with NONE
replace_nan(df,'view', 'NONE')
```

In [23]:
```
# changing the ratings to numbers
substitute(df,'view',['NONE','FAIR','AVERAGE','GOOD','EXCELLENT'],[0,1,2,3,4])
```

In [24]:
```
# checking count
df['view'].value_counts()
```

Out[24]:
```
0    19485
2      957
3      508
1      330
4      317
Name: view, dtype: int64
```

Dealing with `sqft_basement`

In [25]:
```
# investigating the column
print(f'Count:{df.sqft_basement.value_counts()}')
```

```
Count:0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
2300.0        1
704.0         1
274.0         1
1920.0        1
1135.0        1
Name: sqft_basement, Length: 304, dtype: int64
```

The column has `?` as an entry. `0.0` is the most occuring and we change `?` to it.

In [26]:
```
# change ? to 0.0
substitute(df, 'sqft_basement', '?', 0.0)
```

In [27]:
```
df.sqft_basement = df.sqft_basement.astype(float)
```

In [28]:
```
print(f'Count:{df.sqft_basement.value_counts()}')
```

```
Count:0.0       13280
600.0       217
500.0       209
700.0       208
800.0       201
          ...
915.0         1
295.0         1
1281.0        1
2130.0        1
906.0         1
Name: sqft_basement, Length: 303, dtype: int64
```

Dealing with `condition`

In [29]:
```
# investigating the column
print(f'Unique values:{df.condition.unique()}')
print(f'Count:{df.condition.value_counts()}')
```

```
Unique values:['Average' 'Very Good' 'Good' 'Poor' 'Fair']
Count:Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64
```

There are 5 ratings and we decide to ssign them numbers on a scale of 1 to 5 with 5 being `very good`

In [30]:
```
# assigning the ratings numbers
substitute(df,'condition',['Poor','Fair','Average','Good','Very Good'],[1,2,3,4,5])
```

In [31]:
```
print(f'Unique values:{df.condition.unique()}')
print(f'Count:{df.condition.value_counts()}')
```

```
Unique values:[3 5 4 1 2]
Count:3    14020
4     5677
5     1701
2      170
1       29
Name: condition, dtype: int64
```

Dealing with `grade`

In [32]:
```
# investigating the column
print(f'Unique values:{df.grade.unique()}')
print(f'Count:{df.grade.value_counts()}')
```

```
Unique values:['7 Average' '6 Low Average' '8 Good' '11 Excellent' '9 Better' '5 Fair'
 '10 Very Good' '12 Luxury' '4 Low' '3 Poor' '13 Mansion']
Count:7 Average       8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

We will assign the ratings as numbers with the numbers they have beside them.

In [33]:
```
# assigning numbers to ratings
substitute(df,'grade',['7 Average','8 Good','9 Better','6 Low Average','10 Very Good','11 Excellent',
                      '5 Fair','12 Luxury','4 Low','13 Mansion','3 Poor'], [7,8,9,6,10,11,5,12,4,13,3])
```

In [34]:
```
print(f'Count:{df.grade.value_counts()}')
```

```
Count:7     8974
8     6065
9     2615
6     2038
10    1134
11     399
5      242
12      89
4       27
13      13
3        1
Name: grade, dtype: int64
```

Dealing with `bathrooms`

In [35]:
```
# investigating the column
#print(f'Unique values:{df.bathrooms.unique()}')
print(f'Count:{df.bathrooms.value_counts()}')
```

```
Count:2.50    5377
1.00    3851
1.75    3048
2.25    2047
2.00    1930
1.50    1445
2.75    1185
3.00     753
3.50     731
3.25     589
3.75     155
4.00     136
4.50     100
4.25      79
0.75      71
4.75      23
5.00      21
5.25      13
5.50      10
1.25       9
6.00       6
5.75       4
0.50       4
8.00       2
6.25       2
6.75       2
6.50       2
7.50       1
7.75       1
Name: bathrooms, dtype: int64
```

`bathrooms` have float values. We decide to round up to the next integer so as to have whole numbers.
in this case, rounding off might make the `0.5` to be `0` which we don't want.

In [36]:
```
# rounding up the decimals
df['bathrooms'] = df['bathrooms'].apply(np.ceil).astype(int)
```

In [37]:
```
df.bathrooms.value_counts()
```

Out[37]:
```
3    9362
2    6432
1    3926
4    1611
5     223
6      33
7       6
8       4
Name: bathrooms, dtype: int64
```

In [38]:
```
df.head()
```

Out[38]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_b
0	7129300520	2014-10-13	221900.0	3	1	1180	5650	1.0	0	0	...	7	1180	0.0	1
1	6414100192	2014-12-09	538000.0	3	3	2570	7242	2.0	0	0	...	7	2170	400.0	1
2	5631500400	2015-02-25	180000.0	2	1	770	10000	1.0	0	0	...	6	770	0.0	1
3	2487200875	2014-12-09	604000.0	4	3	1960	5000	1.0	0	0	...	7	1050	910.0	1
4	1954400510	2015-02-18	510000.0	3	2	1680	8080	1.0	0	0	...	8	1680	0.0	1

5 rows × 21 columns

Check duplicates

Checking whether we have any duplicates in our dataset.

In [39]:
```
#Function to identify duplicates
duplicates = []
def identify_duplicates(data):
    for i in data.duplicated():
        duplicates.append(i)
    duplicates_set = set(duplicates)
    if(len(duplicates_set) == 1):
        print('The data has no duplicates')
    else:
        duplicates_rows = 0
        for j in duplicates:
            if (j == True):
                duplicates_rows += 1
                #percentage of data represented by duplicates
                duplicates_percentage = np.round(((duplicates_rows/len(data)) * 100), 2)
                print(f'The data has {duplicates_rows} duplicated rows')
                print(f'Duplicated rows constitute of {duplicates_percentage}% of the dataframe')
```

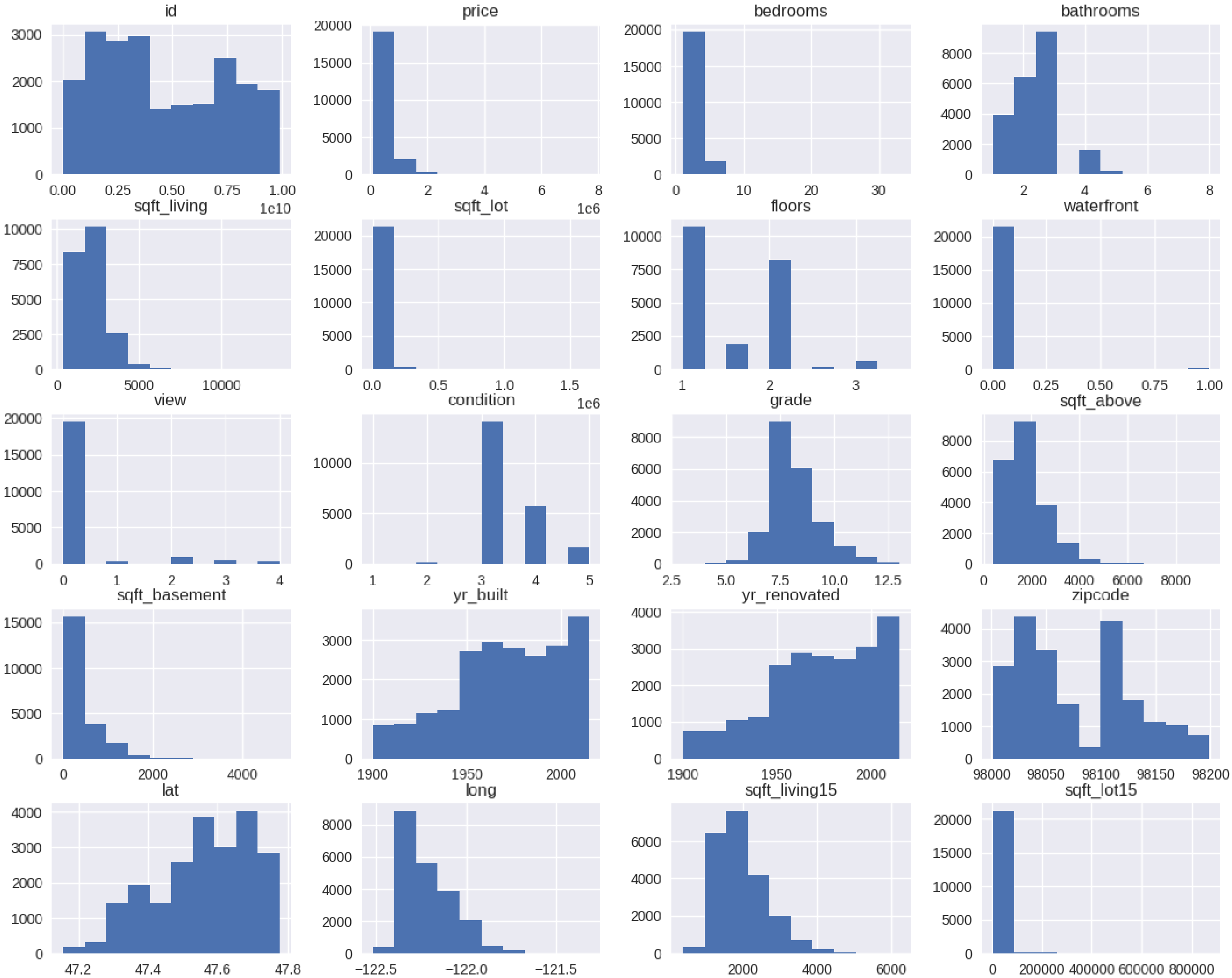
In [40]:
```
identify_duplicates(df)
```

```
The data has no duplicates
```

Checking for outliers

We view the distributions using histograms to get insight of the spread of the various features.

In [41]:
```
df.hist(figsize = (15,12))
plt.show()
```


id
price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
grade
sqft_above
sqft_basement
yr_built
yr_renovated
zipcode
lat
long
sqft_living15
sqft_lot15
1e10
1e6

- `grade` , `condition` and `floors` appear to be on a reasonable scale with no apparent outliers
- `waterfront` is a binary 1/0 features.
- We will consider potential outliers in `bedrooms` , `bathrooms` and the `sqft` -type features.

In [42]:
```
# Investigate bedrooms
df['bedrooms'].value_counts()
```

Out[42]:
```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

There is a 33 bedroom house, we check on it.

In [43]:
```
df[df['bedrooms'] == 33]
```

Out[43]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement
15856	2402100895	2014-06-25	640000.0	33	2	1620	6000	1.0	0	0	...	7	1040	580.0

1 rows × 21 columns

The house has `2` bathrooms and a price of `640,000` . This seem to indicate `33` might have been an error. We replace it with 3

In [44]:
```
# Fix error for bedrooms
df.loc[15856, 'bedrooms'] = 3
```

While this could be an approach to removing outliers, we decide to use the interquartile ranges to generalise it.

In [45]:
```
def remove_outliers(df):
    # define the columns to remove outliers from
    cols = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'sqft_above', 'sqft_bas
            'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15',
            'sqft_lot15']

    # remove outliers from the specified columns
    for col in cols:
        q1 = df[col].quantile(0.25)
        q3 = df[col].quantile(0.75)
        iqr = q3 - q1
        df = df[(df[col] >= q1 - (2.5 * iqr * (len(df[col])/(len(df[col]) + 1)))) & (df[col] <= q3 + (2.5

    # return the modified DataFrame
    return df
```

In [46]:
```
df = remove_outliers(df)
```

In [47]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18678 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             18678 non-null  int64
 1   date           18678 non-null  datetime64[ns]
 2   price          18678 non-null  float64
 3   bedrooms       18678 non-null  int64
 4   bathrooms      18678 non-null  int64
 5   sqft_living    18678 non-null  int64
 6   sqft_lot       18678 non-null  int64
 7   floors         18678 non-null  float64
 8   waterfront     18678 non-null  int64
 9   view           18678 non-null  int64
 10  condition      18678 non-null  int64
 11  grade          18678 non-null  int64
 12  sqft_above     18678 non-null  int64
 13  sqft_basement  18678 non-null  float64
 14  yr_built       18678 non-null  int64
 15  yr_renovated   18678 non-null  float64
 16  zipcode        18678 non-null  int64
 17  lat            18678 non-null  float64
 18  long           18678 non-null  float64
 19  sqft_living15  18678 non-null  int64
 20  sqft_lot15     18678 non-null  int64
dtypes: datetime64[ns](1), float64(6), int64(14)
memory usage: 3.1 MB
```

