Phase 2 project

Business Understanding

Problem Statement

New real estate developers are planning to build new housing facilities and there has been a problem in evaluating homes in King County

Objectives:

1. To develop a model that will help in identifying the attributes that bring more value to the houses, hence bringing maximum profit. Specifically, to uncover:

> Which features have the biggest impact on the sale price of a house?
> How much does location affect the sale price of a house?

2. To create a regression model to advice developers on how to accurately price a property

Importing the data

In [1]:
```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import warnings
%matplotlib inline
sns.set_style('dark')
warnings.filterwarnings('ignore')
data = pd.read_csv('data/kc_house_data.csv')

data.head()
```

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	N
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	

5 rows × 21 columns

In [2]:
```
# grouping bedrooms
x = data.groupby(['bedrooms'])[['price']].mean()
```

Data Understanding

Here we will explore the data to get a better understanding of its state, then decide on the steps we need to take to clean it. We will begin by defining some helper functions for the following tasks:

- getting the shape of the data
- getting data info
- simple check for missing data
- duplicates
- descriptive stats

We will then group together the helper function under a new function that explores the data for the above attributes

In [3]:
```
# helper function for shape of the data

def data_shape(data):
    """Simple function to provide the shape of the data"""
    out = print(f"The DataFrame has:\n\t* {data.shape[0]} rows\n\t* {data

    return out
```

In [4]:
```
# helper function for info of the data

def data_info(data):
    """Simple function to provide the info of the data"""
    out = print(data.info(), '\n')

    return out
```

In [5]:
```
# helper function to check for missing values

def data_missing(data):
    """Identify is the data has missing values"""
    # identify if data has missing values(data.isnull().any())
    # empty dict to store missing values
    missing = []
    for i in data.isnull().any():
        # add the bool values to empty list
        missing.append(i)
    # covert list to set (if data has missing value, the list should have
    missing_set = set(missing)
    if (len(missing_set) == 1):
        out = print("The Data has no missing values", '\n')
    else:
        out = print(f"The Data has missing values.", '\n')

    return out
```

In [6]:
```
# helper function to check for duplicates

def identify_duplicates(data):
    """Simple function to identify any duplicates"""
    # identify the duplicates (dataframename.duplicated() , can add .sum(
    # empty list to store Bool results from duplicated
    duplicates = []
    for i in data.duplicated():
        duplicates.append(i)
    # identify if there is any duplicates. (If there is any we expect a T
    duplicates_set = set(duplicates)
    if (len(duplicates_set) == 1):
        out = print("The Data has no duplicates", '\n')
    else:
        no_true = 0
        for val in duplicates:
            if (val == True):
                no_true += 1
        # percentage of the data represented by duplicates
        duplicates_percentage = np.round(((no_true / len(data)) * 100), 3
        out = print(f"The Data has {no_true} duplicated rows.\nThis const
```

In [7]:
```
# helper function to check for duplicates on the ID column

def unique_column_duplicates(data, column):
    """handling duplicates in unique column"""
    # empty list to store the duplicate bools
    duplicates = []
    for i in data[column].duplicated():
        duplicates.append(i)

    # identify if there are any duplicates
    duplicates_set = set(duplicates)
    if (len(duplicates_set) == 1):
        out = print(f"The column {column.title()} has no duplicates", '\n
    else:
        no_true = 0
        for val in duplicates:
            if (val == True):
                no_true += 1
        # percentage of the data represented by duplicates
        duplicates_percentage = np.round(((no_true / len(data)) * 100), 3
        out = print(f"The column {column.title()} has {no_true} duplicate
```

In [8]:
```
# helper function to check for descriptive stats

def data_describe(data):
    """Simple function to check the descriptive values of the data"""
    out = print(data.describe(), '\n')

    return out
```

In [9]:
```
# overall function for data understanding

def explore(data):
    """Group of functions to explore data """
    out1 = data_shape(data)
    out2 = data_info(data)
    out3 = data_missing(data)
    out4 = identify_duplicates(data)
    out5 = unique_column_duplicates(data, 'id')
    out6 = data_describe(data)

    return out1, out2, out3, out4, out5
```

From below, data has:

- 21597 houses sold
- 21 house features : 6 string variables and 15 numeric variables. `date` column is encoded as string instead of datetime, while `sqft_basement` is enconded as string instead of float. These 2 will be corrected
- Missing values which will be investigated and treated
- No duplicates. However, the `id` column which should contain unique identifiers has 177 duplicated values. These will be checked
- From the descriptive stats, there's also potential for some outliers which will need to be veried. e.g. having max 33 bedrooms

Looking at the `date` column which shows sale date, we will extract the month to see if there is a seasonality sale of houses i.e do houses sale more during some months than others?

We will also use the `zipcode` or `lat` & `long` columns to split the locations into the 4 regions of King County namely : North, East, Seattle & South. We will use this to investigate whether location is a factor in house sales i.e. is there a variation in house prices by location?

In [10]:
```
1 explore(data)
```

```
The DataFrame has:
        * 21597 rows
        * 21 columns

<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
None

The Data has missing values.

The Data has no duplicates

The column Id has 177 duplicated rows.
This constitutes 0.82% of the data set.

                 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_lot1
5
count  21597.000000  21597.000000  21597.000000   21597.000000   21597.00000
0
mean   98077.951845     47.560093   -122.213982    1986.620318   12758.28351
2
std       53.513072      0.138552      0.140724     685.230472   27274.44195
0
min    98001.000000     47.155900   -122.519000     399.000000     651.00000
0
25%    98033.000000     47.471100   -122.328000    1490.000000    5100.00000
0
50%    98065.000000     47.571800   -122.231000    1840.000000    7620.00000
0
75%    98118.000000     47.678000   -122.125000    2360.000000   10083.00000
0
max    98199.000000     47.777600   -121.315000    6210.000000  871200.00000
0
```

Out[10]: (None, None, None, None, None)

