1 Final Project Submission: Real Estate Linear Regression Model Analysis

(Phase 2)

- Student Name: Tenicka Norwood
- Program Pace: self paced
- Scheduled Project Review Time: 1/23/2023 9:30 am
- Instructor name: Joe Comeaux
- Blog post Url:https://medium.com/@tenicka.norwood/working-with-data-while-trying-to-stay-dry-fa4ebf5e5f64 (https://medium.com/@tenicka.norwood/working-with-data-while-trying-to-stay-dry-fa4ebf5e5f64)

Photo by: anyaberkut on Canva (https://www.canva.com)

2 Overview:

LandingPad Realtors is a real estate business that helps families with school-aged children relocate to King County and find the perfect home to meet their families needs. LandingPad provides potential homeowners with home purchase options within their ideal budget.

For this project, I will start by identifying the characteristics of homes that increase housing costs. The effect of each relevant feature will then be identified and communicated to the team at LandingPad. This project will be grounded in performing a statistical analysis of the price of houses in the King County House dataset and creating a multiple linear regression model that accurately predicts the sale price of a house in King County.

Linear Regression is often described as a predictive model based on the sum of weighted independent variables. This mathematical linear relationship between an dependent variable and one or more dependent varibles and is often shown as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n$$

where β_0 is a constant that shows the y-intercept and β_1 to β_n are coefficients that show how the dependent variable y changes with the independent variables x_1 to x_n.

3 Business Understanding

- **Stakeholder**: LandingPad Realtors
- **Busines Case**: I have been hired by LandingPad to accurately predict the housing prices within the King County Housing Market. Executives at LandingPad want to launch a multimedia campaign to reach their target audience of young families moving to the Kings County Area and want a reliable model that can be refined over time as more information becomes available.

4 Objectives

We will use the CRISP DM model to:

- Understand the Data
  - Examine and document surface properties of the data
  - Dig deeper into the data to visualize and identify relationships among the data
- Prepare the Data

    - Select, clean, construct, integrate and format data
- Model the Data
    - Determine which algorithm to try
- Evaluate the Model
    - Determine if the model meets the business success criteria and determine next steps

Then, I will use this to build and refine a **linear regression model** that I can use to answer the following guiding questions:

1. **Which neighborhoods have the highest average home price?**
   Understanding the effect of neighborhood location on home price is key information for potential home owners and realtors
2. **How does the number of bedrooms affect the sale price of a home?**
   Insights on the affect of attributes on the sale price can help new home owners budget appropriately
3. **How does proximity to a highly rated school affect the sale price of a home?**
   Knowing which homes are connected to highly rated schools is vital information for families with school aged children.

The recommendations garnered by answering these questions will be valuable to LandingPad Realtors because they will help prospective home buyers confidently determine which homes yield the best options within their price range.

5 Data Understanding

In this project I will use the CRISP DM method. The dataset selected in this project are from the :

- King County House Sales Dataset found in `kc_house_data.csv`

The dataset can be found in the data folder of this repository along with a file called `column_names.md` which provides description of the features within the dataset. More information about the features on the site of [the King County Assessor. (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)

The King County House Sales Dataset includes sales data for 21,597 homes with 20 features:

Name	Description	Final Datatype	Numeric or Categorical	Target or Feature
`id`	Unique identifier for a house	`int`	Numeric	Feature
`date`	Date house was sold	`datetime`	Numeric	Feature
`price`	Sale price (**prediction target**)	`int`	Numeric	Target
`bedrooms`	Number of bedrooms	`int`	Numeric	Feature
`bathrooms`	Number of bathrooms	`float`	Numeric	Feature
`sqft_living`	Square footage of living space in the home	`int`	Numeric	Feature
`sqft_lot`	Square footage of the lot	`int`	Numeric	Feature
`floors`	Number of floors(levels) in house	`float`	Numeric	Feature
`waterfront`	Whether the house is on a waterfront	`float`	Categorical	Feature
`view`	Quality of view from house	`float`	Categorical	Feature
`condition`	How good the overall condition of the house is. Related to the maintenance of house	`int`	Numeric	Feature
`grade`	Overall grade of the house. Related to the construction and design of the house	`int`	Categorical	Feature
`sqft_above`	Square footage of house apart from basement	`int`	Numeric	Feature
`sqft_basement`	Square footage of the basement	`float`	Numeric	Feature
`yr_built`	Year when house was built	`int`	Numeric	Feature
`yr_renovated`	Year when house was renovated	`int`	Numeric	Feature
`zipcode`	ZIP Code used by the United States Postal Service	`int`	Categorical	Feature
`lat`	Latitude coordinate	`float`	Numeric	Feature
`long`	Longitude coordinate	`float`	Numeric	Feature
`sqft_living15`	The square footage of interior housing living space for the nearest 15 neighbors	`int`	Numeric	Feature
`sqft_lot15`	The square footage of the land lots of the nearest 15 neighbors	`int`	Numeric	Feature

5.1 Data Preparation

5.2 Import libraries and Visualization Packages

Importing libraries at the beginning allows access to modules and other tools throughout this project that help to make the tasks within this project manageable to implement. The main libraries that will be used within this project include:

- `pandas` : a data analysis and manipulation library which allows for flexible reading, writing, and reshaping of data
- `numpy` : a key library that brings the computationaly power of languages like C to Python
- `matplotlib` : a comprehensive visualization library
- `seaborn` : a data visualization library based on matplotlib
- `stasmodels` :
- `selenium` :

- geopy :

In [1]:
```
# Import libraries and visualization packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import statsmodels.api as sm
import geopandas as gpd
import plotly.express as px
from selenium import webdriver
from selenium.common.exceptions import WebDriverException
from geopy.distance import geodesic
import requests
import json
import warnings
warnings.simplefilter(action ='ignore', category = DeprecationWarning)
warnings.simplefilter(action ='ignore', category = FutureWarning)
warnings.filterwarnings("ignore", category=UserWarning, module="pandas")

# Allow plots to display and be stored inline within a notebook
%matplotlib inline

# Used for working with the z-score
from scipy import stats

# Used for working with long url
from urllib.parse import urlencode

# Set display option to readable format
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Filter warnings from pandas
pd.options.mode.chained_assignment = None
```

5.3 Load Data Using Pandas

Read in data from `kc_house_data.csv` using `.read_csv()` from the pandas library.

In [2]:
```
# Read Data from Kings County House Data
df = pd.read_csv('data/kc_house_data.csv', index_col = 0)
```

Let's look at the first five rows of the Kings County Housing Data.

In [3]:
```
df.head()
```

Out[3]:

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	y
7129300520	10/13/2014	221900.00	3	1.00	1180	5650	1.00	NaN	NONE	Average	7 Average	1180	0.0	
6414100192	12/9/2014	538000.00	3	2.25	2570	7242	2.00	NO	NONE	Average	7 Average	2170	400.0	
5631500400	2/25/2015	180000.00	2	1.00	770	10000	1.00	NO	NONE	Average	6 Low Average	770	0.0	
2487200875	12/9/2014	604000.00	4	3.00	1960	5000	1.00	NO	NONE	Very Good	7 Average	1050	910.0	
1954400510	2/18/2015	510000.00	3	2.00	1680	8080	1.00	NO	NONE	Average	8 Good	1680	0.0	

5.3.1 Clean the Data

In order to clean the data, I typically address missing data, place holders and datatypes. This is the most important step of this project because if data is not appropriate for the model, the results will be inherently inaccuarate and my model will result in lackluster predictions.

To dig deeper into the data, I will:

- Review the datatypes found within the entire dataframe
- Address duplicates, missing and placeholder data
- Address incorrect or incongruous datatypes for the model

5.3.2 Review Datatypes within Data Frame

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21597 entries, 7129300520 to 1523300157
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           21597 non-null  object 
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64  
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64  
 5   sqft_lot       21597 non-null  int64  
 6   floors         21597 non-null  float64
 7   waterfront     19221 non-null  object 
 8   view           21534 non-null  object 
 9   condition      21597 non-null  object 
 10  grade          21597 non-null  object 
 11  sqft_above     21597 non-null  int64  
 12  sqft_basement  21597 non-null  object 
 13  yr_built       21597 non-null  int64  
 14  yr_renovated   17755 non-null  float64
 15  zipcode        21597 non-null  int64  
 16  lat            21597 non-null  float64
 17  long           21597 non-null  float64
 18  sqft_living15  21597 non-null  int64  
 19  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(8), object(6)
memory usage: 3.5+ MB
```

5.3.3 Address duplicates, missing and placeholder data

In [5]:
```
# Check for placeholders throughout the entire dataframe
df.isin(['?', '#', 'NaN', 'null', 'N/A', '-']).any()
```

Out[5]:
```
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
view             False
condition        False
grade            False
sqft_above       False
sqft_basement     True
yr_built         False
yr_renovated     False
zipcode          False
lat              False
long             False
sqft_living15    False
sqft_lot15       False
dtype: bool
```

In [6]:
```
# Convert sqft_basement to float
# Replace placeholder ? to NAN values
df['sqft_basement'] = pd.to_numeric(df['sqft_basement'], errors="coerce")
```

In [7]:
```
# Check for placeholders throughout the entire dataframe
df.isin(['?', '#', 'NaN', 'null', 'N/A', '-']).any()
```

Out[7]:
```
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
view             False
condition        False
grade            False
sqft_above       False
sqft_basement    False
yr_built         False
yr_renovated     False
zipcode          False
lat              False
long             False
sqft_living15    False
sqft_lot15       False
dtype: bool
```

Let's look at the columns within the `pandas` dataframe.

In [8]:
```
df.columns
```

Out[8]:
```
Index(['date', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

This dataset has 20 columns with 21597 rows of data. The waterfront, view, condition, grade, sqft_basement and date are object datatypes.

Let's check which columns contain null values.

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement     454
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

5.3.4 Address incorrect or incongruous datatypes for the model

Let's convert the date from a string to a datetime object.

In [10]:
```
# Convert data column in the dataframe to datetime
df['date'] =  pd.to_datetime(df['date'], format='%m/%d/%Y')
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21597 entries, 7129300520 to 1523300157
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64
 5   sqft_lot       21597 non-null  int64
 6   floors         21597 non-null  float64
 7   waterfront     19221 non-null  object
 8   view           21534 non-null  object
 9   condition      21597 non-null  object
 10  grade          21597 non-null  object
 11  sqft_above     21597 non-null  int64
 12  sqft_basement  21143 non-null  float64
 13  yr_built       21597 non-null  int64
 14  yr_renovated   17755 non-null  float64
 15  zipcode        21597 non-null  int64
 16  lat            21597 non-null  float64
 17  long           21597 non-null  float64
 18  sqft_living15  21597 non-null  int64
 19  sqft_lot15     21597 non-null  int64
dtypes: datetime64[ns](1), float64(7), int64(8), object(4)
memory usage: 3.5+ MB
```

In [12]:
```
df.head()
```

Out[12]:

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_bui
7129300520	2014-10-13	221900.00	3	1.00	1180	5650	1.00	NaN	NONE	Average	7 Average	1180	0.00	195
6414100192	2014-12-09	538000.00	3	2.25	2570	7242	2.00	NO	NONE	Average	7 Average	2170	400.00	195
5631500400	2015-02-25	180000.00	2	1.00	770	10000	1.00	NO	NONE	Average	6 Low Average	770	0.00	193
2487200875	2014-12-09	604000.00	4	3.00	1960	5000	1.00	NO	NONE	Very Good	7 Average	1050	910.00	196
1954400510	2015-02-18	510000.00	3	2.00	1680	8080	1.00	NO	NONE	Average	8 Good	1680	0.00	198

From our check, the waterfront column has 2376 null values. The view column has 63 null values and the yr_renovated column has 3842 null values.

In [13]:
```
df.describe()
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	lo
count	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	21143.00	21597.00	17755.00	21597.00	21597.00	21597.
mean	540296.57	3.37	2.12	2080.32	15099.41	1.49	1788.60	291.85	1971.00	83.64	98077.95	47.56	-122.
std	367368.14	0.93	0.77	918.11	41412.64	0.54	827.76	442.50	29.38	399.95	53.51	0.14	0.
min	78000.00	1.00	0.50	370.00	520.00	1.00	370.00	0.00	1900.00	0.00	98001.00	47.16	-122.
25%	322000.00	3.00	1.75	1430.00	5040.00	1.00	1190.00	0.00	1951.00	0.00	98033.00	47.47	-122.
50%	450000.00	3.00	2.25	1910.00	7618.00	1.50	1560.00	0.00	1975.00	0.00	98065.00	47.57	-122.
75%	645000.00	4.00	2.50	2550.00	10685.00	2.00	2210.00	560.00	1997.00	0.00	98118.00	47.68	-122.
max	7700000.00	33.00	8.00	13540.00	1651359.00	3.50	9410.00	4820.00	2015.00	2015.00	98199.00	47.78	-121.

In [14]:
```
df['view'].value_counts()
```

Out[14]:
```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In [15]:
```
#for col in categoricals:
#    print(df[col].value_counts(), "\n")
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21597 entries, 7129300520 to 1523300157
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64
 5   sqft_lot       21597 non-null  int64
 6   floors         21597 non-null  float64
 7   waterfront     19221 non-null  object
 8   view           21534 non-null  object
 9   condition      21597 non-null  object
 10  grade          21597 non-null  object
 11  sqft_above     21597 non-null  int64
 12  sqft_basement  21143 non-null  float64
 13  yr_built       21597 non-null  int64
 14  yr_renovated   17755 non-null  float64
 15  zipcode        21597 non-null  int64
 16  lat            21597 non-null  float64
 17  long           21597 non-null  float64
 18  sqft_living15  21597 non-null  int64
 19  sqft_lot15     21597 non-null  int64
dtypes: datetime64[ns](1), float64(7), int64(8), object(4)
memory usage: 3.5+ MB
```

Next I will impute missing values in the dataframe. I replaced `waterfront` , `sqft_basement` and `view` null values with 0 and replace `yr_renovated` null values with the `yr_built` .