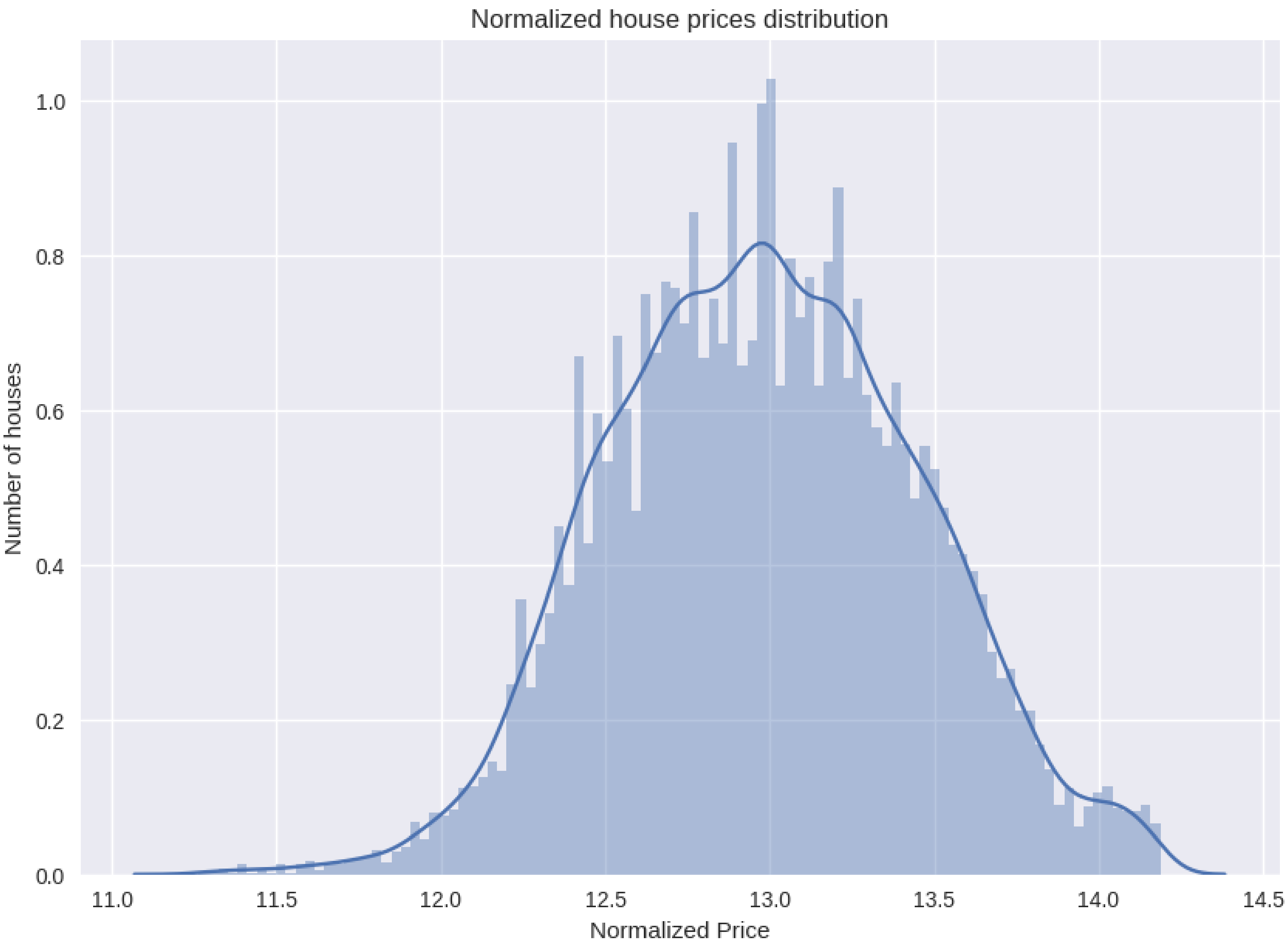
EDA

Price

In [48]:
```
# View price distribution
plt.figure(figsize=(7,6))
dist=sns.distplot(df["price"])
dist.set_title("Price distribution")
plt.xlabel('Price in USD')
plt.title('Distribution of Price')
plt.show()
```


Distribution of Price
1e−6
2.5
2.0
1.5
1.0
0.5
0.0
Density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1e6
Price in USD

In [49]:
```
#Normalizing Price Distribution
fig, ax = plt.subplots(figsize=(10, 7))

sns.distplot(np.log(df['price']), bins = 100)

ax.set_xlabel("Normalized Price")
ax.set_ylabel("Number of houses")
ax.set_title("Normalized house prices distribution")
plt.show()
```


Normalized house prices distribution
Number of houses
1.0
0.8
0.6
0.4
0.2
0.0
11.0
11.5
12.0
12.5
13.0
13.5
14.0
14.5
Normalized Price

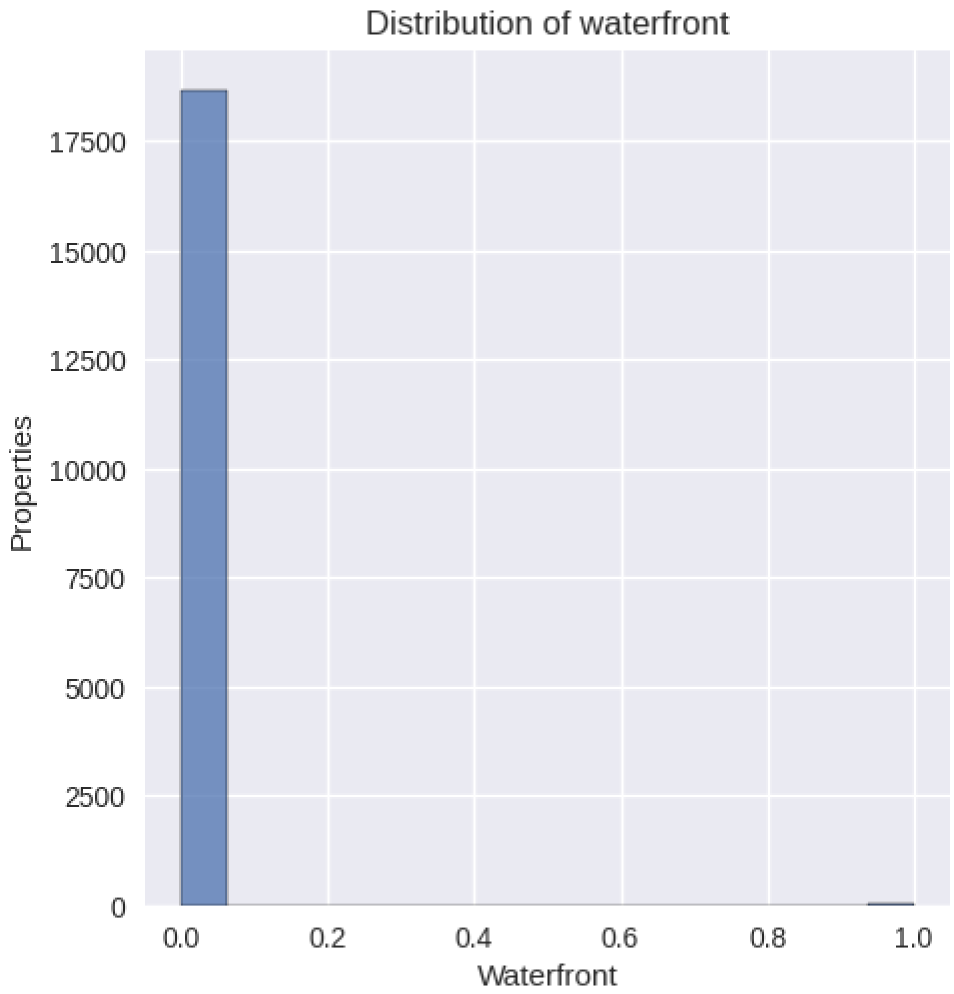
Waterfront

We explore how the `waterfront` feature influnces the price of a house.

In [50]:
```
df.waterfront.unique()
```

Out[50]:
```
array([0, 1])
```

In [51]:
```
# Distribution of waterfront feature
sns.displot(data=df, x='waterfront')
plt.title('Distribution of waterfront')
plt.xlabel('Waterfront')
plt.ylabel('Properties')
plt.show()
```



Majority of the properties do not have a waterfront

In [52]:
```
# Plot boxplot of waterfront feature
sns.boxplot(x = df['waterfront'], y = df['price'])
plt.title("Boxplot of waterfront feature vs. price")
plt.ylabel("price in USD")
plt.xlabel(None)
plt.xticks(np.arange(2), ('No view of waterfront', 'Waterfront view'))
plt.show()
```

In [53]:
```
waterfrontmean = df[df['waterfront'] == 1]['price'].mean()
nowaterfrontmean = df[df['waterfront'] == 0]['price'].mean()
print(f"The mean  price for a house with waterfront  is  {round(waterfrontmean,2)} USD")
print(f"The mean  price for a house without waterfront is  {round(nowaterfrontmean,2)} USD")
print(f"Percentage of houses with waterfront is: {len(df[df['waterfront'] == 1])/len(df)*100}")
```

```
The mean  price for a house with waterfront  is  904180.26 USD
The mean  price for a house without waterfront is  482923.21 USD
Percentage of houses with waterfront is: 0.20344790662811862
```

Conclusion

Waterfront has a significant effect on the price with the mean price of houses with waterfront being almost double of those without. However only about 0.20% of houses have a waterfront.

