notebook

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1 King County Real-estate Analysis and Modelling.

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1.1.3 repostiroy link

github

1.1.4 trello board

trello

1.2 Business Problem

1.3 Introduction

The realestate business has for a long time been of great interest to investors. Any party interested in investing in the realestate business will undoubtedly benefit from prior analysis of already existing data on the state of the market in order to minimize risk and maximize ROI. We got data from various sources such as the `kc_house_data.csv` file from Kaggle that we are going to perform anlysis and modelling on.

1.4 1. Project Overview

In our analysis, we explored the data provided by Alpha Tennent Stakeholders and build a multiple linear regression model with some of the features stipulated in the dataset. Hencefourth, the analaysis done and the results came to a solution and on the following factors that have a significant impact on the price of the King County Dataset:

- Have a house by the waterfront
- Increase the number of bathrooms as the number of bedrooms increases
- Improve the overall grade of the home
- Strive to maintain the house to ensure that its in good condition
- Increase the number of floors and the size of the basement

1.4.1 1.1 Problem Statement

We will be reviewing building grade, square-footage of living space, and location-related factors such as proximity to schools, coffee shops, parks, and scientology churches to determine which factors are highly correlated with home sale prices.

1.4.2 1.2 Objective

Main Objective The main objective is to come up with a predictive /accurate model that is an improvement of the baseline model for better house price prediction in King County.

Specific Objectives

- To find out how renovation status affects sale price?
- To determine whether how the number of bedrooms is related to the pricing of the house?
- To determine if the floor number affects the pricing of the house?
- To relate the year built affects/ is related to the house pricing?
- To find whether the condition of the house is related to the house pricing?

1.4.3 1.3 Experimental Design Taken.

Implement changes as we go on with the project

This phase is broken down into four tasks together with its projected outcome or output in detail:

Collect Initial Data Describe Data Explore Data Verify Data Quality There was no need to collect any data for this project as it was already provided by the stakeholder. The data consists of house data from King County and is in .csv format.

1.4.4 1.4 Columns Descriptions

The main dataset we are using comes from the King County housing dataset that contains information on house sales between May 2014 and May 2015 consist of the following variables:

- date: Date of house sale
- price: The price which the house sold for
- bedrooms: How many bedrooms the house has
- bathrooms: How many bathrooms the house has
- sqft_living: How much square footage the house has

- sqft_lot: How much square footage the lot has
- floors: How many floors the house has
- waterfront: Whether the house is on the - - - - waterfront. Originally contained 'YES' or 'NO', converted to 0 or 1 for comparative purposes
- view: Whether the house has a view and whether it's fair, average, good, or excellent. Converted to numberical (0-4) for comparative purposes
- condition: overall condition of the house: Poor, Fair, Average, Good, Very Good
- grade: Numerical grading for house
- sqft_above: How much of the houses square footage is above ground
- sqft_basement: How much of the square footage is in the basement
- yr_built: Year the house was built
- yr_renovated: Year the house was renovated, if applicable
- zipcode: House zipcode
- lat: House's latitude coordinate
- long: House's longitude coordinate
- sqft_living15: Average size of living space for the closest 15 houses
- sqft_lot15: Average size of lot for the - - closest 15 houses

1.5 2. Data Exploration & Data Preparation

-

[1]:
```
# importing libraries for data handling
import numpy as np
import pandas as pd
# importing libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns
#import missingno as msno confirm how to import it and its purpose
import folium
import warnings
# importing libraries for data handling
import numpy as np
import pandas as pd

# importing libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns
#import missingno as msno confirm how to import it and its purpose
import folium
import warnings
# importing libraries for modeling
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn import metrics as metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

```
from sklearn.metrics import mean_absolute_error
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder

# importing libraries for statistics
import scipy.stats as stats

# importing libraries for styling
plt.style.use('seaborn')
sns.set_style('whitegrid')

warnings.filterwarnings('ignore')

# For Mapping
import geopandas as gpd # geospatial data
from shapely.geometry import Point
import folium #interactive leaflet map
from folium.plugins import FloatImage
from shapely.geometry import Point
```

```
/tmp/ipykernel_53702/981220649.py:38: MatplotlibDeprecationWarning: The seaborn
styles shipped by Matplotlib are deprecated since 3.6, as they no longer
correspond to the styles shipped by seaborn. However, they will remain available
as 'seaborn-v0_8-<style>'. Alternatively, directly use the seaborn API instead.
  plt.style.use('seaborn')
```

-

[2]:
```
#data file path
data_path = 'data/kc_house_data.csv'

#import main data file and view the first 5 columns using the .head function.
raw_data = pd.read_csv(data_path)
raw_data.head()
```

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

```
4  1954400510   2/18/2015  510000.0         3       2.00         1680

   sqft_lot  floors waterfront  view  ...          grade sqft_above  \
0      5650     1.0        NaN  NONE  ...      7 Average       1180
1      7242     2.0         NO  NONE  ...      7 Average       2170
2     10000     1.0         NO  NONE  ...  6 Low Average        770
3      5000     1.0         NO  NONE  ...      7 Average       1050
4      8080     1.0         NO  NONE  ...         8 Good       1680

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

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

[5 rows x 21 columns]
```

- Creating a graph that plots the location of houses sold.

For more information see this blog post: https://towardsdatascience.com/easy-steps-to-plot-geographic-data-on-a-map-python-11217859a2db

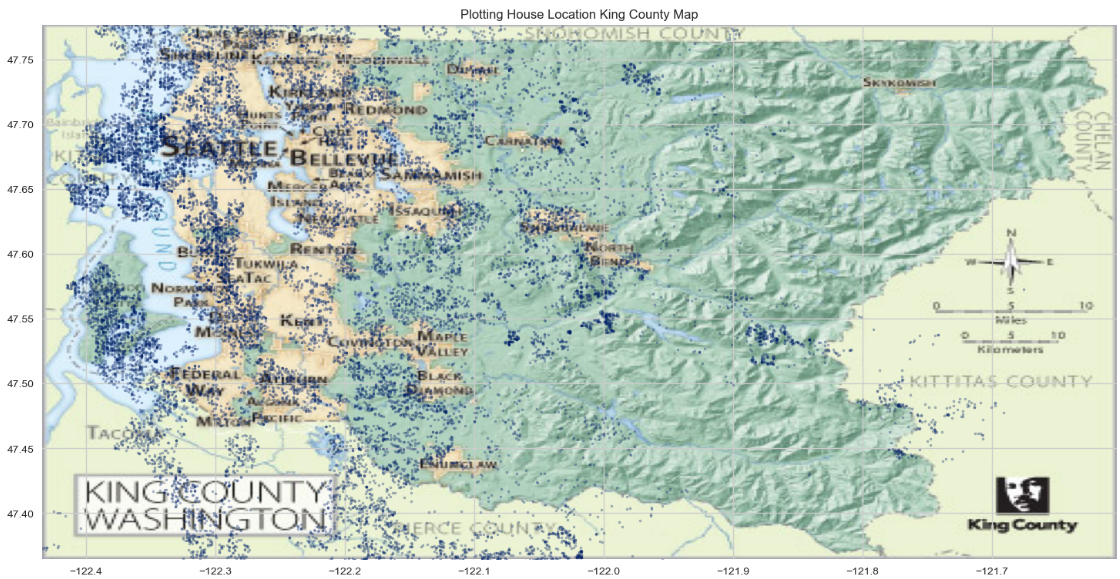
[3]:
```
# Using an online resource to create a map within specefic longitude and
 ↪latitude coordinates
BBox = (-122.434, -121.604,
         47.3643, 47.777)
BBox
```

[3]:
```
(-122.434, -121.604, 47.3643, 47.777)
```

[4]:
```
# create a more interpretable variable for the map
alpha_map = plt.imread(r'KC_simplemap_Oct2013.jpg')
```

[5]:
```
fig, ax = plt.subplots(figsize=(18, 15))

ax.scatter(raw_data.long, raw_data.lat, alpha= 0.3, c='#012169', s=5)
ax.set_title('Plotting House Location King County Map')
ax.set_xlim(BBox[0],BBox[1])
```

```python
ax.set_ylim(BBox[2],BBox[3])
ax.imshow(alpha_map, zorder=0, extent = BBox, aspect= 'equal')
plt.show()
```



[6]:
```python
mymap = folium.Map(location= [47.56 , -122.22], zoom_start =9)

# # Get the highest average house price
maxave = int(raw_data.groupby(['zipcode']).mean()['price'].max())
print("Highest City House Price is: ", maxave)

# # Create a color map to match house prices. White - low price, Black - high price
colormap = ['#00009B' ,'#0099FF' ,'#63FF9B' ,'#FFFB00' ,'#FF2F00' , '#8B0000']

# # Add marker info

for index, row in raw_data.groupby('zipcode').agg({'lat': 'mean','long': 'mean', 'price':'mean', 'zipcode':'count' }).iterrows():
#     # Set icon color based on price
    theCol = colormap[ int((len(colormap) - 1 ) *  float( row['price']) / maxave) ]
    markerText =  ( 'Average price : ' + str(round(row['price'], 2) ) +' $' + '\n' + 'Houses sold : ' + str(row['zipcode']) )
```

```python
    folium.CircleMarker( radius=(row['zipcode'])/15,␣
 ↪location=[row['lat'],row['long']], popup=folium.
 ↪Popup(markerText,max_width=150,min_width=150), color=␣
 ↪theCol,fill=True,fill_color=theCol,  ).add_to(mymap)

FloatImage('https://lh3.googleusercontent.com/proxy/
 ↪SRXTqZngcyOscx1nR1iB9c4IobPtOn0cEROsZ_wK6CO3nfAjD4e4TDXPDjN3AU2ZLJxzJQaoLJnlqk9zZevN7S2wZZc
 ↪bottom=0, left=65).add_to(mymap)
mymap
```

```
Highest City House Price is:  2161300
```

[6]: <folium.folium.Map at 0x7fa170726e20>

[7]:
```python
#Checking for the number of columns in our DataFrame
raw_data.shape
```

[7]: (21597, 21)

[8]:
```python
# Describing the data with inferential statistics.
raw_data.describe()
```

[8]:
```
                 id         price      bedrooms     bathrooms   sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000  21597.000000
mean   4.580474e+09  5.402966e+05      3.373200      2.115826   2080.321850
std    2.876736e+09  3.673681e+05      0.926299      0.768984    918.106125
min    1.000102e+06  7.800000e+04      1.000000      0.500000    370.000000
25%    2.123049e+09  3.220000e+05      3.000000      1.750000   1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors    sqft_above      yr_built  yr_renovated  \
count  2.159700e+04  21597.000000  21597.000000  21597.000000  17755.000000
mean   1.509941e+04      1.494096   1788.596842   1970.999676     83.636778
std    4.141264e+04      0.539683    827.759761     29.375234    399.946414
min    5.200000e+02      1.000000    370.000000   1900.000000      0.000000
25%    5.040000e+03      1.000000   1190.000000   1951.000000      0.000000
50%    7.618000e+03      1.500000   1560.000000   1975.000000      0.000000
75%    1.068500e+04      2.000000   2210.000000   1997.000000      0.000000
max    1.651359e+06      3.500000   9410.000000   2015.000000   2015.000000

            zipcode           lat          long  sqft_living15     sqft_lot15
count  21597.000000  21597.000000  21597.000000   21597.000000   21597.000000
mean   98077.951845     47.560093   -122.213982    1986.620318   12758.283512
std       53.513072      0.138552      0.140724     685.230472   27274.441950
```

min	98001.000000	47.155900	-122.519000	399.000000	651.000000
25%	98033.000000	47.471100	-122.328000	1490.000000	5100.000000
50%	98065.000000	47.571800	-122.231000	1840.000000	7620.000000
75%	98118.000000	47.678000	-122.125000	2360.000000	10083.000000
max	98199.000000	47.777600	-121.315000	6210.000000	871200.000000

[9]:
```python
# Look at the types of data and checking for any missing values
raw_data.info()
display('-'*100)
display(raw_data.isnull().sum()/len(raw_data)*100)
```

```
<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
```

```
'---------------------------------------------------------------------------------------------
```

```
id                 0.000000
date               0.000000
```

```
price             0.000000
bedrooms          0.000000
bathrooms         0.000000
sqft_living       0.000000
sqft_lot          0.000000
floors            0.000000
waterfront       11.001528
view              0.291707
condition         0.000000
grade             0.000000
sqft_above        0.000000
sqft_basement     0.000000
yr_built          0.000000
yr_renovated     17.789508
zipcode           0.000000
lat               0.000000
long              0.000000
sqft_living15     0.000000
sqft_lot15        0.000000
dtype: float64
```

Points to Note:

- We can see that there are NaN/null values in waterfront, view and yr_renovated columns by percentage.
- This accounts for `11%`, `0.3%`, and `18%` of the total number of rows in the dataset respectively.
- We have to think about dealing with these columns given our model will not run with any null values.
- The `bathrooms` feature seems to contain **float** values which shouldnt be the case. Lets attempt to normalize them by rounding.

[10]:
```
# checking for the uniqueness of our DataFrame
raw_data.nunique()
```

[10]:
```
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
dtype: int64
```

Duplicated values

[11]:
```python
#display number of duplicates based on 'id'
raw_data.duplicated().sum()
```

[11]: 0

Observation:

There are no duplicated values in our dataframe.

1.5.1 2.2 Data Munging/Cleaning

[12]:
```python
# Create a new dataframe of the raw data to clean
kc_hses = raw_data.copy()
```

DEALING WITH DUPLICATED VALUES

[13]:
```python
#drop duplicates in the id column as indentified
kc_hses.drop_duplicates(subset=['id'], inplace=True)

#confirming if the duplicates in the id column have been dropped
kc_hses.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  object
 2   price           21420 non-null  float64
 3   bedrooms        21420 non-null  int64
 4   bathrooms       21420 non-null  float64
 5   sqft_living     21420 non-null  int64
 6   sqft_lot        21420 non-null  int64
 7   floors          21420 non-null  float64
```

```
 8   waterfront     19067 non-null  object
 9   view           21357 non-null  object
 10  condition      21420 non-null  object
 11  grade          21420 non-null  object
 12  sqft_above     21420 non-null  int64
 13  sqft_basement  21420 non-null  object
 14  yr_built       21420 non-null  int64
 15  yr_renovated   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: float64(6), int64(9), object(6)
memory usage: 3.6+ MB
```

[14]:
```
#normalize 'bathrooms' column
kc_hses['bathrooms'] = kc_hses['bathrooms'].apply(lambda x: int(round(x, 0)))
```

[15]:
```
# Change the date column datetime format and add month column
kc_hses['date'] = pd.to_datetime(kc_hses['date'])
kc_hses['month'] = pd.DatetimeIndex(kc_hses['date']).month

# Change the yr_built column to datetime
kc_hses['yr_built'] = pd.to_datetime(kc_hses['yr_built'],format='%Y').dt.year
```

DEALING WITH THE NULL/MISSING VALUES IN THE INDENTIFIED COLUMNS

[16]:
```
kc_hses.waterfront.value_counts()
```

[16]:
```
NO     18921
YES      146
Name: waterfront, dtype: int64
```

[17]:
```
# Change waterfront column missing value to NO, then to binary values.
kc_hses.loc[raw_data.waterfront.isnull(), 'waterfront'] = 'NO'
kc_hses['waterfront'] = kc_hses['waterfront'].apply(lambda x: 0 if x == 'NO'
 ↪else 1)
kc_hses.waterfront.isna().value_counts()
```

[17]:
```
False    21420
Name: waterfront, dtype: int64
```

- We can confirm that there are no missing values in the waterfront column

[18]:
```
kc_hses.yr_renovated.isna().value_counts()
```

[18]:
```
False    17616
True      3804
Name: yr_renovated, dtype: int64
```

1.5.2 Convert missing values in yr_renovated

[19]:
```
# Change yr_renovated missing values to 0
kc_hses.loc[raw_data.yr_renovated.isnull(), 'yr_renovated'] = 0
# kc_hses['renovated_year'] = kc_hses['yr_renovated'].apply(lambda x: 0 if x ==␣
↪0 else 1)
```

[20]:
```
kc_hses['yr_renovated'] = kc_hses['yr_renovated'].astype(int)# convert to int␣
↪from float
kc_hses.yr_renovated.head()
```

[20]:
```
0       0
1    1991
2       0
3       0
4       0
Name: yr_renovated, dtype: int64
```

[21]:
```
## Change yr_renovated missing values to 0
kc_hses.loc[raw_data.yr_renovated.isnull(), 'yr_renovated'] = 0
#select all where yr_renovated - yr_build > 0; meaning the house has had work␣
↪done after being build
kc_hses['renovated'] = 0 #initialize 'renovated' column as 0 for all to store␣
↪renovation status in binary
kc_hses.loc[(kc_hses['yr_renovated']-kc_hses['yr_built'] > 0), 'renovated'] = 1