In [17]:
```
df["waterfront"].value_counts()
```

Out[17]:
```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

In [18]:
```
df["view"].value_counts()
```

Out[18]:
```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In [19]:
```
df["zipcode"].value_counts()
```

Out[19]:
```
98103    602
98038    589
98115    583
98052    574
98117    553
        ...
98102    104
98010    100
98024     80
98148     57
98039     50
Name: zipcode, Length: 70, dtype: int64
```

In [20]:
```
df["waterfront"].fillna(0, inplace = True)
df["sqft_basement"].fillna(0, inplace = True)
df["view"].fillna(0, inplace = True)
df['yr_renovated'].fillna(df['yr_built'], inplace=True)
```

In [21]:
```
for col in df.columns:
    print('{} : {}'.format(col, df[col].nunique()))
```

```
date : 372
price : 3622
bedrooms : 12
bathrooms : 29
sqft_living : 1034
sqft_lot : 9776
floors : 6
waterfront : 3
view : 6
condition : 5
grade : 11
sqft_above : 942
sqft_basement : 303
yr_built : 116
yr_renovated : 117
zipcode : 70
lat : 5033
long : 751
sqft_living15 : 777
sqft_lot15 : 8682
```

Now let's check to see if there are any null values in any of the columns of our dataframe.

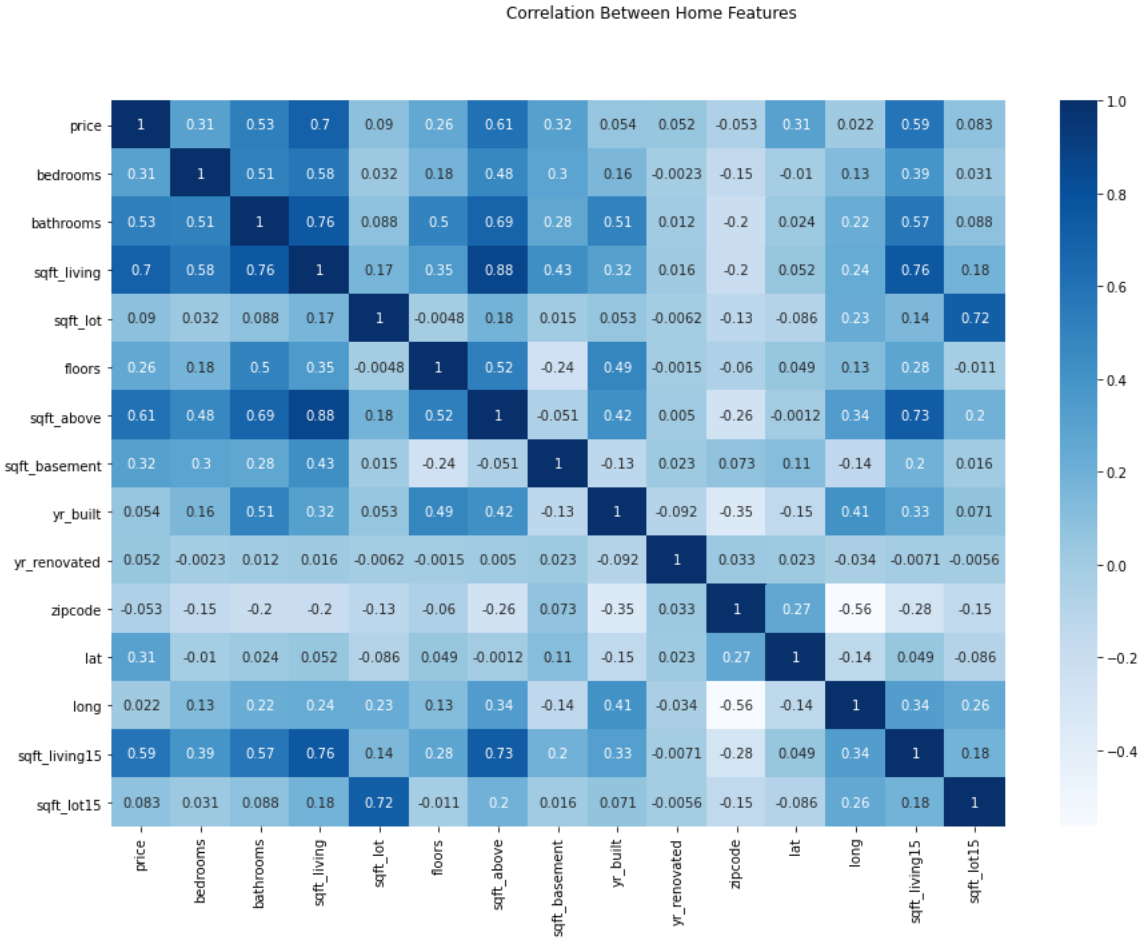
In [22]:
```
df.isnull().sum()
```

Out[22]:
```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

In [23]:
```
df['yr_renovated'] = df['yr_renovated'].astype('int64')
```

Great, now let's check out the correlation of features within my dataframe.

In [24]:
```
# Review correlations on filtered dataset
plt.figure(figsize = (15,10)).suptitle("Correlation Between Home Features")
sns.heatmap(df.corr(), annot = True, cmap = "Blues");
```



The correlation shown is called a Pearson correlation and is given by the ratio below:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}}$$

A commonly held rule for interpreting the Pearson correlation is that:

- Very Strong Correlation → 0.8 to 1
- Strong Correlation → 0.6 to 0.799
- Moderate Correlation → 0.4 to 0.599
- Weak Correlation → 0.2 to 0.399
- Very Weak Correlation → 0 to 0.199

From the heatmap, it appears that house `price` (the target) has the **strongest correlation** with `sqft_living` (0.7), a weak correlation with floors `floors` (0.26),a **strong correlation** with `sqft_above` (0.61), a weak correlation with `lat` (0.31) and a moderate correlation with `sqft_living_15` (0.59). The `sqft_living` , `bathrooms` , `sqft_above` and `sqft_living_15` features all seem to be highly correlated (> 0.7) to one another as well. This will be helpful when building our baseline model and refining it after reviewing our metrics.

Looking at a heatmap this complex may be a stretch. Let's create a more elegant way to determine which pairs of features have strong correlation values.

In [25]:
```
_df = df.corr().abs().stack().reset_index().sort_values(0, ascending = False)

_df['pairs'] = list(zip(_df.level_0, _df.level_1))

_df.set_index(['pairs'], inplace = True)

_df.drop(columns = ['level_1' , 'level_0'], inplace = True)

_df.columns = ['cc']

_df.drop_duplicates(inplace = True)

_df[(_df.cc > 0.6) & (_df.cc < 1)]
```

Out[25]:

pairs	cc
(sqft_above, sqft_living)	0.88
(sqft_living, sqft_living15)	0.76
(bathrooms, sqft_living)	0.76
(sqft_above, sqft_living15)	0.73
(sqft_lot, sqft_lot15)	0.72
(price, sqft_living)	0.70
(bathrooms, sqft_above)	0.69
(sqft_above, price)	0.61

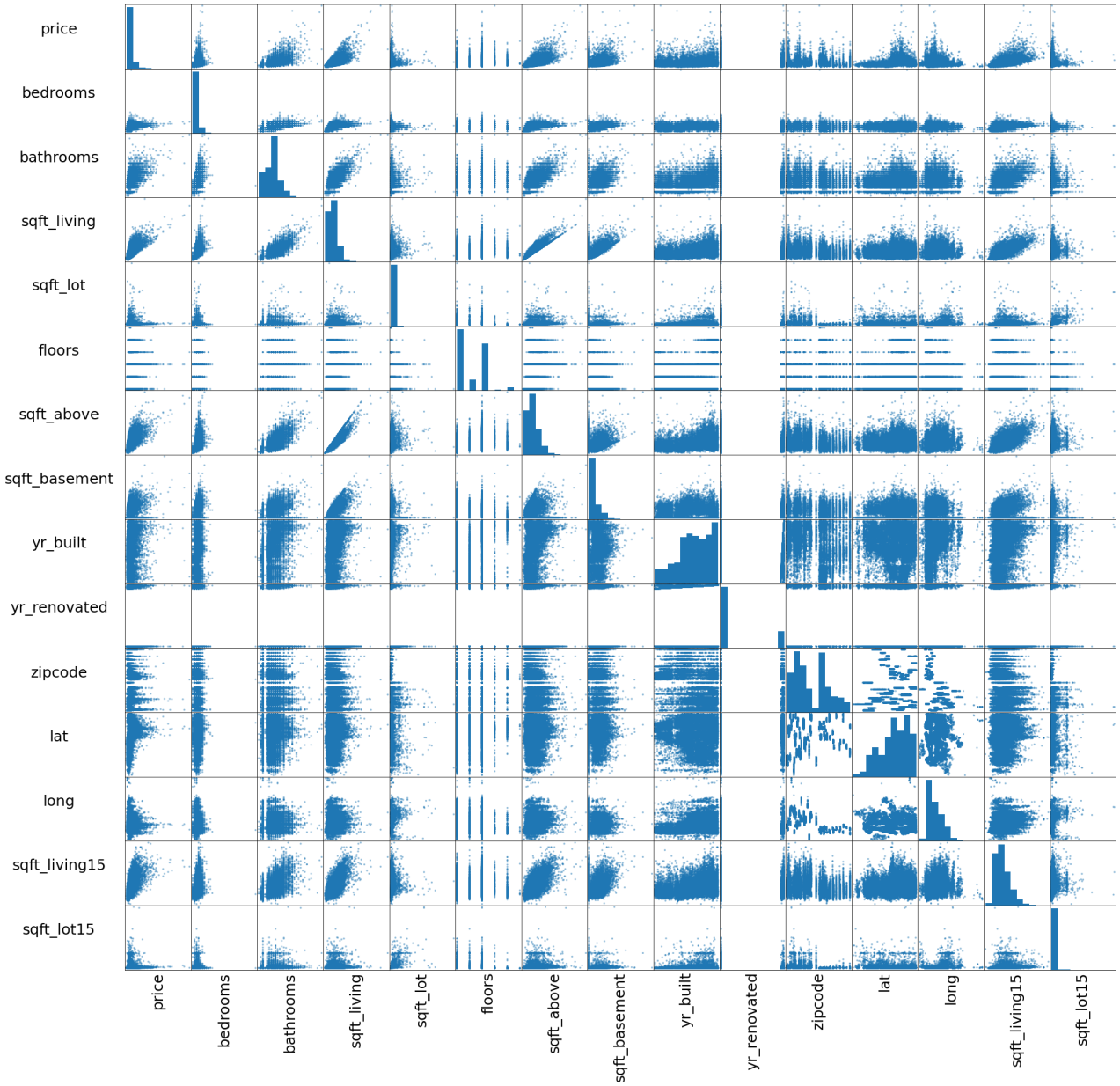
Viewing a simplied table is a bit more helpful than a heatmap, but maybe a visual that shows how each feature is related may also be helpful, so we will try that next.

5.3.5 Scatter matrix

Create a scatter matrix for the King County House data. (This takes awhile (~25 s) to run and generate a plot)

In [26]:

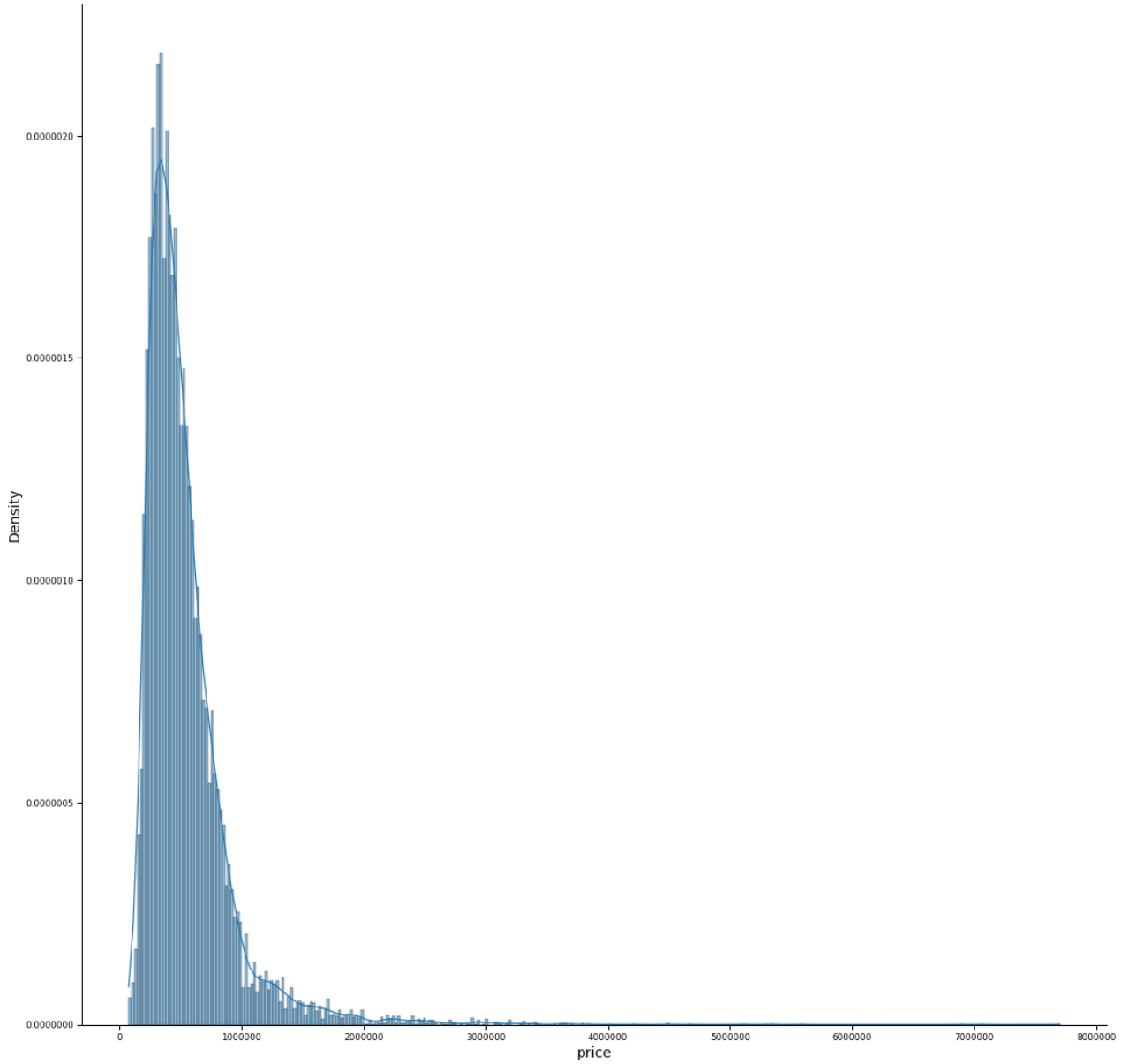
```
%%time
# create scatter matrix
smat = pd.plotting.scatter_matrix(df, figsize=[30, 30]);