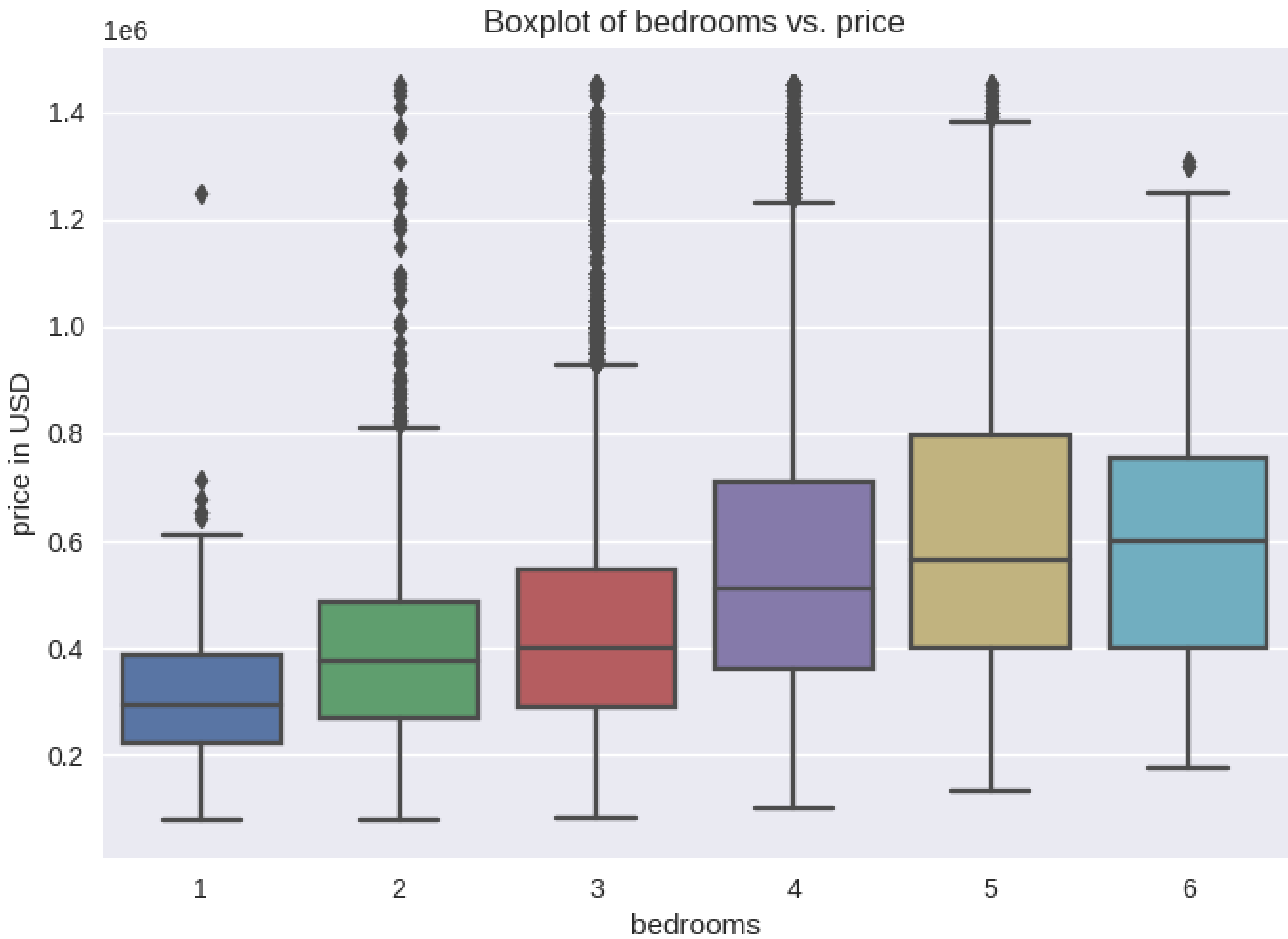
House features

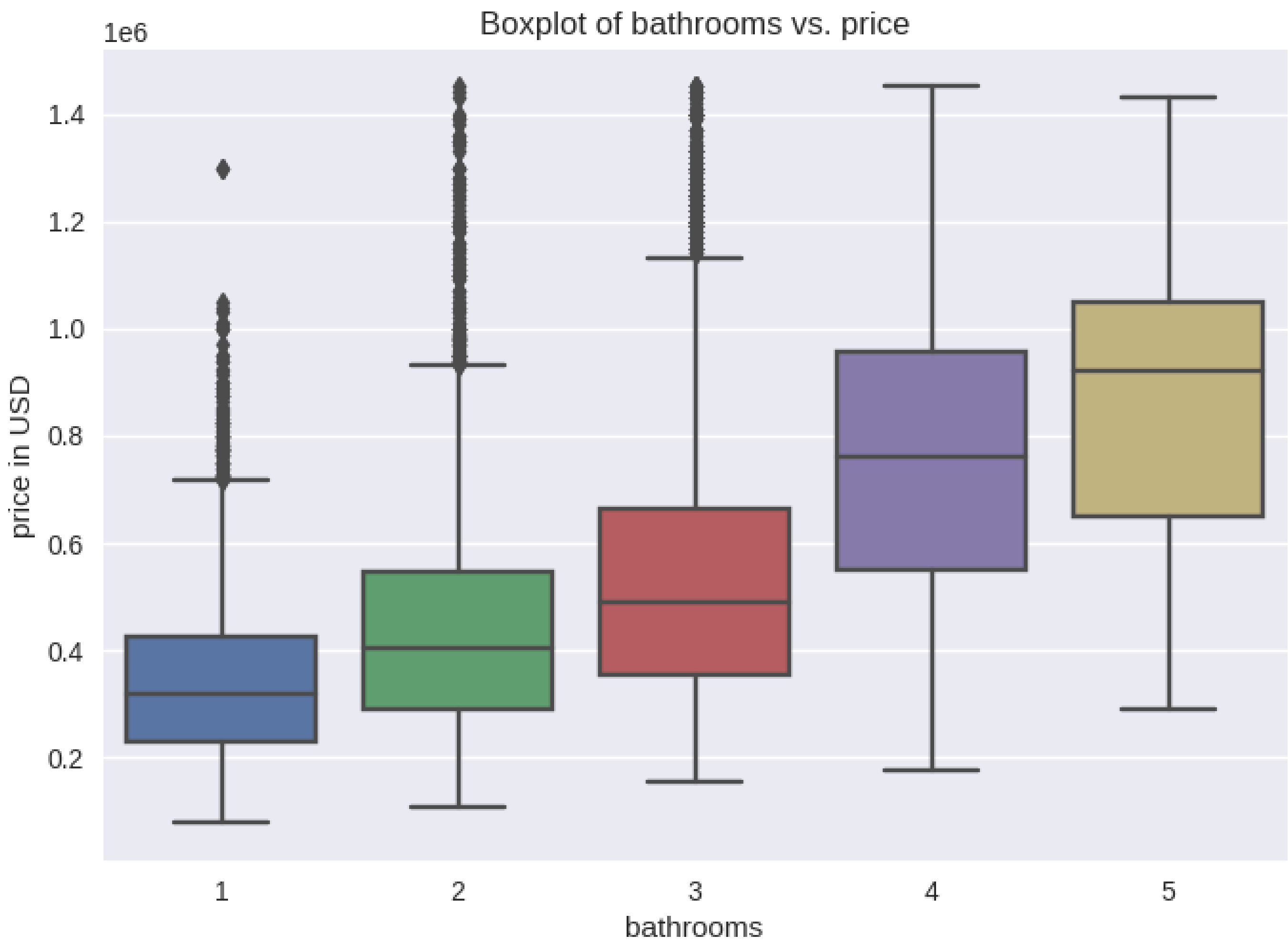
These are the features that can be considered to be 'attached' to the house.

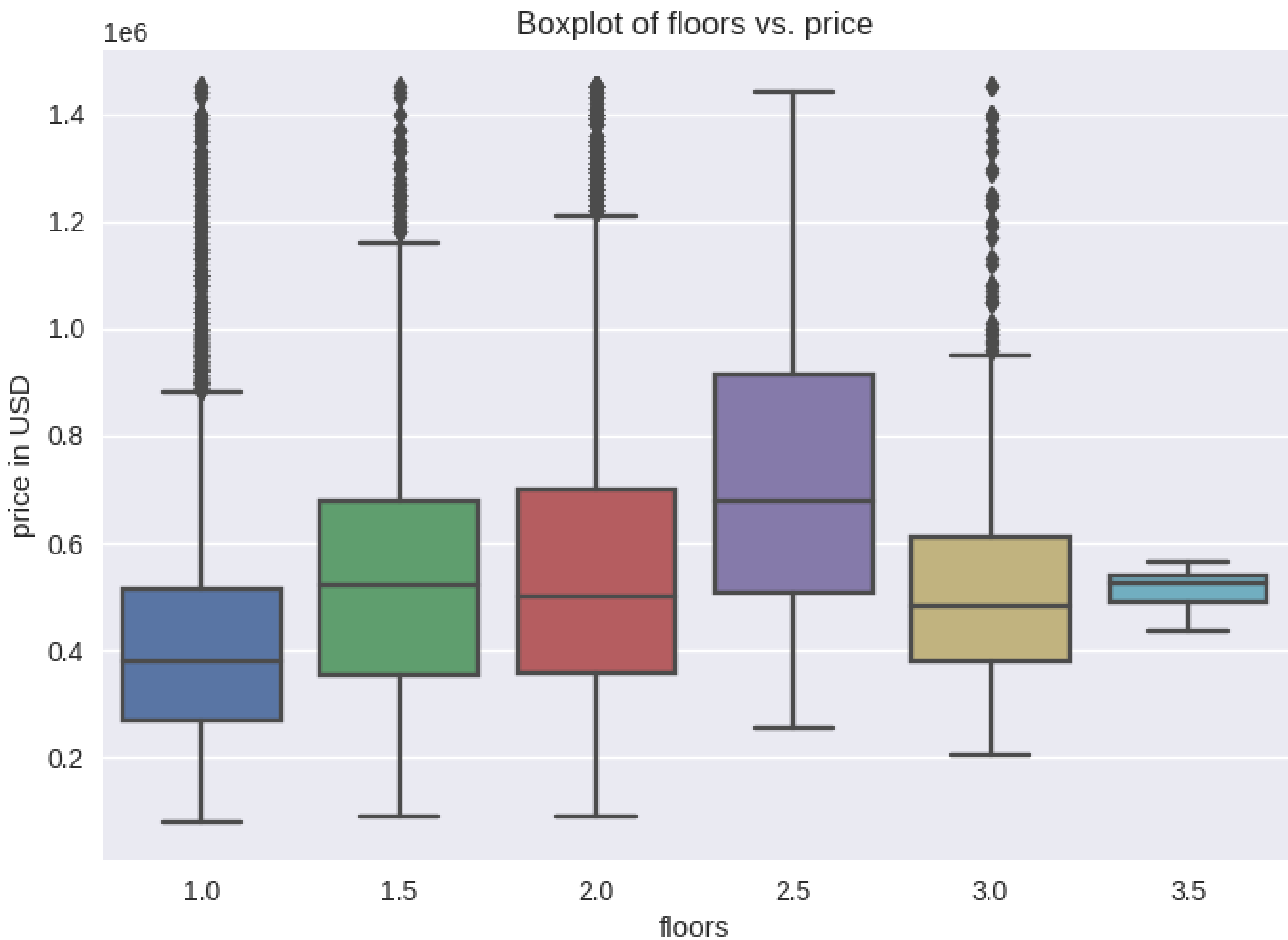
In [54]:
```
df.columns
```

Out[54]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

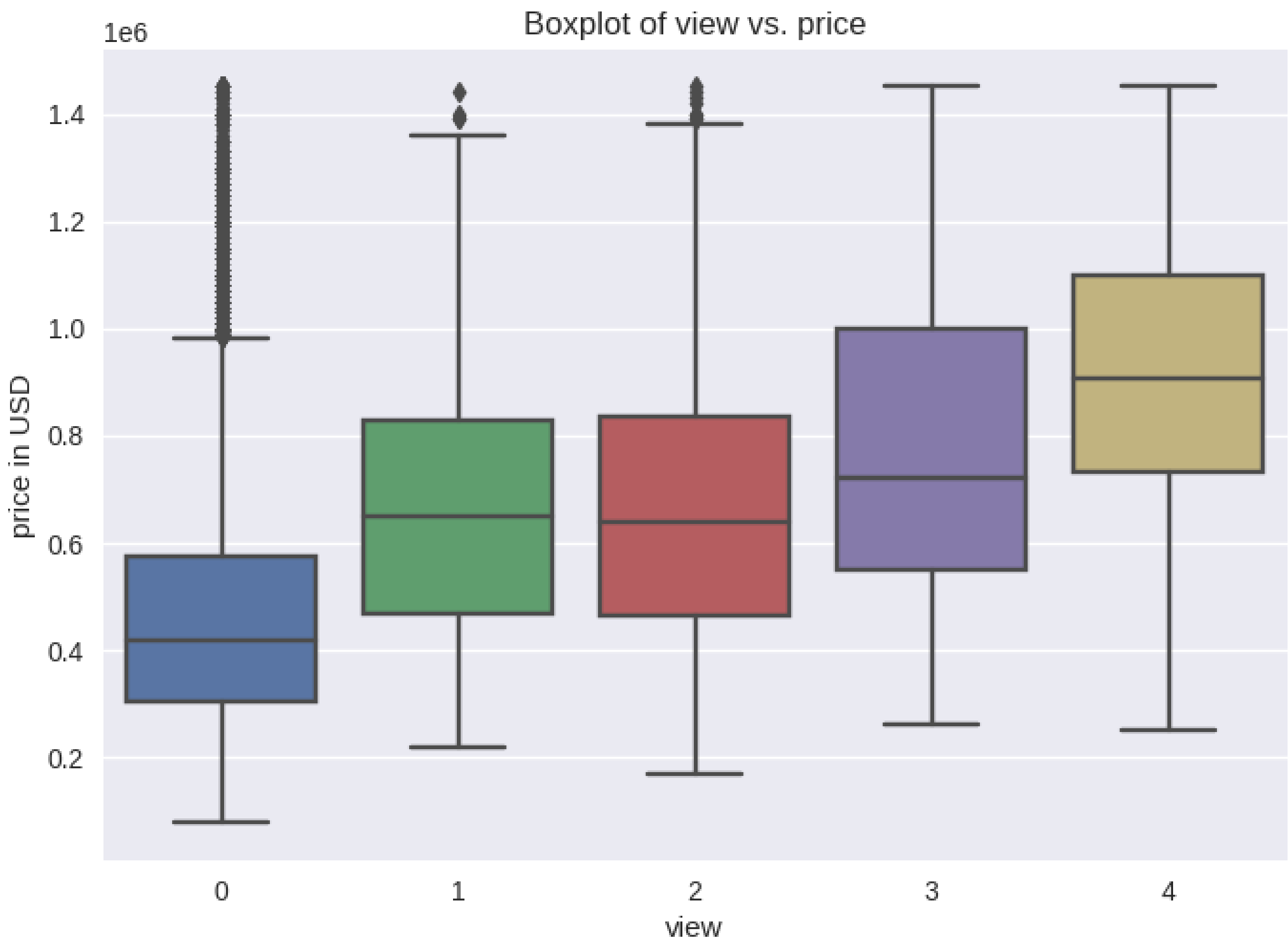
In [55]:
```
# categorical variables
features = ['bedrooms', 'bathrooms', 'floors', 'view', 'grade', 'condition']

# plot boxplots
for feature in features:
    sns.boxplot(x = df[feature], y = df['price'])
    plt.title(f"Boxplot of {feature} vs. price")
    plt.ylabel("price in USD")
    plt.xlabel(f"{feature}")
    plt.show()
```