# Dropping the yr_renovated column since we don't need it.
kc_hses.drop('yr_renovated',axis=1,inplace=True)
kc_hses
```

[21]:
```
               id        date     price  bedrooms  bathrooms  sqft_living  \
0      7129300520  2014-10-13  221900.0         3          1         1180
1      6414100192  2014-12-09  538000.0         3          2         2570
2      5631500400  2015-02-25  180000.0         2          1          770
3      2487200875  2014-12-09  604000.0         4          3         1960
4      1954400510  2015-02-18  510000.0         3          2         1680
…             …          …         …         …          …
21592   263000018  2014-05-21  360000.0         3          2         1530
21593  6600060120  2015-02-23  400000.0         4          2         2310
21594  1523300141  2014-06-23  402101.0         2          1         1020
21595   291310100  2015-01-16  400000.0         3          2         1600
21596  1523300157  2014-10-15  325000.0         2          1         1020
```

```
       sqft_lot  floors  waterfront  view  … sqft_above sqft_basement  \
0          5650     1.0           0  NONE  …       1180           0.0
1          7242     2.0           0  NONE  …       2170         400.0
2         10000     1.0           0  NONE  …        770           0.0
3          5000     1.0           0  NONE  …       1050         910.0
4          8080     1.0           0  NONE  …       1680           0.0
…           …     …          …   …   …       …          …
21592      1131     3.0           0  NONE  …       1530           0.0
21593      5813     2.0           0  NONE  …       2310           0.0
21594      1350     2.0           0  NONE  …       1020           0.0
21595      2388     2.0           0  NONE  …       1600           0.0
21596      1076     2.0           0  NONE  …       1020           0.0

       yr_built zipcode      lat     long sqft_living15  sqft_lot15  month  \
0          1955   98178  47.5112 -122.257           1340        5650     10
1          1951   98125  47.7210 -122.319           1690        7639     12
2          1933   98028  47.7379 -122.233           2720        8062      2
3          1965   98136  47.5208 -122.393           1360        5000     12
4          1987   98074  47.6168 -122.045           1800        7503      2
…           …     …     …     …           …     …    …
21592      2009   98103  47.6993 -122.346           1530        1509      5
21593      2014   98146  47.5107 -122.362           1830        7200      2
21594      2009   98144  47.5944 -122.299           1020        2007      6
21595      2004   98027  47.5345 -122.069           1410        1287      1
21596      2008   98144  47.5941 -122.299           1020        1357     10

       renovated
0              0
1              1
2              0
3              0
4              0
…            …
21592          0
21593          0
21594          0
21595          0
21596          0

[21420 rows x 22 columns]
```

[22]:

```
# Changing sqft_basement column to numeric data type
# The 'errors='coerce'' parameter is used to convert any non-numeric values to␣
↪NaN values
```

```
kc_hses['sqft_basement'] = pd.
 ↪to_numeric(kc_hses['sqft_basement'],errors='coerce')
```

[23]:
```
# Add house_age column
kc_hses['house_age'] = kc_hses['date'].dt.year - kc_hses['yr_built']

#Extracting the year from the date column
kc_hses['Sale_year'] = kc_hses['date'].dt.year
```

[24]:
```
kc_hses.drop(['date', 'id'], axis=1, inplace=True)
```

[25]:
```
# Count the frequency of each unique value in the 'grade' column of 'clean_data'
kc_hses.grade.value_counts()

# Split each string in the 'grade' column by whitespace characters and extract␣
 ↪the second element (at index 1)
# This extracts the numerical grade value from the string
# Apply this lambda function to each value in the 'grade' column
# Assign the modified 'grade' column back to 'clean_data'
kc_hses.grade = kc_hses.grade.apply(lambda x: x.split(" ").pop(1))
```

SELECTING CATEGORICAL AND NUMERICAL VARIABLES IN OUR DATAFRAME

[26]:
```
#Selecting Categorical columns
categorical_df = kc_hses.select_dtypes(include='object')

#Selecting Numerical columns
numerical_df = kc_hses.select_dtypes(exclude='object')
numerical_df.head()
```

[26]:
```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
0  221900.0         3          1         1180      5650     1.0           0
1  538000.0         3          2         2570      7242     2.0           0
2  180000.0         2          1          770     10000     1.0           0
3  604000.0         4          3         1960      5000     1.0           0
4  510000.0         3          2         1680      8080     1.0           0

   sqft_above  sqft_basement  yr_built  zipcode      lat     long  \
0        1180            0.0      1955    98178  47.5112 -122.257
1        2170          400.0      1951    98125  47.7210 -122.319
2         770            0.0      1933    98028  47.7379 -122.233
3        1050          910.0      1965    98136  47.5208 -122.393
4        1680            0.0      1987    98074  47.6168 -122.045

   sqft_living15  sqft_lot15  month  renovated  house_age  Sale_year
0           1340        5650     10          0         59       2014
1           1690        7639     12          1         63       2014
```

```
2          2720        8062      2          0          82        2015
3          1360        5000     12          0          49        2014
4          1800        7503      2          0          28        2015
```

[27]:
```
# Viewing the categorical columns
categorical_df.head()
```

[27]:
```
   view  condition    grade
0  NONE    Average  Average
1  NONE    Average  Average
2  NONE    Average      Low
3  NONE  Very Good  Average
4  NONE    Average     Good
```

[28]:
```
#Created a list to store our categorical and numericals variables
categorical_list = list(kc_hses.select_dtypes(include='object'))
numerical_list = list(kc_hses.select_dtypes(exclude='object'))
```

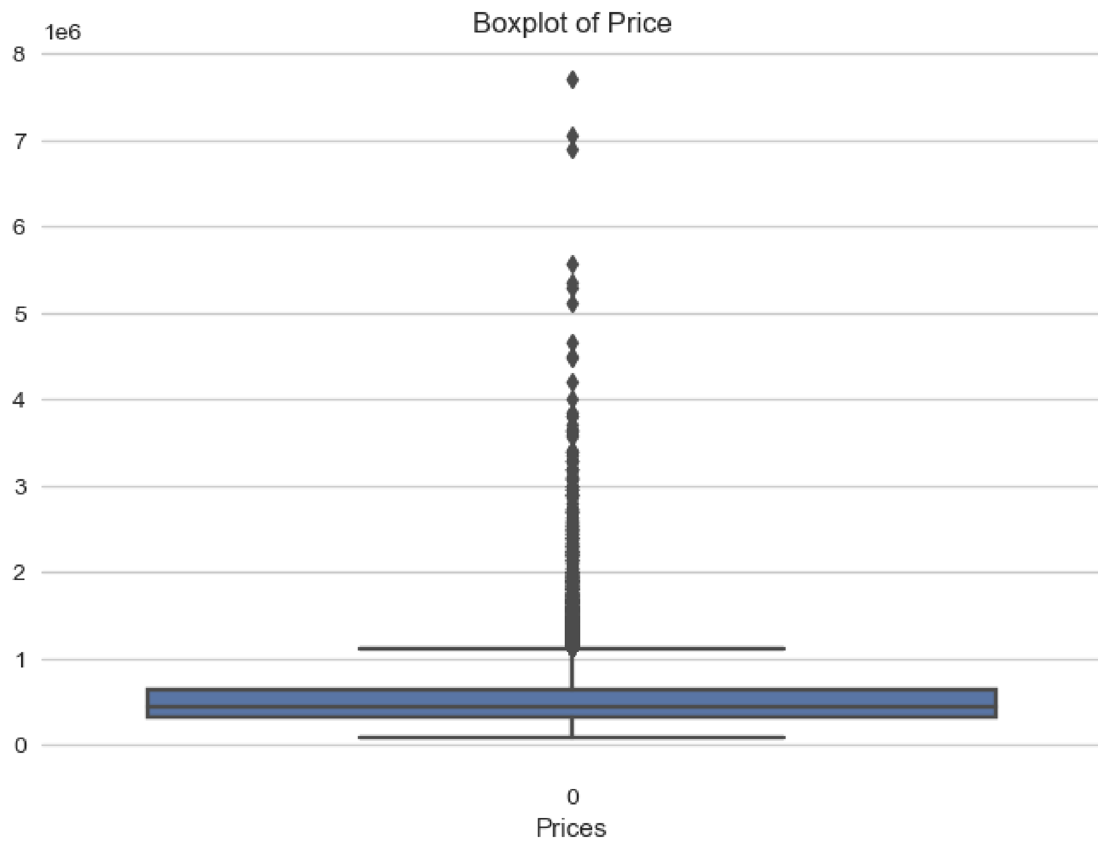
1.5.3 2.3 EDA

-

1.6 Handling outliers

Let's plot some of the variables to look for outliers:

[29]:
```
# Create a list of columns to include in the boxplot
columns = ['price', 'sqft_lot']

# Create the boxplot
sns.boxplot(kc_hses.price)

# Add a title and labels for the axes
plt.title('Boxplot of Price')
plt.xlabel('Prices')

# Display the plot
plt.show()
```

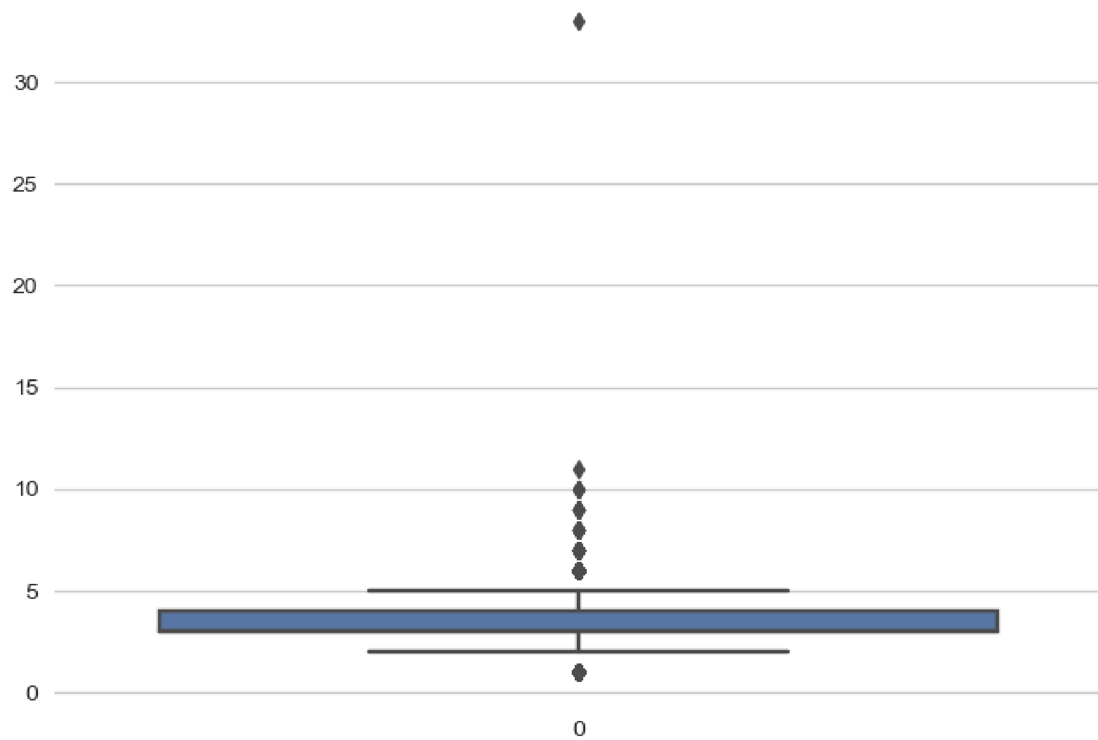



```
[30]: #This code selects the 99.0% of prices in clean_data that fall between the 0.
      ↪5th percentile and the 99.5th percentile of prices.
      #This effectively removes the top and bottom 0.25% of prices, which are likely
      ↪outliers.

      kc_hses = kc_hses[(kc_hses.price < kc_hses.price.quantile(.995))
                              & (kc_hses.price > kc_hses.price.quantile(.005))]
```

`Note`: There are numerous outliers within the price column hence dropping would be unwise.

- BEDROOMS

```
[31]: # Let's look at the bedrooms
      sns.boxplot(kc_hses['bedrooms']);
```



`Note:`From the above boxplot, it's clear that there are outliers. Before handling them, we went ahead and looked at the description of the bedroom column

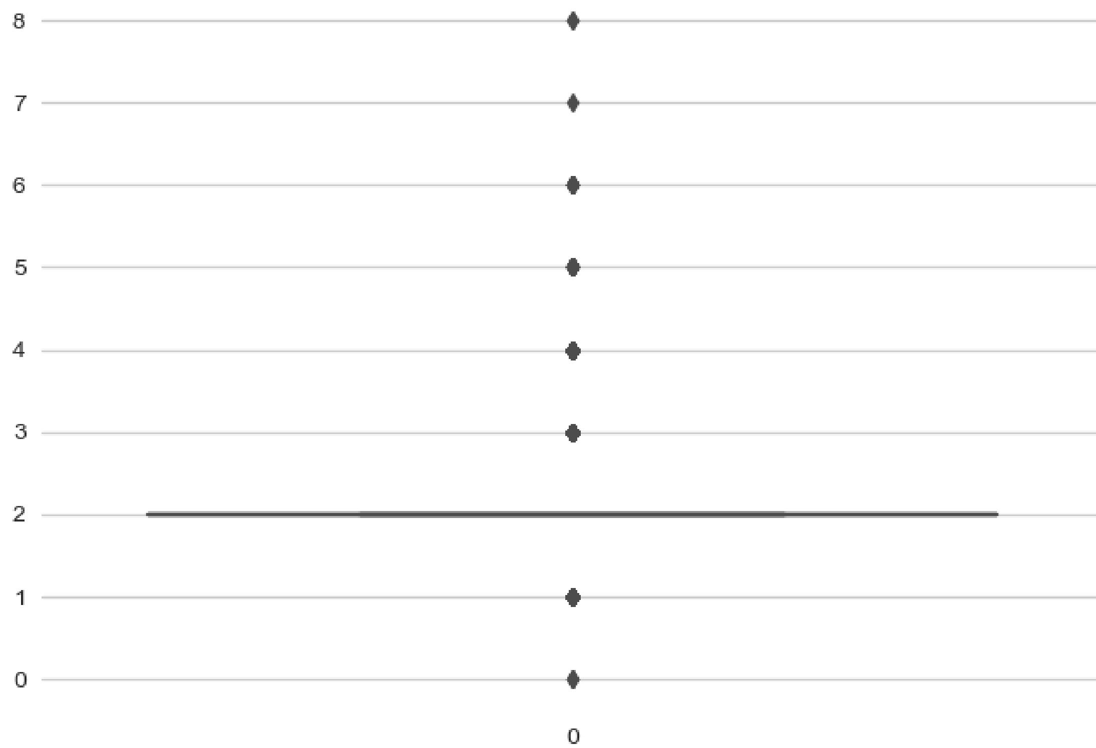
[32]:
```
kc_hses.bedrooms.describe()
```

[32]:
```
count    21203.000000
mean         3.374334
std          0.919347
min          1.000000
25%          3.000000
50%          3.000000
75%          4.000000
max         33.000000
Name: bedrooms, dtype: float64
```

[33]:
```
# We see the outlier on bedrooms that we change to 3 bedrooms, likely due to a␣
↪typographic error
# we Change to 3 since it's the average number of bedrooms.
kc_hses.loc[(kc_hses.bedrooms == 33), 'bedrooms'] = 3
```

- BATHROOMS

[34]:
```
# Let's look at the bedrooms
sns.boxplot(kc_hses['bathrooms']);
```



1.6.1 3.1 Univariate Analysis

`univariate Analysis` refers to the analysis of a single variable or data set, typically using statistical methods.

> In this section, we'll explore each column in the dataset to see the distributions of features and obtain some useful insights. The main two parts in this section are: - Categorical Columns(Categorical df) - Numerical Columns(numerical df)

- `CATEGORICAL COLUMNS`

We defined a function below that will take in the categorical dataframe created above that contains the categorical columns, that is, `Condition` and `Grade`.

[35]:
```
# Fuction to get the value counts of the data in the columns
def get_value_counts(categorical_df, col):
    ''' Returns the value counts of a column in a dataframe '''
    counts = categorical_df[col].value_counts(dropna=False)
    return counts