# Rotates the text
[s.xaxis.label.set_rotation(90) for s in smat.reshape(-1)]
[s.yaxis.label.set_rotation(0) for s in smat.reshape(-1)]

#May need to offset label when rotating to prevent overlap of figure
[s.get_yaxis().set_label_coords(-1,0.5) for s in smat.reshape(-1)]

#Hide all ticks
[s.set_xticks(()) for s in smat.reshape(-1)]
[s.set_yticks(()) for s in smat.reshape(-1)]
[plt.setp(item.xaxis.get_label(), "size", 25) for item in smat.ravel()]
[plt.setp(item.yaxis.get_label(), "size", 25) for item in smat.ravel()]

plt.show()
```




```
Wall time: 22.8 s
```

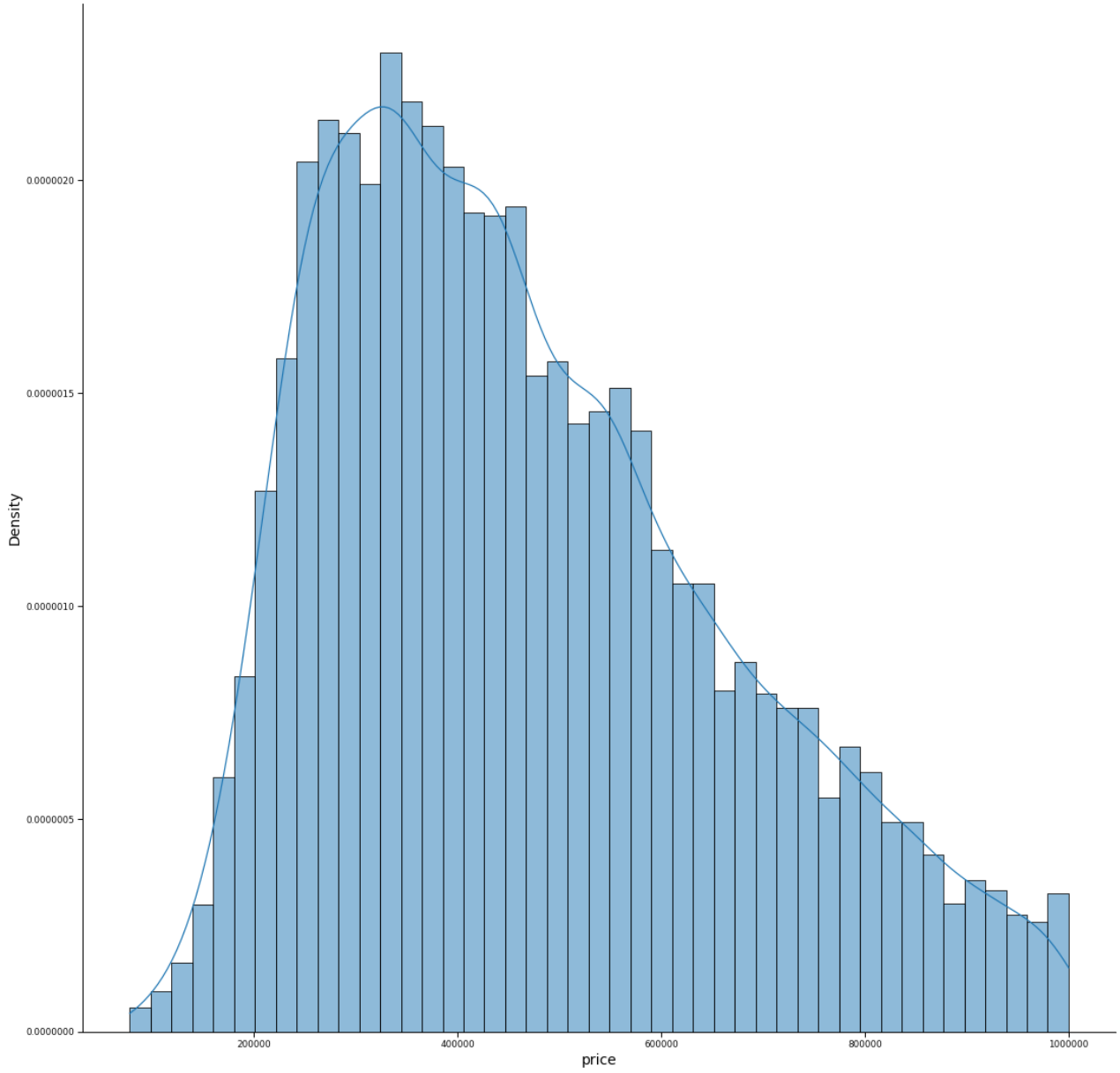
Visualize target using `seaborn` figure level plot called `displot` .

In [27]:
```
sns.set_context("paper", rc={"font.size":12,"axes.labelsize":14})
sns.displot(df['price'], stat = 'density', kde = True, height = 15)
plt.ticklabel_format(style='plain', axis= 'both')
plt.show();
```



The displot shows that most of the houses in the KC House data set are priced below 1 million dollars.

In [28]:
```
# Rough filter investigating dataframe upper limit
new_df = df[df['price'] <= 1000000]
sns.set_context("paper", rc={"font.size":12,"axes.labelsize":14})
sns.displot(new_df['price'], stat = 'density', kde = True, height = 15)
plt.ticklabel_format(style='plain', axis= 'both')
plt.show();
```



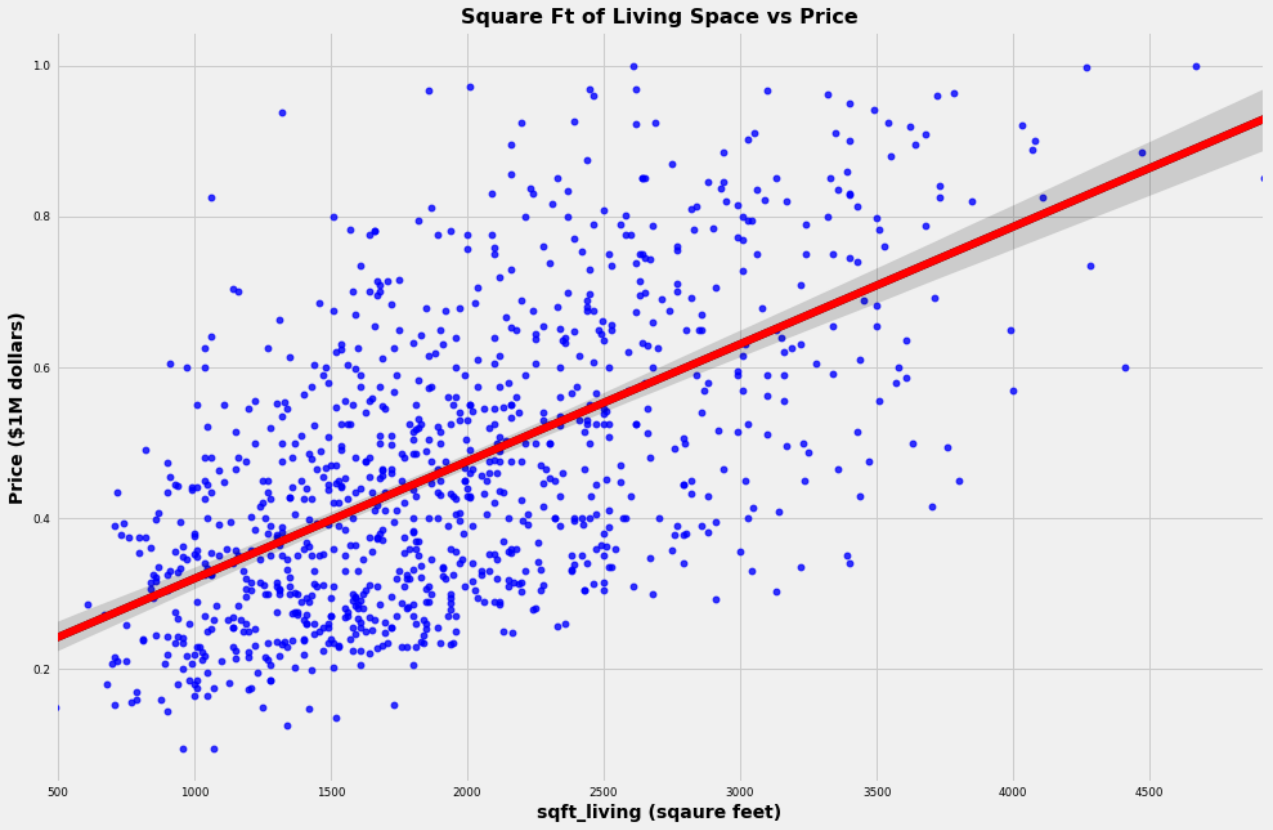
In [29]:
```
# Identify the name of the predictor column with strongest correlation
most_correlated = 'sqft_living'
```

From reviewing dataframe df with correlation coefficient values between 0.6 and 1, we can drop the following features from our original dataframe (`df` to create a new dataframe called `df_subset` :

- sqft_above
- sqft_living15
- bathrooms
- sqft_lot
- sqft_lot15

In [30]:
```
df_subset = new_df.drop(["sqft_above", "sqft_living15", "bathrooms"
                         , "sqft_lot", "sqft_lot15"], axis = 1)
```

In [31]:
```
plt.style.use('fivethirtyeight')
values = np.array(df_subset.sample(1000, random_state = 1).price)/1000000
# Set up plot
fig, ax = plt.subplots(figsize = (15, 10))
sns.regplot(data = df_subset.sample(1000, random_state = 1), x = most_correlated, y = values
                , scatter = True, ci = 95, fit_reg = True,scatter_kws={"color": "blue"}, line_kws={"color": "black"} );
sns.regplot(data = df_subset.sample(1000, random_state = 1), x = most_correlated, y = values, scatter = False
                , ci = 0, fit_reg = True, color = 'red');
ax.set_title("Square Ft of Living Space vs Price", weight = 'bold').set_fontsize('16');
ax.set_xlabel("sqft_living (sqaure feet)", fontsize = '14', weight = 'bold');
ax.set_ylabel("Price ($1M dollars)" , fontsize = '14', weight = 'bold');
```



6 Build a Simple Linear Regression model

First, I will set the dependent variable (`y`) to be the `price` . Next I will choose the most highly correlated features from the dataframe to be the baseline independent variable (`X`). Afterwards, I will:

- Build a linear regression using `statsModels`
- Describe the overall model performance
- Interpret its coefficients.

In [32]:
```
# Explore correlation to find a good starting point
df_subset.corr()['price'].sort_values()
```

Out[32]:
```
zipcode         -0.02
yr_renovated     0.03
yr_built         0.06
long             0.08
sqft_basement    0.22
floors           0.27
bedrooms         0.29
lat              0.44
sqft_living      0.60
price            1.00
Name: price, dtype: float64
```

In [33]:
```
# Set price as the dependent variable
y = df_subset["price"]
```

In [34]:
```
# sqft_living had the highest correlation
X_baseline = df_subset[[most_correlated]]
```

6.1 Creating and Fitting Simple Linear Regression

In [35]:
```
baseline_model = sm.OLS(y, sm.add_constant(X_baseline))
baseline_results = baseline_model.fit()
```

7 Evaluate and Interpret Baseline Model Results

In [36]:
```
print(baseline_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.365
Model:                            OLS   Adj. R-squared:                  0.365
Method:                 Least Squares   F-statistic:                 1.158e+04
Date:                Sun, 22 Jan 2023   Prob (F-statistic):               0.00
Time:                        19:28:30   Log-Likelihood:            -2.6946e+05
No. Observations:               20139   AIC:                         5.389e+05
Df Residuals:                   20137   BIC:                         5.389e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        1.607e+05   3061.929     52.468      0.000    1.55e+05    1.67e+05
sqft_living   157.1496      1.461    107.596      0.000     154.287     160.012
==============================================================================
Omnibus:                      704.434   Durbin-Watson:                   1.961
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              780.694
Skew:                           0.482   Prob(JB):                    2.98e-170
Kurtosis:                       2.973   Cond. No.                     5.82e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.82e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

This simple linear regression model is statistically significant overall, and explains **49.3% of the variance in house price**. Both the intercept and the coefficient for `sqft_living` are statistically significant.