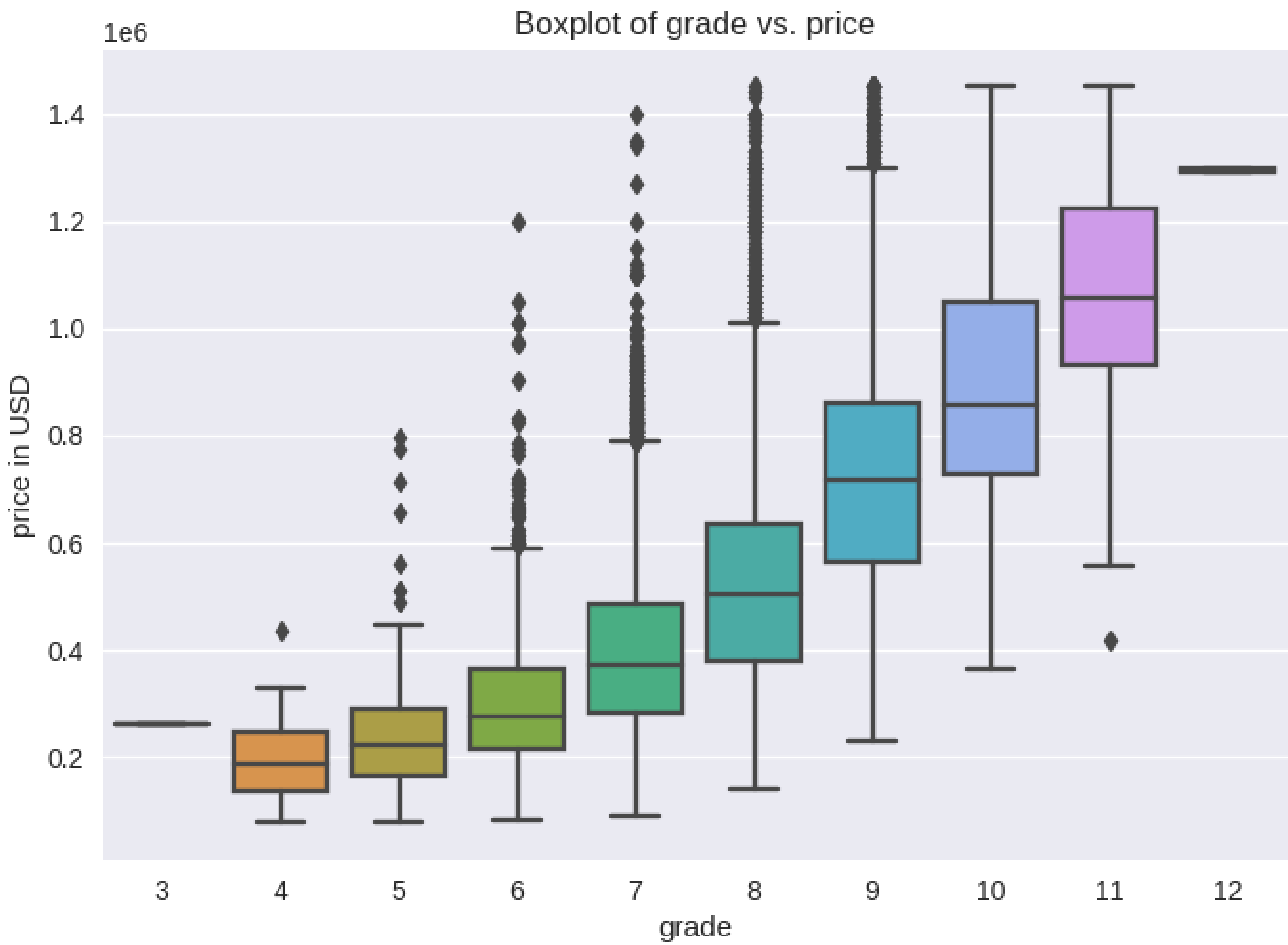


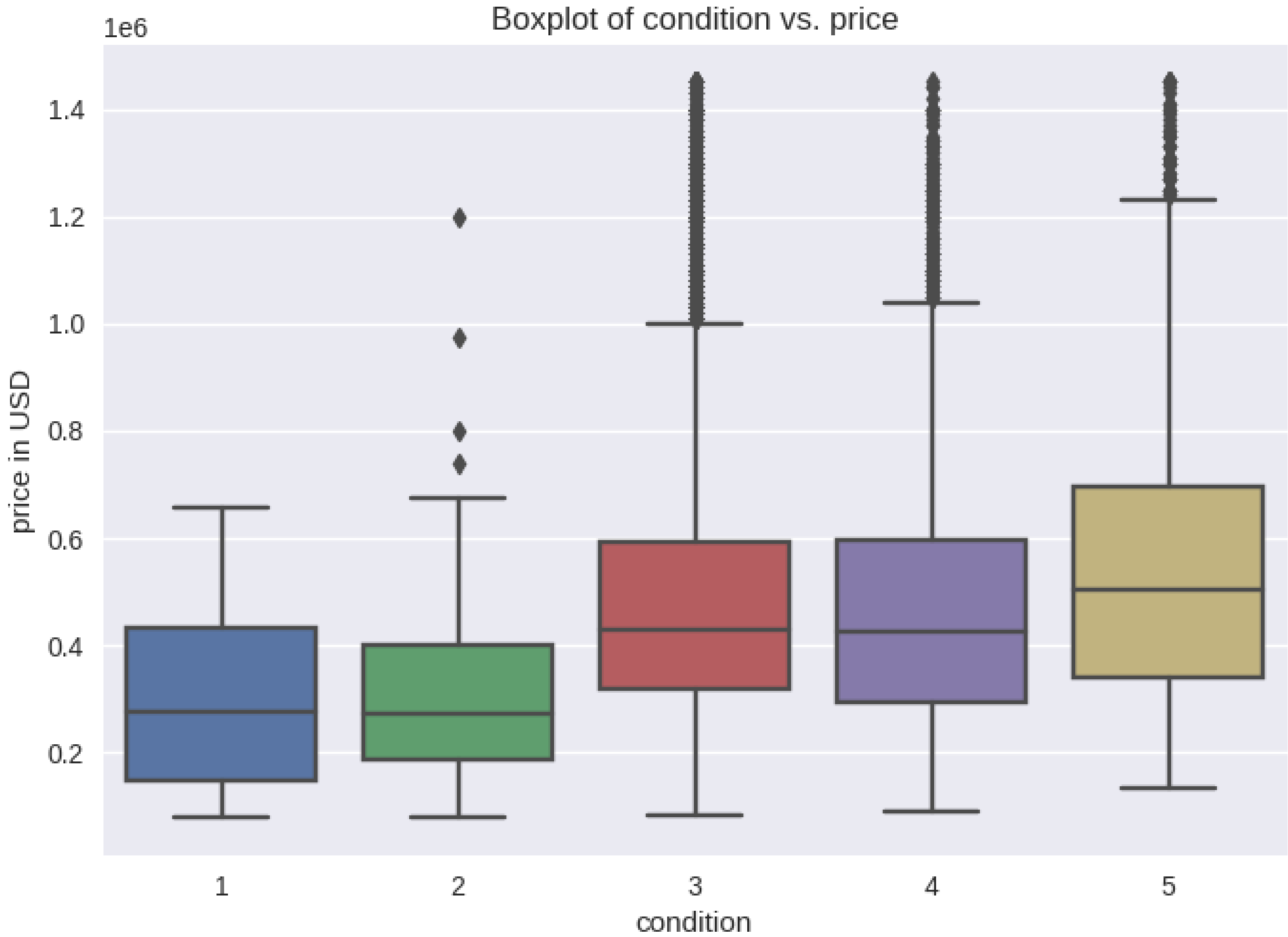

Boxplot of bathrooms vs. price
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price in USD
1
2
3
4
5
bathrooms



Boxplot of floors vs. price
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price in USD
1.0
1.5
2.0
2.5
3.0
3.5
floors


Boxplot of view vs. price
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price in USD
0
1
2
3
4
view


Boxplot of grade vs. price
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price in USD
3
4
5
6
7
8
9
10
11
12
grade



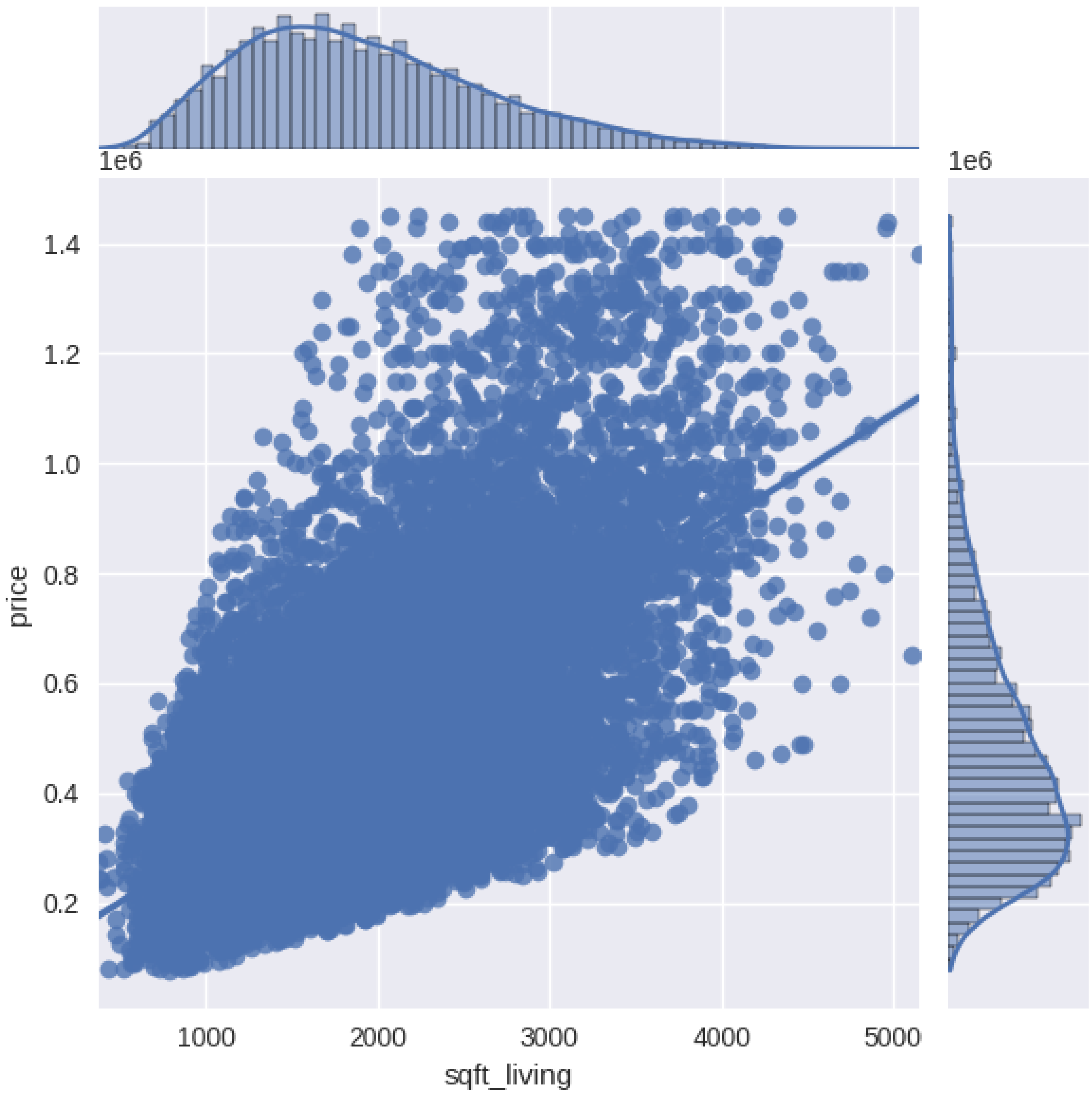
As `bedrooms` increase so does the `price`. `5` bedrooms seem to be the most preferred.
As the `bathrooms` increase the price increases.
`Floors` also seem to affect the price and `2.5` seems to be the most common.
The `view` also increases the price with `4: Excellent` being the most expensive.
The `grade` is affecting the price increase.