Data Preparation

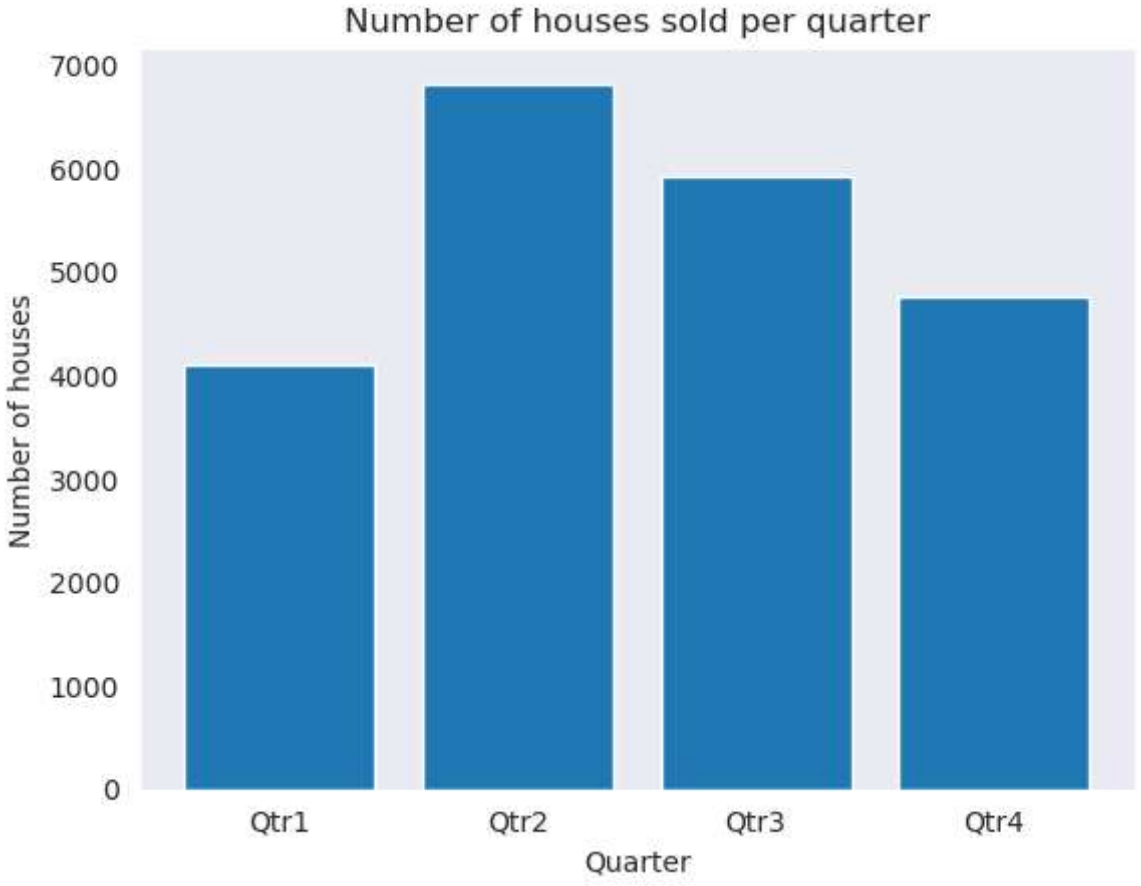
Change floors from float to int

In [11]:
```
# change float to int
data['floors'] = data['floors'].astype(int)
```

Cleaning date column

Here we will change the `date` column to string, and then create a new column `month_sold` extracting the sale month from the date column. From the plot below, we see that there is a seasonality trend to house sales. To simplify analysis, we will group the month column into 4 quarters: Q1 (1, 2, 3), Q2 (4, 5, 6), Q3 (7, 8, 9), Q4 (10, 11, 12)

In [12]:
```
# transform and extract month
data['date'] = pd.to_datetime(data['date'])
data['month_sold'] = data.date.dt.month

# change month to quarters
Q1 = {1: 'Qtr1', 2: 'Qtr1', 3: 'Qtr1'}
Q2 = {4: 'Qtr2', 5: 'Qtr2', 6: 'Qtr2'}
Q3 = {7: 'Qtr3', 8: 'Qtr3', 9: 'Qtr3'}
Q4 = {10: 'Qtr4', 11: 'Qtr4', 12: 'Qtr4'}
quarters = {**Q1, **Q2, **Q3, **Q4}
data['month_sold'] = data['month_sold'].replace(quarters)

a = data.month_sold.value_counts().sort_index()
plt.bar(x=a.index, height=a.values)
plt.xticks(a.index)
plt.title('Number of houses sold per quarter')
plt.xlabel('Quarter')
plt.ylabel('Number of houses');
```



Cleaning sqft_basement column

This column is coded as string, yet it should be float. We change that below. We also discover that the column contains missing values encoded as '?'. Since this accounts for only 2.1% of the data, we can drop them

In [13]:
```
# inspect columns
print(f'sqft_basement col is encoded as {data.sqft_basement.dtype}')
a1 = data.sqft_basement.value_counts(normalize=True)[1]

def check_qn(data):
    """check for ? in data"""
    for col in data.columns:
        if ('?' in data[col].unique()) == True:
            out = print(f'{col} contains "?". This is {round(a1*100, 2)}%
            return out

check_qn(data)
```

```
sqft_basement col is encoded as object
sqft_basement contains "?". This is 2.1% of the data
```

In [14]:
```
# since the missing values are insignifcantly small, we drop them
data['sqft_basement'] = pd.to_numeric(data['sqft_basement'].replace('?',
data = data.dropna(subset=['sqft_basement'])

# check again for ?
print('"?" in sqft_basement: ','?' in data['sqft_basement'].unique())

#check dtype
print(f'sqft_basement col is encoded as {data.sqft_basement.dtype}')
```

```
"?" in sqft_basement:  False
sqft_basement col is encoded as float64
```

Missing values

We have missing values below, however, since these columns will not be used in the analysis. We will not treat the missing data as the columns will be dropped later on

In [15]:

```
def missing_values(data):
    """A simple function to identify data has missing values"""
    # identify the total missing values per column
    # sort in order
    miss = data.isnull().sum().sort_values(ascending = False)

    # calculate percentage of the missing values
    percentage_miss = ((data.isnull().sum() / len(data))*100).sort_values

    # store in a dataframe
    missing = pd.DataFrame({"Missing Values": miss, "Percentage(%)": perc

    # remove values that are missing
    missing.drop(missing[missing["Percentage(%)"] == 0].index, inplace =

    return missing


missing_data = missing_values(data)
missing_data
```

Out[15]:

	Missing Values	Percentage(%)
yr_renovated	3754	17.755285
waterfront	2339	11.062763
view	61	0.288512

In [16]:

```
#function to fill missing values
def fill_missing_values(data):
    # Fill missing values in "view" with "NONE"
    data["view"].fillna("NONE", inplace=True)

    # Fill missing values in "waterfront" with mode
    mode_waterfront = data["waterfront"].mode()[0]
    data["waterfront"].fillna(mode_waterfront, inplace=True)

    # Fill missing values in "yr_renovated" with mode
    mode_yr_renovated = data["yr_renovated"].mode()[0]
    data["yr_renovated"].fillna(mode_yr_renovated, inplace=True)

    return data

fill_missing_values(data)
```

Out[16]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1	
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2	
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1	
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1	
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1	
...	...	...	...	...	...	...	...	...	
21592	263000018	2014-05-21	360000.0	3	2.50	1530	1131	3	
21593	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	2	
21594	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	2	
21595	291310100	2015-01-16	400000.0	3	2.50	1600	2388	2	
21596	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	2	

21143 rows × 22 columns

In [17]:

```
missing_values(data)
```

Out[17]:

	Missing Values	Percentage(%)

Duplicated Id Column

Id column duplicates to be dropped in the process below

In [18]:
```
print(identify_duplicates(data))
print(unique_column_duplicates(data, 'id'))
```

```
The Data has no duplicates

None
The column Id has 173 duplicated rows.
This constitutes 0.818% of the data set.

None
```

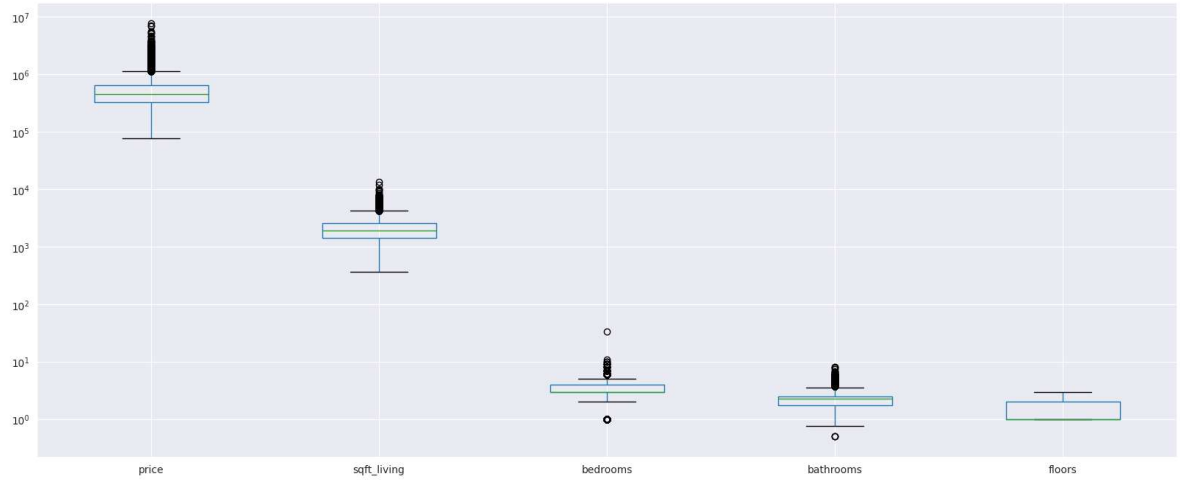
In [19]:
```
def drop_duplicates(df, column):
    """function to drop duplicated rows"""

    df.drop_duplicates(subset=column, keep='first', inplace=True)
    confirmation = unique_column_duplicates(data, 'id')
    return confirmation

drop_duplicates(data, 'id')
```

```
The column Id has no duplicates
```