The intercept is a small negative number, meaning a home with 0 square feet of living would cost around $0.

The coefficient for `sqft_living` is about 280, which means that for each additional square foot of living space, I expect the price to increase about **$280**.

8 Prepare Categorical Features for Multiple Regression Modeling

The categorical features that need to be replaced with dummies are `grade`, `view`, `waterfront`, and `zipcode`. First, let's review how many values each of these features has.

In [37]:
```
new_df["grade"].value_counts()
```

Out[37]:
```
7 Average        8951
8 Good           5873
9 Better         2224
6 Low Average    2033
10 Very Good      694
5 Fair            242
11 Excellent       92
4 Low              27
12 Luxury           2
3 Poor              1
Name: grade, dtype: int64
```

In [38]:
```
new_df["view"].value_counts()
```

Out[38]:
```
NONE         18611
AVERAGE        763
GOOD           319
FAIR           260
EXCELLENT      129
0               57
Name: view, dtype: int64
```

In [39]:
```
new_df["waterfront"].value_counts()
```

Out[39]:
```
NO     17862
0       2227
YES       50
Name: waterfront, dtype: int64
```

In [40]:
```
new_df["zipcode"].value_counts()
```

Out[40]:
```
98038    586
98103    581
98052    553
98115    549
98042    547
        ...
98109     82
98102     81
98024     72
98148     57
98039      6
Name: zipcode, Length: 70, dtype: int64
```

Next, lets make a new dataframe that includes these categoricals called `df_updated` .

In [41]:
```
df_updated = new_df[['bedrooms','sqft_living', 'lat', 'long', "grade", "view", "zipcode", "waterfront"]]
df_updated.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20139 entries, 7129300520 to 1523300157
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   bedrooms     20139 non-null  int64
 1   sqft_living  20139 non-null  int64
 2   lat          20139 non-null  float64
 3   long         20139 non-null  float64
 4   grade        20139 non-null  object
 5   view         20139 non-null  object
 6   zipcode      20139 non-null  int64
 7   waterfront   20139 non-null  object
dtypes: float64(2), int64(3), object(3)
memory usage: 1.4+ MB
```

Now let's use **dummy variables** to make this dataframe usuable for a linnear regression model.

In [42]:
```
# Create a new data frame with view dummy variables
df_with_dummies = pd.get_dummies(data = df_updated, columns = ["view", "zipcode", "grade", "waterfront"], drop_first = True)
```

In [43]:
```
df_with_dummies.head()
```

Out[43]:

id	bedrooms	sqft_living	lat	long	view_AVERAGE	view_EXCELLENT	view_FAIR	view_GOOD	view_NONE	zipcode_98002	...	grade_12 Luxury	g
7129300520	3	1180	47.51	-122.26	0	0	0	0	1	0	...	0	
6414100192	3	2570	47.72	-122.32	0	0	0	0	1	0	...	0	
5631500400	2	770	47.74	-122.23	0	0	0	0	1	0	...	0	
2487200875	4	1960	47.52	-122.39	0	0	0	0	1	0	...	0	
1954400510	3	1680	47.62	-122.05	0	0	0	0	1	0	...	0	

5 rows × 89 columns

In [44]:
```
target = new_df["price"]
```

In [45]:
```
target
```

Out[45]:
```
id
7129300520   221900.00
6414100192   538000.00
5631500400   180000.00
2487200875   604000.00
1954400510   510000.00
                ...
263000018    360000.00
6600060120   400000.00
1523300141   402101.00
291310100    400000.00
1523300157   325000.00
Name: price, Length: 20139, dtype: float64
```

In [46]:
```
iterated_model = sm.OLS(target, sm.add_constant(df_with_dummies))
iterated_results = iterated_model.fit()
```

In [47]:
```
print(iterated_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.813
Model:                            OLS   Adj. R-squared:                  0.812
Method:                 Least Squares   F-statistic:                     978.0
Date:                Sun, 22 Jan 2023   Prob (F-statistic):               0.00
Time:                        19:28:30   Log-Likelihood:            -2.5717e+05
No. Observations:               20139   AIC:                         5.145e+05
Df Residuals:                   20049   BIC:                         5.152e+05
Df Model:                          89
Covariance Type:            nonrobust
================================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                -1.142e+07   3.34e+06     -3.419      0.001    -1.8e+07   -4.87e+06
bedrooms              -428.4762    860.000     -0.498      0.618   -2114.147    1257.195
sqft_living            109.9166      1.387     79.261      0.000     107.198     112.635
lat                   1.465e+05   3.47e+04      4.223      0.000    7.85e+04    2.14e+05
long                  -3.85e+04   2.47e+04     -1.560      0.119   -8.69e+04    9863.715
view_AVERAGE          4.543e+04   1.17e+04      3.873      0.000    2.24e+04    6.84e+04
```

8.1 Remove the values with high p-values

In [48]:
```
revised_df = df_with_dummies.drop(["view_AVERAGE", "view_FAIR", "zipcode_98002"
                                   , "zipcode_98003", "zipcode_98011", "zipcode_98014"
                                   ,"zipcode_98077","zipcode_98028","zipcode_98030"
                                   ,"zipcode_98031", "zipcode_98032", "zipcode_98042"
                                   ,"zipcode_98055", "zipcode_98058", "zipcode_98077", "zipcode_98188"
                                   , "zipcode_98148","zipcode_98168","zipcode_98092","zipcode_98198"
                                   ,"zipcode_98070","grade_3 Poor","waterfront_NO"], axis = 1)
```

In [49]:
```
revised_model = sm.OLS(target, sm.add_constant(revised_df))
revised_results = revised_model.fit()
```

In [50]:
```
print(revised_results.summary())
```

OLS Regression Results

Dep. Variable:	price	R-squared:	0.810
Model:	OLS	Adj. R-squared:	0.809
Method:	Least Squares	F-statistic:	1274.
Date:	Sun, 22 Jan 2023	Prob (F-statistic):	0.00
Time:	19:28:31	Log-Likelihood:	-2.5734e+05
No. Observations:	20139	AIC:	5.148e+05
Df Residuals:	20071	BIC:	5.153e+05
Df Model:	67		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.736e+07	1.55e+06	-11.190	0.000	-2.04e+07	-1.43e+07
bedrooms	-1100.0639	864.564	-1.272	0.203	-2794.680	594.553
sqft_living	110.9095	1.395	79.485	0.000	108.174	113.644
lat	3.45e+05	8638.089	39.943	0.000	3.28e+05	3.62e+05
long	-1.065e+04	1.16e+04	-0.920	0.358	-3.33e+04	1.2e+04
view_EXCELLENT	9.417e+04	9003.015	10.460	0.000	7.65e+04	1.12e+05
view_GOOD	2.571e+04	5505.471	4.669	0.000	1.49e+04	3.65e+04
view_NONE	-6.075e+04	2779.500	-21.858	0.000	-6.62e+04	-5.53e+04
zipcode_98004	4.075e+05	7588.574	53.699	0.000	3.93e+05	4.22e+05
zipcode_98005	2.463e+05	7371.820	33.414	0.000	2.32e+05	2.61e+05
zipcode_98006	1.987e+05	4725.756	42.041	0.000	1.89e+05	2.08e+05
zipcode_98007	1.649e+05	7683.570	21.455	0.000	1.5e+05	1.8e+05
zipcode_98008	1.513e+05	5694.763	26.569	0.000	1.4e+05	1.62e+05
zipcode_98010	9.98e+04	9111.519	10.953	0.000	8.19e+04	1.18e+05
zipcode_98019	-3.58e+04	7246.918	-4.940	0.000	-5e+04	-2.16e+04
zipcode_98022	6.779e+04	6769.352	10.014	0.000	5.45e+04	8.11e+04
zipcode_98023	-1.83e+04	4495.090	-4.071	0.000	-2.71e+04	-9490.531
zipcode_98024	9.049e+04	1.08e+04	8.397	0.000	6.94e+04	1.12e+05
zipcode_98027	1.297e+05	4906.830	26.437	0.000	1.2e+05	1.39e+05
zipcode_98029	1.443e+05	5598.263	25.779	0.000	1.33e+05	1.55e+05
zipcode_98033	1.932e+05	5219.876	37.007	0.000	1.83e+05	2.03e+05
zipcode_98034	4.701e+04	4654.291	10.101	0.000	3.79e+04	5.61e+04
zipcode_98038	2.925e+04	4376.620	6.682	0.000	2.07e+04	3.78e+04
zipcode_98039	5.598e+05	3.51e+04	15.936	0.000	4.91e+05	6.29e+05
zipcode_98040	3.479e+05	7302.947	47.638	0.000	3.34e+05	3.62e+05
zipcode_98045	6.236e+04	7893.578	7.900	0.000	4.69e+04	7.78e+04
zipcode_98052	1.361e+05	4407.164	30.880	0.000	1.27e+05	1.45e+05
zipcode_98053	1.245e+05	5343.599	23.295	0.000	1.14e+05	1.35e+05
zipcode_98056	3.89e+04	4518.904	8.609	0.000	3e+04	4.78e+04
zipcode_98059	5.175e+04	4361.658	11.864	0.000	4.32e+04	6.03e+04
zipcode_98065	6.351e+04	6434.366	9.870	0.000	5.09e+04	7.61e+04
zipcode_98072	3.898e+04	6071.862	6.421	0.000	2.71e+04	5.09e+04
zipcode_98074	1.155e+05	4954.809	23.307	0.000	1.06e+05	1.25e+05
zipcode_98075	1.573e+05	5560.670	28.293	0.000	1.46e+05	1.68e+05
zipcode_98102	2.692e+05	9928.257	27.119	0.000	2.5e+05	2.89e+05
zipcode_98103	1.877e+05	4731.373	39.666	0.000	1.78e+05	1.97e+05
zipcode_98105	2.555e+05	7113.987	35.911	0.000	2.42e+05	2.69e+05
zipcode_98106	2.181e+04	5294.405	4.120	0.000	1.14e+04	3.22e+04
zipcode_98107	1.888e+05	6270.634	30.116	0.000	1.77e+05	2.01e+05
zipcode_98108	2.576e+04	6626.665	3.887	0.000	1.28e+04	3.87e+04
zipcode_98109	2.914e+05	9922.805	29.370	0.000	2.72e+05	3.11e+05
zipcode_98112	2.993e+05	7421.443	40.329	0.000	2.85e+05	3.14e+05
zipcode_98115	1.88e+05	4660.527	40.344	0.000	1.79e+05	1.97e+05
zipcode_98116	1.962e+05	5723.631	34.270	0.000	1.85e+05	2.07e+05
zipcode_98117	1.769e+05	5056.509	34.991	0.000	1.67e+05	1.87e+05
zipcode_98118	7.413e+04	4271.551	17.353	0.000	6.58e+04	8.25e+04
zipcode_98119	2.776e+05	7731.911	35.899	0.000	2.62e+05	2.93e+05
zipcode_98122	2.003e+05	5760.419	34.776	0.000	1.89e+05	2.12e+05
zipcode_98125	5.19e+04	5292.516	9.806	0.000	4.15e+04	6.23e+04
zipcode_98126	1.005e+05	5291.665	18.983	0.000	9.01e+04	1.11e+05
zipcode_98133	3779.5949	5221.256	0.724	0.469	-6454.496	1.4e+04
zipcode_98136	1.635e+05	6074.849	26.913	0.000	1.52e+05	1.75e+05
zipcode_98144	1.342e+05	5347.013	25.095	0.000	1.24e+05	1.45e+05
zipcode_98146	3.219e+04	5630.675	5.717	0.000	2.12e+04	4.32e+04
zipcode_98155	-1.072e+04	5314.075	-2.017	0.044	-2.11e+04	-301.328
zipcode_98166	5.433e+04	5892.126	9.221	0.000	4.28e+04	6.59e+04
zipcode_98177	7.358e+04	6822.137	10.785	0.000	6.02e+04	8.69e+04
zipcode_98178	-2.26e+04	5557.390	-4.067	0.000	-3.35e+04	-1.17e+04
zipcode_98199	2.256e+05	6371.699	35.413	0.000	2.13e+05	2.38e+05
grade_11 Excellent	5.693e+04	9570.733	5.948	0.000	3.82e+04	7.57e+04
grade_12 Luxury	-2.176e+05	6.11e+04	-3.561	0.000	-3.37e+05	-9.78e+04
grade_4 Low	-1.767e+05	1.72e+04	-10.285	0.000	-2.1e+05	-1.43e+05
grade_5 Fair	-1.836e+05	7084.645	-25.918	0.000	-1.98e+05	-1.7e+05
grade_6 Low Average	-1.76e+05	4683.078	-37.575	0.000	-1.85e+05	-1.67e+05
grade_7 Average	-1.543e+05	4057.989	-38.012	0.000	-1.62e+05	-1.46e+05
grade_8 Good	-1.173e+05	3822.404	-30.684	0.000	-1.25e+05	-1.1e+05
grade_9 Better	-4.505e+04	3850.252	-11.701	0.000	-5.26e+04	-3.75e+04
waterfront_YES	1.851e+05	1.4e+04	13.260	0.000	1.58e+05	2.13e+05

Omnibus:	1674.547	Durbin-Watson:	1.985
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5577.670
Skew:	0.406	Prob(JB):	0.00