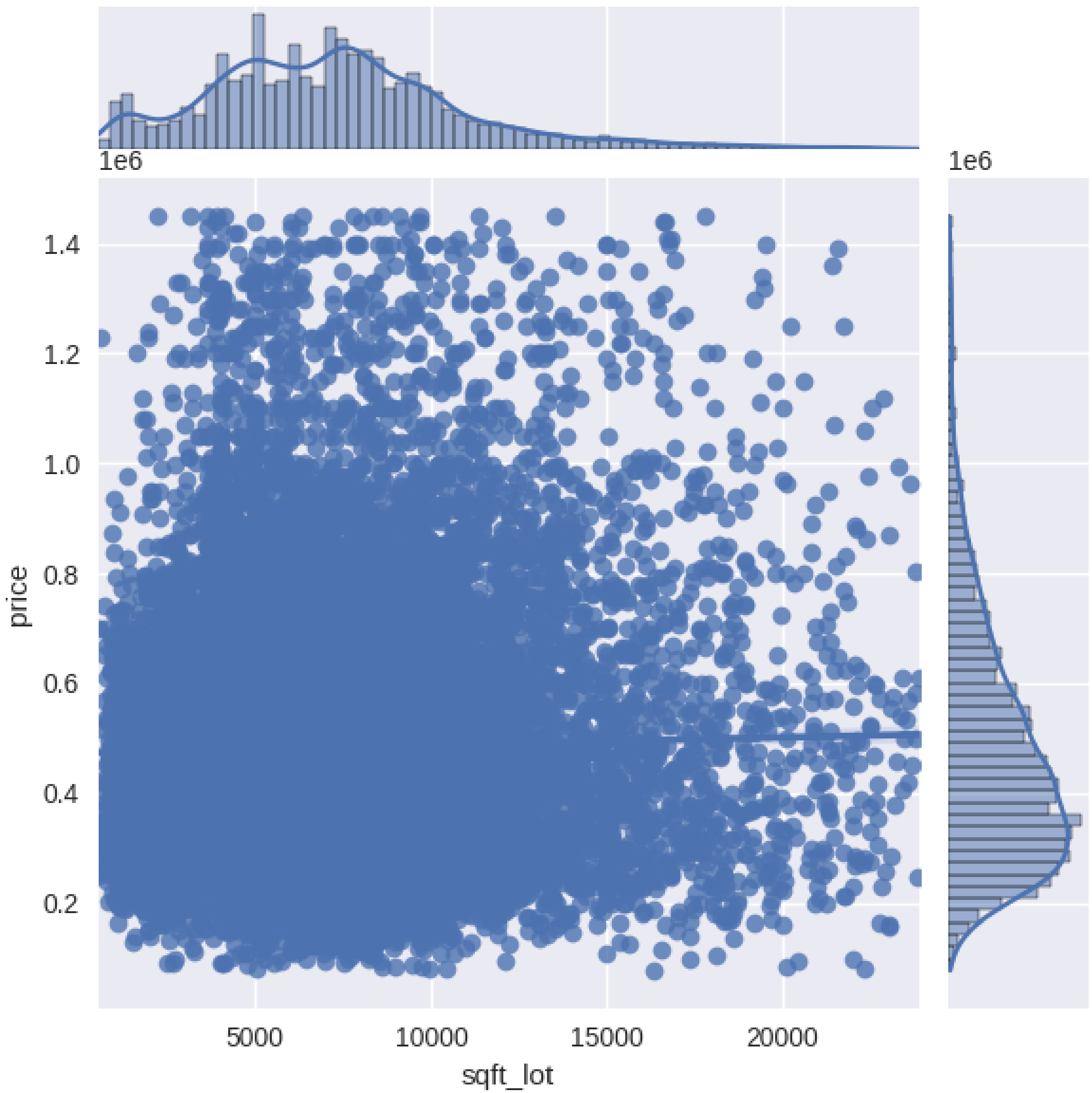
Preparing data for modelling

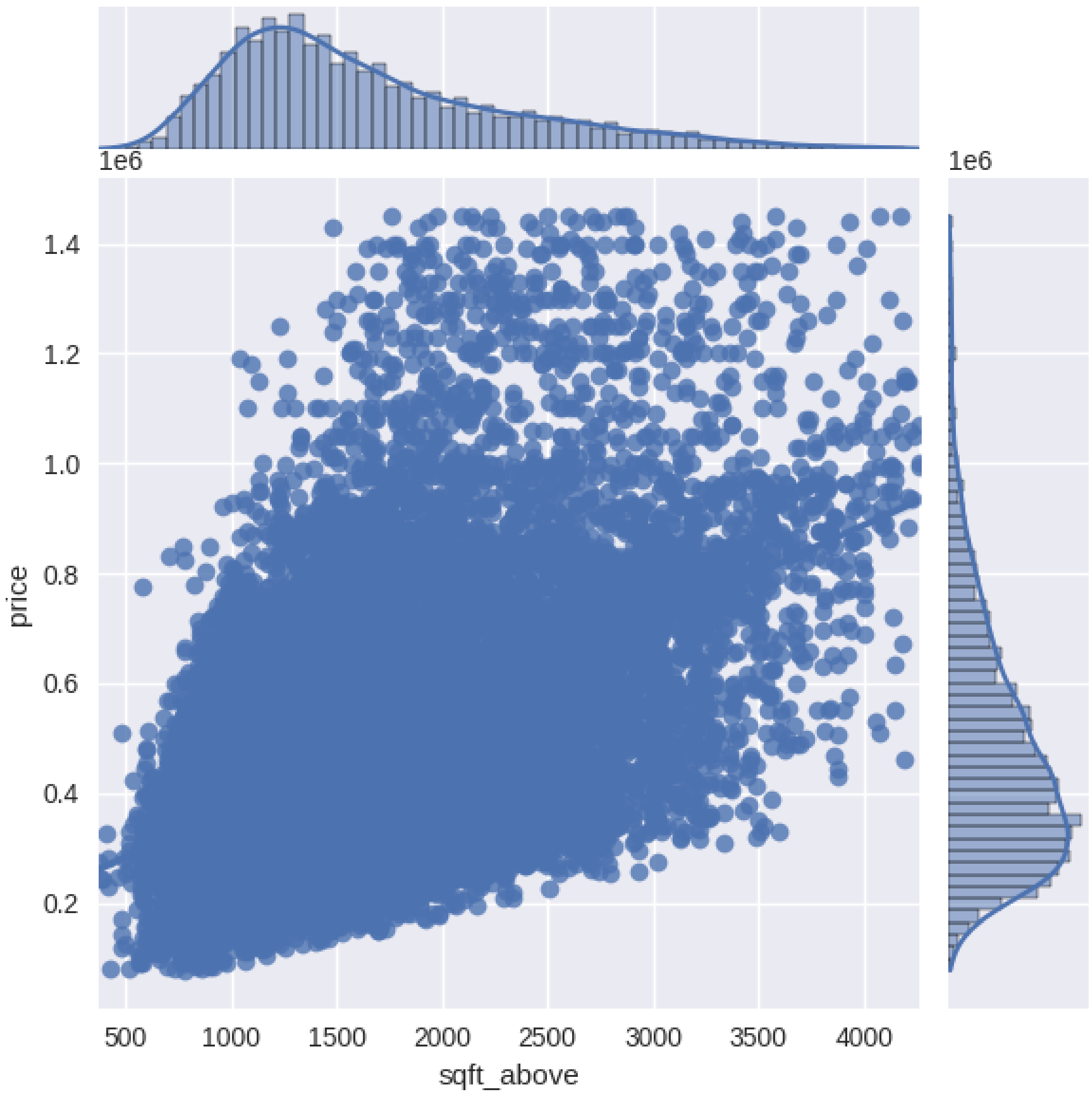
Investigate for linearity assumption

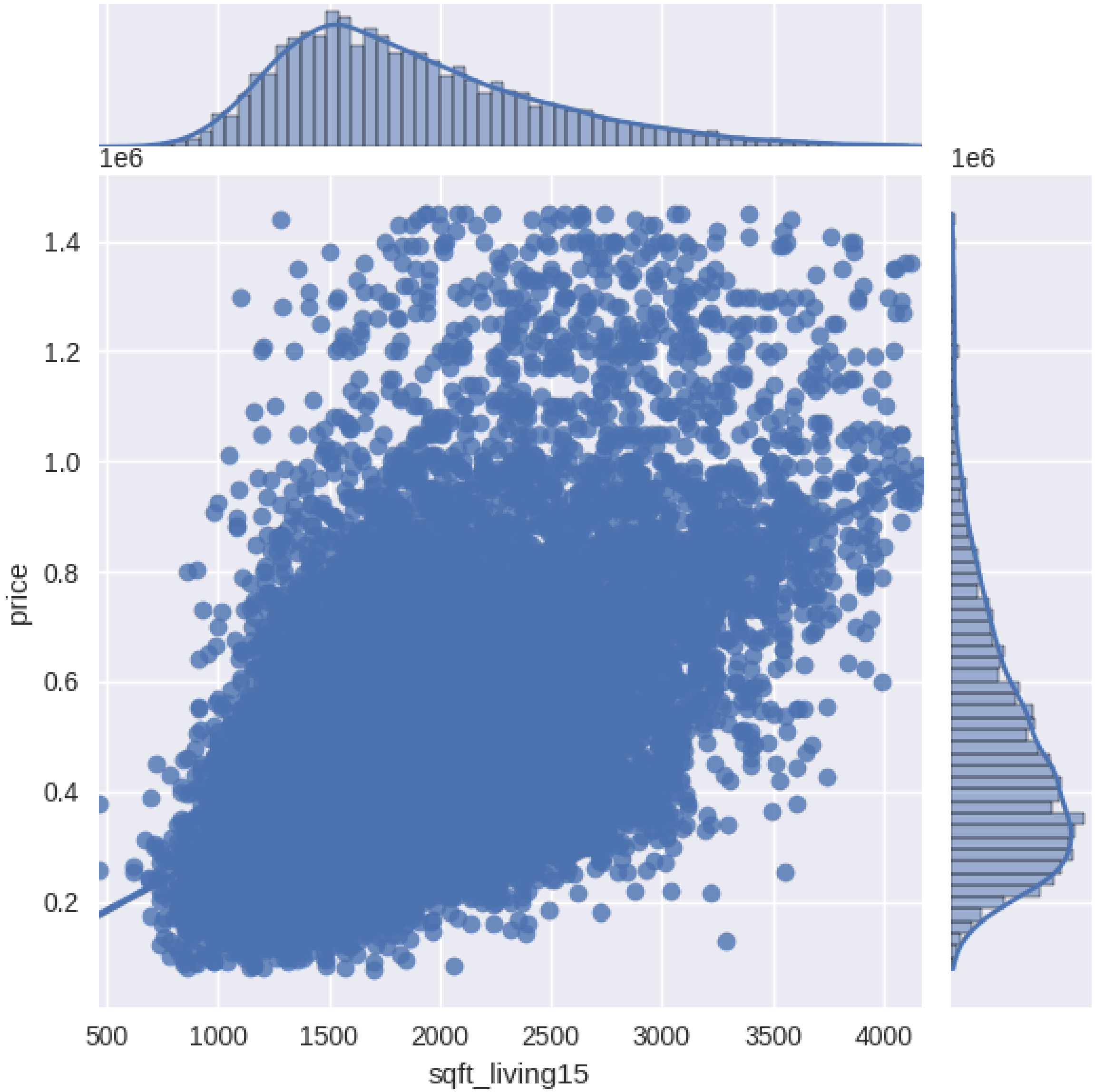
We would like to investigate the relationship between `price` and the continuous variables in our data. We will use seaborn's `jointplot` to inspect linearity and distributions.

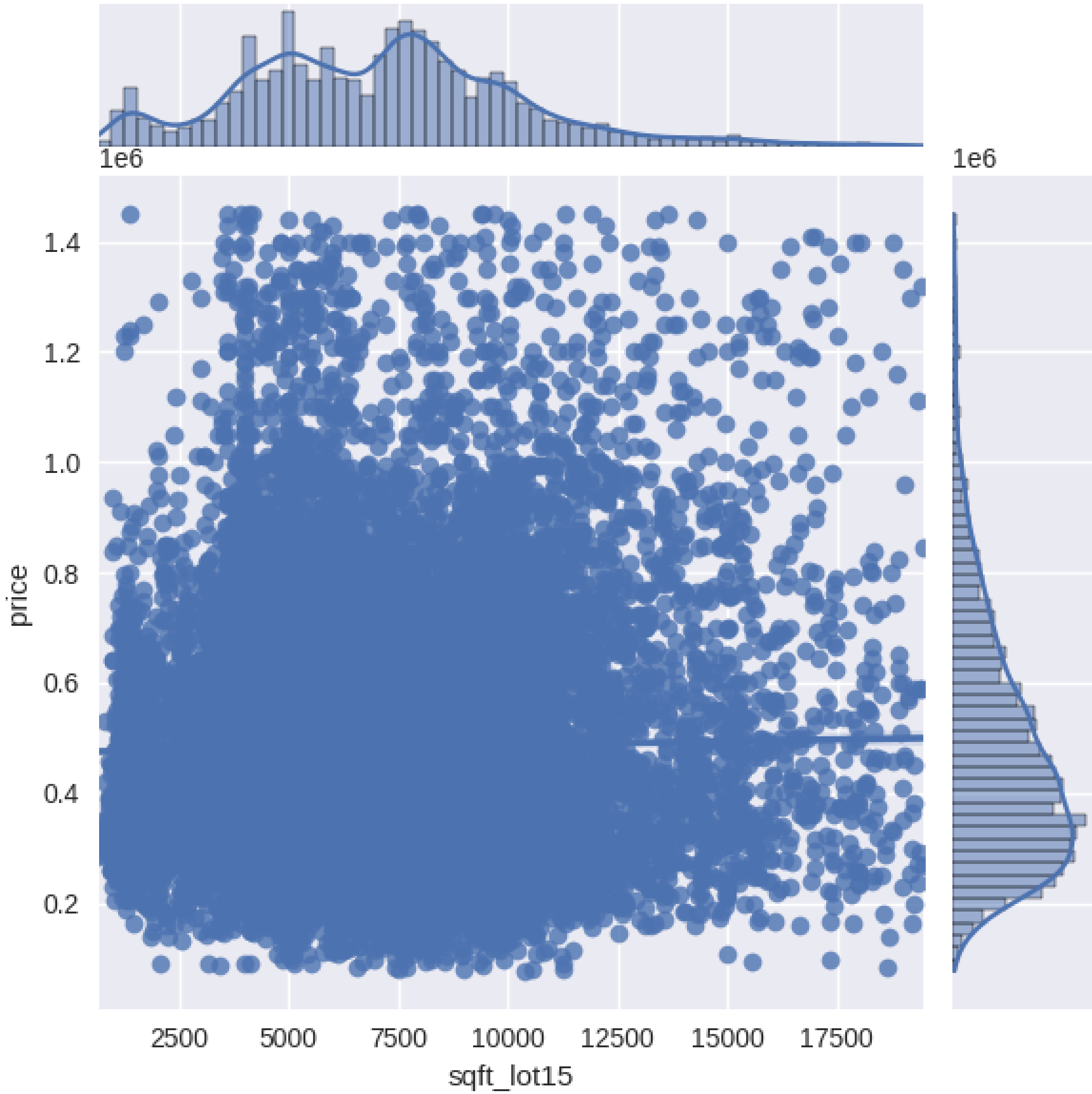
In [56]:
```
# continuous variables
features = ['sqft_living', 'sqft_lot', 'sqft_above', 'sqft_living15', 'sqft_lot15']


#  Plot jointplots
for feature in features:
    sns.jointplot(x = df[feature], y = df['price'], kind = 'reg')
    plt.show()
```


1e6
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price
1000
2000
3000
4000
5000
sqft_living


1e6
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price
5000
10000
15000
20000
sqft_lot


1e6
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price
500
1000
1500
2000
2500
3000
3500
4000
sqft_above


1e6
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
price
500
1000
1500
2000
2500
3000
3500
4000
sqft_living15