# Function to visualise the the data in the columns
```

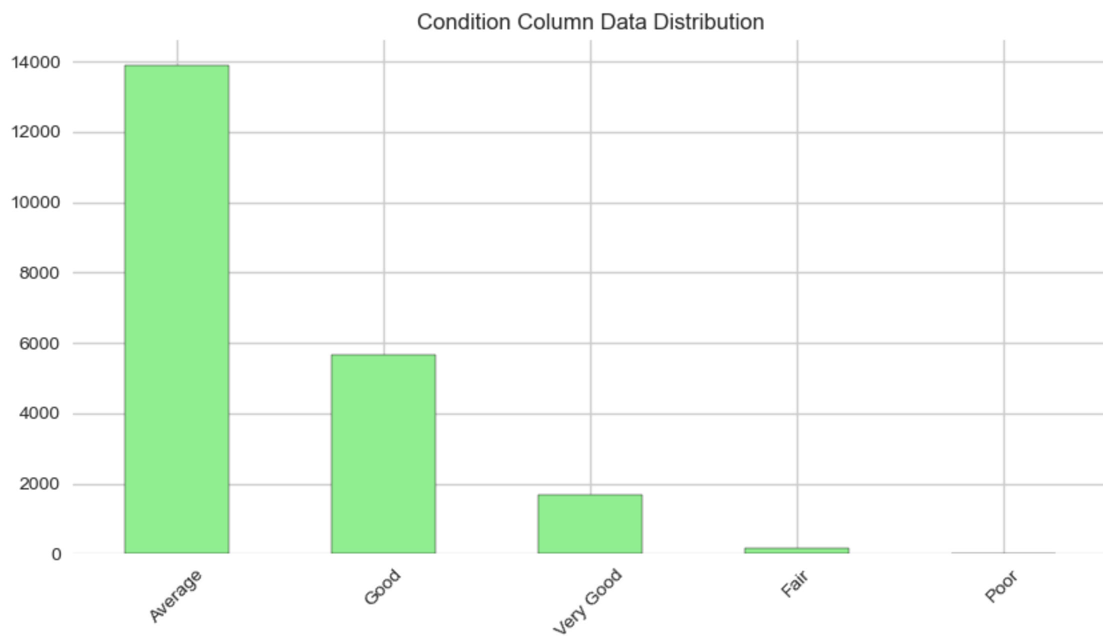
```python
def plot_data(categorical_df, col, title):
    ''' Plots the value counts of a column in a dataframe as a bar chart '''
    get_value_counts(categorical_df, col).plot(kind='bar', figsize=(10, 5),␣
 ↪color='lightgreen', edgecolor='black')
    plt.title(title)
    plt.xticks(rotation=45);
```

2.1.1.4 Condition

The condition column identifies the condition of the house.

[36]:
```python
# Identify the unique values (and counts) in the 'condition' column
print(get_value_counts(categorical_df, 'condition'))

# Visualise the data distribution
plot_data(categorical_df, 'condition', 'Condition Column Data Distribution')
```

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



`Note:` From the distribution above, we can observe the following:

We can observe that the majority of the residences in the dataset are in `average condition` from the distribution above and the least lies in `poor condition`

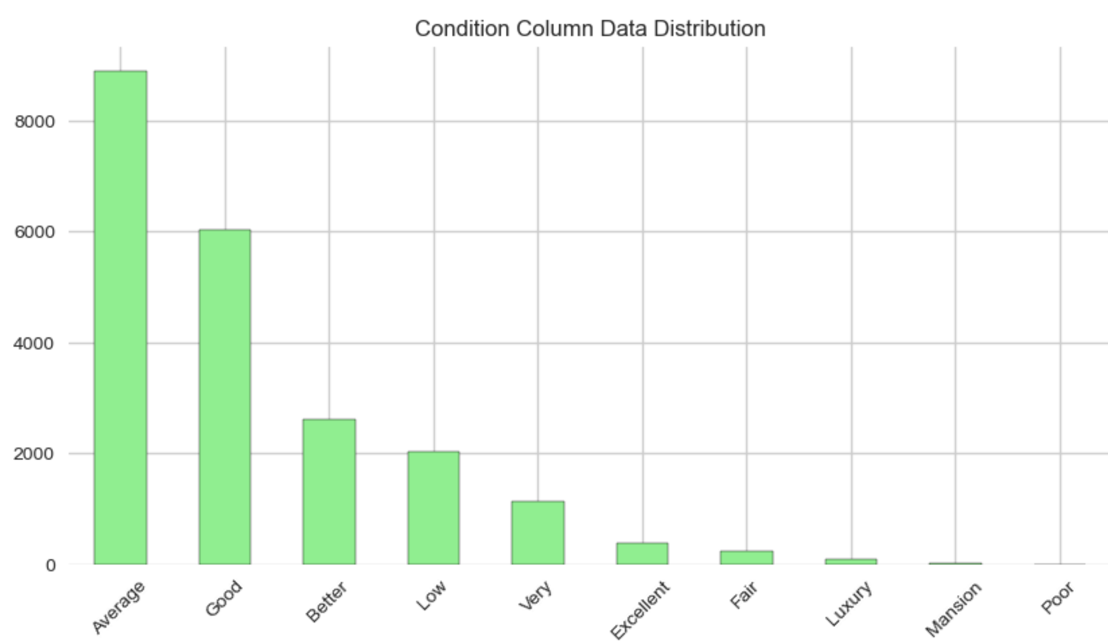
- Average 13900
- Good 5643
- Very Good 1687
- Fair 162
- Poor 28

2.1.1.4. Grade

The grade column describes the home's building and design excellence. The grade corresponds to the caliber of the upgrades' construction. There are 13 grade levels.

[37]:
```python
# Identify the unique values (and counts) in the 'condition' column
print(get_value_counts(categorical_df, 'grade'))

# Visualise the data distribution
plot_data(categorical_df, 'grade', 'Condition Column Data Distribution')
```

```
Average      8889
Good         6041
Better       2606
Low          2022
Very         1130
Excellent     396
Fair          234
Luxury         88
Mansion        13
Poor            1
Name: grade, dtype: int64
```



`Observations:`

Majority of the houses in this dataset range in grade level `Average` with `8889` houses and the least range in the grade level `poor` with `1` house.

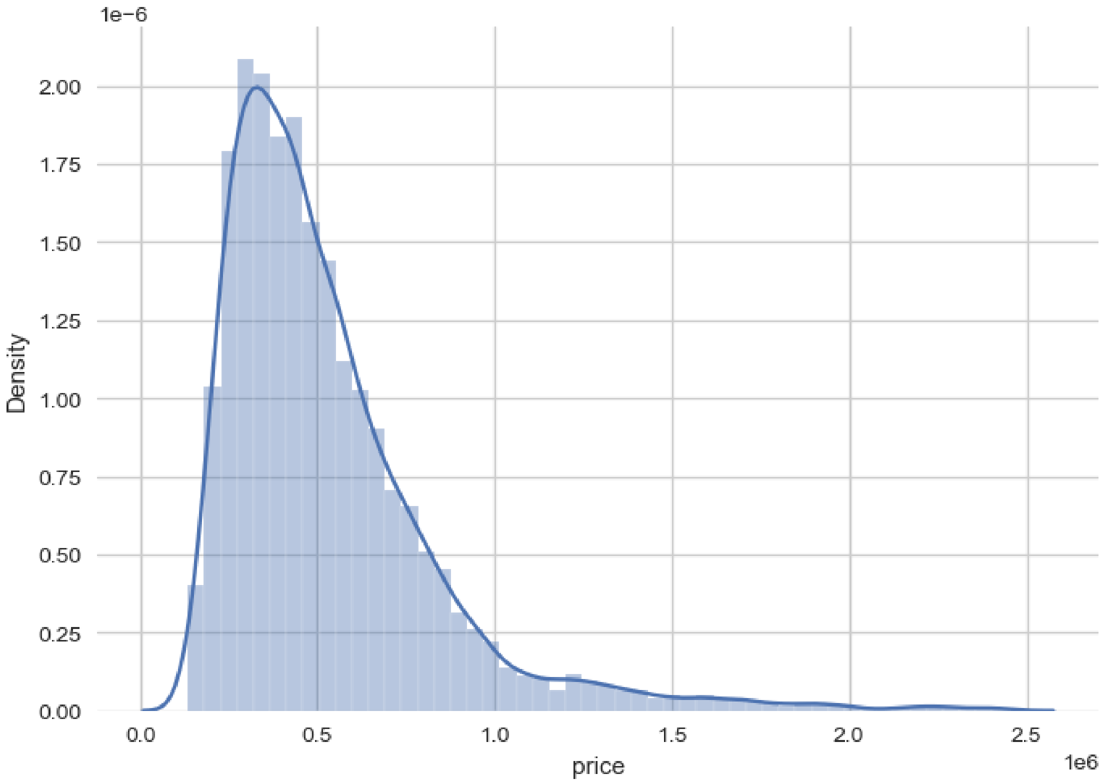
- `NUMERICAL COLUMNS`

We defined a function below that will take in the categorical dataframe created above that contains the numerical columns which are price, bedrooms, bathrooms, 'sqft_living, 'sqft_lot, floors, 'waterfront, view, sqft_above, sqft_basement, yr_built, zipcode, lat, long, sqft_living15, sqft_lot15, month, renovated_year, renovated, house_age, Sale_year.

[38]:
```
# Function to describe the data and plot the histogram, kde and boxplot of the␣
↪data
def desc_and_plot(df, col, title, bins_='auto'):
    ''' Describes and Plots the distribution of a column in a dataframe as a␣
↪histogram, kde and boxplot '''
    print(df[col].describe())
    # creating a figure composed of two matplotlib.Axes objects (ax_box and␣
↪ax_hist)
    f, (ax_box, ax_hist) = plt.subplots(2, sharex=True,␣
↪gridspec_kw={"height_ratios": (.15, .85)}, figsize=(10, 5))

    # assign a graph to each ax
    sns.boxplot(df[col], ax=ax_box, color='lightgreen')
    sns.histplot(data=df, x=col, ax=ax_hist, kde=True, color='lightgreen',␣
↪bins=bins_, edgecolor='black')
    plt.suptitle(title)
    plt.tight_layout();
```

1. `PRICE`

[39]:
```
#Visualize price
sns.distplot(kc_hses['price'], kde=True)
plt.show();
```



`Observation`:

Price is normally distributed although skewed to the right. There may be outliers causing the skew. In the context of realestate these outliers may be valid and may not warrant dropping.

We are going to improve on the skewness using `Log Transformation` with an aim to increase correlation

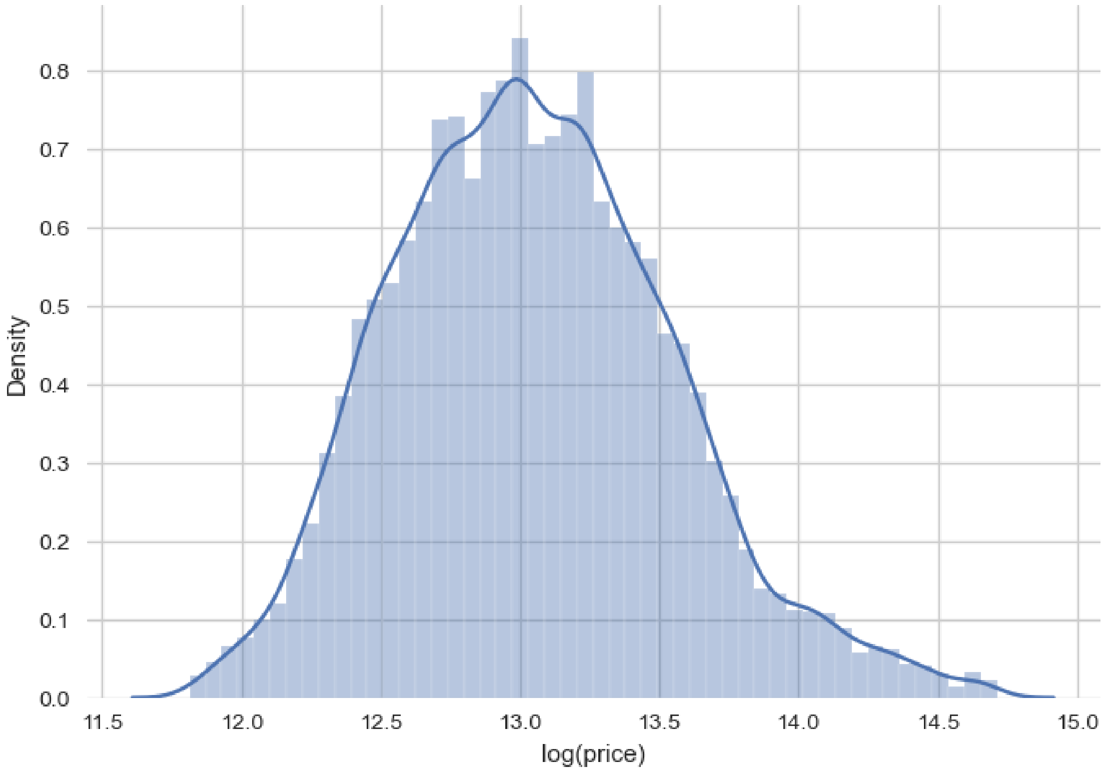
`Dealing with Skewness in our data`

[40]:
```
# use Log Transformation to deal with the skewness in the price column
kc_hses["log(price)"] = np.log(kc_hses["price"])
kc_hses[["log(price)"]].head()
```

[40]:

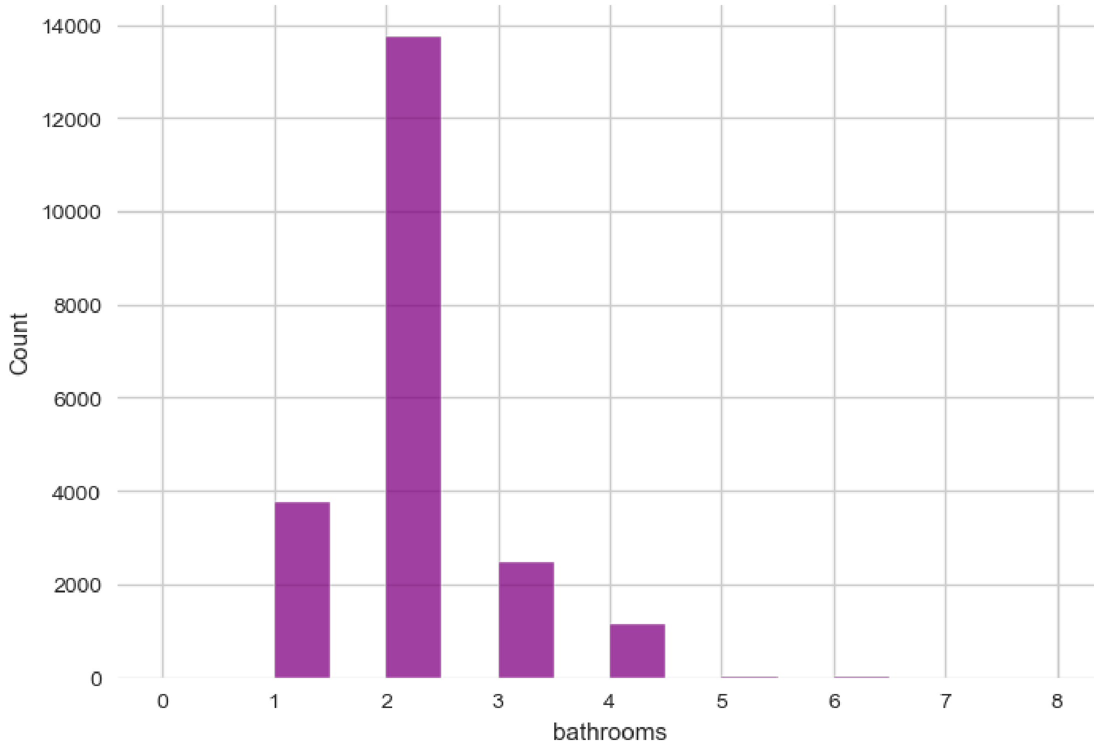
	log(price)
0	12.309982
1	13.195614
2	12.100712
3	13.311329
4	13.142166

[41]:
```
#Visualize the price using the logprice column after log transformation
sns.distplot(kc_hses['log(price)'], kde=True)
plt.show();
```



2. Bathrooms

[42]:
```
#plot bathrooms distribution
sns.histplot(kc_hses['bathrooms'], kde=False, color='purple')
plt.show();
```



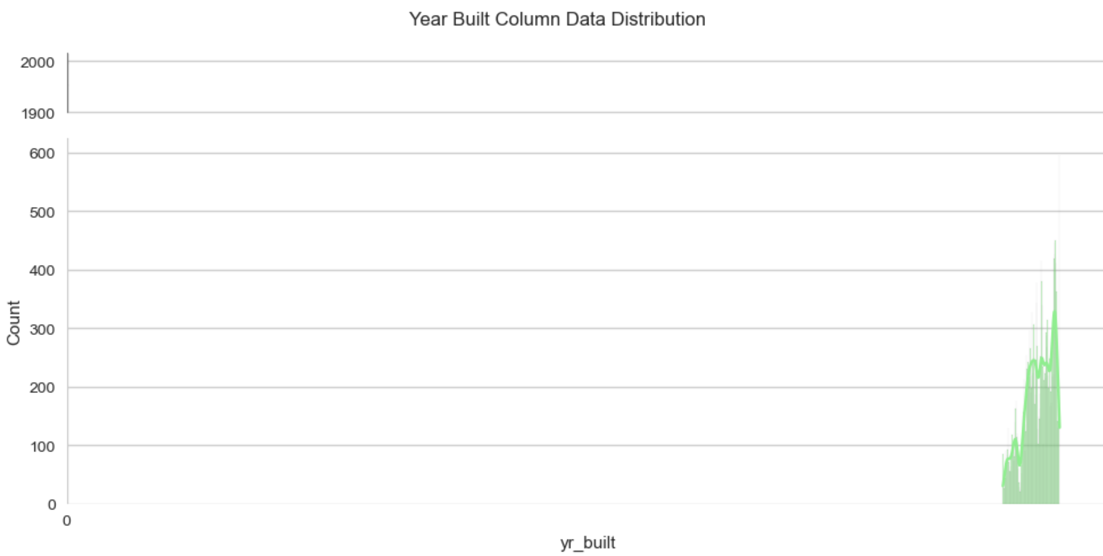
Observation

- Most properties seem to have 2 bathrooms on average. The kde function seems to look a bit strange owing to `bathrooms` beign a categorical feature.

3. Year_built

[43]:
```
# Visualise 'yr_built' distribution
desc_and_plot(kc_hses, 'yr_built', 'Year Built Column Data Distribution', 115)
```