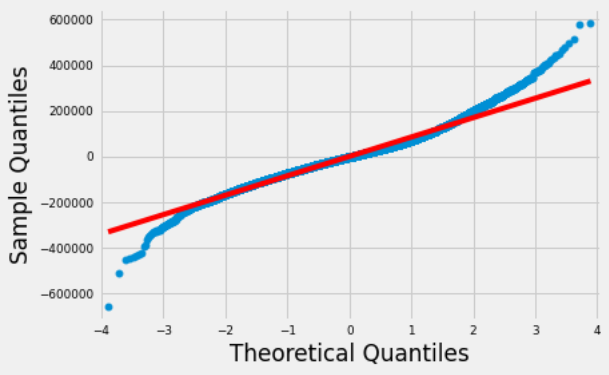
```
Kurtosis:                       5.447   Cond. No.                     5.38e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.38e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [51]:
```
baseline_results.rsquared_adj, revised_results.rsquared_adj
```

Out[51]:
```
(0.365011142951163, 0.8089660021397984)
```

In [52]:
```
# check for the normality of the residuals
sm.qqplot(iterated_results.resid, line='s')
# also check that the mean of the residuals is approx. 0.
mean_residuals = sum(iterated_results.resid)/ len(iterated_results.resid)
print("The mean of the residuals is {:.4}".format(mean_residuals))
```

```
The mean of the residuals is 1.99e-07
```



In [53]:
```
revised_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20139 entries, 7129300520 to 1523300157
Data columns (total 67 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   bedrooms             20139 non-null  int64  
 1   sqft_living          20139 non-null  int64  
 2   lat                  20139 non-null  float64
 3   long                 20139 non-null  float64
 4   view_EXCELLENT       20139 non-null  uint8  
 5   view_GOOD            20139 non-null  uint8  
 6   view_NONE            20139 non-null  uint8  
 7   zipcode_98004        20139 non-null  uint8  
 8   zipcode_98005        20139 non-null  uint8  
 9   zipcode_98006        20139 non-null  uint8  
 10  zipcode_98007        20139 non-null  uint8  
 11  zipcode_98008        20139 non-null  uint8  
 12  zipcode_98010        20139 non-null  uint8  
 13  zipcode_98019        20139 non-null  uint8  
 14  zipcode_98022        20139 non-null  uint8  
 15  zipcode_98023        20139 non-null  uint8  
 16  zipcode_98024        20139 non-null  uint8  
 17  zipcode_98027        20139 non-null  uint8  
 18  zipcode_98029        20139 non-null  uint8  
 19  zipcode_98033        20139 non-null  uint8  
 20  zipcode_98034        20139 non-null  uint8  
 21  zipcode_98038        20139 non-null  uint8  
 22  zipcode_98039        20139 non-null  uint8  
 23  zipcode_98040        20139 non-null  uint8  
 24  zipcode_98045        20139 non-null  uint8  
 25  zipcode_98052        20139 non-null  uint8  
 26  zipcode_98053        20139 non-null  uint8  
 27  zipcode_98056        20139 non-null  uint8  
 28  zipcode_98059        20139 non-null  uint8  
 29  zipcode_98065        20139 non-null  uint8  
 30  zipcode_98072        20139 non-null  uint8  
 31  zipcode_98074        20139 non-null  uint8  
 32  zipcode_98075        20139 non-null  uint8  
 33  zipcode_98102        20139 non-null  uint8  
 34  zipcode_98103        20139 non-null  uint8  
 35  zipcode_98105        20139 non-null  uint8  
 36  zipcode_98106        20139 non-null  uint8  
 37  zipcode_98107        20139 non-null  uint8  
 38  zipcode_98108        20139 non-null  uint8  
 39  zipcode_98109        20139 non-null  uint8  
 40  zipcode_98112        20139 non-null  uint8  
 41  zipcode_98115        20139 non-null  uint8  
 42  zipcode_98116        20139 non-null  uint8  
 43  zipcode_98117        20139 non-null  uint8  
 44  zipcode_98118        20139 non-null  uint8  
 45  zipcode_98119        20139 non-null  uint8  
 46  zipcode_98122        20139 non-null  uint8  
 47  zipcode_98125        20139 non-null  uint8  
 48  zipcode_98126        20139 non-null  uint8  
 49  zipcode_98133        20139 non-null  uint8  
 50  zipcode_98136        20139 non-null  uint8  
 51  zipcode_98144        20139 non-null  uint8  
 52  zipcode_98146        20139 non-null  uint8  
 53  zipcode_98155        20139 non-null  uint8  
 54  zipcode_98166        20139 non-null  uint8  
 55  zipcode_98177        20139 non-null  uint8  
 56  zipcode_98178        20139 non-null  uint8  
 57  zipcode_98199        20139 non-null  uint8  
 58  grade_11 Excellent   20139 non-null  uint8  
 59  grade_12 Luxury      20139 non-null  uint8  
 60  grade_4 Low          20139 non-null  uint8  
 61  grade_5 Fair         20139 non-null  uint8  
 62  grade_6 Low Average  20139 non-null  uint8  
 63  grade_7 Average      20139 non-null  uint8  
 64  grade_8 Good         20139 non-null  uint8  
 65  grade_9 Better       20139 non-null  uint8  
 66  waterfront_YES       20139 non-null  uint8  
dtypes: float64(2), int64(2), uint8(63)
memory usage: 2.0 MB
```

In [54]:
```
final_df = pd.concat([target, revised_df], axis=1)
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20139 entries, 7129300520 to 1523300157
Data columns (total 68 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   price                20139 non-null  float64
 1   bedrooms             20139 non-null  int64  
 2   sqft_living          20139 non-null  int64  
 3   lat                  20139 non-null  float64
 4   long                 20139 non-null  float64
 5   view_EXCELLENT       20139 non-null  uint8  
 6   view_GOOD            20139 non-null  uint8  
 7   view_NONE            20139 non-null  uint8  
 8   zipcode_98004        20139 non-null  uint8  
 9   zipcode_98005        20139 non-null  uint8  
 10  zipcode_98006        20139 non-null  uint8  
 11  zipcode_98007        20139 non-null  uint8  
 12  zipcode_98008        20139 non-null  uint8  
 13  zipcode_98010        20139 non-null  uint8  
 14  zipcode_98019        20139 non-null  uint8  
 15  zipcode_98022        20139 non-null  uint8  
 16  zipcode_98023        20139 non-null  uint8  
 17  zipcode_98024        20139 non-null  uint8  
 18  zipcode_98027        20139 non-null  uint8  
 19  zipcode_98029        20139 non-null  uint8  
 20  zipcode_98033        20139 non-null  uint8  
 21  zipcode_98034        20139 non-null  uint8  
 22  zipcode_98038        20139 non-null  uint8  
 23  zipcode_98039        20139 non-null  uint8  
 24  zipcode_98040        20139 non-null  uint8  
 25  zipcode_98045        20139 non-null  uint8  
 26  zipcode_98052        20139 non-null  uint8  
 27  zipcode_98053        20139 non-null  uint8  
 28  zipcode_98056        20139 non-null  uint8  
 29  zipcode_98059        20139 non-null  uint8  
 30  zipcode_98065        20139 non-null  uint8  
 31  zipcode_98072        20139 non-null  uint8  
 32  zipcode_98074        20139 non-null  uint8  
 33  zipcode_98075        20139 non-null  uint8  
 34  zipcode_98102        20139 non-null  uint8  
 35  zipcode_98103        20139 non-null  uint8  
 36  zipcode_98105        20139 non-null  uint8  
 37  zipcode_98106        20139 non-null  uint8  
 38  zipcode_98107        20139 non-null  uint8  
 39  zipcode_98108        20139 non-null  uint8  
 40  zipcode_98109        20139 non-null  uint8  
 41  zipcode_98112        20139 non-null  uint8  
 42  zipcode_98115        20139 non-null  uint8  
 43  zipcode_98116        20139 non-null  uint8  
 44  zipcode_98117        20139 non-null  uint8  
 45  zipcode_98118        20139 non-null  uint8  
 46  zipcode_98119        20139 non-null  uint8  
 47  zipcode_98122        20139 non-null  uint8  
 48  zipcode_98125        20139 non-null  uint8  
 49  zipcode_98126        20139 non-null  uint8  
 50  zipcode_98133        20139 non-null  uint8  
 51  zipcode_98136        20139 non-null  uint8  
 52  zipcode_98144        20139 non-null  uint8  
 53  zipcode_98146        20139 non-null  uint8  
 54  zipcode_98155        20139 non-null  uint8  
 55  zipcode_98166        20139 non-null  uint8  
 56  zipcode_98177        20139 non-null  uint8  
 57  zipcode_98178        20139 non-null  uint8  
 58  zipcode_98199        20139 non-null  uint8  
 59  grade_11 Excellent   20139 non-null  uint8  
 60  grade_12 Luxury      20139 non-null  uint8  
 61  grade_4 Low          20139 non-null  uint8  
 62  grade_5 Fair         20139 non-null  uint8  
 63  grade_6 Low Average  20139 non-null  uint8  
 64  grade_7 Average      20139 non-null  uint8  
 65  grade_8 Good         20139 non-null  uint8  
 66  grade_9 Better       20139 non-null  uint8  
 67  waterfront_YES       20139 non-null  uint8  
dtypes: float64(3), int64(2), uint8(63)
memory usage: 2.1 MB
```

In [55]:

```
bedrooms_counts = final_df['bedrooms'].value_counts()
print(bedrooms_counts)
```

```
3     9519
4     6147
2     2727
5     1286
6      218
1      195
7       30
8        9
9        4
10       2
11       1
33       1
Name: bedrooms, dtype: int64
```

In [56]:

```
# Remove Bedrooms that are 9 or larger from final dataframe
final_df = final_df[final_df['bedrooms'] < 9]
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20131 entries, 7129300520 to 1523300157
Data columns (total 68 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   price                20131 non-null  float64
 1   bedrooms             20131 non-null  int64  
 2   sqft_living          20131 non-null  int64  
 3   lat                  20131 non-null  float64
 4   long                 20131 non-null  float64
 5   view_EXCELLENT       20131 non-null  uint8  
 6   view_GOOD            20131 non-null  uint8  
 7   view_NONE            20131 non-null  uint8  
 8   zipcode_98004        20131 non-null  uint8  
 9   zipcode_98005        20131 non-null  uint8  
 10  zipcode_98006        20131 non-null  uint8  
 11  zipcode_98007        20131 non-null  uint8  
 12  zipcode_98008        20131 non-null  uint8  
 13  zipcode_98010        20131 non-null  uint8  
 14  zipcode_98019        20131 non-null  uint8  
 15  zipcode_98022        20131 non-null  uint8  
 16  zipcode_98023        20131 non-null  uint8  
 17  zipcode_98024        20131 non-null  uint8  
 18  zipcode_98027        20131 non-null  uint8  
 19  zipcode_98029        20131 non-null  uint8  
 20  zipcode_98033        20131 non-null  uint8  
 21  zipcode_98034        20131 non-null  uint8  
 22  zipcode_98038        20131 non-null  uint8  
 23  zipcode_98039        20131 non-null  uint8  
 24  zipcode_98040        20131 non-null  uint8  
 25  zipcode_98045        20131 non-null  uint8  
 26  zipcode_98052        20131 non-null  uint8  
 27  zipcode_98053        20131 non-null  uint8  
 28  zipcode_98056        20131 non-null  uint8  
 29  zipcode_98059        20131 non-null  uint8  
 30  zipcode_98065        20131 non-null  uint8  
 31  zipcode_98072        20131 non-null  uint8  
 32  zipcode_98074        20131 non-null  uint8  
 33  zipcode_98075        20131 non-null  uint8  
 34  zipcode_98102        20131 non-null  uint8  
 35  zipcode_98103        20131 non-null  uint8  
 36  zipcode_98105        20131 non-null  uint8  
 37  zipcode_98106        20131 non-null  uint8  
 38  zipcode_98107        20131 non-null  uint8  
 39  zipcode_98108        20131 non-null  uint8  
 40  zipcode_98109        20131 non-null  uint8  
 41  zipcode_98112        20131 non-null  uint8  
 42  zipcode_98115        20131 non-null  uint8  
 43  zipcode_98116        20131 non-null  uint8  
 44  zipcode_98117        20131 non-null  uint8  
 45  zipcode_98118        20131 non-null  uint8  
 46  zipcode_98119        20131 non-null  uint8  
 47  zipcode_98122        20131 non-null  uint8  
 48  zipcode_98125        20131 non-null  uint8  
 49  zipcode_98126        20131 non-null  uint8  
 50  zipcode_98133        20131 non-null  uint8  
 51  zipcode_98136        20131 non-null  uint8  
 52  zipcode_98144        20131 non-null  uint8  
 53  zipcode_98146        20131 non-null  uint8  
 54  zipcode_98155        20131 non-null  uint8  
 55  zipcode_98166        20131 non-null  uint8  
 56  zipcode_98177        20131 non-null  uint8  
 57  zipcode_98178        20131 non-null  uint8  
 58  zipcode_98199        20131 non-null  uint8  
 59  grade_11 Excellent   20131 non-null  uint8  
 60  grade_12 Luxury      20131 non-null  uint8  
 61  grade_4 Low          20131 non-null  uint8  
 62  grade_5 Fair         20131 non-null  uint8  
 63  grade_6 Low Average  20131 non-null  uint8  
 64  grade_7 Average      20131 non-null  uint8  
 65  grade_8 Good         20131 non-null  uint8  
 66  grade_9 Better       20131 non-null  uint8  
 67  waterfront_YES       20131 non-null  uint8  
dtypes: float64(3), int64(2), uint8(63)
memory usage: 2.1 MB
```

In [57]:
```
bedrooms_counts = final_df['bedrooms'].value_counts()
print(bedrooms_counts)
```