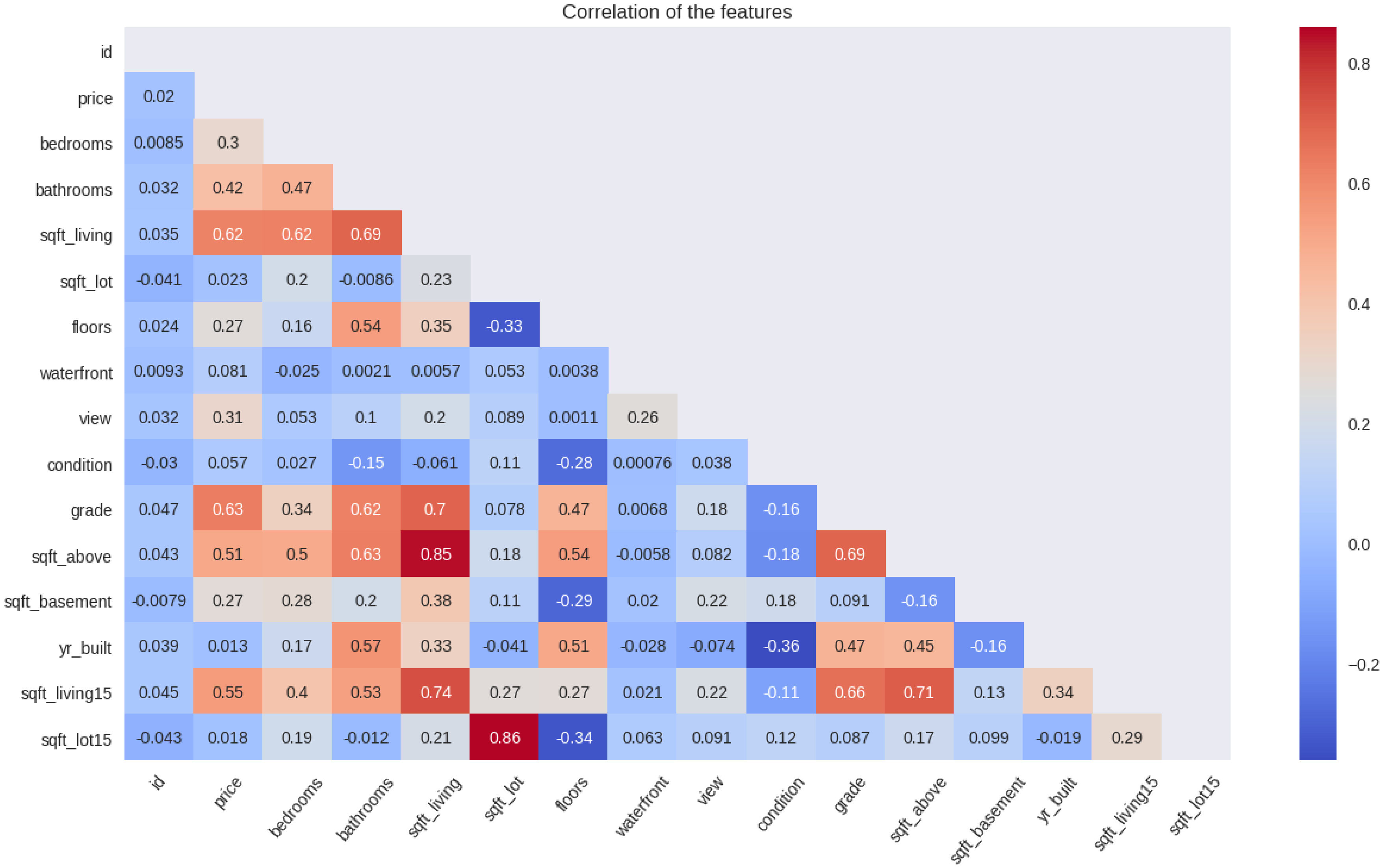
The features appear to be linear. Multicollinearity will be explored further. `sqft_living` and `sqft_above` show the best linearity with respect to `price` .

Investigating for multicollinearity

We will use a correlation heatmap to investigate

In [57]:
```
# dropping columns we will not need.
cor_df = df.drop(['yr_renovated','zipcode','lat','long'], axis=1)
```

In [58]:
```
fig, ax = plt.subplots(figsize = (15,8))
mask = np.triu(np.ones_like(cor_df.corr()))
sns.heatmap(cor_df.corr(), cmap="coolwarm", annot=True, mask=mask)
plt.title('Correlation of the features')
plt.xticks(rotation=50)
plt.show()
```



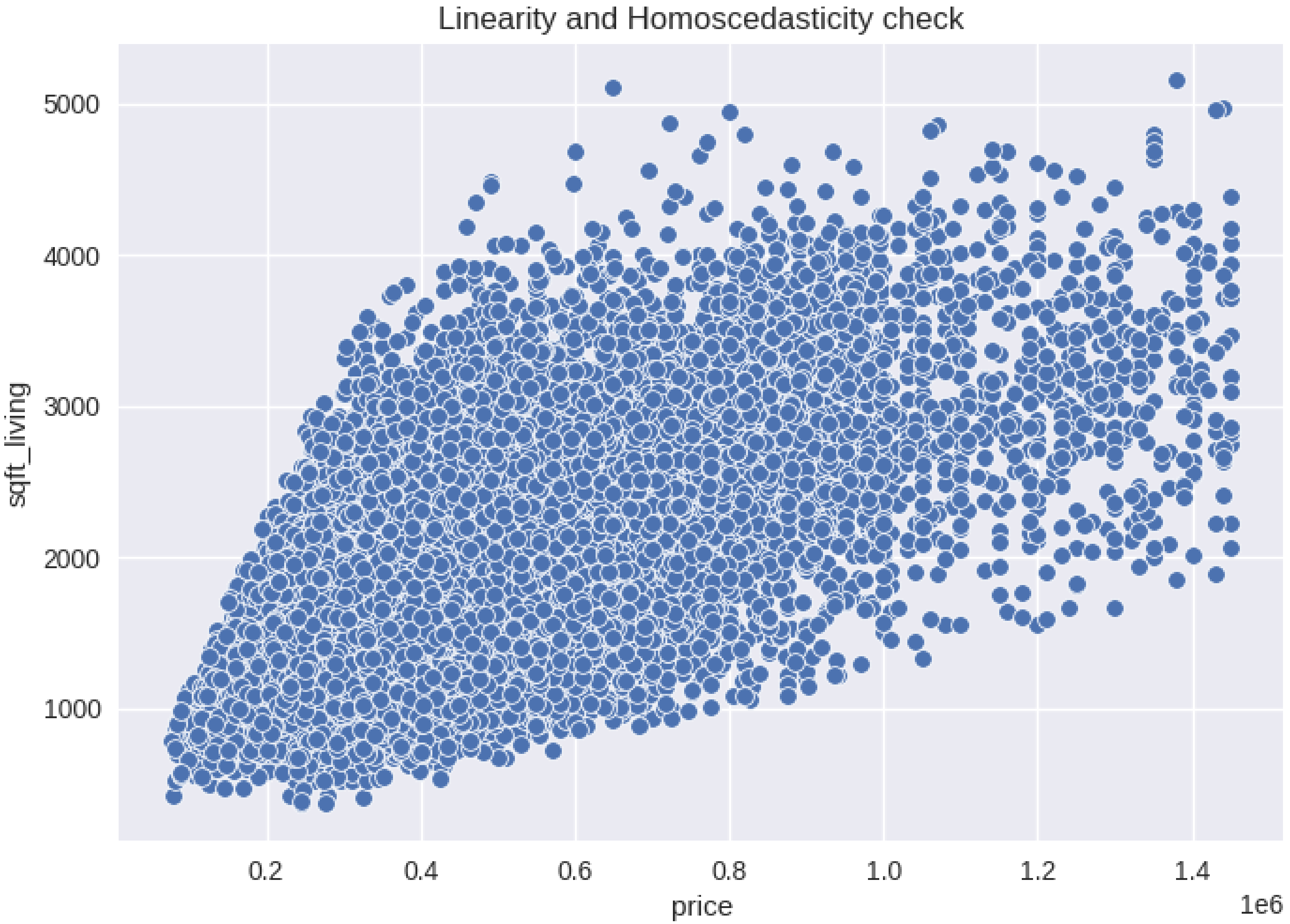
There are multicollinearity issues which must be solved. `sqft_above` and `sqft_living` have a high correlation which is not a surprise because `sqft_above` is the square footage of the house apart from basement.
We will keep `sqft_living` because it has more information and then drop `sqft_above` and `sqft_living15` .
`sqft_lot` and `sqft_lot15` have a high correlation and we will keep `sqft_lot` as it is related to the property directly.

In [59]:
```
# removing the features
df = df.drop(['sqft_above', 'sqft_living15', 'sqft_lot15'], axis = 1)
```

Modelling

Basic Model sqft_living

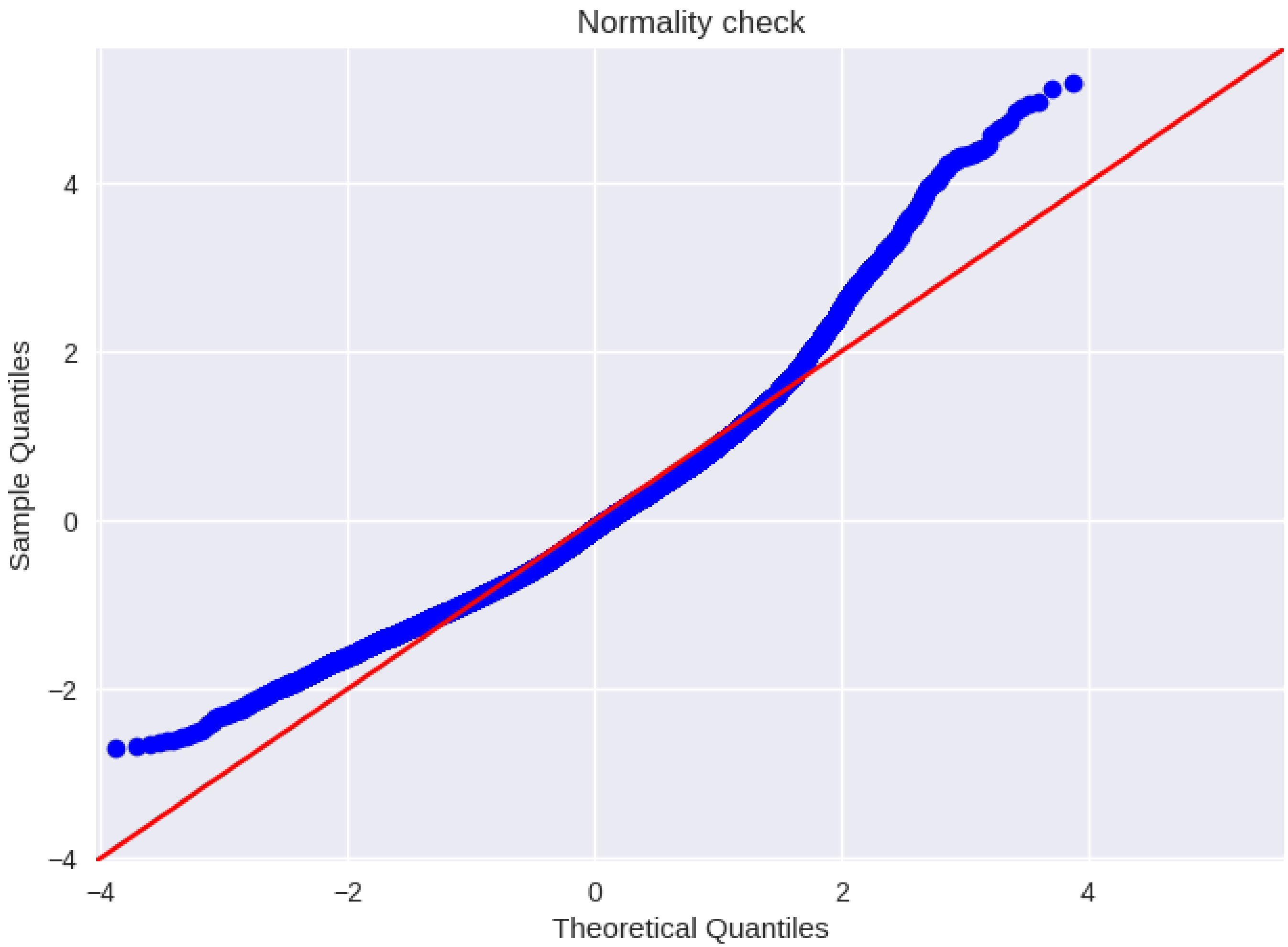
In [60]:
```
# check for linearity and Homoscedasticity
sns.scatterplot(x=df['price'], y=df['sqft_living'])
plt.title("Linearity and Homoscedasticity check");
```



In [61]:
```
# create predictors
predictors = df['sqft_living']
# create model intercept
predictors_int = sm.add_constant(predictors)
# fit model
baseline_model = sm.OLS(df['price'], predictors_int).fit()

# check model
print(baseline_model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.384
Model:                            OLS   Adj. R-squared:                  0.384
Method:                 Least Squares   F-statistic:                 1.165e+04
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        07:50:46   Log-Likelihood:            -2.5291e+05
No. Observations:               18678   AIC:                         5.058e+05
Df Residuals:                   18676   BIC:                         5.058e+05
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        1.025e+05   3780.585     27.109      0.000    9.51e+04     1.1e+05
sqft_living   197.4017      1.829    107.916      0.000     193.816     200.987
==============================================================================
Omnibus:                     2452.438   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4263.774
Skew:                           0.878   Prob(JB):                         0.00
Kurtosis:                       4.548   Cond. No.                     5.81e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.81e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [62]:
```
# check normality assumption

residuals = baseline_model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```