Outliers to be completed

We will focus on the columns specified below, which we have chosen for the modelling to check outliers

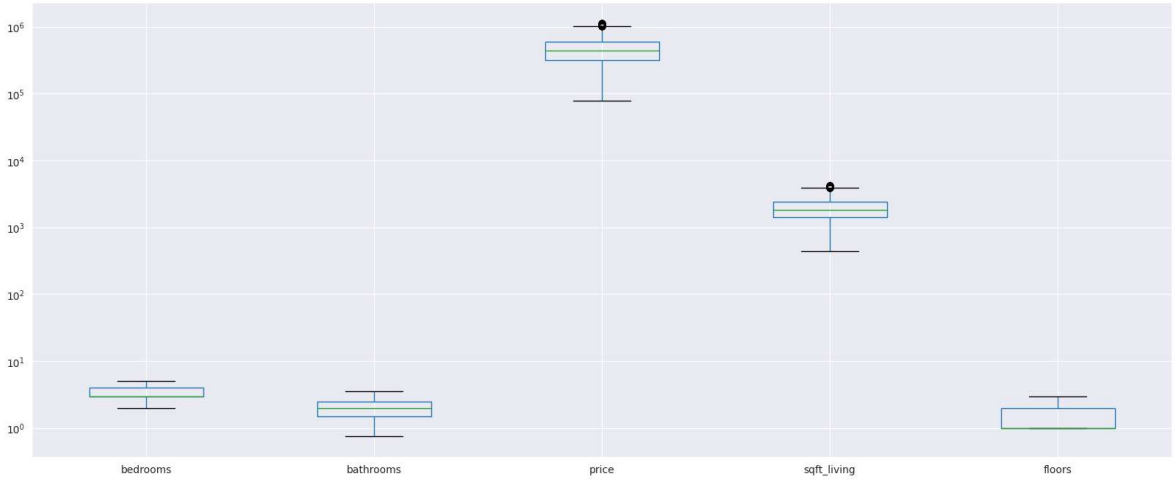
In [20]:
```
# visualize data to assess outliers

columns = ['price', 'sqft_living', 'bedrooms','bathrooms', 'floors']
data[columns].boxplot(figsize = (20,8))
plt.yscale('log')
plt.show()
```



In [21]:
```
# Define the columns to check for outliers
columns = ['bedrooms', 'bathrooms', 'price', 'sqft_living', 'floors']

print("Summary statistics before removing outliers:")
print(data[columns].describe())

# Calculate the IQR for each column
Q1 = data[columns].quantile(0.25)
Q3 = data[columns].quantile(0.75)
IQR = Q3 - Q1

# Remove outliers from each column
data = data[~((data[columns] < (Q1 - 1.5 * IQR)) | (data[columns] > (Q3 +

print("\nSummary statistics after removing outliers:")
print(data[columns].describe())
```

```
Summary statistics before removing outliers:
            bedrooms     bathrooms         price   sqft_living        floors
count  20970.000000  20970.000000  2.097000e+04  20970.000000  20970.000000
mean       3.373343      2.118693  5.409766e+05   2083.747592      1.447639
std        0.924136      0.768475  3.686345e+05    919.294297      0.551640
min        1.000000      0.500000  7.800000e+04    370.000000      1.000000
25%        3.000000      1.750000  3.225000e+05   1430.000000      1.000000
50%        3.000000      2.250000  4.500000e+05   1920.000000      1.000000
75%        4.000000      2.500000  6.450000e+05   2550.000000      2.000000
max       33.000000      8.000000  7.700000e+06  13540.000000      3.000000

Summary statistics after removing outliers:
            bedrooms     bathrooms         price   sqft_living        floors
count  19106.000000  19106.000000  1.910600e+04  19106.000000  19106.000000
mean       3.298440      2.026052  4.715314e+05   1943.632262      1.426097
std        0.780765      0.661820  2.026963e+05    712.547044      0.549376
min        2.000000      0.750000  7.800000e+04    440.000000      1.000000
25%        3.000000      1.500000  3.150000e+05   1400.000000      1.000000
50%        3.000000      2.000000  4.350000e+05   1840.000000      1.000000
75%        4.000000      2.500000  5.950000e+05   2400.000000      2.000000
max        5.000000      3.500000  1.120000e+06   4230.000000      3.000000
```

In [22]:
```
data[columns].boxplot(figsize = (20,8))
plt.yscale('log')
plt.show()
```



Turning Zipcodes into Regions

The code below turns zip codes into the regions for King County.

In [2]:
```
# Determine the minimum and maximum latitude and longitude values in the
min_lat = data['lat'].min()
max_lat = data['lat'].max()
min_long = data['long'].min()
max_long = data['long'].max()
# Define the latitude and longitude ranges for each of the four regions
north_lat = max_lat - (max_lat - min_lat) / 2
east_long = min_long + (max_long - min_long) / 2
south_lat = min_lat + (max_lat - min_lat) / 2
# Assign each data point to one of the four regions based on its latitude
data['region'] = ''
data.loc[(data['lat'] >= north_lat) & (data['long'] <= east_long), 'regio
data.loc[(data['lat'] >= north_lat) & (data['long'] > east_long), 'region
data.loc[(data['lat'] < south_lat) & (data['long'] <= east_long), 'region
data.loc[(data['lat'] < south_lat) & (data['long'] > east_long), 'region'
```

folium map

In [3]:
```
# visualize the different regions
import folium
from IPython.display import display
from folium.plugins import MarkerCluster
# create a list of coordinates
latlon = list(zip(data.lat, data.long))
# create a map with the Stamen Terrain tileset
base_map = folium.Map(location=[data.lat.mean(), data.long.mean()], zoom_
# add the markers to the map
marker_cluster = MarkerCluster().add_to(base_map)
for coord in latlon:
    folium.Marker(location=[coord[0], coord[1]], icon=None).add_to(marker
display(base_map)
```

Explolatory Data Analysis

We will explore the following areas to set context for the presentation

- Average Price of property based on number of bedrooms
- Average Price of property based on the condition of the property
- Regions (North, East, Seattle & South)
- Price distribution
- Houses Sold Per Quarter

Average Price of property based on number of bedrooms

- As the bedrooms increase, price increases, upto 8 bedrooms.

- Afterwards the price decreases.