```
count    21203.000000
mean      1971.205395
std         29.355245
min       1900.000000
25%       1952.000000
50%       1975.000000
75%       1997.000000
max       2015.000000
Name: yr_built, dtype: float64
```



Observation

- From the distributions above we can see that the data is slightly skewed to the left.
- The oldest house in the dataset was built in 1900, and the newest house in the dataset was built in 2015.
- The mean year the houses in the dataset were built is 1971, and the median year the houses in the dataset were built is 1975.
- The standard deviation of the year built column is 29.37

We are going to improve on the skewness using `Log Transformation`

[44]:
```
# use Log Transformation to deal with the skewness in the price column
kc_hses["log(yr_built)"] = np.log(kc_hses["yr_built"])
kc_hses[["log(yr_built)"]].head()
```

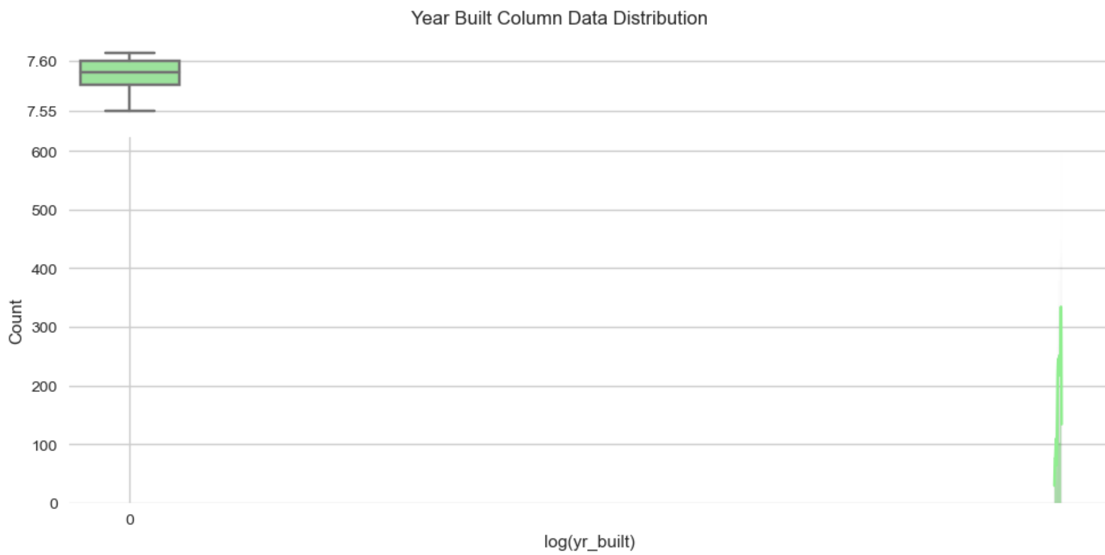
[44]:

	log(yr_built)
0	7.578145
1	7.576097
2	7.566828
3	7.583248
4	7.594381

[45]:
```
#Visualize the yr_built using the log(yr_built) column after log transformation
desc_and_plot(kc_hses, 'log(yr_built)', 'Year Built Column Data Distribution',␣
↪115)
```

```
count    21203.000000
mean         7.586289
std          0.014948
min          7.549609
```

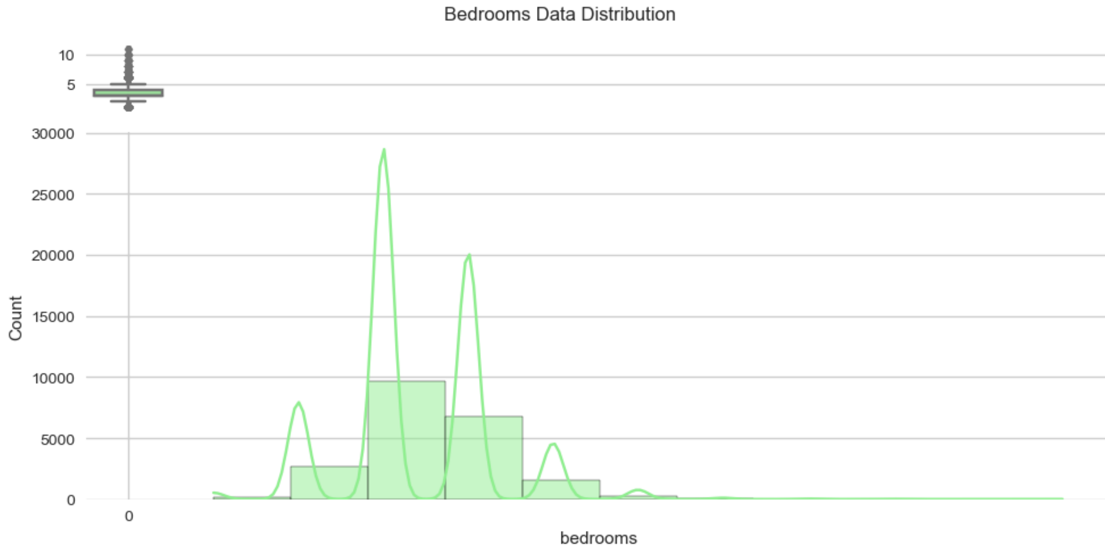
```
25%            7.576610
50%            7.588324
75%            7.599401
max            7.608374
Name: log(yr_built), dtype: float64
```



4. Bedrooms

[46]:
```
desc_and_plot(kc_hses, 'bedrooms', 'Bedrooms Data Distribution', 11)
```

```
count    21203.000000
mean         3.372919
std          0.896553
min          1.000000
25%          3.000000
50%          3.000000
75%          4.000000
max         11.000000
Name: bedrooms, dtype: float64
```



Observation

- The maximum number of bedrooms in the dataset in 11
- The minimum number of bedrooms in the dataset is 1
- The mean number of mean number of bedrooms is 3.37 and the median number of bedrooms is 3.
- The standard deviation of the bedroom column is 0.93

5. Bathrooms

[47]:
```
#plot bathrooms distribution
desc_and_plot(kc_hses, 'bathrooms', 'Bathrooms Data Distribution', 8)
```

```
count    21203.000000
mean         2.056832
std          0.735983
min          0.000000
25%          2.000000
50%          2.000000
75%          2.000000
max          8.000000
Name: bathrooms, dtype: float64
```

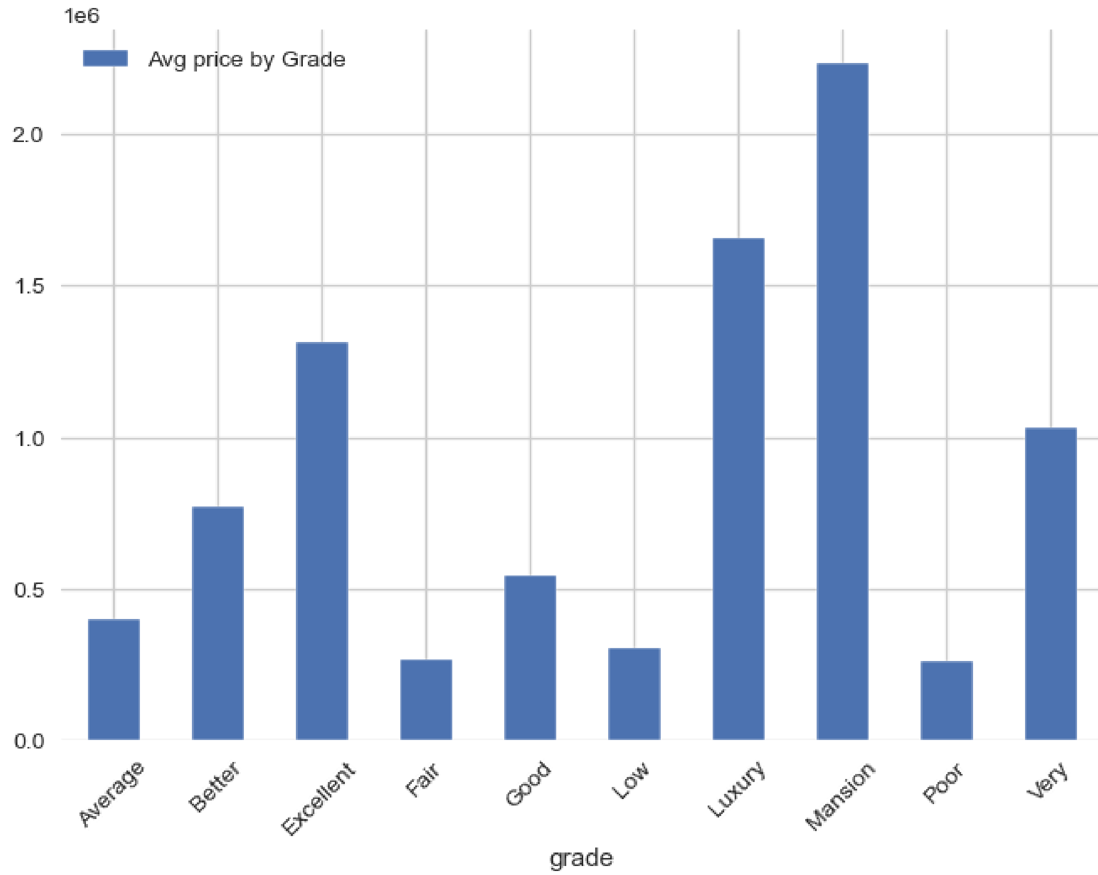
Observation

- The maximum number of bathrooms in the dataset in 8
- The minimum number of bathrooms in the dataset is 0
- The mean number of mean number of bathroomsis 2.06 and the median number of bedrooms is 2.
- The standard deviation of the bathrooms column is 0.735983.

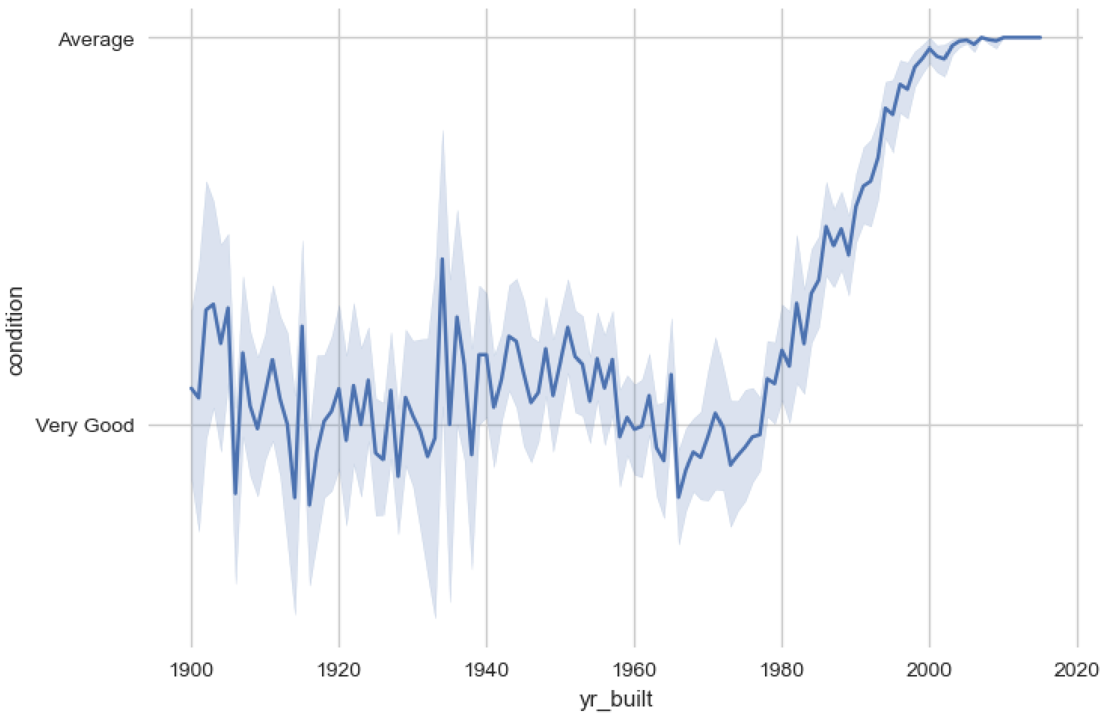
1.6.2 3.2 Bivariate Analysis

`Bivariate Analysis` refers to the analysis of a two variable or data set, typically using statistical methods.

[48]:
```
#plot bar of Grade against price
kc_hses.groupby('grade')['price'].mean().plot.bar(x='grade', label='Avg price␣
↪by Grade')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```