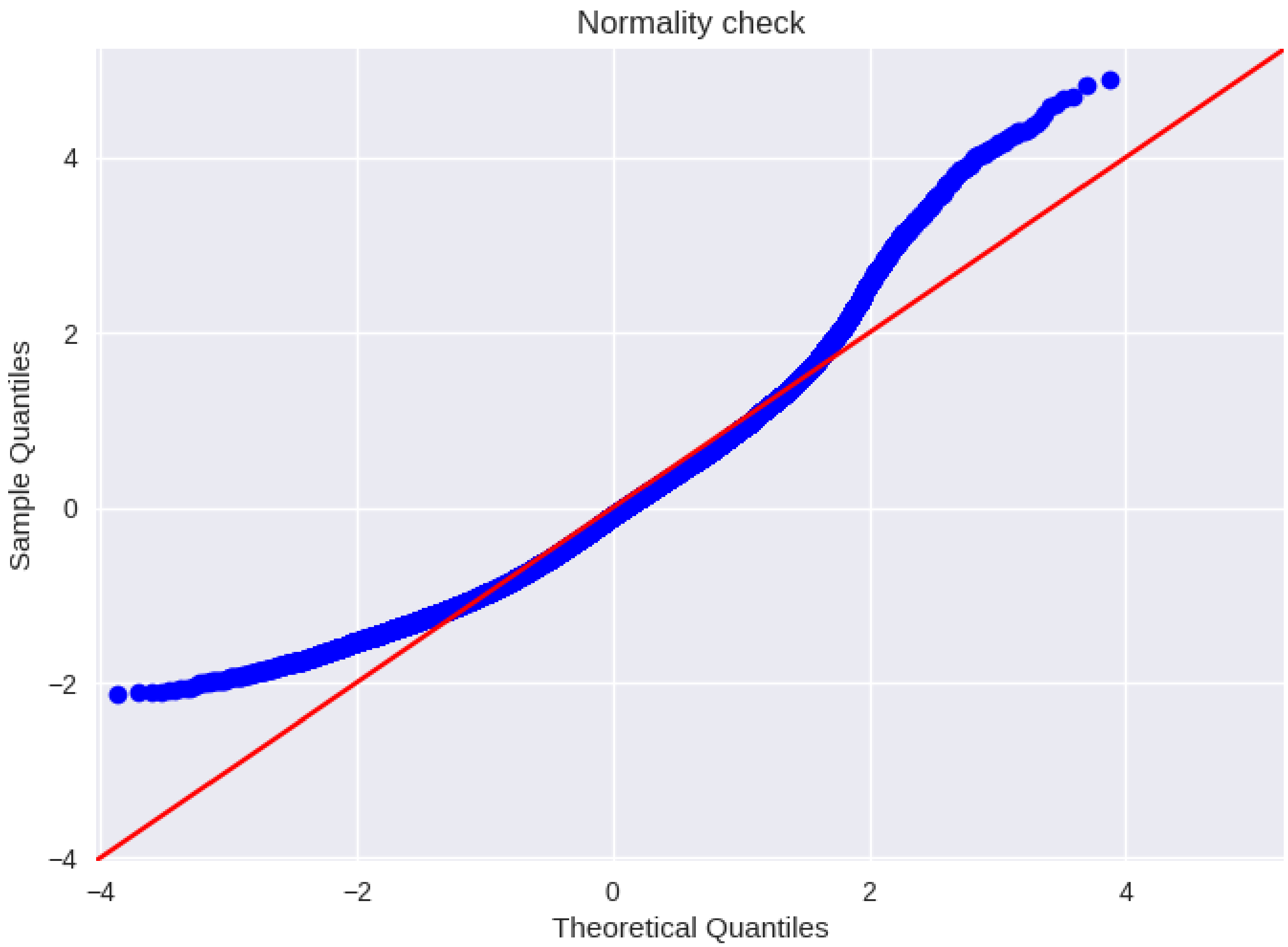


So we see that 2/3 of the assumptions of linearity are violated here - the residuals aren't normally distributed, and the data isn't homoscedastic. We'll get a summary of the model as is, see if performing a log transformation on price and `sqft_living` will help with these conditions, and then see if adding in some other variables to our model will improve our R^2 .

In [64]:
```
# apply logarithmic function to independant variable
df['log_sqft_living'] = np.log(df['sqft_living'])


# re-create the model with `log_sqft_living`
# create predictors
predictors = df['log_sqft_living']
# create model intercept
predictors_int = sm.add_constant(predictors)
# fit model
log_model1 = sm.OLS(df['price'], predictors_int).fit()

# check model
print(log_model1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.343
Model:                            OLS   Adj. R-squared:                  0.343
Method:                 Least Squares   F-statistic:                     9735.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        07:50:46   Log-Likelihood:            -2.5352e+05
No. Observations:               18678   AIC:                         5.070e+05
Df Residuals:                   18676   BIC:                         5.071e+05
Df Model:                           1
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
const           -2.157e+06   2.68e+04    -80.485      0.000   -2.21e+06    -2.1e+06
log_sqft_living  3.525e+05   3572.479     98.667      0.000    3.45e+05    3.59e+05
==============================================================================
Omnibus:                     2466.792   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4065.810
Skew:                           0.907   Prob(JB):                         0.00
Kurtosis:                       4.391   Cond. No.                         147.
==============================================================================

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

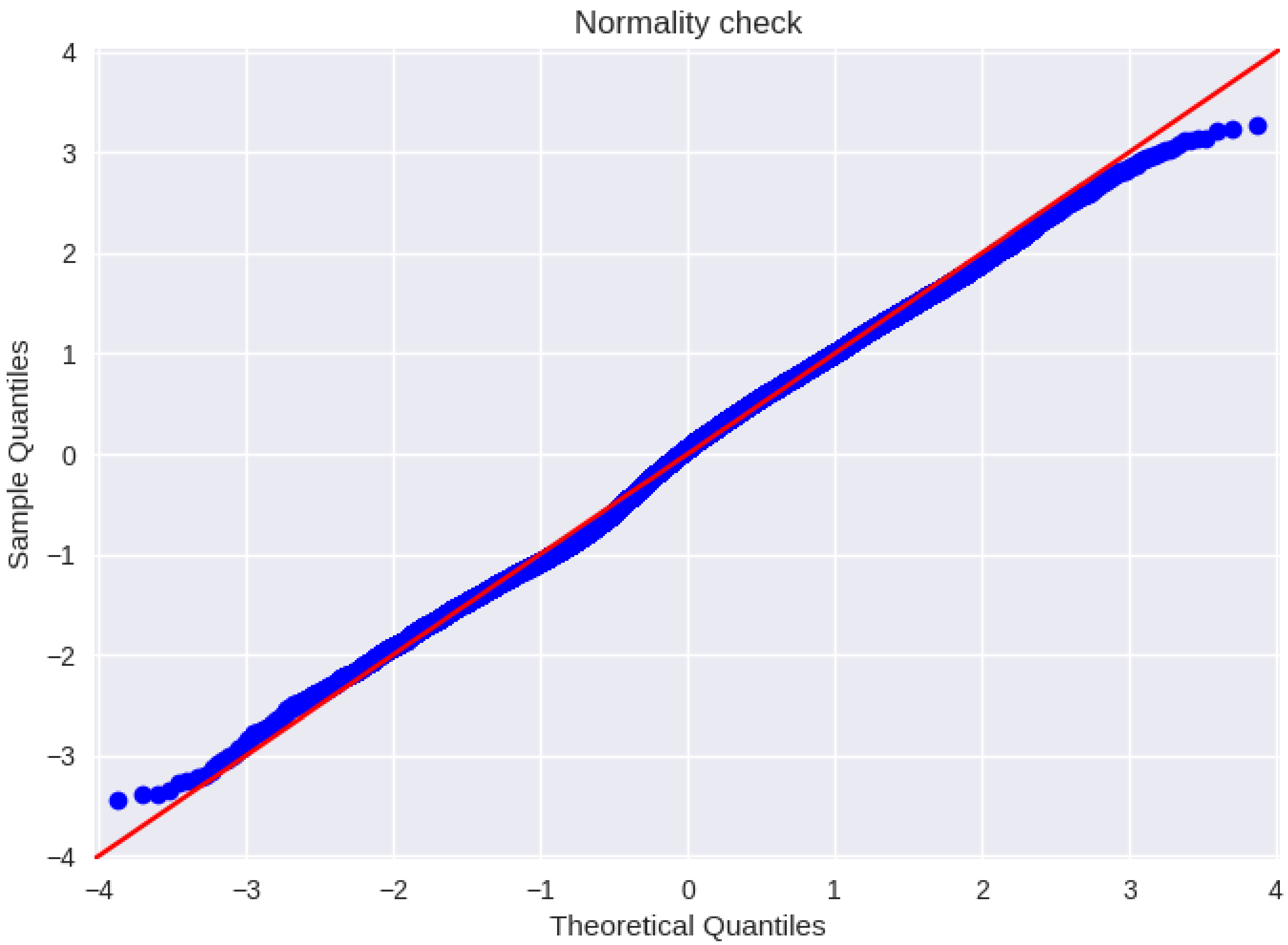
In [65]:
```
residuals = log_model1.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```



In [68]:
```
# apply logarithmic function to dependant variable
df['log_price'] = np.log(df['price'])


# re-create the model with `sqft_living`
# create predictors
predictors = df['sqft_living']
# create model intercept
predictors_int = sm.add_constant(predictors)
# fit model
log_model2 = sm.OLS(df['log_price'], predictors_int).fit()

# check model
print(log_model2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.372
Model:                            OLS   Adj. R-squared:                  0.372
Method:                 Least Squares   F-statistic:                 1.108e+04
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        07:54:15   Log-Likelihood:                -7916.0
No. Observations:               18678   AIC:                         1.584e+04
Df Residuals:                   18676   BIC:                         1.585e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          12.2331      0.008   1608.940      0.000      12.218      12.248
sqft_living     0.0004   3.68e-06    105.243      0.000       0.000       0.000
==============================================================================
Omnibus:                      179.609   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              117.663
Skew:                          -0.038   Prob(JB):                     2.82e-26
Kurtosis:                       2.619   Cond. No.                     5.81e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.81e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [69]:
```
residuals = log_model2.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```



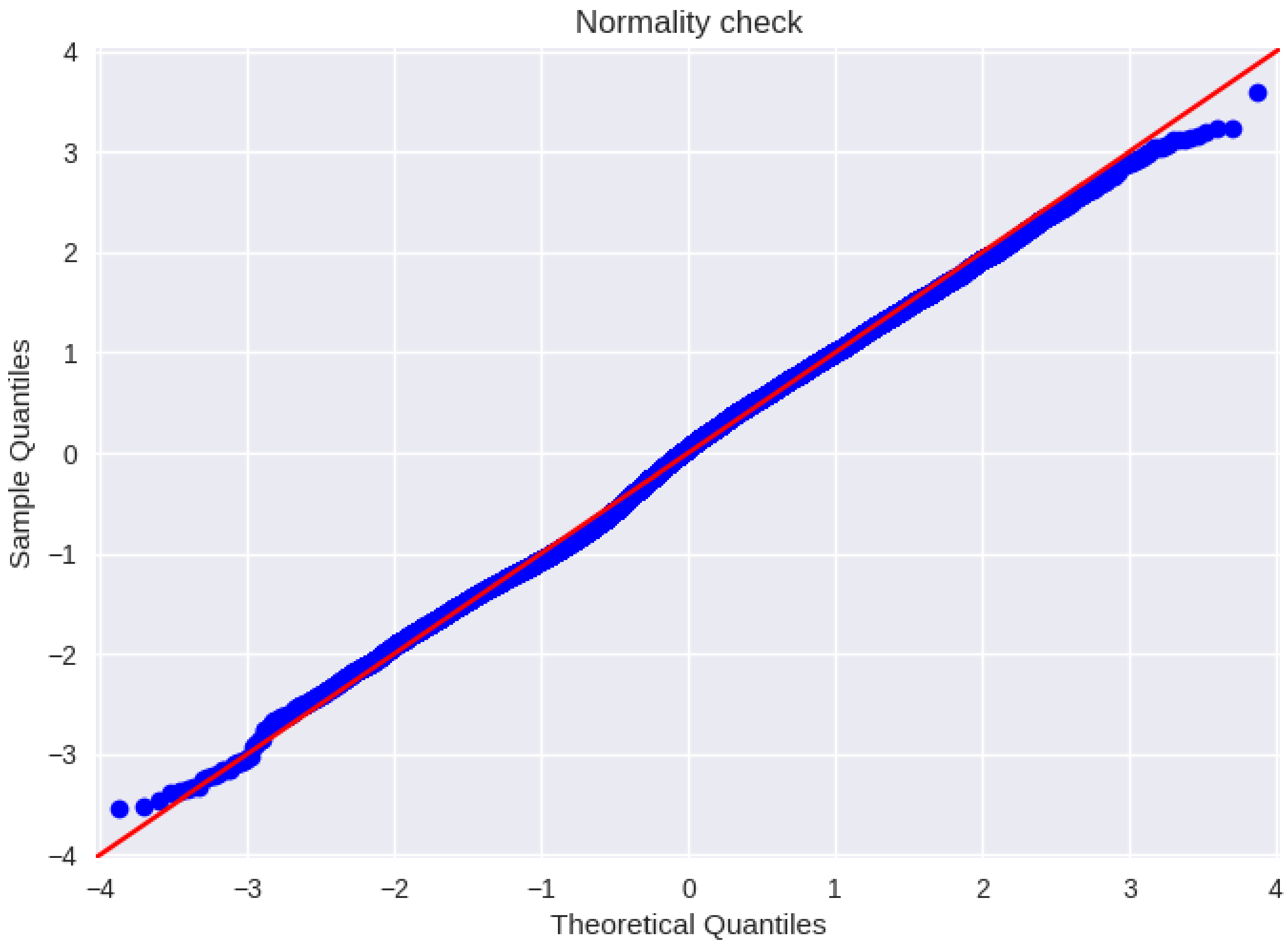
Bedrooms

In [71]:
```
# create predictors
predictors = df[['sqft_living', 'bedrooms']]
# create model intercept
predictors_int = sm.add_constant(predictors)
# fit model
second_model = sm.OLS(df['log_price'], predictors_int).fit()

# check model
print(second_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.381
Model:                            OLS   Adj. R-squared:                  0.381
Method:                 Least Squares   F-statistic:                     5741.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        07:55:21   Log-Likelihood:                -7789.5
No. Observations:               18678   AIC:                         1.558e+04
Df Residuals:                   18675   BIC:                         1.561e+04
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          12.3543      0.011   1153.439      0.000      12.333      12.375
sqft_living     0.0004   4.66e-06     92.996      0.000       0.000       0.000
bedrooms       -0.0634      0.004    -15.959      0.000      -0.071      -0.056
==============================================================================
Omnibus:                      117.586   Durbin-Watson:                   2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               83.564
Skew:                          -0.036   Prob(JB):                     7.15e-19
Kurtosis:                       2.680   Cond. No.                     8.54e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.54e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

So we see here that in this model, our R^2 has dropped a little. That may be due to high multicollinearity between sqft_living and bedrooms.

In [72]:
```python
# check normality assumption