In [25]:
```
# plot the output
sns.set(rc={'figure.figsize':(10,4)})
sns.barplot(data=x,
            x=x.index,
            y='price').set(title='Average Price of property based on numbe
                                  xlabel='number of bedrooms', ylabel='Pr
```

In [26]:
```
# lets see price against bedrooms
bed_df = data[['bedrooms', 'price']]
bed_df2 = bed_df.groupby(['bedrooms'])[['price']].mean()

# plot the output
sns.set(rc={'figure.figsize':(10,4)})
sns.barplot(data=bed_df2,
            x=bed_df2.index,
            y='price').set(title='Average Price of property based on numbe
                                  xlabel='number of bedrooms', ylabel='Pr
```

Average Price of property based on the condition of the property

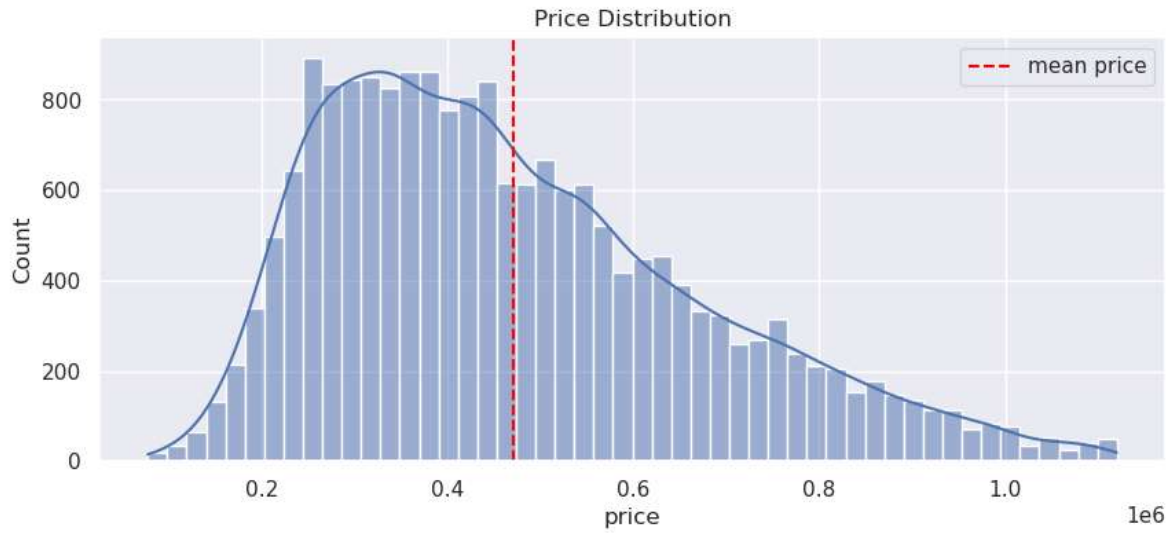
As the condition of the house improves, price increases - houses with a very good condition have higher prices. Thus keeping property in a good condition will higher valuation

In [27]:
```
# lets see price of against bedrooms
condition_df = data[['condition', 'price']]
condition_df2 = condition_df.groupby(['condition'])[['price']].mean()

# plot the output
sns.set(rc={'figure.figsize':(10,4)})
sns.barplot(data=condition_df2,
            x=condition_df2.index,
            y='price').set(title='Average Price of property based on the c
                                  xlabel='condition', ylabel='Price (USD)
```

Price Distribution

Price is almost normally distributed, with a positve skew. There are more lower priced houses, than highly priced houses.

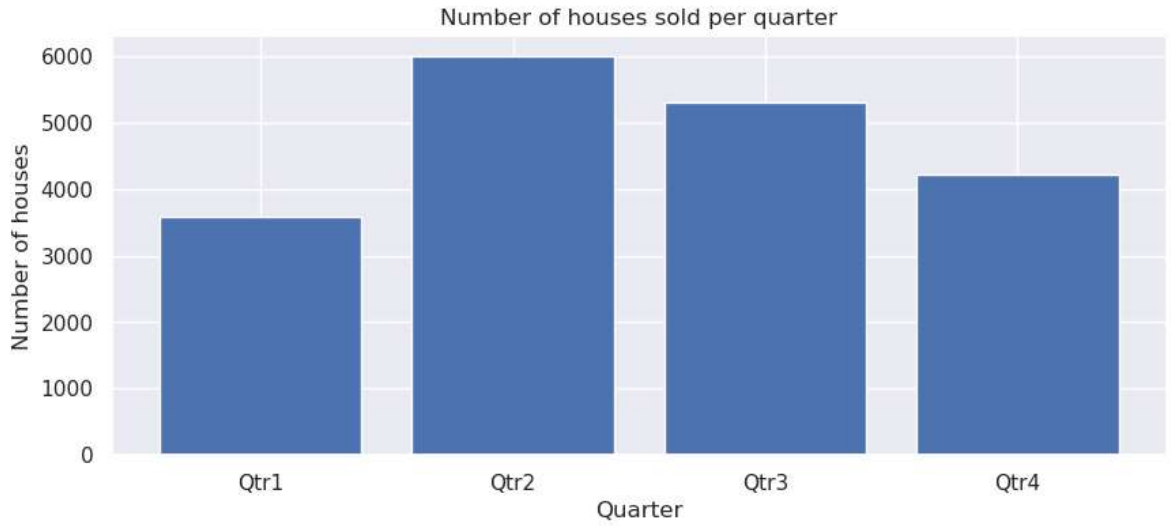
In [28]:
```
sns.histplot(data.price, kde=True)
plt.title('Price Distribution')
plt.axvline(x=data.price.mean(), label='mean price', linestyle='--', colo
plt.legend();
```



Houses Sold Per Quarter

Houses sold in quarter 2 have the highest price - trend shows seasonality of house sales

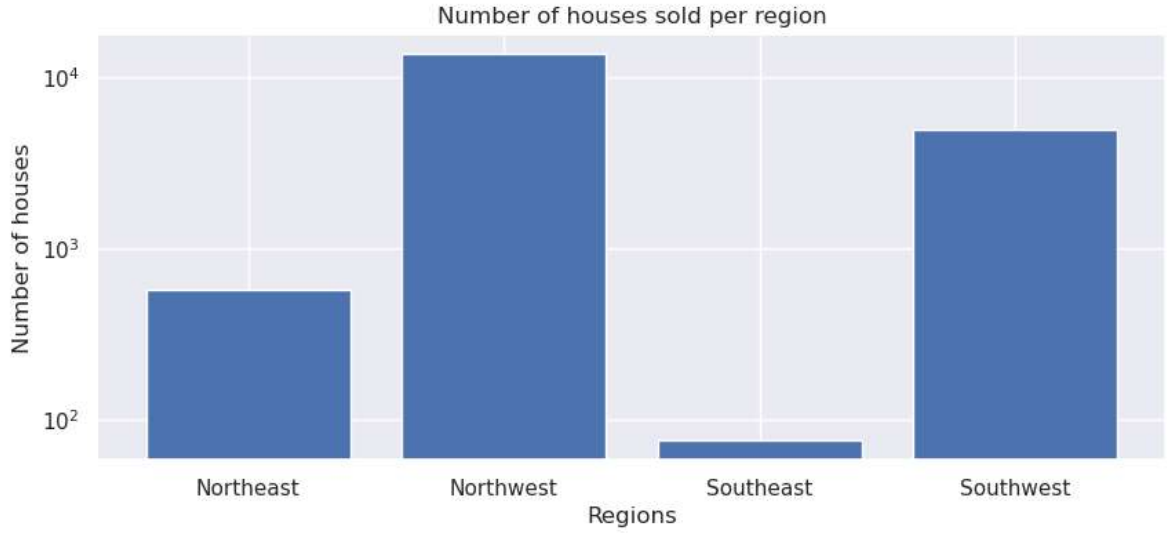
In [29]:
```
a = data.month_sold.value_counts().sort_index()
plt.bar(x=a.index, height=a.values)
plt.xticks(a.index)
plt.title('Number of houses sold per quarter')
plt.xlabel('Quarter')
plt.ylabel('Number of houses');
```