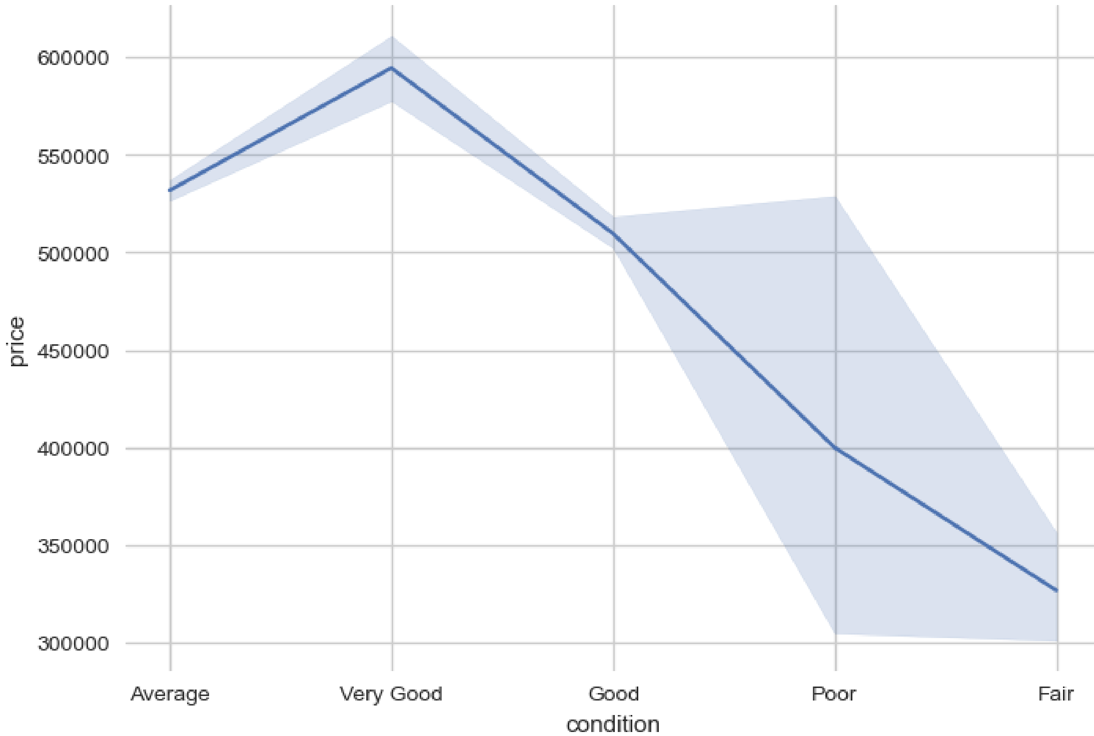
[49]:
```
#plot barchart of 'condition' against 'year built'
sns.lineplot(x='yr_built', y='condition', data=kc_hses)
plt.show();
```



Observation

- For most houses built in the 20*th* century *i.e* 1900-early 1990s houses were in Very good condition.
- For most houses built from the begining of the 21*st* century, the condition is Average. There seems to be a decline in condition of houses built over time

[50]:
```
#plot barchart of 'condition' against 'year built'
sns.lineplot(x='condition', y='price', data=kc_hses)
plt.show();
```



Observation

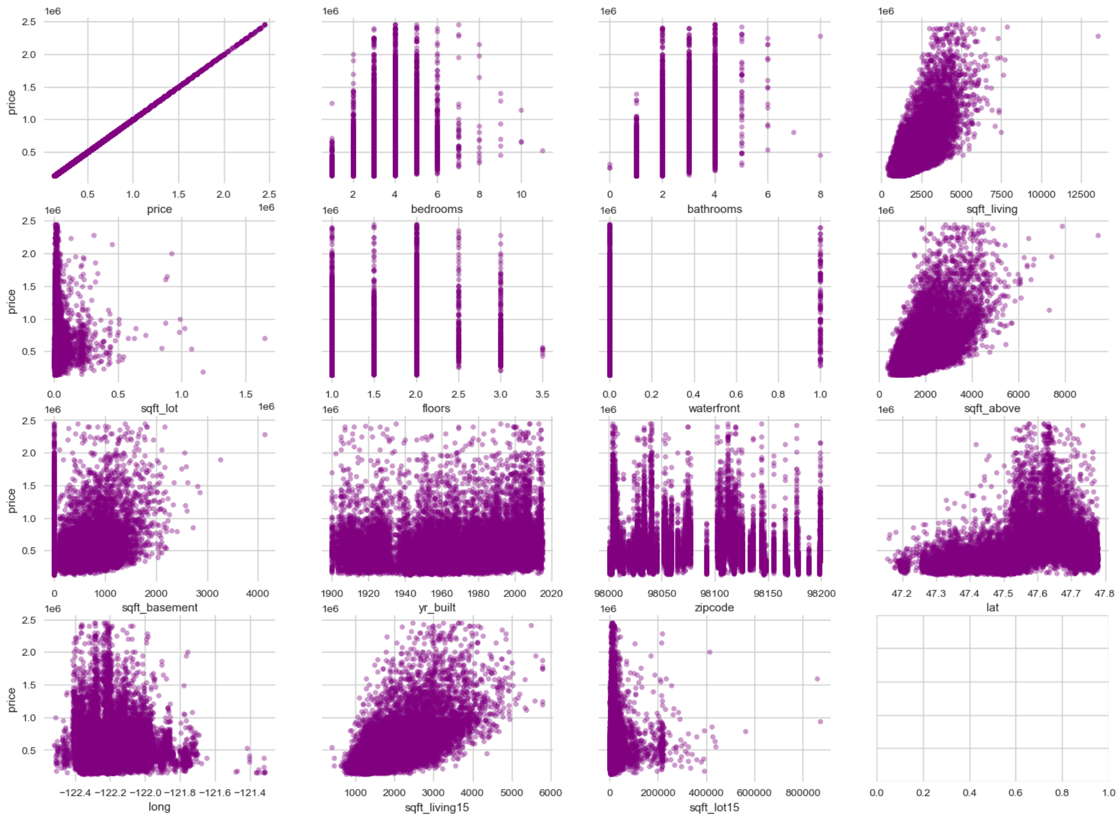
- The price decreases as the condition of the houses deteriorates.
- However, It appears in the graph that the houses with poor condition are more expensive compared to the ones that have fair condition which should be investigated.

1.6.3 3.3 Multivariate Analysis

`Multivariate Analysis` refers to the analysis of more than two variable or data set, typically using statistical methods.

- Below is a plot to show the relationship between `price` and the other variables created in the `numerical_list` created above.

[51]:
```
#plot scatter plots of all features against price
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(18,13))
axes = axes.flatten() # flatten the array to make it easier to iterate over

for i, xcol in enumerate(numerical_list[0:15]):
    kc_hses.plot(kind='scatter', x=xcol, y='price', ax=axes[i], alpha=0.4,␣
 ↪color='purple', sharey=True)

plt.show() # add this to display the plot
```

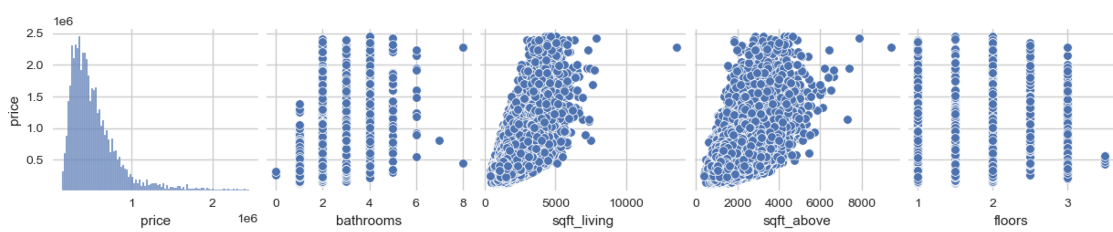


Observations

From the plots above,we can observe that some of the relationships within the variable are linear while other are non-linear.

- Below is a plot to show the relationship between `price` and `price`,‘`bathrooms`,`sqft_living`,`sqft_above`,`floors`.

[52]:
```
#plot scatterplots of selected features
xvars = ['price', 'bathrooms', 'sqft_living', 'sqft_above', 'floors']#selected␣
 ↪features
yvars = ['price']
sns.pairplot(kc_hses, x_vars=xvars, y_vars=yvars)
plt.show();
```



Observations:

- `sqft-living` and `sqft_above` seem to have a linear relationship with `price`

2 3.0 CORRELATION MATRIX

-

[53]:
```
#plot correlation heatmap
kc_hses_correlation = kc_hses.corr().style.background_gradient(cmap='coolwarm').
↪set_precision(2)
# convert all features that have a correlation to price of more than 0.3
kc_hses_correlation
```

[53]:
```
<pandas.io.formats.style.Styler at 0x7fa16cd8c7c0>
```

Observation:

We see Strong positive correlation between `price` and the features: `bathrooms`, `sqft_living` and `sqft_above`,

[54]:
```
#dropping the following columns  lat, sqft_living15, zipcode, long, floors,␣
↪sqft_lot15
cols_to_drop = ['lat','sqft_living15','long', 'sqft_lot15']
kc_hses.drop(cols_to_drop, axis=1, inplace=True)
kc_hses.info()
```

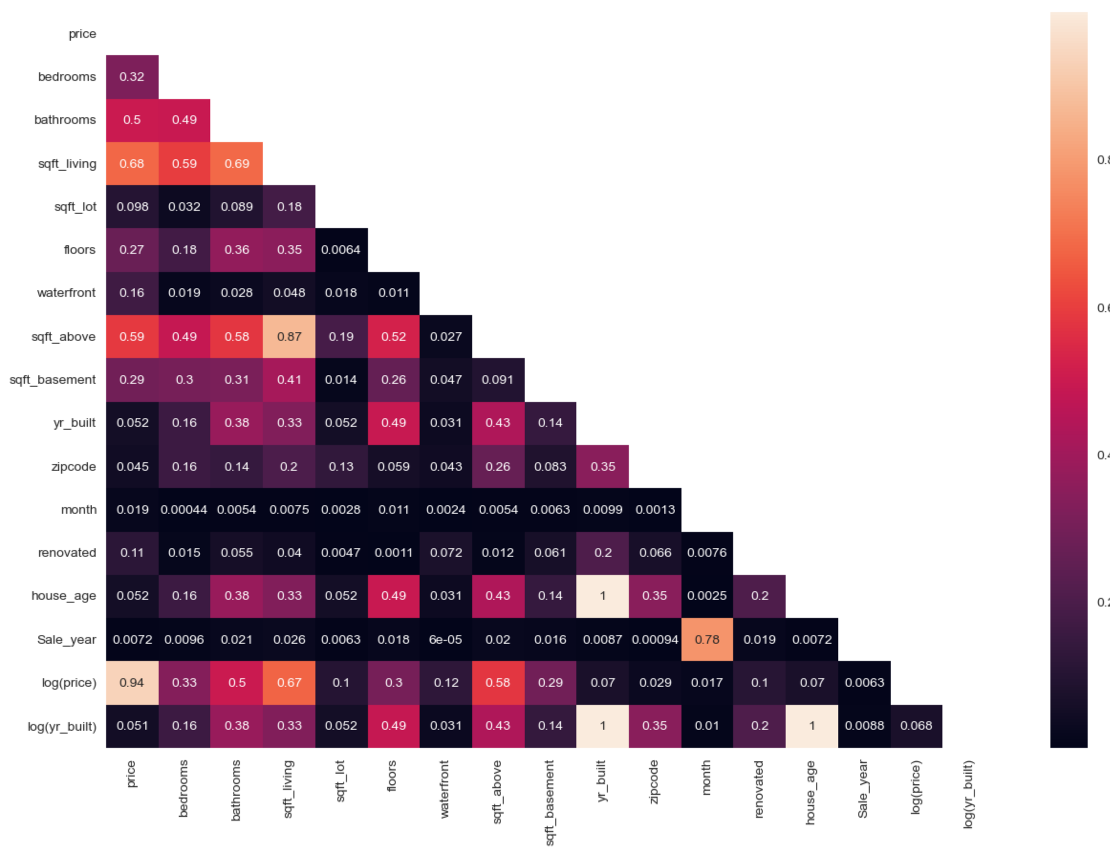
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21203 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21203 non-null  float64
 1   bedrooms       21203 non-null  int64
 2   bathrooms      21203 non-null  int64
 3   sqft_living    21203 non-null  int64
 4   sqft_lot       21203 non-null  int64
 5   floors         21203 non-null  float64
 6   waterfront     21203 non-null  int64
 7   view           21141 non-null  object
 8   condition      21203 non-null  object
 9   grade          21203 non-null  object
 10  sqft_above     21203 non-null  int64
 11  sqft_basement  20757 non-null  float64
 12  yr_built       21203 non-null  int64
```

```
 13  zipcode        21203 non-null  int64
 14  month          21203 non-null  int64
 15  renovated      21203 non-null  int64
 16  house_age      21203 non-null  int64
 17  Sale_year      21203 non-null  int64
 18  log(price)     21203 non-null  float64
 19  log(yr_built)  21203 non-null  float64
dtypes: float64(5), int64(12), object(3)
memory usage: 3.9+ MB
```

Observation:

- The above columns were dropped because they don't have strong correlation with the `price` that is to say ,they are not the high determinant influencing the houses' prices.

[55]:
```python
#correlation heat map after dropping
corr = kc_hses.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))

plt.figure(figsize=(15, 10))
sns.heatmap(kc_hses.corr().abs(), annot=True, mask=mask);
```



Observations:

`sqft_above` is strongly correlated with `sqft_living`. This may be because living space are typycally located above ground. In this case we may drop `sqft_above` to prevent **multicollinearity** issues in the model. We can also drop `sqft_lot`.

[56]:
```
#drop columns that are correlated to sqft_living
drop_these = ['sqft_above', 'sqft_lot']
kc_hses.drop(drop_these, axis=1, inplace=True)
kc_hses.columns
```

[56]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront',
       'view', 'condition', 'grade', 'sqft_basement', 'yr_built', 'zipcode',
       'month', 'renovated', 'house_age', 'Sale_year', 'log(price)',
       'log(yr_built)'],
      dtype='object')
```

Observations: * For most houses built in the 20*th* century *i.e* 1900-early 1990s houses were in Very good condition. * For most houses built from the begining of the 21*st* century, the condition is Average. There seems to be a decline in condition of houses built over time

2.1 4. Data Preparation

[57]:
```
#Checking for the highest correlated variables with the Log(price)
kc_hses.corr()['log(price)'].sort_values()
```

[57]:
```
house_age        -0.069895
zipcode          -0.028766
month            -0.017148
Sale_year         0.006326
log(yr_built)     0.068393
yr_built          0.069994
renovated         0.102287
waterfront        0.122127
sqft_basement     0.291451
floors            0.303617
bedrooms          0.332808
bathrooms         0.497994
sqft_living       0.673382
price             0.935780
log(price)        1.000000
Name: log(price), dtype: float64
```

Observation

sqft_living has the highest correlation with the log price of 0.67 compared to the other columns.