```
3    9519
4    6147
2    2727
5    1286
6     218
1     195
7      30
8       9
Name: bedrooms, dtype: int64
```

In [58]:
```
final_df.describe()
```

Out[58]:

	price	bedrooms	sqft_living	lat	long	view_EXCELLENT	view_GOOD	view_NONE	zipcode_98004	zipcode_98005	...	zipcode_9819
count	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	...	20131.0
mean	467900.80	3.32	1955.09	47.56	-122.21	0.01	0.02	0.92	0.01	0.01	...	0.0
std	196484.62	0.88	755.07	0.14	0.14	0.08	0.12	0.26	0.08	0.08	...	0.1
min	78000.00	1.00	370.00	47.16	-122.52	0.00	0.00	0.00	0.00	0.00	...	0.0
25%	314500.00	3.00	1390.00	47.46	-122.33	0.00	0.00	1.00	0.00	0.00	...	0.0
50%	434900.00	3.00	1840.00	47.57	-122.23	0.00	0.00	1.00	0.00	0.00	...	0.0
75%	594000.00	4.00	2410.00	47.68	-122.12	0.00	0.00	1.00	0.00	0.00	...	0.0
max	1000000.00	8.00	7480.00	47.78	-121.31	1.00	1.00	1.00	1.00	1.00	...	1.0

8 rows × 68 columns

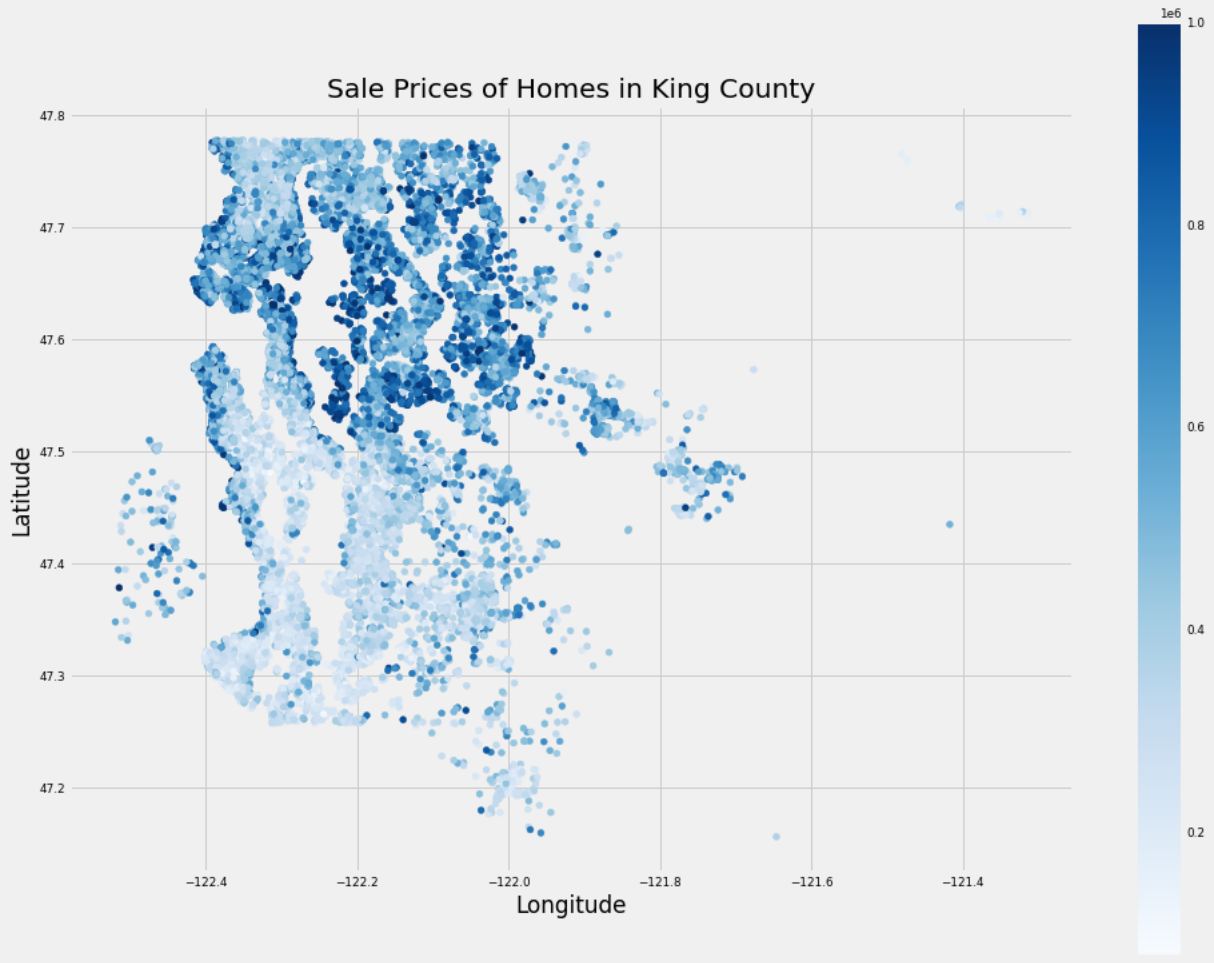
8.2 Exploratory Data Analysis Q1

8.3 Which neighborhoods have the highest average home price?

Looking at the `df_subset` for correlations helped to answer this question. The first thought I had when trying to answer this question was that I should leverage the location of homes in the dataset and use a sequential color palette. The first way that I tried to visualize which neighborhoods have the highest home price was to plot the longitude and lattitude against one another so that I could get a quick geographical visual on where the more expensive homes were located.

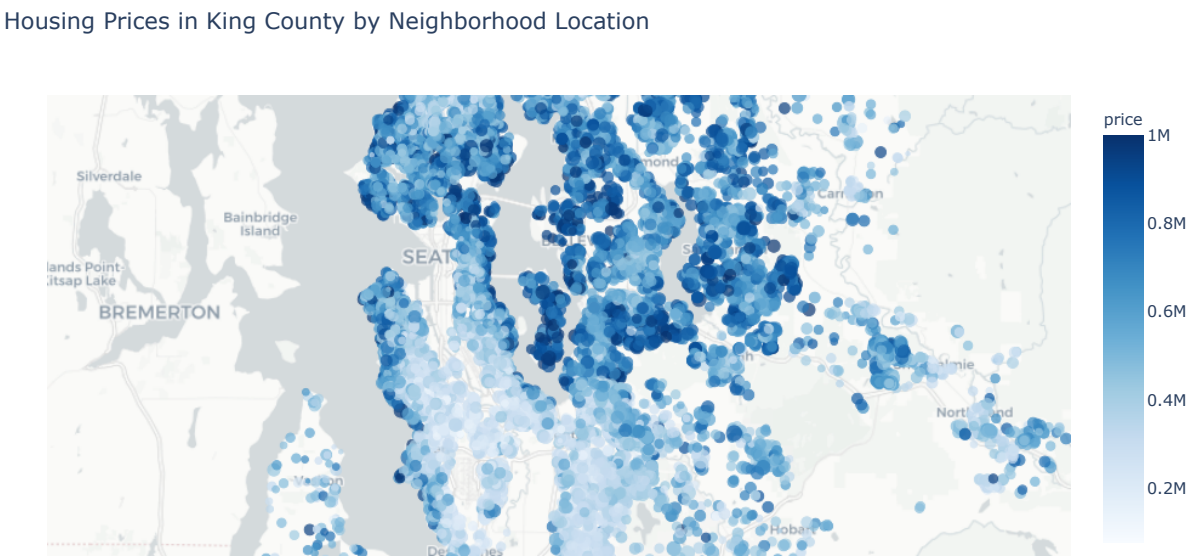
In [59]:
```
def sale_price_map(df: pd.DataFrame) -> plt.show():
    """
    Creates a map of sale prices for homes in king county dataset using geopandas

    Inputs:
    df: pandas dataframe with columns 'bedrooms', 'lat', 'long', and 'price'

    Output:
    map of sale prices for homes in king county
    """
    # Set up plot
    #plt.figure(figsize = (20,15))
    # Create a GeoDataFrame from the pandas dataframe
    gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df.long, df.lat))
    # Set the CRS (coordinate reference system) of the GeoDataFrame
    gdf.crs = {'init': 'epsg:4326'}
    # Create a map of sale prices for homes in king county
    gdf.plot(column='price', cmap='Blues', legend=True, figsize = (15,12))
    plt.title("Sale Prices of Homes in King County")
    plt.xlabel("Longitude")
    plt.ylabel("Latitude")
    plt.show()
```

In [60]:
```
sale_price_map(df_subset)
```



This visualization gave a general idea that the neighborhoods in the North Eastern section of King County were the most pricey and the neighborhoods to the South and Western sections of King County were more affordable. I wanted to make connections at the neighborhood level based on client need, so I used `plotly.express` as `px` and created a figure using a `scatter_mapbox` where I could zoom and hover over individual homes in different neighborhoods.

In [61]:
```
# Create an interactive Map that shows housing prices in King Coundty by Neighborhood and zipcode
# load the data
data = df_subset

# create the map
fig = px.scatter_mapbox(data_frame=data,
                        lat='lat', # column in data that contains latitude
                        lon='long', # column in data that contains longitude
                        color='price', # column in data that contains housing prices
                        title='Housing Prices in King County by Neighborhood Location',
                        hover_name='zipcode', # column in data that contains address of the property
                        size='bedrooms', # column in data that contains square footage of the property
                        zoom=9,
                        color_continuous_scale="Blues",
                        mapbox_style='carto-positron')

fig.show()
```



The map allows users to zoom in and see the sale prices of homes up to 1 million dollars in King County. The map shows a larger concentration of **homes with sale prices between 800 K and 1 million dollars in the ClydeHill neighborhood** within the Belleview section of the interactive map. The map shows a larger concentration of **homes with sale prices between 660K and 800K dollars in the Fremont, Queen Anne and Wallingford neighbords**. The map shows the zipcode, location and sale price of each home once you hover over the scattermap box. There are **less expensive (200K to 400K) homes in the southern and western boundaries of King County like in the Allentown and Lakeland North neighborhoods**.

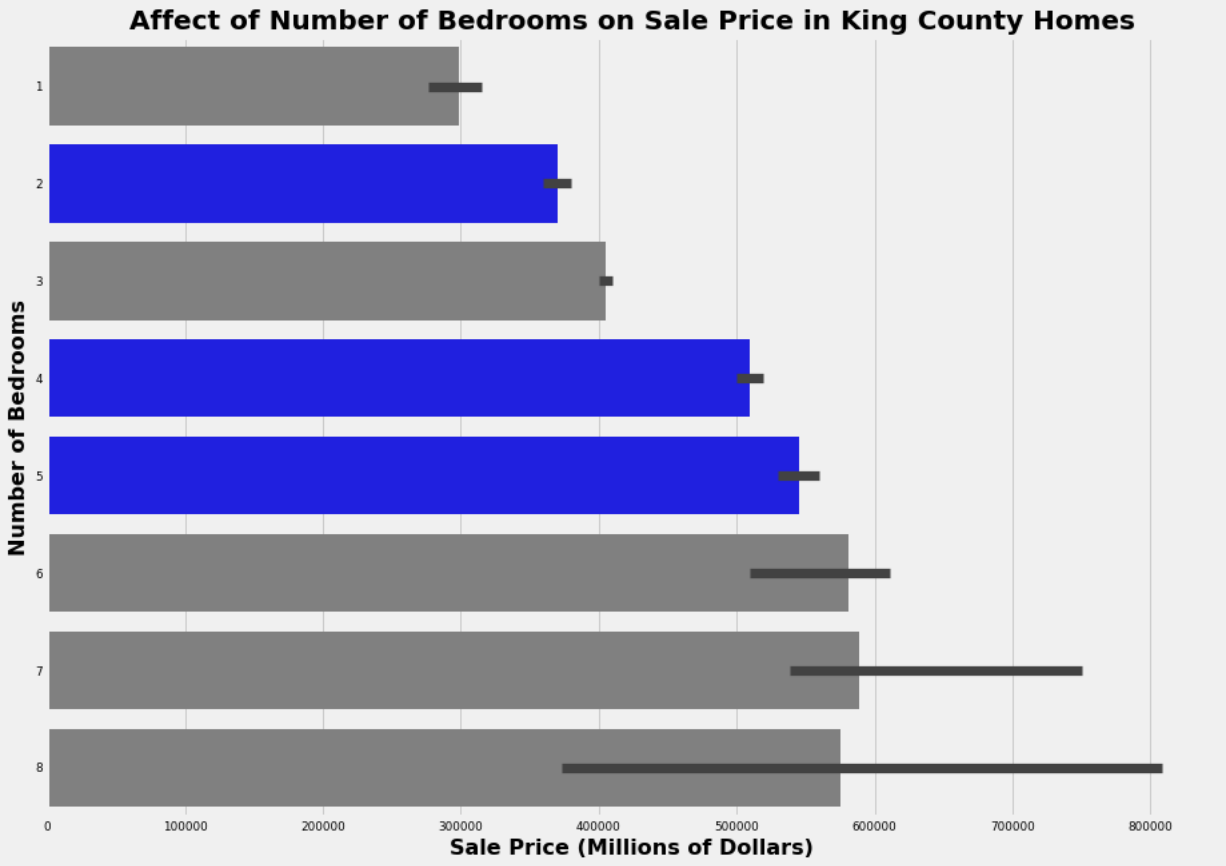
8.4 Exploratory Data Analysis Q2

8.5 How does the number of bedrooms affect the sale price of a home?

Looking at the `df` dataframe for correlations helped to answer this question. First I cleaned up the dataset by removing duplicates and reviewed correlations. After I applied both a simple `sm.ols` and multiple linear regression model and improved the Rsquared values from ~0.39 to ~0.810 by removing high **p-value** features, I created a dataframe called `final_df` and plotted the affect of the number of bedrooms on the median sale price of the subset of the King County dataset that yielded my revised model fit of **0.810** using a dataframe called `final_df` .

In [62]:
```
def plot_bedrooms_price(df:pd.DataFrame) -> sns.barplot:
    """
    Plot bar graph of number of bedrooms vs price