Houses Sold Per Region

Majority of houses are sold in the NorthWest and SouthWest regions - making them ideal locations for developing property

In [30]:
```
# visaulize houses sold regionally
a = data.region.value_counts().sort_index()
plt.bar(x=a.index, height=a.values)
plt.xticks(a.index)
plt.title('Number of houses sold per region')
plt.xlabel('Regions')
plt.ylabel('Number of houses')
plt.yscale('log');
```



Modelling

In [31]:
```
#creating a matrix to check correlation of the different columns  and sto
# the matrix will help us identfy which columns have the highest and lowe
corr_matrix= data.corr()
corr_matrix
```

Out[31]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sq
id	1.000000	0.015135	0.016616	0.034731	0.016772	-0.130394	0.034496	
price	0.015135	1.000000	0.274690	0.421374	0.602168	0.079732	0.230469	
bedrooms	0.016616	0.274690	1.000000	0.469553	0.589332	0.019679	0.131108	
bathrooms	0.034731	0.421374	0.469553	1.000000	0.690325	0.047827	0.532462	
sqft_living	0.016772	0.602168	0.589332	0.690325	1.000000	0.138520	0.333412	
sqft_lot	-0.130394	0.079732	0.019679	0.047827	0.138520	1.000000	-0.031858	
floors	0.034496	0.230469	0.131108	0.532462	0.333412	-0.031858	1.000000	
sqft_above	0.021584	0.500525	0.466446	0.609172	0.842568	0.147151	0.522153	
sqft_basement	-0.007292	0.217201	0.253434	0.187261	0.340865	-0.005913	-0.307423	-
yr_built	0.030090	0.040955	0.175322	0.567630	0.354732	0.035677	0.602583	
yr_renovated	-0.007312	0.084315	-0.008797	0.013293	0.015402	0.006399	-0.023488	-
zipcode	-0.011717	-0.008629	-0.164037	-0.214504	-0.205708	-0.124305	-0.097505	-
lat	-0.000311	0.441134	-0.048682	-0.016260	0.008123	-0.096278	0.015620	-
long	0.024306	0.058221	0.161532	0.252868	0.286447	0.214265	0.162828	
sqft_living15	0.017120	0.543671	0.395160	0.515735	0.736994	0.132657	0.276676	
sqft_lot15	-0.143371	0.069861	0.018214	0.049552	0.156016	0.690255	-0.036578	

In [32]:
```
price_corr = corr_matrix['price'].sort_values(ascending=False)
price_corr
```

Out[32]:
```
price            1.000000
sqft_living      0.602168
sqft_living15    0.543671
sqft_above       0.500525
lat              0.441134
bathrooms        0.421374
bedrooms         0.274690
floors           0.230469
sqft_basement    0.217201
yr_renovated     0.084315
sqft_lot         0.079732
sqft_lot15       0.069861
long             0.058221
yr_built         0.040955
id               0.015135
zipcode         -0.008629
Name: price, dtype: float64
```

Baseline Model

From the correlation analysis, the column `sqft_living` has the strongest correlation to price. We will build our baseline model with this variable. The scatter plot below shows a linear relationship between our predictor and target variable, thus a good candidate for the baseline model

In [33]:
```
fig, ax = plt.subplots(figsize=(10, 4))
ax.scatter(x = 'sqft_living', y='price', data=data)
ax.set_xlabel('Living space (sq feet)')
ax.set_ylabel('house price')
ax.set_title('Living space vs house price');
```

We then build the baseline model using the code below

In [34]:
```
# function for ols regression
def reg_model(X, y):
    """Function to create regression model
    & display summary"""
    model = sm.OLS(y, sm.add_constant(X)).fit()
    results = model.summary()
    return results
```

In [35]:
```
import statsmodels.api as sm
#selecting columns for our simple linear regression
y = data['price']
X = data['sqft_living']
#creating a linear regression and fitting data into it
results_baseline = reg_model(X, y)
results_baseline
```

Out[35]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.363
Model:	OLS	**Adj. R-squared:**	0.363
Method:	Least Squares	**F-statistic:**	1.087e+04
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:29	**Log-Likelihood:**	-2.5627e+05
No. Observations:	19106	**AIC:**	5.125e+05
Df Residuals:	19104	**BIC:**	5.126e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.386e+05	3401.496	40.745	0.000	1.32e+05	1.45e+05
sqft_living	171.2969	1.643	104.250	0.000	168.076	174.518

Omnibus:	920.239	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1057.149
Skew:	0.565	**Prob(JB):**	2.77e-230
Kurtosis:	3.226	**Cond. No.**	6.01e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.01e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

From the above results:

- The model is statistically significant.
- The model explains about **36.3%** of the variance in house prices
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.
- An increase of 1 sq foot in `sqft_living` will result in an increase in house price by **USD 171.29**
- When `sqft_living` is zero, the house price will be **USD 138600**

We explored standardization of baseline model

Standardization below did not improve the r2 of the model. Thus we don't explore it in the mutiple regression. We will explore other ways of tuning the model

In [36]:
```
# standardize baseline model
X_mean = data['sqft_living'].mean()
X_std = data['sqft_living'].std()
X_standardized = (X - X_mean) / X_std

results_baseline_stdized = reg_model(X_standardized, y)
results_baseline_stdized
```

Out[36]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.363
Model:	OLS	**Adj. R-squared:**	0.363
Method:	Least Squares	**F-statistic:**	1.087e+04
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:29	**Log-Likelihood:**	-2.5627e+05
No. Observations:	19106	**AIC:**	5.125e+05
Df Residuals:	19104	**BIC:**	5.126e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.715e+05	1170.783	402.749	0.000	4.69e+05	4.74e+05
sqft_living	1.221e+05	1170.813	104.250	0.000	1.2e+05	1.24e+05

Omnibus:	920.239	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1057.149
Skew:	0.565	**Prob(JB):**	2.77e-230
Kurtosis:	3.226	**Cond. No.**	1.00

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

From the above results:

- The model is statistically significant. The column sqft_living explains **36.3%** of the variance in house prices
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.

- An increase of 1 sq foot in sqft_living will result in an increase in house price by **USD 122100**
- When sqft_living is zero, the house price will be **USD 471500.0**

Success Metrics

We will use RSQUARED and MAE to meet 2 objectives:

- Rsquared will help us asses model improvements in prediction variation in house prices
- mean absolute error will help us to measure the distance of the predicted prices from the actual prices. From the code below, we have chosen mae over rmse because it is less infuenced by outliers

In [37]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error

# function to check mean absolute error and RMSE

def error_fun(data, colx, coly):
    """Function to calculate mae"""

    #reshape columns
    X = data[colx].values.reshape(-1,1)
    y = data[coly].values.reshape(-1,1)

    # fit reg model
    regressor = LinearRegression()
    regressor.fit(X,y)

    # calculate errors
    y_pred = regressor.predict(X)
    mae = mean_absolute_error(y, y_pred)
    rmse = (mean_squared_error(y, y_pred))**0.5

    return mae, rmse

mae, rmse = error_fun(data, 'sqft_living', 'price')

#findning the coeefficient of the regression
print( f'mae : {mae}')