2.1.1 ONE-HOT-ENCODING FOR THE CATEGORICAL VARIABLES

[58]:
```
# Initialize LabelEncoder
le = LabelEncoder()
kc_hses['grade_idx'] = le.fit_transform(kc_hses['grade'])
kc_hses['condition_idx'] = le.fit_transform(kc_hses['condition'])
# Checking if the columns have been encoded
kc_hses[['grade_idx']].value_counts().sort_values()
```

[58]:
```
grade_idx
8            1
7            4
6           62
3          203
2          354
9         1104
5         1961
1         2603
4         6039
0         8872
dtype: int64
```

[59]:
```
# creating instance of one-hot-encoder
enc = OneHotEncoder(handle_unknown='error')
# passing bridge-types-cat column (label encoded values of bridge_types)
enc_df = pd.DataFrame(enc.fit_transform(kc_hses[['grade_idx']]).toarray())
enc_df
# merge with main df bridge_df on key values
kc_hses = kc_hses.merge(enc_df, right_index = True, left_index = True)
kc_hses.rename(columns={0: 'grade_3', 1: 'grade_4', 2: 'grade_5', 3: 'grade_6',␣
↪4: 'grade_7', 5: 'grade_8',
                   6: 'grade_9', 7: 'grade_10', 8: 'grade_11', 9: 'grade_12',␣
↪10: 'grade_13'
                  }, inplace = True)
kc_hses.columns
```

[59]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront',
       'view', 'condition', 'grade', 'sqft_basement', 'yr_built', 'zipcode',
       'month', 'renovated', 'house_age', 'Sale_year', 'log(price)',
       'log(yr_built)', 'grade_idx', 'condition_idx', 'grade_3', 'grade_4',
       'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9', 'grade_10',
       'grade_11', 'grade_12'],
      dtype='object')
```

observation

We have transformed categorical columns that is grade and condition columns and renamed them as 'grade_idx' and 'condition_idx'

[60]:
```
# created a new dataframe called data for modelling
data = kc_hses

#Declared the independent and dependent variables
y = data['log(price)']
X = data.
 ↪drop(columns=['price','log(price)','yr_built','zipcode','grade_idx','view','house_age','Sal
 ↪axis=1)
```

[61]:
```
#confirming the remaining columns after dropping form the above cell
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20812 entries, 0 to 21202
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   bedrooms       20812 non-null  int64
 1   bathrooms      20812 non-null  int64
 2   sqft_living    20812 non-null  int64
 3   floors         20812 non-null  float64
 4   waterfront     20812 non-null  int64
 5   renovated      20812 non-null  int64
 6   condition_idx  20812 non-null  int64
 7   grade_3        20812 non-null  float64
 8   grade_4        20812 non-null  float64
 9   grade_5        20812 non-null  float64
 10  grade_6        20812 non-null  float64
 11  grade_7        20812 non-null  float64
 12  grade_8        20812 non-null  float64
 13  grade_9        20812 non-null  float64
 14  grade_10       20812 non-null  float64
 15  grade_11       20812 non-null  float64
 16  grade_12       20812 non-null  float64
dtypes: float64(11), int64(6)
memory usage: 2.9 MB
```

LOG TRANSFORMED BASE MODEL

- For our mode, we assuming an alpha level of `0.05`

[62]:
```
#building our log transformed base model
log_mod = sm.OLS(y, sm.add_constant(X)).fit()
log_mod.summary()
```

[62]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:             log(price)   R-squared:                       0.488
Model:                            OLS   Adj. R-squared:                  0.487
Method:                 Least Squares   F-statistic:                     1237.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:23:11   Log-Likelihood:                -8196.1
No. Observations:               20812   AIC:                         1.643e+04
Df Residuals:                   20795   BIC:                         1.656e+04
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
=
                  coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
const          11.1113      0.038    290.288      0.000      11.036
11.186
bedrooms       -0.0612      0.004    -17.458      0.000      -0.068
-0.054
bathrooms       0.0441      0.005      9.163      0.000       0.035
0.053
sqft_living     0.0004   4.35e-06     87.184      0.000       0.000
0.000
floors          0.0890      0.005     16.795      0.000       0.079
0.099
waterfront      0.5391      0.034     15.829      0.000       0.472
0.606
renovated       0.2041      0.014     14.932      0.000       0.177
0.231
condition_idx   0.0424      0.002     20.692      0.000       0.038
0.046
grade_3         1.0888      0.037     29.388      0.000       1.016
1.161
grade_4         1.0873      0.037     29.033      0.000       1.014
1.161
grade_5         1.0603      0.041     25.946      0.000       0.980
1.140
grade_6         1.0828      0.043     24.925      0.000       0.998
1.168
grade_7         1.0873      0.037     29.284      0.000       1.014
1.160
grade_8         1.0900      0.038     28.982      0.000       1.016
1.164
```

```
grade_9             1.0724       0.056      19.297      0.000       0.964
1.181
grade_10            1.1715       0.166       7.038      0.000       0.845
1.498
grade_11            1.2930       0.327       3.957      0.000       0.653
1.933
grade_12            1.0778       0.038      28.224      0.000       1.003
1.153
==============================================================================
Omnibus:                       10.976   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               10.700
Skew:                           0.041   Prob(JB):                      0.00475
Kurtosis:                       2.925   Cond. No.                     2.99e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.17e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

`Observations from our base model:`

- An R-squared value of 0.503 means that approximately 50.3% of the variance of the data is explained by the model *Prob(F-statistics) is 0.0 which is is below 0.05 which has a statistical significant* Constant is 12.27 when X is zero Y(log_price) is 12.27 in other words its the Y intercept *With 1 unit increase in bedrooms it leads to 0.0489 decrease in log_price* With 1 unit increase in bathrooms it leads to 0.0453 increase in log_price *With 1 unit increase in sqft_living it leads to 0.0003 increase in log_price* With 1 unit increase in floors it leads to 0.0910 increase in log_price *With 1 unit increase in waterfront it leads to 0.2593 increase in log_price* With 1 unit increase in review it leads to 0.0918 increase in log_price *With 1 unit renovated results to 6.362e-16 increases in log_price* With 1 unit increase in grade_idx it leads to 0.0107 increase in log_price *With 1 unit increase in condition_idx it leads to 0.0384 increase in log_pric

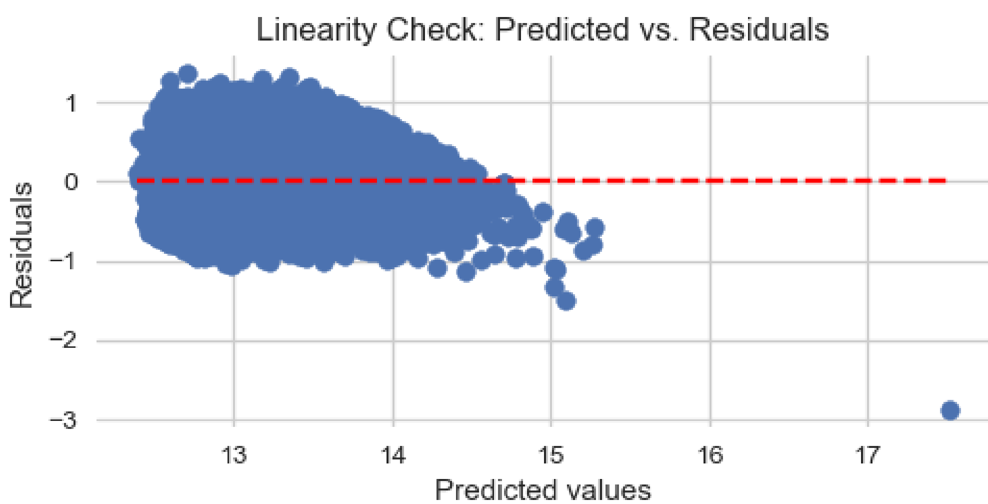
2.1.2 Assumption for Linear Regression in our model

1. *Linearity*

The dependent variable and the independent variable(s) should have a linear relationship.

[63]:
```
def linearity(model):
    # Calculate the fitted values and residuals of the model
    fitted_y = model.fittedvalues
    residuals = model.resid

    # Create a scatter plot of the predicted values (fitted values) against the␣
    ↪residuals
```

```
    fig, ax = plt.subplots(figsize=(6, 2.5))
    _ = ax.scatter(fitted_y, residuals)

    # Add a horizontal line at y=0 to help visualize the deviations of the
 ↪residuals from the line
    ax.hlines(y=0, xmin=fitted_y.min(), xmax=fitted_y.max(), colors='r',
 ↪linestyles='--')

    # Set the x-axis label to 'Predicted values', the y-axis label to
 ↪'Residuals', and the plot title to 'Linearity Check: Predicted vs. Residuals'
    ax.set_xlabel('Predicted values')
    ax.set_ylabel('Residuals')
    ax.set_title('Linearity Check: Predicted vs. Residuals')

    # Display the plot
    plt.show()

# Call the linearity function with a linear regression model as an argument to
 ↪check for linearity
linearity(log_mod)
```



Observation

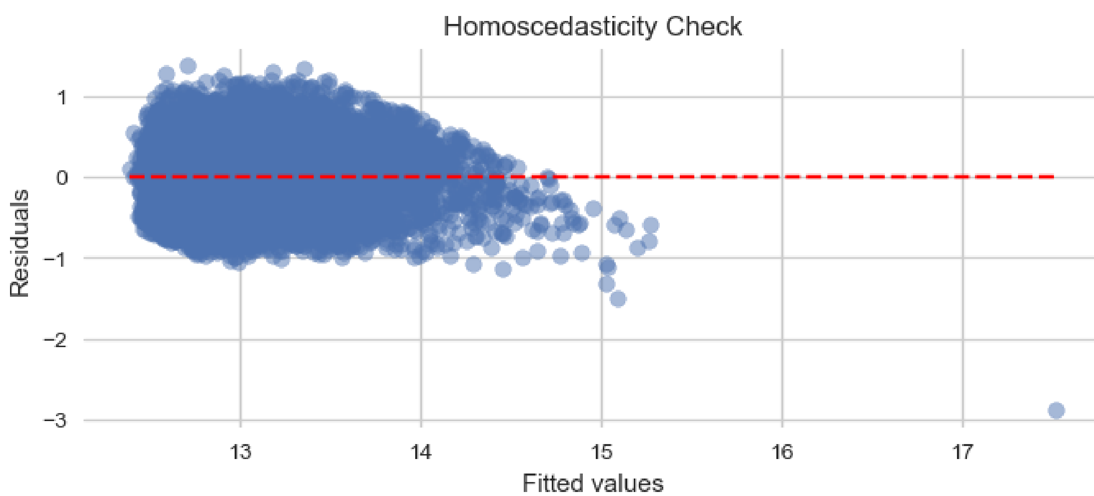
From the above graph, we can clearly say that there is no linearity and there is an observed outlier.

2. *Homoscedasticity*:

For all values of the independent variable, the variance of the errors (residuals) should be constant (s). This indicates that for all values of the independent variable, the spread of the residuals should be the same (s).

[64]:

```
def homoscedasticity(model):
    # Get the residuals and fitted values of the model
    residuals = model.resid
    fitted_y = model.fittedvalues

    # Create a scatter plot of the fitted values against the residuals
    fig, ax = plt.subplots(figsize=(8, 3))
    _ = ax.scatter(fitted_y, residuals, alpha=.5)

    # Add a horizontal line at y=0 to help visualize the deviations of the␣
 ↪residuals from the line
    ax.hlines(y=0, xmin=fitted_y.min(), xmax=fitted_y.max(), colors='r',␣
 ↪linestyles='--')

    # Set the x-axis label to 'Fitted values', the y-axis label to 'Residuals',␣
 ↪and the plot title to 'Homoscedasticity Check'
    ax.set_xlabel('Fitted values')
    ax.set_ylabel('Residuals')
    ax.set_title('Homoscedasticity Check')

    # Display the plot
    plt.show()

# Call the homoscedasticity function with a linear regression model as an␣
 ↪argument to check for homoscedasticity
homoscedasticity(log_mod)
```



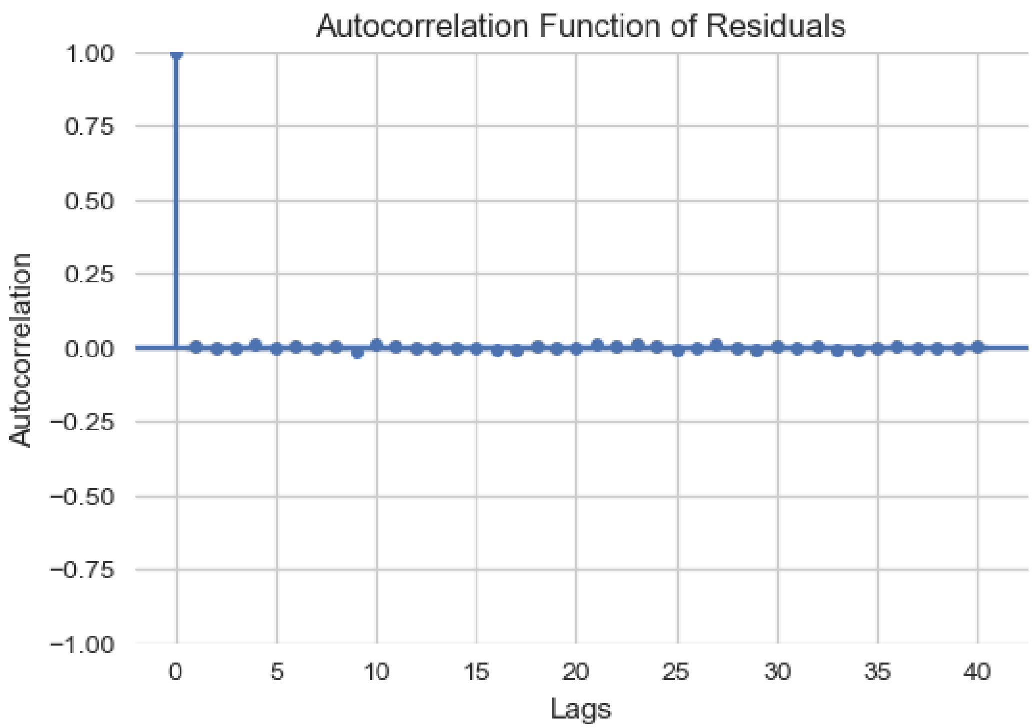
`Observation`

There is a cone-shaped pattern in the spread of the variables hence it is `heteroscedastic`

3. *Independence*:

The observations ought to stand alone from one another. This implies that the dependent variable's value for one observation shouldn't be changed by the dependent variable's value for another observation.

[65]:
```
def independence(residuals):
    fig, ax = plt.subplots(figsize=(6,4))
    _ = sm.graphics.tsa.plot_acf(residuals, lags=40, ax=ax)
    ax.set_xlabel('Lags')
    ax.set_ylabel('Autocorrelation')
    ax.set_title('Autocorrelation Function of Residuals')
    plt.show()