    Inputs:
    df: pandas dataframe
    Output:
    bar plot
    """
    # Create plot variables
    prices = np.array(df.price)
    bedrooms = np.array(df.bedrooms)
    median_price = np.median(prices)

    # Create plot labels
    x_label = "Sale Price (Millions of Dollars)"
    y_label = "Number of Bedrooms"
    title = "Affect of Number of Bedrooms on Sale Price in King County Homes"

    # Create a palette that highlights the top 5 sale price values as a function of the number of bedrooms"
    clrs = ['grey' if (x < median_price) else 'blue' for x in prices]
    # Set up plot figure size
    plt.figure(figsize = (14,10))

    # Plot bar using input of bedrooms, price, index and palette
    ax = sns.barplot(x = prices, y = bedrooms, palette = clrs, estimator = np.median, orient = 'h')
    # Setup titles and axes labels
    ax.set_title(title, weight='bold').set_fontsize('20')
    ax.set_ylabel(y_label, fontsize='16', weight='bold')
    ax.set_xlabel(x_label, fontsize='16', weight='bold')
```

In [63]:
```
plot_bedrooms_price(final_df)
```



In [64]:
```
final_df.describe()
```

Out[64]:

	price	bedrooms	sqft_living	lat	long	view_EXCELLENT	view_GOOD	view_NONE	zipcode_98004	zipcode_98005	...	zipcode_9819
count	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	20131.00	...	20131.0
mean	467900.80	3.32	1955.09	47.56	-122.21	0.01	0.02	0.92	0.01	0.01	...	0.0
std	196484.62	0.88	755.07	0.14	0.14	0.08	0.12	0.26	0.08	0.08	...	0.1
min	78000.00	1.00	370.00	47.16	-122.52	0.00	0.00	0.00	0.00	0.00	...	0.0
25%	314500.00	3.00	1390.00	47.46	-122.33	0.00	0.00	1.00	0.00	0.00	...	0.0
50%	434900.00	3.00	1840.00	47.57	-122.23	0.00	0.00	1.00	0.00	0.00	...	0.0
75%	594000.00	4.00	2410.00	47.68	-122.12	0.00	0.00	1.00	0.00	0.00	...	0.0
max	1000000.00	8.00	7480.00	47.78	-121.31	1.00	1.00	1.00	1.00	1.00	...	1.0

8 rows × 68 columns

8.6 Exploratory Data Analysis Q3

8.7 How does proximity to a highly rated school affect the sale price of a home?

As a mom with a school aged child, one of the first things I and other parents who are looking to purchase a home investigate is the proximity of our potential homes to effective schools. One of the most popular tools for this is greatschools.com. I used selenium to pull tabular data from a greatschools query for the king count WA area. While this data is for current school information, it gives some insight into the name, rating and locations of schools that are pertinent to the King County Dataset.

In [65]:
```
# Read Tables from the GreatSchools Website
param = {'lat': 47.5480339, 'locationLabel': 'King County, WA, USA',
         'locationType': 'street_address', 'lon': -121.9836029,
         'st[]': ['public_charter', 'public'], 'state': 'WA', 'view': 'table'}

url = "https://www.greatschools.org/search/search.page?" + urlencode(param)
driver = webdriver.Chrome('C:/chromedriver_win32/chromedriver.exe')

try:
    driver.get(url)
except WebDriverException:
    print("page down")

html = driver.page_source

table = pd.read_html(html)
king_county_schools_df = table[0]

driver.close()
```

In [66]:
```
king_county_schools_df.head(28)
```

Out[66]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District
0	Assigned school7/10Above averageGrand Ridge El...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
1	Assigned school7/10Above averagePacific Cascad...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
2	Assigned school8/10Above averageIssaquah High ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
3	10/10Above averageSkyline High School2 awardsA...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District
4	9/10Above averageSunny Hills Elementary School...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District
5	9/10Above averageDiscovery Elementary School23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District
6	8/10Above averageFall City Elementary School33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District
7	8/10Above averageCascade Ridge Elementary Scho...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District
8	8/10Above averageCreekside Elementary School20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District
9	8/10Above averageIssaquah High School2 awardsA...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
10	8/10Above averagePine Lake Middle School3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District
11	8/10Above averageEndeavour Elementary School26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District
12	7/10Above averageGrand Ridge Elementary School...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
13	7/10Above averagePacific Cascade Middle School...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
14	7/10Above averageIssaquah Middle School600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District
15	7/10Above averageBeaver Lake Middle School2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District
16	6/10AverageIssaquah Valley Elementary School55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District
17	6/10AverageClark Elementary School335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District
18	6/10AverageChallenger Elementary School25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District
19	5/10AverageChief Kanim Middle School32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District
20	Currently unratedSnoqualmie Valley Christian S...	Private	PK-7	nan	NaN	0 Reviews	NaN
21	Currently unratedEastside Catholic School232 2...	Private	6-12	841.00	NaN	17 Reviews	NaN
22	Currently unratedArbor Schools1107 228th Avenu...	Private	PK-6	108.00	NaN	16 Reviews	NaN
23	Currently unratedEmerald Heights Academy1420 N...	Private	PK-8	50.00	NaN	17 Reviews	NaN
24	Currently unratedSt Joseph School220 Mountain ...	Private	PK-8	169.00	NaN	9 Reviews	NaN
25	Currently unratedIssaquah Montessori School243...	Private	PK-K	88.00	NaN	3 Reviews	NaN
26	Currently unratedDartmoor School22500 SE 64th ...	Private	1-12	nan	NaN	0 Reviews	NaN
27	Currently unratedSnoqualmie Springs School2523...	Private	PK-2	55.00	NaN	8 Reviews	NaN

In [67]:
```
king_county_schools_df['School'][0]
```

Out[67]:
```
'Assigned school7/10Above averageGrand Ridge Elementary School1739 Northeast Park Drive, Issaquah, WA, 98029 Homes for sale'
```

In [68]:
```
king_county_schools_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28 entries, 0 to 27
Data columns (total 7 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   School                   28 non-null     object
 1   Type                     28 non-null     object
 2   Grades                   28 non-null     object
 3   Total students enrolled  26 non-null     float64
 4   Students per teacher     20 non-null     object
 5   Reviews                  28 non-null     object
 6   District                 20 non-null     object
dtypes: float64(1), object(6)
memory usage: 1.7+ KB
```

In [69]:
```
king_county_schools_df['Type'].value_counts()
```

Out[69]:
```
Public district    20
Private             8
Name: Type, dtype: int64
```

In [70]:
```
king_county_schools_df.head(28)
```

Out[70]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District
0	Assigned school7/10Above averageGrand Ridge El...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
1	Assigned school7/10Above averagePacific Cascad...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
2	Assigned school8/10Above averageIssaquah High ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
3	10/10Above averageSkyline High School2 awardsA...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District
4	9/10Above averageSunny Hills Elementary School...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District
5	9/10Above averageDiscovery Elementary School23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District
6	8/10Above averageFall City Elementary School33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District
7	8/10Above averageCascade Ridge Elementary Scho...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District
8	8/10Above averageCreekside Elementary School20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District
9	8/10Above averageIssaquah High School2 awardsA...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
10	8/10Above averagePine Lake Middle School3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District
11	8/10Above averageEndeavour Elementary School26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District
12	7/10Above averageGrand Ridge Elementary School...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
13	7/10Above averagePacific Cascade Middle School...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
14	7/10Above averageIssaquah Middle School600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District
15	7/10Above averageBeaver Lake Middle School2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District
16	6/10AverageIssaquah Valley Elementary School55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District
17	6/10AverageClark Elementary School335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District
18	6/10AverageChallenger Elementary School25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District
19	5/10AverageChief Kanim Middle School32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District
20	Currently unratedSnoqualmie Valley Christian S...	Private	PK-7	nan	NaN	0 Reviews	NaN
21	Currently unratedEastside Catholic School232 2...	Private	6-12	841.00	NaN	17 Reviews	NaN
22	Currently unratedArbor Schools1107 228th Avenu...	Private	PK-6	108.00	NaN	16 Reviews	NaN
23	Currently unratedEmerald Heights Academy1420 N...	Private	PK-8	50.00	NaN	17 Reviews	NaN
24	Currently unratedSt Joseph School220 Mountain ...	Private	PK-8	169.00	NaN	9 Reviews	NaN
25	Currently unratedIssaquah Montessori School243...	Private	PK-K	88.00	NaN	3 Reviews	NaN
26	Currently unratedDartmoor School22500 SE 64th ...	Private	1-12	nan	NaN	0 Reviews	NaN
27	Currently unratedSnoqualmie Springs School2523...	Private	PK-2	55.00	NaN	8 Reviews	NaN

In [71]:
```
# Filter out non-Public School data
king_county_schools_df = king_county_schools_df[king_county_schools_df['Type'] == 'Public district']
```

In [72]:
```
king_county_schools_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20 entries, 0 to 19
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   School                  20 non-null     object 
 1   Type                    20 non-null     object 
 2   Grades                  20 non-null     object 
 3   Total students enrolled  20 non-null     float64
 4   Students per teacher    20 non-null     object 
 5   Reviews                 20 non-null     object 
 6   District                20 non-null     object 
dtypes: float64(1), object(6)
memory usage: 1.2+ KB
```

In [73]:
```
king_county_schools_df.head(20)
```

Out[73]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District
0	Assigned school7/10Above averageGrand Ridge El...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
1	Assigned school7/10Above averagePacific Cascad...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
2	Assigned school8/10Above averageIssaquah High ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
3	10/10Above averageSkyline High School2 awardsA...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District
4	9/10Above averageSunny Hills Elementary School...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District
5	9/10Above averageDiscovery Elementary School23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District
6	8/10Above averageFall City Elementary School33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District
7	8/10Above averageCascade Ridge Elementary Scho...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District
8	8/10Above averageCreekside Elementary School20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District
9	8/10Above averageIssaquah High School2 awardsA...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
10	8/10Above averagePine Lake Middle School3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District
11	8/10Above averageEndeavour Elementary School26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District
12	7/10Above averageGrand Ridge Elementary School...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
13	7/10Above averagePacific Cascade Middle School...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
14	7/10Above averageIssaquah Middle School600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District
15	7/10Above averageBeaver Lake Middle School2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District
16	6/10AverageIssaquah Valley Elementary School55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District
17	6/10AverageClark Elementary School335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District
18	6/10AverageChallenger Elementary School25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District
19	5/10AverageChief Kanim Middle School32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District

In [74]:
```
# Explore a row from the king_county_schools_df dataframe
king_county_schools_df['School'][0]
```

Out[74]:
```
'Assigned school7/10Above averageGrand Ridge Elementary School1739 Northeast Park Drive, Issaquah, WA, 98029 Homes for sale'
```

In [75]:
```
#df['column'] = df['column'].str.replace('string_to_remove', '')
# Remove a string from a column
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('Assigned school', '')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('See all winners in Washington',
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('2 awardsAwards & BadgesCollege S
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('WA', 'WA,')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('/10', ',')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('average', 'average,')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace('Average', 'Average,')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace("School", 'School,')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace("Homes", ',Homes')
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace("None", ',None')
king_county_schools_df.head(20)
```

Out[75]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District
0	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
1	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
2	8,Above average,Issaquah High School,, 2020700...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
3	10,Above average,Skyline High School,, 2020112...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District
4	9,Above average,Sunny Hills Elementary School,...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District
5	9,Above average,Discovery Elementary School,23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District
6	8,Above average,Fall City Elementary School,33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District
7	8,Above average,Cascade Ridge Elementary Schoo...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District
8	8,Above average,Creekside Elementary School,20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District
9	8,Above average,Issaquah High School,, 2020700...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District
10	8,Above average,Pine Lake Middle School,3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District
11	8,Above average,Endeavour Elementary School,26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District
12	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District
13	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District
14	7,Above average,Issaquah Middle School,600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District
15	7,Above average,Beaver Lake Middle School,2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District
16	6,Average,Issaquah Valley Elementary School,55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District
17	6,Average,Clark Elementary School,335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District
18	6,Average,Challenger Elementary School,25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District
19	5,Average,Chief Kanim Middle School,32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District

In [76]:
```
# Replace Strings in the king_county_schools_df dataframe
king_county_schools_df.loc[:,'School'] = king_county_schools_df.loc[:,'School'].str.replace("2020", '')
king_county_schools_df.loc[:,'School']= king_county_schools_df.loc[:,'School'].str.replace(",,", ',')
king_county_schools_df.loc[:,'School']= king_county_schools_df.loc[:,'School'].str.replace("Trossachs Boulevard Southeast", "
```

In [77]:
```
# Split a single column into multiple columns using the ',' as a delimiter
split_df = king_county_schools_df.loc[:,'School'].str.split(",", expand=True)
print("Shape of split dataframe:", split_df.shape)
# create a list of column names that matches the number of elements in the split dataframe
column_names = ["col{}".format(i) for i in range(split_df.shape[1])]
# assign the split dataframe to the target dataframe with the new column names
king_county_schools_df[column_names] = split_df
# drop the original column
#king_county_schools_df.drop('School', axis=1, inplace=True)
```