#finding the y intercept of the regression
print( f'rmse : {rmse}')
```

```
mae : 130224.67018401195
rmse : 161822.32195752443
```

- From the results above the MAE gives the difference between the predicted value (price) and the actual value (mean price).

First Multiple Regression model

For our first multiple regression model we begin with the numerical variables, then as we proceed we add categorical variables.

In [38]:
```
#selecting columns for our simple linear regression
X_first_mult = data[['bedrooms', 'bathrooms', 'sqft_living', 'floors']]
#creating a linear regression and fitting data into it
First_model = reg_model(X_first_mult, y)
First_model
```

Out[38]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.373
Model:	OLS	**Adj. R-squared:**	0.373
Method:	Least Squares	**F-statistic:**	2842.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:36	**Log-Likelihood:**	-2.5611e+05
No. Observations:	19106	**AIC:**	5.122e+05
Df Residuals:	19101	**BIC:**	5.123e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.934e+05	5615.542	34.433	0.000	1.82e+05	2.04e+05
bedrooms	-3.174e+04	1872.788	-16.948	0.000	-3.54e+04	-2.81e+04
bathrooms	4345.9659	2741.965	1.585	0.113	-1028.527	9720.459
sqft_living	187.1479	2.476	75.580	0.000	182.294	192.001
floors	7229.6064	2529.592	2.858	0.004	2271.383	1.22e+04

Omnibus:	1019.674	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1192.069
Skew:	0.590	**Prob(JB):**	1.40e-259
Kurtosis:	3.326	**Cond. No.**	1.04e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.04e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Interpretation

From the above results:

- At an alpha of 0.05 the model is statistically significant.
- The model explains about **37.3%** of the variance in price.
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.
- An increase of 1 sq foot in sqft_living will result in an increase in house price by USD 187.14
- An increase in 1 bedroom results in a decrease in price by USD 31740
- An increase in 1 bathroom results in an increase in price by USD 4345.96
- For every floor added there is an increase in price by USD 7229.60
- Controlling for all other variables, the price of the house is USD 193400.0
- From the R-squared and the coefficient values, this model is better than the baseline model.

Function to calculate errors for multiple columns

In [39]:
```
# function to calculate errors for multiple columns
def error_multix(data, colx, coly):
    """Function to calculate mae for
    multiple X columns"""

    #reshape columns
    X = data[colx].values.reshape(-1,len(colx))
    y = data[coly].values.reshape(-1,1)

    # fit reg model
    regressor = LinearRegression()
    regressor.fit(X,y)

    # calculate errors
    y_pred = regressor.predict(X)
    mae = mean_absolute_error(y, y_pred)
    rmse = (mean_squared_error(y, y_pred))**0.5

    return mae, rmse
```

In [40]:
```
# mae for first multiple model
X1 = ['bedrooms', 'bathrooms', 'sqft_living', 'floors']
mae_first_mult, rmse_first_mult = error_multix(data, X1, 'price')

#findning the coeefficient of the regression
print( f'mae : {mae_first_mult}')

```

```
mae : 128531.47151055187
```

interpretation

- From the results above the MAE gives the difference between the predicted value (price) and the actual value (mean price)
- Compared to the baseline model, there is a decrease in MAE, meaning this model makes better prediction of the target.

One Hot Encode Categorial Variables For Modelling

For the next step, we will one-hot-encode the following categorical variables for modelling

- `quarters` column: we transformed the date to month, then combined to quarters
- `condition` column with ratings of house condition
- `regions` column: we transfored zipcode to the 4 regions of King County

In [41]:
```
# Function to one hot encode categorical variables
def categorical_ohe(data, col):
    ohe = pd.get_dummies(data[col], drop_first=True)
    return ohe

# compute ohe for the 3 columns
quarters_ohe =  categorical_ohe(data, 'month_sold')
condition_ohe =  categorical_ohe(data, 'condition')
region_ohe =  categorical_ohe(data, 'region')

# merge the ohe columns with the original data
data_list = [data, quarters_ohe, condition_ohe, region_ohe]
data_ohe = pd.concat(data_list, axis=1)
```

Second Multiple Regression model

In this second model we will combine model_1 columns plus the above encoded categorical variables: `months_sold` , `condition` & `region`

In [42]:

```
# defining predictor variables
X_multi_second = data_ohe[['bedrooms', 'bathrooms', 'sqft_living', 'floor
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast', '
Second_model = reg_model(X_multi_second, y)
Second_model
```

Out[42]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.590
Model:	OLS	**Adj. R-squared:**	0.589
Method:	Least Squares	**F-statistic:**	1960.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:37	**Log-Likelihood:**	-2.5206e+05
No. Observations:	19106	**AIC:**	5.042e+05
Df Residuals:	19091	**BIC:**	5.043e+05
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.841e+04	7508.043	13.108	0.000	8.37e+04	1.13e+05
bedrooms	-2.59e+04	1521.323	-17.022	0.000	-2.89e+04	-2.29e+04
bathrooms	1.469e+04	2228.625	6.590	0.000	1.03e+04	1.91e+04
sqft_living	179.0673	2.010	89.080	0.000	175.127	183.007
floors	1.463e+04	2139.473	6.839	0.000	1.04e+04	1.88e+04
Qtr2	4374.8836	2743.960	1.594	0.111	-1003.521	9753.288
Qtr3	-9987.6335	2812.502	-3.551	0.000	-1.55e+04	-4474.882
Qtr4	-1.369e+04	2951.776	-4.639	0.000	-1.95e+04	-7908.703
Fair	-4.627e+04	1.09e+04	-4.243	0.000	-6.76e+04	-2.49e+04
Good	3.818e+04	2293.713	16.647	0.000	3.37e+04	4.27e+04
Poor	-7.279e+04	2.78e+04	-2.623	0.009	-1.27e+05	-1.84e+04
Very Good	6.46e+04	3693.883	17.489	0.000	5.74e+04	7.18e+04
Northwest	1.073e+05	5577.243	19.239	0.000	9.64e+04	1.18e+05
Southeast	-1.69e+04	1.59e+04	-1.065	0.287	-4.8e+04	1.42e+04
Southwest	-1.029e+05	5780.962	-17.802	0.000	-1.14e+05	-9.16e+04

Omnibus:	1583.742	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2615.878
Skew:	0.621	**Prob(JB):**	0.00
Kurtosis:	4.320	**Cond. No.**	6.11e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.11e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Interpretation

From the above results:

- At an alpha of 0.05 the model is statistically significant.
- The model explains about **59%** of the variance in price.
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.

Holding all other variables constant:

- An increase of 1 sq foot in sqft_living will result in an increase in house price by USD 179.06
- An increase in 1 bedroom results in a decrease in price by USD 25900.0
- An increase in 1 bathroom results in an increase in price by USD 14690.0
- For every floor added there is an increase in price by USD 14630.0
- Controlling for all other variables, the price of the house is USD 98410.0
- In reference to Qr1, Qr2 has an associated increase in price of about USD 4374.88
- In reference to Qr1, Qr3 has an associated decrease in price of about USD 9987.63
- In reference to Qr1, Qr4 has an associated decrease in price of about USD 13690.0
- In reference to Average condition, Fair condition has an associated decrease in price of about USD 46270.0
- In reference to Average condition, Good condition has an associated increase in price of about USD 38180.0
- In reference to Average condition, Poor condition has an associated decrease in price of about USD 72790.0
- In reference to Average condition, very good condition has an associated increase in price of about USD 64600.0
- In reference to North east region, north west has an associated increase in price of about USD 107300.0
- In reference to North east region, south east has an associated decrease in price of about USD 16900.0
- In reference to North east region, south west has an associated decrease in price of about USD 102900.0
- From the R-squared and the coefficient values, this model is better than the baseline model, the first multiple regression model.

In [43]:
```
# mae for second multiple model
X2 = ['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'Qtr2', 'Qtr3',
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast', '

mae_second_mult, rmse_second_mult = error_multix(data_ohe, X2, 'price')