independence(log_mod.resid)
```



`Observation`

From the graph above, we can make an observation that there are residuals.

2.1.3 Perform a train and test split

[66]:
```
#Split into testing and training sets and set random state
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=.2,
                                                    random_state=42)
```

2.1.4 Perfoming a linear Regression on our Train and Test Variables using SciKit Learn

[67]:
```
def linear_model_sklearn(X, y):
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)
    linreg = LinearRegression()
    linreg.fit(x_train, y_train)
    y_hat_train = linreg.predict(x_train)  # these are our prediction values
    y_hat_test = linreg.predict(x_test)
    print('the r2_score:', r2_score(y_test, y_hat_test), '\n')
    train_mae = mean_absolute_error(y_train, y_hat_train)
    test_mae = mean_absolute_error(y_test, y_hat_test)
    train_mse = mean_squared_error(y_train, y_hat_train)
    test_mse = mean_squared_error(y_test, y_hat_test)
    print('train MAE:', train_mae)
    print('test MAE:', test_mae, '\n')
    print('train MSE:', train_mse)
    print('test MSE:', test_mse, '\n')
    print('train root Mean squared Error: ', train_mse** 0.5)
    print('test root Mean squared Error: ', test_mse** 0.5, '\n')
    plt.scatter(y_train, y_hat_train,alpha=0.5,color='y',label='train')
    sns.regplot(x=y_train, y=y_hat_train, scatter=False,␣
 ↪color='r',label='train')
    plt.scatter(y_test, y_hat_test,label='test')
    plt.xlabel('Actual Price')
    plt.ylabel('Predicted Price')
    plt.title('Actual Price vs Predicted Price')
    plt.scatter(x=y, y=y,color ='maroon',label='actual')
    plt.legend()

    ml =LinearRegression()
    ml.fit(x_train,y_train)

    y_pred = ml.predict(x_test)
    pred_y_df = pd.DataFrame({'Actual Values': y_test, 'Predicted Value' :␣
 ↪y_pred, 'Difference' :abs(y_test-y_pred) , 'Percentage Difference' :␣
 ↪abs((y_test-y_pred)/y_test*100)})
    mean_percentage = pred_y_df['Percentage Difference'].mean()
```

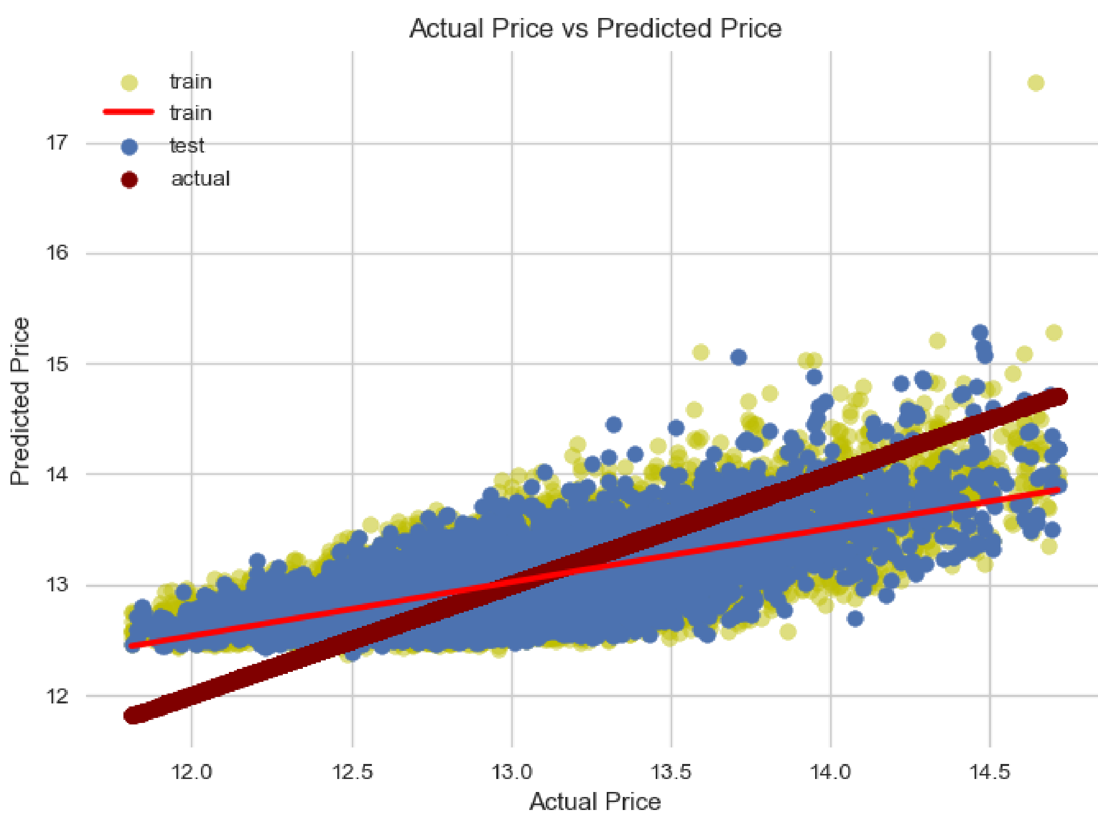
```
    print('mean_diff:', mean_percentage)
    return pred_y_df[0:5]
```

[68]:
```
linear_model_sklearn(X, y)
```

```
the r2_score: 0.4869732649749572

train MAE: 0.29295622674366883
test MAE: 0.29249383379043914

train MSE: 0.12885695479091885
test MSE: 0.1286723520604515

train root Mean squared Error:  0.35896650928870627
test root Mean squared Error:  0.358709286275741

mean_diff: 2.241824360050527
```

[68]:

	Actual Values	Predicted Value	Difference	Percentage Difference
15933	13.393154	13.609841	0.216688	1.617899
11066	12.807653	12.728277	0.079375	0.619749
823	12.568978	12.909395	0.340417	2.708390
3752	12.911642	13.095299	0.183657	1.422411
2174	13.541074	13.258455	0.282619	2.087120



Observations from our base model: *The Mean absolute Error(mae) of the Train is 28.9% while the Mean absolute Error(mae) for test is 28.8%

*The mean_squared_errorr(mse) of the Train is 12.5% while the mean_squared_error(mse) for test is 12.3%

*The root Mean squared Error(rmse) of the Train is 35.4% while the root Mean squared Erro(rmse) for test is 35.1%

*r2_score is 51.1% that is to say our model explains a 51.1% variance in Price

2.1.5 Define functions for Modelling

[69]:
```
#This function fits our model
def model(ind_variable, data):
    formula = 'price ~ ' + ' + '.join(ind_variable)
    multi_model = ols(formula, data).fit()
    multi_model_summ = multi_model.summary()
    return multi_model,multi_model_summ
```

[70]:
```
def assess(model):
    tr_preds=model.predict(X_train)
    te_preds=model.predict(X_test)
    y_tr = y_train
    y_te = y_test
# Format the string output using f-strings
    print(f"Train R2: {r2_score(y_tr, tr_preds)}")
    print(f"Test R2: {r2_score(y_te, te_preds)}")
    print('----')
    print(f"Train RMSE: {mean_squared_error(y_tr, tr_preds, squared = False)}")
    print(f"Test RMSE: {mean_squared_error(y_te, te_preds, squared = False)}")
    print('----')
    print(f"Train MAE: {mean_absolute_error(y_tr, tr_preds)}")
    print(f"Test MAE: {mean_absolute_error(y_te, te_preds)}")


# Set Variables for graphing
    tr_res= y_tr - tr_preds
    te_res= y_te - te_preds

# Graph Syntax
    plt.scatter(tr_preds, tr_res, label = 'Train')
    plt.scatter(te_preds, te_res, label = 'Test')

    plt.axhline(y=0, color = 'red', label = '0')
    plt.xlabel('predictions')
```

```
    plt.ylabel('residuals')
    plt.legend()
    plt.show
```

[71]:
```
# This function standardizes our model features
def scaled_model(ind_variable, data):
    formula = 'price ~ ' + ' + '.join(ind_variable)
    data_scaled = (data - np.mean(data)) / np.std(data)
    model_scaled = ols(formula, data_scaled).fit()
    model_scaled_summ = model_scaled.summary()
    return model_scaled_summ
```

[72]:
```
def model_and_assess(ind_variable, data):
    multi_model, multi_model_summ = model(ind_variable,data)
    assessment = assess(multi_model)
    scaled_summ = scaled_model(ind_variable,data)
    qq = sm.graphics.qqplot(multi_model.resid, dist=stats.norm, line='45',␣
 ↪fit=True)
    print('        ')
    print('This is the summary of the model')
    print('        ')
    print(multi_model_summ)
    print('        ')
    print('This is the summary of the scaled model')
    print('        ')
    print(scaled_summ)
    print('        ')
    print('This is the correlation table between variables')
    print('        ')
    print(data[ind_variable].corr())
    print('        ')
    print('This is the residual plot and qq plot')
    print('        ')
    print(assessment)
    print(qq)
```

[73]:
```
model_and_assess(['sqft_living', 'bedrooms', ], data)
```

```
Train R2: -1288471427096.7275
Test R2: -1286292430765.8271
----
Train RMSE: 567639.2903707522
Test RMSE: 573480.9165533697
----
Train MAE: 527029.1746031909
Test MAE: 532145.6220345316
```

This is the summary of the model

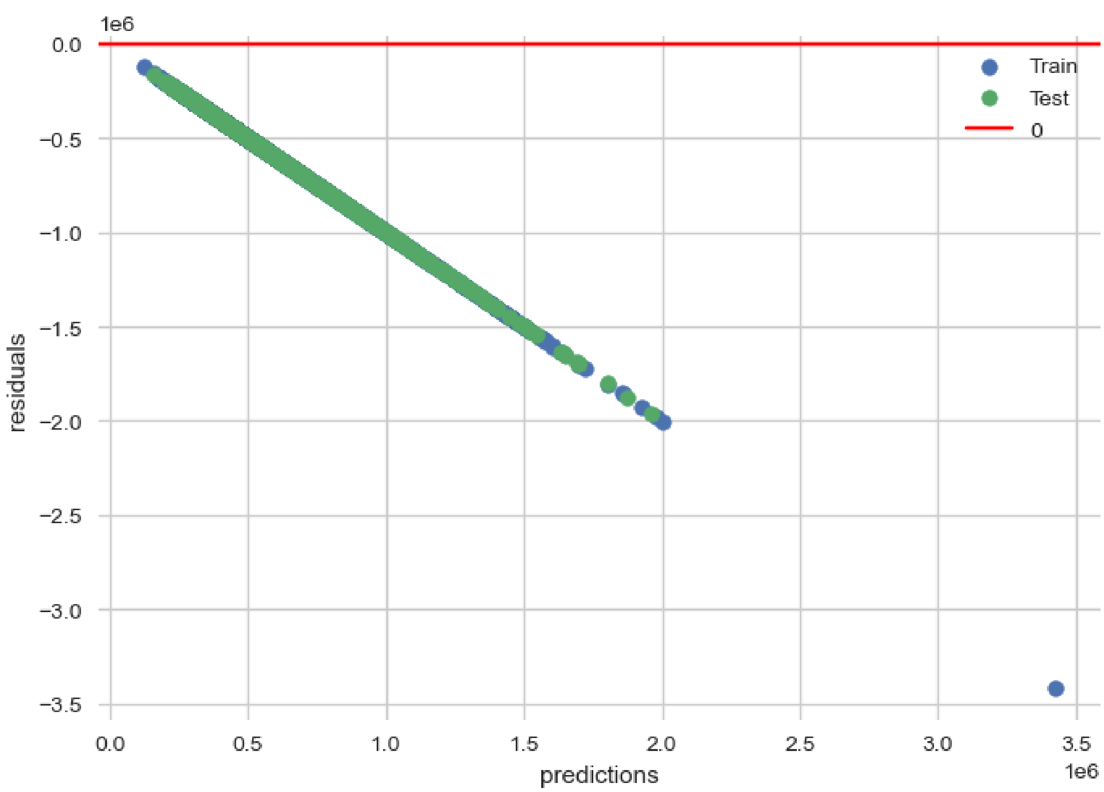
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.474
Model:                            OLS   Adj. R-squared:                  0.474
Method:                 Least Squares   F-statistic:                     9387.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:23:12   Log-Likelihood:            -2.8579e+05
No. Observations:               20812   AIC:                         5.716e+05
Df Residuals:                   20809   BIC:                         5.716e+05
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept    1.317e+05   6013.684     21.899      0.000     1.2e+05    1.43e+05
sqft_living   266.7522      2.191    121.770      0.000     262.458     271.046
bedrooms    -4.594e+04   2137.052    -21.498      0.000   -5.01e+04   -4.18e+04
==============================================================================
Omnibus:                     6985.517   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            36850.976
Skew:                           1.530   Prob(JB):                         0.00
Kurtosis:                       8.756   Cond. No.                     9.07e+03
==============================================================================
```

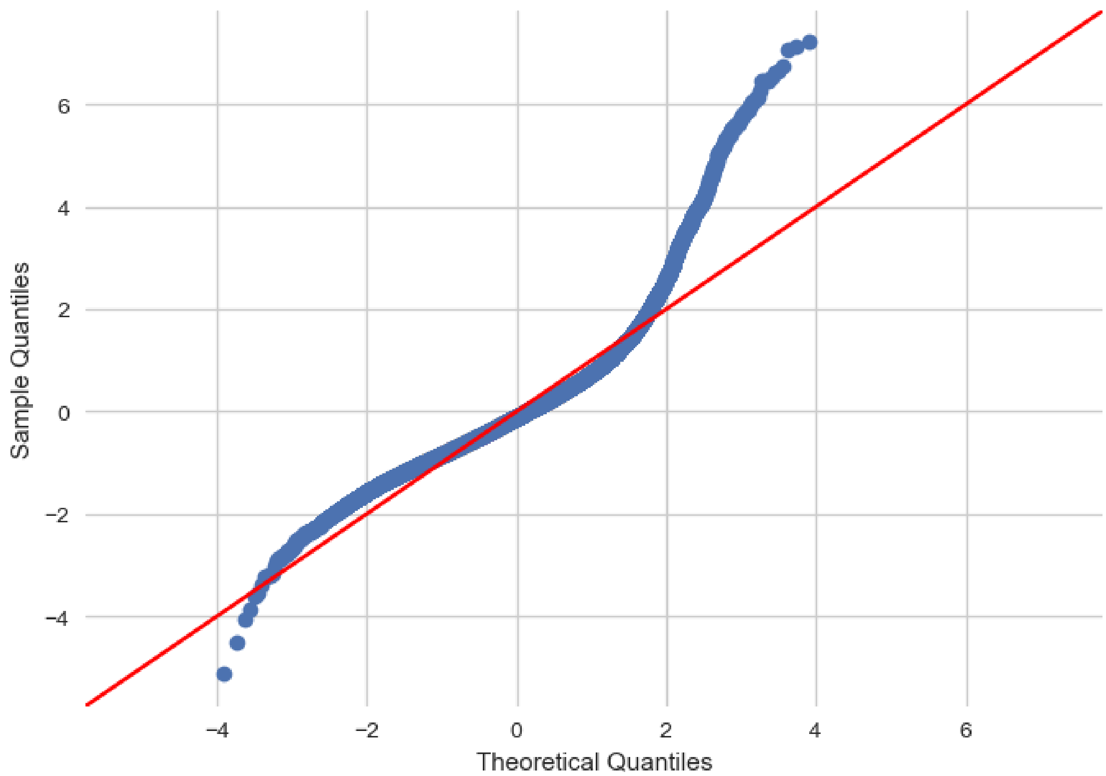
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.07e+03. This might indicate that there are strong multicollinearity or other numerical problems.