residuals = second_model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```



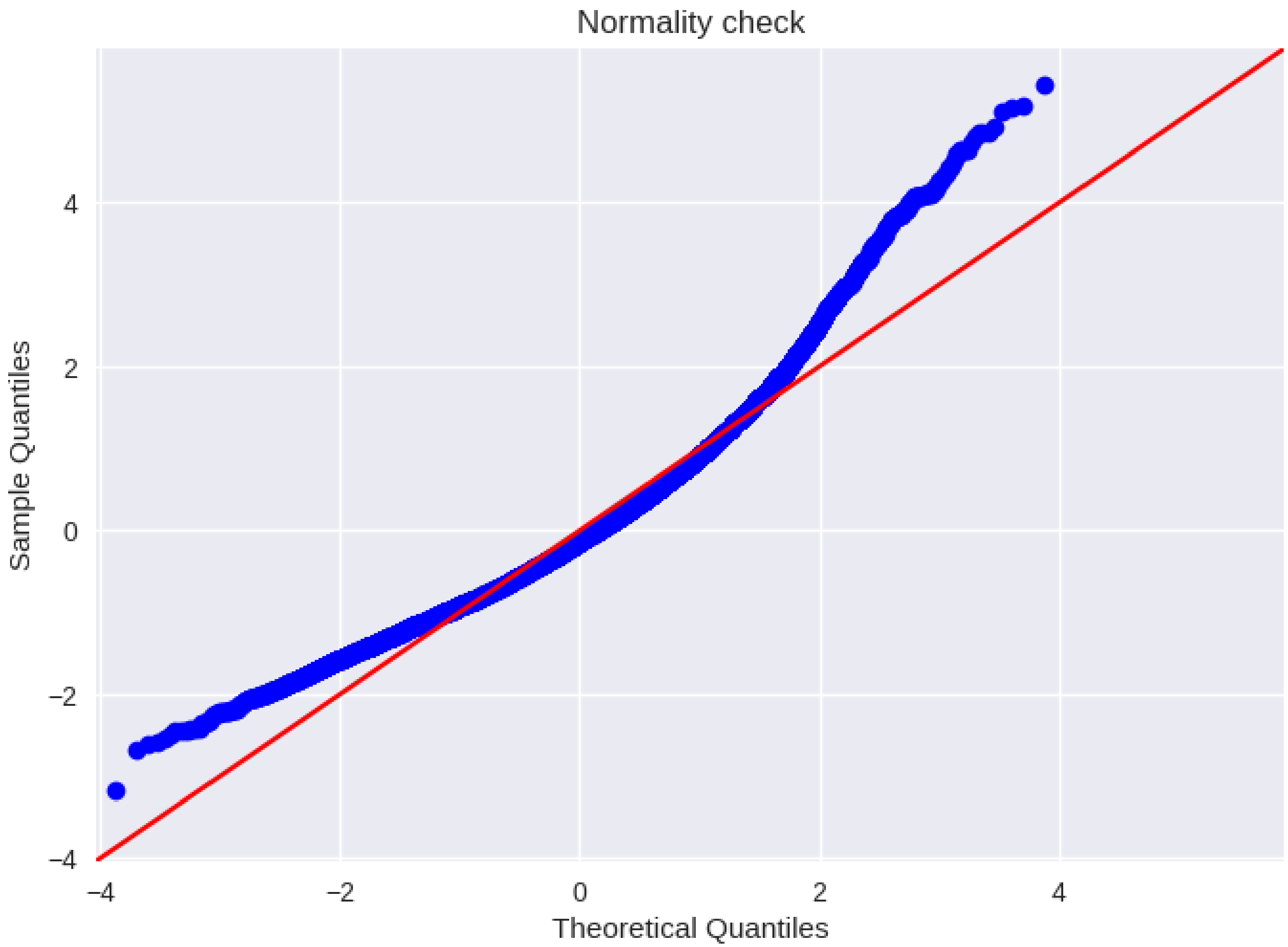
Grade

In [76]:
```
# Creating a simple linear model using grade
y = df["price"]
X = df[["grade"]]
model_grade = sm.OLS(endog=y, exog=sm.add_constant(X))
grade_results = model_grade.fit()
print(grade_results.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.397
Model:                            OLS   Adj. R-squared:                  0.397
Method:                 Least Squares   F-statistic:                 1.230e+04
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        07:57:24   Log-Likelihood:            -2.5271e+05
No. Observations:               18678   AIC:                         5.054e+05
Df Residuals:                   18676   BIC:                         5.054e+05
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -6.139e+05   9987.993    -61.467      0.000   -6.34e+05   -5.94e+05
grade       1.463e+05   1318.935    110.892      0.000    1.44e+05    1.49e+05
==============================================================================
Omnibus:                     2845.280   Durbin-Watson:                   1.960
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5209.713
Skew:                           0.974   Prob(JB):                         0.00
Kurtosis:                       4.702   Cond. No.                         57.8
==============================================================================

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

- The model explains about 40% of the variance in price
- The model coefficient grade is all statistically significant, with t-statistic p-values well below 0.05

In [78]:
```
# check normality assumption

residuals = grade_results.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```

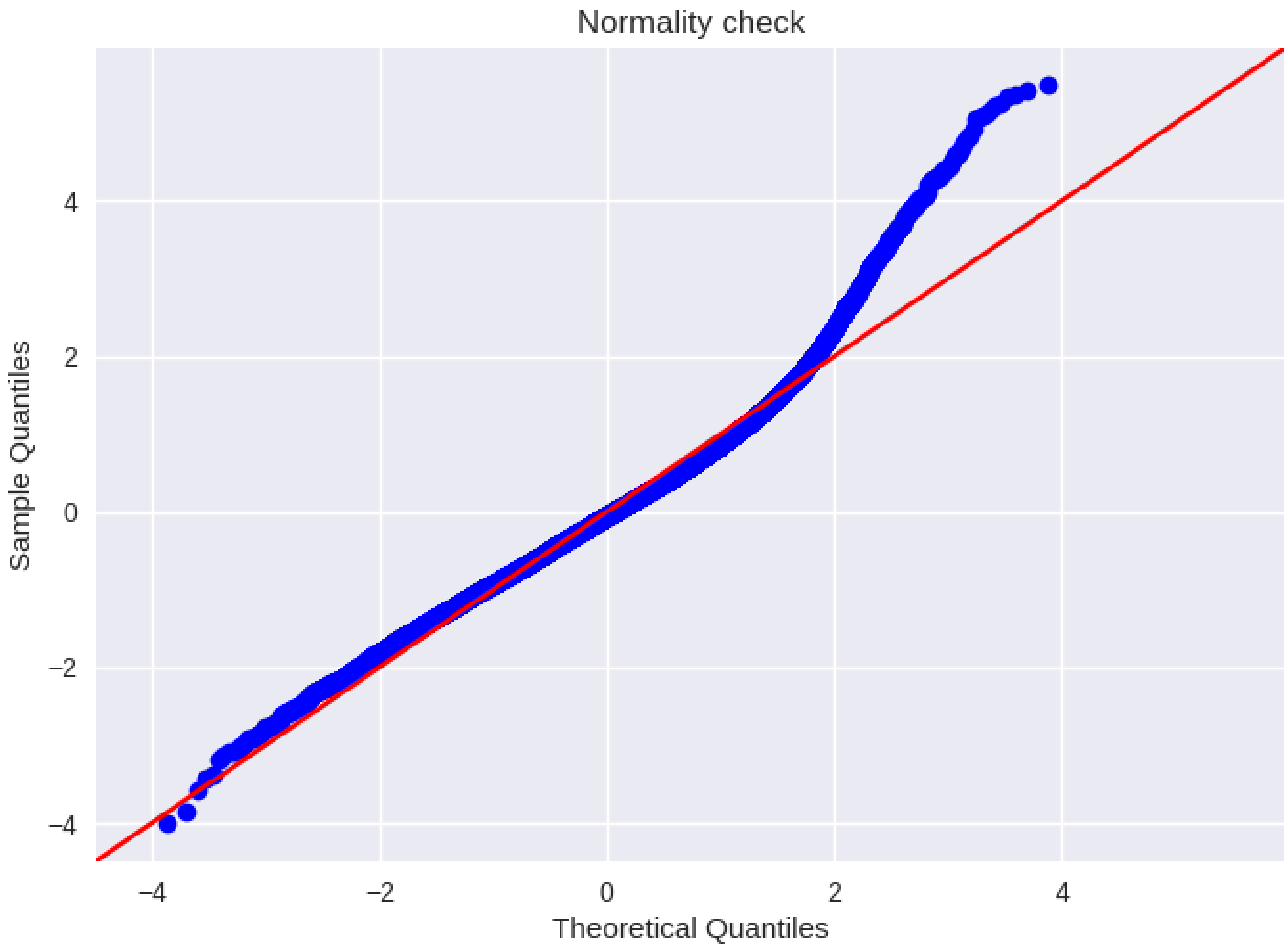


Multiple Linear Regression

In [82]:
```
X = df[['sqft_living','bedrooms','yr_built','grade']]
y = df['price']
predictors_int = sm.add_constant(X)
# fit model
multilinear = sm.OLS(df['price'], predictors_int).fit()

# check model
print(multilinear.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.568
Model:                            OLS   Adj. R-squared:                  0.567
Method:                 Least Squares   F-statistic:                     6126.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        08:00:01   Log-Likelihood:            -2.4961e+05
No. Observations:               18678   AIC:                         4.992e+05
Df Residuals:                   18673   BIC:                         4.993e+05
Df Model:                           4
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        4.977e+06   8.02e+04     62.094      0.000    4.82e+06    5.13e+06
sqft_living   131.4278      2.609     50.371      0.000     126.314     136.542
bedrooms     -2.13e+04   1691.051    -12.594      0.000   -2.46e+04    -1.8e+04
yr_built    -2851.3244     42.612    -66.914      0.000   -2934.847   -2767.802
grade        1.253e+05   1691.531     74.085      0.000    1.22e+05    1.29e+05
==============================================================================
Omnibus:                     2065.924   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4370.007
Skew:                           0.695   Prob(JB):                         0.00
Kurtosis:                       4.919   Cond. No.                     2.00e+05
==============================================================================

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

In [83]:
```
# check normality assumption

residuals = multilinear.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.title("Normality check")
fig.show()
```



- R-squared value is 0.568, which means that 56.8% of the variation in the price can be explained by the independent variables in the model.

- F-statistic is 6126, which is a very high value and indicates that the model is a good fit for the data.
- sqft_living: This coefficient represents the effect of one unit increase in square footage on the price, holding all other variables constant. The coefficient is 131.4278, which means that a one-unit increase in square footage is associated with an increase in price of $131.43.
- bedrooms: This coefficient represents the effect of one additional bedroom on the price, holding all other variables constant. The coefficient is -2.13e+04, which means that adding one more bedroom is associated with a decrease in price of $21,300.
- yr_built: This coefficient represents the effect of one year increase in the year built on the price, holding all other variables constant. The coefficient is -2851.3244, which means that a one-year increase in the year built is associated with a decrease in price of $2,851.
- grade: This coefficient represents the effect of one unit increase in the grade on the price, holding all other variables constant. The coefficient is 1.253e+05, which means that a one-unit increase in the grade is associated with an increase in price of $125,300.

Results and Conclusion

- From our model, we can conclude that `sqft_living` , `bedrooms` , `yr_built` and `grade` are affecting the price of the house.
- There are limitations to the model. To meet our assumptions, we had to try log-transformation on some variables.

Recommendations

- Build houses that have a high grade rating.
- Target houses with a big living square footage.
- The bedrooms are also a factor in the price so they can look for buildings with atleast 4 bedrooms.

Next Steps

- Increase the size of data.
- Test the predictions against test data

In [ ]:

```

```