#findning the coeefficient of the regression
print( f'mae for second multiple model : {mae_second_mult}')

```

```
mae for second multiple model : 97193.09849811278
```

interpretation

- From the results above the MAE gives the difference between the predicted value (price) and the actual value (mean price)
- Compared to the baseline model and first multiple model, there is a decrease in MAE, meaning this model makes better prediction of the target.

Third Mutiple Regression Model

We will explore adding **view** column to the model to improve accuracy. Below we will one hot econde, merge, then fit the third model.

In [44]:
```
# one hot encode view column and concatenate
view_ohe =  categorical_ohe(data_ohe, 'view')
list_concat = [data_ohe, view_ohe]
data_ohe2 = pd.concat(list_concat, axis=1)
```

In [45]:

```
# defining predictor variables
X_multi_third = data_ohe2[['bedrooms', 'bathrooms', 'sqft_living', 'floor
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast', '
                           'EXCELLENT', 'FAIR', 'GOOD', 'NONE']]
Third_model = reg_model(X_multi_third, y)
Third_model
```

Out[45]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.608
Model:	OLS	**Adj. R-squared:**	0.607
Method:	Least Squares	**F-statistic:**	1643.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:38	**Log-Likelihood:**	-2.5164e+05
No. Observations:	19106	**AIC:**	5.033e+05
Df Residuals:	19087	**BIC:**	5.035e+05
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.715e+05	8627.201	19.880	0.000	1.55e+05	1.88e+05
bedrooms	-2.214e+04	1493.563	-14.825	0.000	-2.51e+04	-1.92e+04
bathrooms	1.404e+04	2179.981	6.443	0.000	9771.708	1.83e+04
sqft_living	169.8137	1.992	85.248	0.000	165.909	173.718
floors	1.917e+04	2099.373	9.131	0.000	1.51e+04	2.33e+04
Qtr2	4734.6413	2683.645	1.764	0.078	-525.540	9994.823
Qtr3	-9589.7486	2750.944	-3.486	0.000	-1.5e+04	-4197.656
Qtr4	-1.372e+04	2886.757	-4.751	0.000	-1.94e+04	-8057.201
Fair	-4.469e+04	1.07e+04	-4.190	0.000	-6.56e+04	-2.38e+04
Good	3.612e+04	2244.257	16.097	0.000	3.17e+04	4.05e+04
Poor	-8.299e+04	2.71e+04	-3.057	0.002	-1.36e+05	-2.98e+04
Very Good	6.248e+04	3613.383	17.293	0.000	5.54e+04	6.96e+04
Northwest	1.076e+05	5457.399	19.711	0.000	9.69e+04	1.18e+05
Southeast	-1.54e+04	1.55e+04	-0.992	0.321	-4.58e+04	1.5e+04
Southwest	-1.019e+05	5657.222	-18.016	0.000	-1.13e+05	-9.08e+04
EXCELLENT	1.391e+05	1.24e+04	11.178	0.000	1.15e+05	1.63e+05
FAIR	4415.2982	9185.920	0.481	0.631	-1.36e+04	2.24e+04
GOOD	2.421e+04	8616.336	2.809	0.005	7317.482	4.11e+04
NONE	-7.989e+04	4852.572	-16.464	0.000	-8.94e+04	-7.04e+04

Omnibus:	1437.688	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2450.536
Skew:	0.566	**Prob(JB):**	0.00
Kurtosis:	4.341	**Cond. No.**	6.12e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.12e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Interpretation

From the above results:

- At an alpha of 0.05 the model is statistically significant.
- The model explains about **60.8%** of the variance in price.
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.

Holding all other variables constant:

- An increase of 1 sq foot in sqft_living will result in an increase in house price by USD 170
- An increase in 1 bedroom results in a decrease in price by USD 22140.0
- An increase in 1 bathroom results in an increase in price by USD 14040.0
- For every floor added there is an increase in price by USD 191710.0
- Controlling for all other variables, the price of the house is USD 1715000.0
- In reference to Qr1, Qr2 has an associated increase in price of about USD 4735
- In reference to Qr1, Qr3 has an associated decrease in price of about USD 9590
- In reference to Qr1, Qr4 has an associated decrease in price of about USD 13720.0
- In reference to Average condition, Fair condition has an associated decrease in price of about USD 44690.0
- In reference to Average condition, Good condition has an associated increase in price of about USD 36120=0.0
- In reference to Average condition, Poor condition has an associated decrease in price of about USD 82990.0
- In reference to Average condition, very good condition has an associated increase in price of about USD 62480.0
- In reference to North east region, north west has an associated increase in price of about USD 107600.0
- In reference to North east region, south east has an associated decrease in price of about USD 15400.0
- In reference to North east region, south west has an associated decrease in price of about USD 101900.0
- In reference to Average view, EXCELLENT view has an associated increase in price of about USD 139100.0
- In reference to Average view, FAIR view has an associated increase in price of about USD 4415.11
- In reference to Average view, GOOD view has an associated increase in price of about USD 24200.0
- In reference to Average view, NONE view has an associated decrease in price of about USD 79890.0
- From the R-squared and the coefficient values, this model is better than the baseline model, the first multiple regression model and the second multiple model.

In [46]:
```
# mae for third multiple model
X3 = ['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'Qtr2', 'Qtr3',
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast',
      'Southwest', 'EXCELLENT', 'FAIR', 'GOOD', 'NONE']

mae_third_mult, rmse_third_mult = error_multix(data_ohe2, X3, 'price')

#findning the coeefficient of the regression
print( f'mae for third multiple model : {mae_third_mult}')
```

```
mae for third multiple model : 95121.58576864422
```

interpretation

- From the results above the MAE gives the difference between the predicted value (price) and the actual value (mean price)
- Compared to the baseline model, first multiple model,second multiple model, there is a decrease in MAE, meaning this model makes better prediction of the target.

Check for Multicollinearity

Below we do a correlation matrix for all predictor variables. bathrooms and square foot living are highly correlated. In our fourth model, we take out bathrooms to address this

In [47]:
```
1 X_multi_third.corr()
```

Out[47]:

	bedrooms	bathrooms	sqft_living	floors	Qtr2	Qtr3	Qtr4	
bedrooms	1.000000	0.469553	0.589332	0.131108	0.003128	0.005490	-0.003772	-0.04
bathrooms	0.469553	1.000000	0.690325	0.532462	0.009323	0.017551	-0.008252	-0.07
sqft_living	0.589332	0.690325	1.000000	0.333412	0.005147	0.018949	-0.003497	-0.06
floors	0.131108	0.532462	0.333412	1.000000	0.000174	0.011455	0.001346	-0.04
Qtr2	0.003128	0.009323	0.005147	0.000174	1.000000	-0.419281	-0.359826	-0.00
Qtr3	0.005490	0.017551	0.018949	0.011455	-0.419281	1.000000	-0.329626	-0.02
Qtr4	-0.003772	-0.008252	-0.003497	0.001346	-0.359826	-0.329626	1.000000	0.00
Fair	-0.044242	-0.072928	-0.065772	-0.048067	-0.003285	-0.021871	0.005857	1.00
Good	-0.006551	-0.179136	-0.085111	-0.278585	0.004950	0.009145	-0.013543	-0.05
Poor	-0.026816	-0.040980	-0.034135	-0.023525	0.006958	-0.003809	-0.003168	-0.00
Very Good	0.016998	-0.048342	-0.037945	-0.158093	-0.003094	0.023793	0.003196	-0.02
Northwest	-0.056524	-0.048306	-0.023909	-0.003006	0.019477	0.004542	0.003279	-0.01
Southeast	-0.018831	-0.010655	-0.013696	-0.012689	0.003829	-0.005739	0.004496	0.01
Southwest	0.058042	0.030188	0.001436	-0.021706	-0.022705	-0.008780	0.000604	0.00
EXCELLENT	0.006388	0.020177	0.056692	-0.005961	-0.003265	0.010484	0.001741	-0.00
FAIR	0.008914	0.021316	0.052878	-0.023671	-0.001593	0.000856	-0.003630	-0.01
GOOD	0.017581	0.054622	0.093538	-0.010176	0.005660	-0.003052	-0.000576	-0.00
NONE	-0.032514	-0.079527	-0.156762	0.032348	0.001659	0.004927	-0.003793	0.01

Fourth Model Addressing Multicollinearity

In [48]:

```
# defining predictors
X_multi_fourth = data_ohe2[['bedrooms', 'sqft_living', 'floors', 'Qtr2',
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast', '
                            'EXCELLENT', 'FAIR', 'GOOD', 'NONE']]
Fourth_model = reg_model(X_multi_fourth, y)
Fourth_model
```

Out[48]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.607
Model:	OLS	**Adj. R-squared:**	0.606
Method:	Least Squares	**F-statistic:**	1733.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	08:02:39	**Log-Likelihood:**	-2.5166e+05
No. Observations:	19106	**AIC:**	5.033e+05
Df Residuals:	19088	**BIC:**	5.035e+05
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.744e+05	8624.322	20.227	0.000	1.58e+05	1.91e+05
bedrooms	-2.059e+04	1475.682	-13.956	0.000	-2.35e+04	-1.77e+04
sqft_living	176.2486	1.725	102.154	0.000	172.867	179.630
floors	2.494e+04	1900.545	13.123	0.000	2.12e+04	2.87e+04
Qtr2	4936.7353	2686.308	1.838	0.066	-328.665	1.02e+04
Qtr3	-9434.0060	2753.755	-3.426	0.001	-1.48e+04	-4036.403
Qtr4	-1.374e+04	2889.816	-4.754	0.000	-1.94e+04	-8073.679
Fair	-4.685e+04	1.07e+04	-4.391	0.000	-6.78e+04	-2.59e+04
Good	3.523e+04	2242.338	15.712	0.000	3.08e+04	3.96e+04
Poor	-8.652e+04	2.72e+04	-3.184	0.001	-1.4e+05	-3.33e+04
Very Good	6.301e+04	3616.291	17.424	0.000	5.59e+04	7.01e+04
Northwest	1.076e+05	5463.186	19.688	0.000	9.68e+04	1.18e+05
Southeast	-1.481e+04	1.55e+04	-0.953	0.341	-4.53e+04	1.57e+04
Southwest	-1.012e+05	5662.176	-17.877	0.000	-1.12e+05	-9.01e+04
EXCELLENT	1.38e+05	1.25e+04	11.082	0.000	1.14e+05	1.62e+05
FAIR	4321.9548	9195.650	0.470	0.638	-1.37e+04	2.23e+04
GOOD	2.453e+04	8625.322	2.844	0.004	7628.305	4.14e+04
NONE	-8.03e+04	4857.311	-16.532	0.000	-8.98e+04	-7.08e+04

Omnibus:	1399.873	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2388.419
Skew:	0.554	**Prob(JB):**	0.00
Kurtosis:	4.332	**Cond. No.**	6.11e+04

Notes:

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

[2] The condition number is large, 6.11e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Interpretation

From the above results:

- At an alpha of 0.05 the model is statistically significant.
- The model explains about **60.7%** of the variance in price.
- Both the intercept and the target variable p-values show that the coefficients are statistically significant.

Holding all other variables constant:

- An increase of 1 sq foot in sqft_living will result in an increase in house price by USD 176.24
- An increase in 1 bedroom results in a decrease in price by USD 20590.0
- For every floor added there is an increase in price by USD 24940.0
- Controlling for all other variables, the price of the house is USD 174,400.0
- In reference to Qr1, Qr2 has an associated increase in price of about USD 4937.33
- In reference to Qr1, Qr3 has an associated decrease in price of about USD 9434.0
- In reference to Qr1, Qr4 has an associated decrease in price of about USD 13740.0
- In reference to Average condition, Fair condition has an associated decrease in price of about USD 46859.0
- In reference to Average condition, Good condition has an associated increase in price of about USD 35230.0
- In reference to Average condition, Poor condition has an associated decrease in price of about USD 86520.0
- In reference to Average condition, very good condition has an associated increase in price of about USD 63010.0
- In reference to North east region, north west has an associated increase in price of about USD 107600.0
- In reference to North east region, south east has an associated decrease in price of about USD 14810.0
- In reference to North east region, south west has an associated decrease in price of about USD 101200.0
- In reference to Average view, EXCELLENT view has an associated increase in price of about USD 138900.0
- In reference to Average view, FAIR view has an associated increase in price of about USD 4322.19
- In reference to Average view, GOOD view has an associated increase in price of about USD 24530.0
- In reference to Average view, NONE view has an associated decrease in price of about USD 80300.0
- From the R-squared and the coefficient values, this model is better than all the others except the third model.

In [49]:
```
# mae for fourth multiple model
X4 = ['bedrooms', 'sqft_living', 'floors', 'Qtr2', 'Qtr3',
 'Qtr4', 'Fair', 'Good', 'Poor', 'Very Good', 'Northwest', 'Southeast',
      'Southwest', 'EXCELLENT', 'FAIR', 'GOOD', 'NONE']

mae_fourth_mult, rmse_fourth_mult = error_multix(data_ohe2, X4, 'price')

#findning the coeefficient of the regression
print( f'mae for fourth multiple model : {mae_fourth_mult}')
```

```
mae for fourth multiple model : 95232.8069500008
```

interpretation

- From the results above the MAE gives the difference between the predicted value (price) and the actual value (mean price)
- Compared to the baseline model, first multiple model,second multiple model, there is a decrease in MAE.
- Compared to the third model there is a slight increase in MAE meaning the third model is better.

Conclusions:

1. Bedrooms, bathrooms, square footage of living space, number of floors, and the condition of the house are all significant predictors of the price of a house.
2. The quarter of the year in which the house was sold also appears to have a small effect on the price.
3. The third model explains only about 60.8% of the variance in the price of the house.
4. The limitations of the data used to train the model should be considered.

Recommendations

Based on the results provided, here are some recommendations that we came up with to provide to realtors:

1. Focus on important features: realtors should consider the importance of the number of bedrooms, number of bathrooms, and square footage of the living area when determining a property's value. In particular, an increase of 1 sq foot in sqft_living will result in an increase in house price by USD 176, and an increase in 1 bathroom results in an increase in price by USD 14040.0. However, an increase in 1 bedroom results in a decrease in price by USD 20590.0. Realtors should consider these features when pricing a property or advising sellers on what features to highlight in a property.
2. Highlight desirable locations: realtors to consider the location of a property, especially in terms of the region it is located in. Realtors should inform clients that different regions have different associated increases or decreases in price. In particular, the north-west

region has an associated increase in price of about USD 107600.0, while the south-west has an associated decrease in price of about USD 101200.0.

3. Emphasize condition of the property and view: Realtors should also emphasize the importance of the condition of the property and the view of the property. For example, having an "EXCELLENT" view is associated with an increase in price of about USD 138000.0, while having a "NONE" view is associated with a decrease in price of about USD 80300.0. Similarly, having a "GOOD" condition is associated with an increase in price of about USD 24530.0, while having a "FAIR" condition is associated with a decrease in price of about USD 4322.0. Realtors should ensure that the condition of a property is highlighted in any marketing materials or listings, and they should take steps to