This is the summary of the scaled model

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.474
Model:                            OLS   Adj. R-squared:                  0.474
Method:                 Least Squares   F-statistic:                     9387.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:23:13   Log-Likelihood:                -22840.
No. Observations:               20812   AIC:                         4.569e+04
Df Residuals:                   20809   BIC:                         4.571e+04
Df Model:                           2
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
```

```
Intercept   -4.163e-17      0.005  -8.28e-15      1.000      -0.010       0.010
sqft_living     0.7596      0.006    121.770      0.000       0.747       0.772
bedrooms       -0.1341      0.006    -21.498      0.000      -0.146      -0.122
==============================================================================
Omnibus:                     6985.517   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            36850.976
Skew:                           1.530   Prob(JB):                         0.00
Kurtosis:                       8.756   Cond. No.                         1.98
==============================================================================

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

This is the correlation table between variables

             sqft_living  bedrooms
sqft_living     1.000000  0.592237
bedrooms        0.592237  1.000000

This is the residual plot and qq plot

None
Figure(800x550)
```





[74]:
```
#Model using `sqft_living`, 'bedrooms', 'bathrooms', and all the grades
features = ['sqft_living', 'bathrooms', 'renovated',
            'grade_3', 'grade_4','grade_5', 'grade_6',
            'grade_7', 'grade_8', 'grade_9', 'grade_10',
            'grade_11', 'grade_12']
model_and_assess(features, data)
```

```
Train R2: -1288725848426.3235
Test R2: -1280522024228.9353
----
Train RMSE: 567695.3305790912
Test RMSE: 572193.1309573285
----
Train MAE: 527213.5578295465
Test MAE: 531408.2220019568

This is the summary of the model

                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:                  price   R-squared:                       0.472
Model:                            OLS   Adj. R-squared:                  0.471
Method:                 Least Squares   F-statistic:                     1548.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:23:13   Log-Likelihood:            -2.8584e+05
No. Observations:               20812   AIC:                         5.717e+05
Df Residuals:                   20799   BIC:                         5.718e+05
Df Model:                          12
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept    1.087e+04   2.33e+04      0.467      0.641   -3.48e+04    5.65e+04
sqft_living   225.7011      2.431     92.847      0.000     220.936     230.466
bathrooms    2.082e+04   2908.436      7.158      0.000    1.51e+04    2.65e+04
renovated    1.448e+05   8460.110     17.113      0.000    1.28e+05    1.61e+05
grade_3      3082.7666     2.3e+04      0.134      0.894   -4.21e+04    4.82e+04
grade_4      2369.9353   2.33e+04      0.102      0.919   -4.33e+04     4.8e+04
grade_5     -4306.1296   2.54e+04     -0.169      0.865   -5.41e+04    4.55e+04
grade_6      1.839e+04     2.7e+04      0.681      0.496   -3.45e+04    7.13e+04
grade_7      3824.5309   2.31e+04      0.166      0.868   -4.14e+04    4.91e+04
grade_8      6051.4144   2.34e+04      0.259      0.796   -3.98e+04    5.19e+04
grade_9     -1.436e+04   3.46e+04     -0.416      0.678   -8.21e+04    5.34e+04
grade_10     2.953e+04   1.04e+05      0.285      0.775   -1.73e+05    2.32e+05
grade_11    -2.926e+04   2.03e+05     -0.144      0.886   -4.28e+05    3.69e+05
grade_12    -4466.7782   2.37e+04     -0.188      0.851    -5.1e+04    4.21e+04
==============================================================================
Omnibus:                     6895.471   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            35806.716
Skew:                           1.513   Prob(JB):                         0.00
Kurtosis:                       8.668   Cond. No.                     2.37e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.87e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

This is the summary of the scaled model

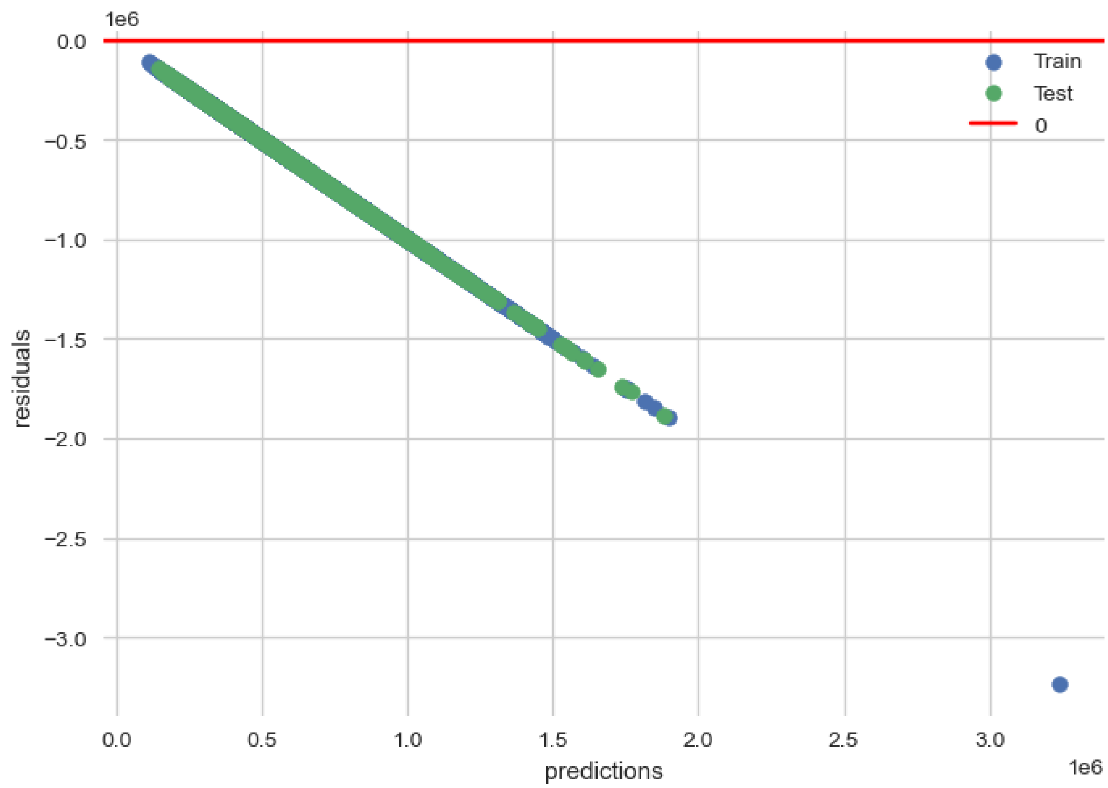
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.472
Model:                            OLS   Adj. R-squared:                  0.471
Method:                 Least Squares   F-statistic:                     1548.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        20:23:14   Log-Likelihood:                -22891.
```

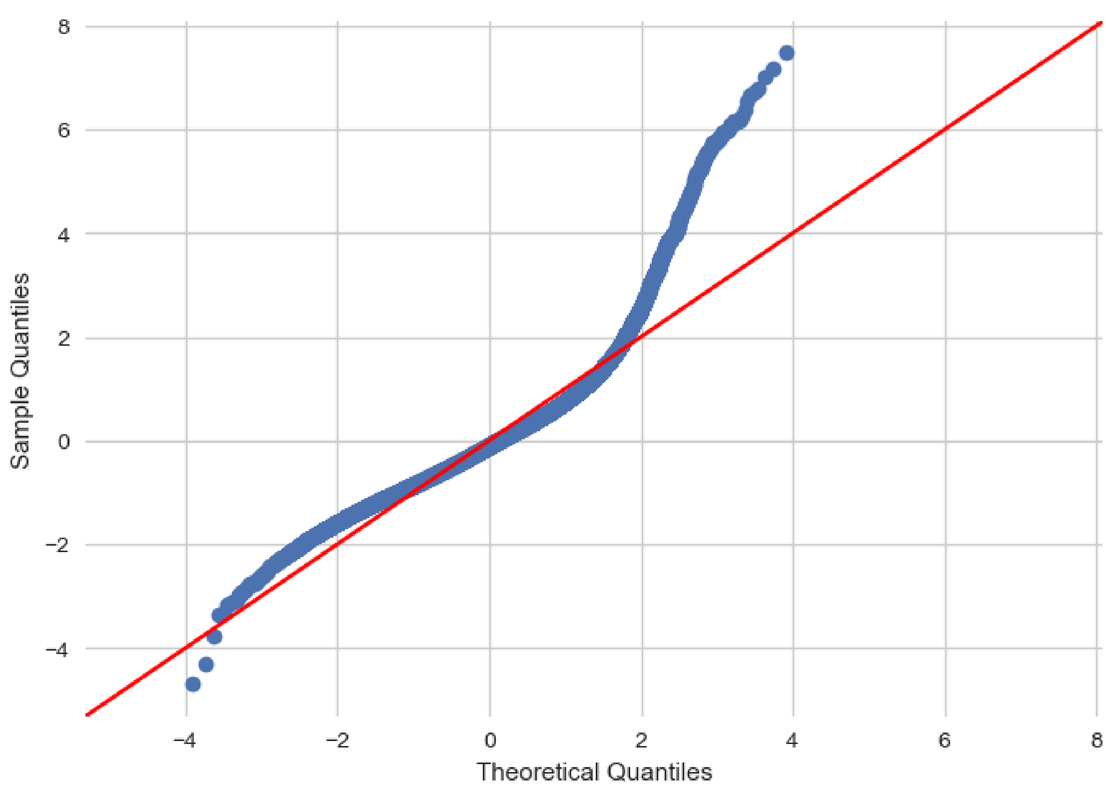
```
No. Observations:               20812   AIC:                         4.581e+04
Df Residuals:                   20799   BIC:                         4.591e+04
Df Model:                          12
Covariance Type:            nonrobust
===============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept   -4.163e-17      0.005  -8.26e-15      1.000      -0.010       0.010
sqft_living     0.6427      0.007     92.847      0.000       0.629       0.656
bathrooms       0.0496      0.007      7.158      0.000       0.036       0.063
renovated       0.0864      0.005     17.113      0.000       0.077       0.096
grade_3         0.0002      0.003      0.046      0.963      -0.006       0.007
grade_4        -0.0007      0.004     -0.153      0.878      -0.009       0.008
grade_5        -0.0030      0.005     -0.612      0.541      -0.013       0.007
grade_6         0.0049      0.005      0.984      0.325      -0.005       0.015
grade_7         0.0012      0.004      0.339      0.735      -0.006       0.008
grade_8         0.0029      0.004      0.651      0.515      -0.006       0.012
grade_9        -0.0031      0.005     -0.609      0.543      -0.013       0.007
grade_10        0.0012      0.005      0.238      0.812      -0.009       0.011
grade_11       -0.0007      0.005     -0.144      0.885      -0.011       0.009
grade_12       -0.0054      0.005     -1.149      0.251      -0.015       0.004
==============================================================================
Omnibus:                     6895.471   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            35806.716
Skew:                           1.513   Prob(JB):                         0.00
Kurtosis:                       8.668   Cond. No.                     3.15e+15
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 3.56e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

This is the correlation table between variables

```
             sqft_living  bathrooms  renovated   grade_3   grade_4   grade_5  \
sqft_living     1.000000   0.685441   0.041996 -0.007332  0.009895  0.003336
bathrooms       0.685441   1.000000   0.058404 -0.018953  0.015474  0.006459
renovated       0.041996   0.058404   1.000000  0.007115  0.006515 -0.007978
grade_3        -0.007332  -0.018953   0.007115  1.000000 -0.316951 -0.109375
grade_4         0.009895   0.015474   0.006515 -0.316951  1.000000 -0.048272
grade_5         0.003336   0.006459  -0.007978 -0.109375 -0.048272  1.000000
grade_6        -0.007124  -0.007195  -0.007949 -0.083476 -0.036842 -0.012713
grade_7         0.003225   0.011741  -0.010665 -0.535067 -0.236147 -0.081490
grade_8        -0.011881  -0.015543   0.000619 -0.271321 -0.119745 -0.041322
grade_9         0.002191   0.004915  -0.005443 -0.045947 -0.020278 -0.006998
grade_10        0.000370  -0.000918  -0.002632 -0.011750 -0.005186 -0.001789
```

```
grade_11        0.003436  -0.000459  -0.001316 -0.005874 -0.002593 -0.000895
grade_12        0.011193   0.014020   0.005020 -0.198744 -0.087714 -0.030269

              grade_6   grade_7   grade_8   grade_9  grade_10  grade_11  \
sqft_living -0.007124  0.003225 -0.011881  0.002191  0.000370  0.003436
bathrooms   -0.007195  0.011741 -0.015543  0.004915 -0.000918 -0.000459
renovated   -0.007949 -0.010665  0.000619 -0.005443 -0.002632 -0.001316
grade_3     -0.083476 -0.535067 -0.271321 -0.045947 -0.011750 -0.005874
grade_4     -0.036842 -0.236147 -0.119745 -0.020278 -0.005186 -0.002593
grade_5     -0.012713 -0.081490 -0.041322 -0.006998 -0.001789 -0.000895
grade_6      1.000000 -0.062195 -0.031538 -0.005341 -0.001366 -0.000683
grade_7     -0.062195  1.000000 -0.202150 -0.034233 -0.008754 -0.004377
grade_8     -0.031538 -0.202150  1.000000 -0.017359 -0.004439 -0.002219
grade_9     -0.005341 -0.034233 -0.017359  1.000000 -0.000752 -0.000376
grade_10    -0.001366 -0.008754 -0.004439 -0.000752  1.000000 -0.000096
grade_11    -0.000683 -0.004377 -0.002219 -0.000376 -0.000096  1.000000
grade_12    -0.023101 -0.148076 -0.075086 -0.012715 -0.003252 -0.001626

             grade_12
sqft_living  0.011193
bathrooms    0.014020
renovated    0.005020
grade_3     -0.198744
grade_4     -0.087714
grade_5     -0.030269
grade_6     -0.023101
grade_7     -0.148076
grade_8     -0.075086
grade_9     -0.012715
grade_10    -0.003252
grade_11    -0.001626
grade_12     1.000000

This is the residual plot and qq plot

None
Figure(800x550)
```


1e6
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
residuals
Train
Test
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
predictions
1e6


8
6
4
2
0
−2
−4
Sample Quantiles
−4
−2
0
2
4
6
8
Theoretical Quantiles

```
Observations from our base model:
```

TRAIN

- An R-squared value of 0.477 means that approximately 47,7% of the variance of the data is explained by the model
- Prob(F-statistics) is 0.0 which is is below 0.05 hence has a statistical significant
- Constant is 1.328e+05 when X is zero Y(price) is 1.328e+05 in other words its the Y intercept
- With 1 unit increase in sqft_living of the train leads to 267.5183 increase in price
- With 1 unit increase in bedrooms of the train leads to -4.675e+04 decrease in price #### TEST
- An R-squared value of 0.477 means that approximately 47,7% of the variance of the data is explained by the model
- Prob(F-statistics) is 0.0 which is is below 0.05 hence has a statistical significant
- Constant is -1.561e-16 when X is zero Y(price) is -1.561e-16 in other words its the Y intercept
- With 1 unit increase in sqft_living of the test leads to 0.7631 increase in price
- With 1 unit increase in bedrooms of the test leads to -0.1361 decrease in price

[75]:
```
def poly(X, y):# Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

    # Create a PolynomialFeatures object to transform the input data X
    poly = PolynomialFeatures(degree=2)
    X_train_poly = poly.fit_transform(X_train)
    X_test_poly = poly.transform(X_test)

    # Create a LinearRegression object to perform the regression
    lin_reg = LinearRegression()

    # Fit the model to the transformed input data and output data
    lin_reg.fit(X_train_poly, y_train)

    # Predict the output for the test data
    y_pred = lin_reg.predict(X_test_poly)

    # Calculate the R-squared value of the model
    r2 = lin_reg.score(X_test_poly, y_test)

    print('POLYNOMIAL R-squared:', r2)
```

[76]:
```
#create polynomial model
poly(X, y)
```

```
POLYNOMIAL R-squared: 0.5052526483789097
```

2.2 Conclusion

After analysing the King County data in our final model takes into account 50.3% of the variance in price. The main factors increasing the property value are sqft_living and the grade. In grade, we refer to the construction quality materials used, which were of high quality. Majority of the tennants consider quality over quantity, since most of them are in houses that are graded to be of a very good condition.

2.3 Recommendations

Other methods that can improve our model would be to include crime data by zip code, school rating data by school zone, and including more years of data.