```
Shape of split dataframe: (20, 8)
```

In [78]:
```
king_county_schools_df.head(20)
```

Out[78]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	col0	col1	col2	col3	col4	col5	col6	col7
0	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	Grand Ridge Elementary School	1739 Northeast Park Drive	Issaquah	WA	98029	Homes for sale
1	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	Pacific Cascade Middle School	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	Homes for sale
2	8,Above average,Issaquah High School, 700 2nd ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	Issaquah High School	700 2nd Avenue Southeast	Issaquah	WA	98027	Homes for sale
3	10,Above average,Skyline High School, 1122 228...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District	10	Above average	Skyline High School	1122 228th Avenue Southeast	Sammamish	WA	98075	Homes for sale
4	9,Above average,Sunny Hills Elementary School,...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District	9	Above average	Sunny Hills Elementary School	3200 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	Homes for sale
5	9,Above average,Discovery Elementary School,23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District	9	Above average	Discovery Elementary School	2300 228TH AVE SE	ISSAQUAH	WA	98075	Homes for sale
6	8,Above average,Fall City Elementary School,33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District	8	Above average	Fall City Elementary School	33314 Southeast 42nd Street	Fall City	WA	98024	Homes for sale
7	8,Above average,Cascade Ridge Elementary Schoo...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District	8	Above average	Cascade Ridge Elementary School	2020 Trossachs Boulevard Southeast	Sammamish	WA	98075	Homes for sale
8	8,Above average,Creekside Elementary School,20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District	8	Above average	Creekside Elementary School	20777 Southeast 16th Street	Sammamish	WA	98075	Homes for sale
9	8,Above average,Issaquah High School, 700 2nd ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	Issaquah High School	700 2nd Avenue Southeast	Issaquah	WA	98027	Homes for sale
10	8,Above average,Pine Lake Middle School,3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District	8	Above average	Pine Lake Middle School	3095 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	Homes for sale
11	8,Above average,Endeavour Elementary School,26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District	8	Above average	Endeavour Elementary School	26205 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	Homes for sale
12	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	Grand Ridge Elementary School	1739 Northeast Park Drive	Issaquah	WA	98029	Homes for sale
13	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	Pacific Cascade Middle School	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	Homes for sale
14	7,Above average,Issaquah Middle School,600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District	7	Above average	Issaquah Middle School	600 2nd Avenue Southeast	Issaquah	WA	98027	Homes for sale
15	7,Above average,Beaver Lake Middle School,2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District	7	Above average	Beaver Lake Middle School	25025 Southeast 32nd Street	Issaquah	WA	98029	Homes for sale
16	6,Average,Issaquah Valley Elementary School,55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District	6	Average	Issaquah Valley Elementary School	555 Northwest Holly Street	Issaquah	WA	98027	Homes for sale
17	6,Average,Clark Elementary School,335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District	6	Average	Clark Elementary School	335 1st Avenue Southeast	Issaquah	WA	98027	Homes for sale
18	6,Average,Challenger Elementary School,25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District	6	Average	Challenger Elementary School	25200 Southeast Klahanie Boulevard	Issaquah	WA	98029	Homes for sale

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	col0	col1	col2	col3	col4	col5	col6	col7
19	5,Average,Chief Kanim Middle School,32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District	5	Average	Chief Kanim Middle School	32627 Redmond-Fall City Road Southeast	Fall City	WA	98024	Homes for sale

Let's clean up this dataframe so that it's a bit more clear to parse.

In [79]:
```
# Get all columns name
#cols = df.columns.tolist()
cols = king_county_schools_df.columns.to_list()
cols

# Replace 'col0' with 'rating'
cols[cols.index('col0')] = 'rating_score'
cols[cols.index('col1')] = 'rating'
cols[cols.index('col2')] = 'school_name'
cols[cols.index('col3')] = 'school_address'
cols[cols.index('col4')] = 'school_city'
cols[cols.index('col5')] = 'school_state'
cols[cols.index('col6')] = 'school_zip'

king_county_schools_df.columns = cols

# drop the original column
king_county_schools_df.drop('col7', axis=1, inplace=True)
```

In [80]:
```
king_county_schools_df['School'][3]
```

Out[80]:
```
'10,Above average,Skyline High School, 1122 228th Avenue Southeast, Sammamish, WA, 98075 ,Homes for sale'
```

In [81]:
```
king_county_schools_df.head(20)
```

Out[81]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	rating_score	rating	school_name	school_address	school_city	scho
0	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	Grand Ridge Elementary School	1739 Northeast Park Drive	Issaquah	
1	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	Pacific Cascade Middle School	24635 Southeast Issaquah-Fall City Road	Issaquah	
2	8,Above average,Issaquah High School, 700 2nd ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	Issaquah High School	700 2nd Avenue Southeast	Issaquah	
3	10,Above average,Skyline High School, 1122 228...	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District	10	Above average	Skyline High School	1122 228th Avenue Southeast	Sammamish	
4	9,Above average,Sunny Hills Elementary School,...	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District	9	Above average	Sunny Hills Elementary School	3200 Issaquah-Pine Lake Road Southeast	Sammamish	
5	9,Above average,Discovery Elementary School,23...	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District	9	Above average	Discovery Elementary School	2300 228TH AVE SE	ISSAQUAH	
6	8,Above average,Fall City Elementary School,33...	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District	8	Above average	Fall City Elementary School	33314 Southeast 42nd Street	Fall City	
7	8,Above average,Cascade Ridge Elementary Schoo...	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District	8	Above average	Cascade Ridge Elementary School	2020 Trossachs Boulevard Southeast	Sammamish	
8	8,Above average,Creekside Elementary School,20...	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District	8	Above average	Creekside Elementary School	20777 Southeast 16th Street	Sammamish	
9	8,Above average,Issaquah High School, 700 2nd ...	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	Issaquah High School	700 2nd Avenue Southeast	Issaquah	
10	8,Above average,Pine Lake Middle School,3095 I...	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District	8	Above average	Pine Lake Middle School	3095 Issaquah-Pine Lake Road Southeast	Sammamish	
11	8,Above average,Endeavour Elementary School,26...	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District	8	Above average	Endeavour Elementary School	26205 Southeast Issaquah-Fall City Road	Issaquah	
12	7,Above average,Grand Ridge Elementary School,...	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	Grand Ridge Elementary School	1739 Northeast Park Drive	Issaquah	
13	7,Above average,Pacific Cascade Middle School,...	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	Pacific Cascade Middle School	24635 Southeast Issaquah-Fall City Road	Issaquah	
14	7,Above average,Issaquah Middle School,600 2nd...	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District	7	Above average	Issaquah Middle School	600 2nd Avenue Southeast	Issaquah	
15	7,Above average,Beaver Lake Middle School,2502...	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District	7	Above average	Beaver Lake Middle School	25025 Southeast 32nd Street	Issaquah	
16	6,Average,Issaquah Valley Elementary School,55...	Public district	K-5	620.00	16:1	13 Reviews	Issaquah School District	6	Average	Issaquah Valley Elementary School	555 Northwest Holly Street	Issaquah	
17	6,Average,Clark Elementary School,335 1st Aven...	Public district	K-5	739.00	16:1	14 Reviews	Issaquah School District	6	Average	Clark Elementary School	335 1st Avenue Southeast	Issaquah	
18	6,Average,Challenger Elementary School,25200 S...	Public district	K-5	558.00	17:1	10 Reviews	Issaquah School District	6	Average	Challenger Elementary School	25200 Southeast Klahanie Boulevard	Issaquah	
19	5,Average,Chief Kanim Middle School,32627 Redm...	Public district	6-8	795.00	21:1	12 Reviews	Snoqualmie Valley School District	5	Average	Chief Kanim Middle School	32627 Redmond-Fall City Road Southeast	Fall City	

In [82]:
```
# Filter out average schools
king_county_schools_df = king_county_schools_df[king_county_schools_df['rating'] != 'Average']
```

In [83]:
```
king_county_schools_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 0 to 15
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   School                   16 non-null     object 
 1   Type                     16 non-null     object 
 2   Grades                   16 non-null     object 
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher     16 non-null     object 
 5   Reviews                  16 non-null     object 
 6   District                 16 non-null     object 
 7   rating_score             16 non-null     object 
 8   rating                   16 non-null     object 
 9   school_name              16 non-null     object 
 10  school_address           16 non-null     object 
 11  school_city              16 non-null     object 
 12  school_state             16 non-null     object 
 13  school_zip               16 non-null     object 
dtypes: float64(1), object(13)
memory usage: 1.9+ KB
```

In [84]:
```
king_county_schools_df.loc[:,'School']=king_county_schools_df.loc[:,'school_name']
# drop original column
king_county_schools_df.drop('school_name', axis=1, inplace=True)
```

In [85]:
```
king_county_schools_df.head(16)
```

Out[85]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	rating_score	rating	school_address	school_city	school_state	school_zip
0	Grand Ridge Elementary School	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	1739 Northeast Park Drive	Issaquah	WA	98029
1	Pacific Cascade Middle School	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029
2	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027
3	Skyline High School	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District	10	Above average	1122 228th Avenue Southeast	Sammamish	WA	98075
4	Sunny Hills Elementary School	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District	9	Above average	3200 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075
5	Discovery Elementary School	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District	9	Above average	2300 228TH AVE SE	ISSAQUAH	WA	98075
6	Fall City Elementary School	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District	8	Above average	33314 Southeast 42nd Street	Fall City	WA	98024
7	Cascade Ridge Elementary School	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District	8	Above average	2020 Trossachs Boulevard Southeast	Sammamish	WA	98075
8	Creekside Elementary School	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District	8	Above average	20777 Southeast 16th Street	Sammamish	WA	98075
9	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027
10	Pine Lake Middle School	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District	8	Above average	3095 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075
11	Endeavour Elementary School	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District	8	Above average	26205 Southeast Issaquah-Fall City Road	Issaquah	WA	98029
12	Grand Ridge Elementary School	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	1739 Northeast Park Drive	Issaquah	WA	98029
13	Pacific Cascade Middle School	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029
14	Issaquah Middle School	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District	7	Above average	600 2nd Avenue Southeast	Issaquah	WA	98027
15	Beaver Lake Middle School	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District	7	Above average	25025 Southeast 32nd Street	Issaquah	WA	98029

In [86]:
```
king_county_schools_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 0 to 15
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   School                  16 non-null     object
 1   Type                    16 non-null     object
 2   Grades                  16 non-null     object
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher    16 non-null     object
 5   Reviews                 16 non-null     object
 6   District                16 non-null     object
 7   rating_score            16 non-null     object
 8   rating                  16 non-null     object
 9   school_address          16 non-null     object
 10  school_city             16 non-null     object
 11  school_state            16 non-null     object
 12  school_zip              16 non-null     object
dtypes: float64(1), object(12)
memory usage: 1.8+ KB
```

In [87]:
```
# df[column_name] = df[column_name].astype(int)
# Convert a dataframe column to a different datatype ex. object-> integer
king_county_schools_df['rating_score'] = king_county_schools_df['rating_score'].astype(int)
```

In [88]:
```
king_county_schools_df = king_county_schools_df.assign(school_id = [i for i in range(1, 17)])
```

In [89]:
```
# df = df.sort_values(by='col0', ascending=False)
# sort a dataframe from largest to smallest value in a column
king_county_schools_df = king_county_schools_df.sort_values(by = 'rating_score', ascending = False)
```

In [90]:
```
king_county_schools_df.head(16)
```

Out[90]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	rating_score	rating	school_address	school_city	school_state	school_zip	sch
3	Skyline High School	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District	10	Above average	1122 228th Avenue Southeast	Sammamish	WA	98075	
4	Sunny Hills Elementary School	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District	9	Above average	3200 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	
5	Discovery Elementary School	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District	9	Above average	2300 228TH AVE SE	ISSAQUAH	WA	98075	
2	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027	
6	Fall City Elementary School	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District	8	Above average	33314 Southeast 42nd Street	Fall City	WA	98024	
7	Cascade Ridge Elementary School	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District	8	Above average	2020 Trossachs Boulevard Southeast	Sammamish	WA	98075	
8	Creekside Elementary School	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District	8	Above average	20777 Southeast 16th Street	Sammamish	WA	98075	
9	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027	
10	Pine Lake Middle School	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District	8	Above average	3095 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	
11	Endeavour Elementary School	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District	8	Above average	26205 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	
0	Grand Ridge Elementary School	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	1739 Northeast Park Drive	Issaquah	WA	98029	
1	Pacific Cascade Middle School	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	
12	Grand Ridge Elementary School	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	1739 Northeast Park Drive	Issaquah	WA	98029	
13	Pacific Cascade Middle School	Public district	6-8	1000.00	23:1	6 Reviews	Issaquah School District	7	Above average	24635 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	
14	Issaquah Middle School	Public district	6-8	988.00	22:1	13 Reviews	Issaquah School District	7	Above average	600 2nd Avenue Southeast	Issaquah	WA	98027	
15	Beaver Lake Middle School	Public district	6-8	852.00	22:1	8 Reviews	Issaquah School District	7	Above average	25025 Southeast 32nd Street	Issaquah	WA	98029	

In [91]:
```
king_county_schools_df.drop_duplicates(inplace = True)
king_county_schools_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 3 to 15
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   School                  16 non-null     object 
 1   Type                    16 non-null     object 
 2   Grades                  16 non-null     object 
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher    16 non-null     object 
 5   Reviews                 16 non-null     object 
 6   District                16 non-null     object 
 7   rating_score            16 non-null     int32  
 8   rating                  16 non-null     object 
 9   school_address          16 non-null     object 
 10  school_city             16 non-null     object 
 11  school_state            16 non-null     object 
 12  school_zip              16 non-null     object 
 13  school_id               16 non-null     int64  
dtypes: float64(1), int32(1), int64(1), object(11)
memory usage: 1.8+ KB
```

In [92]:
```
api_key = 'AIzaSyC8OclweMPAyVV58cfbZyQWiU_ZIGFmBD8'
```

In [93]:
```
def get_school_lat_long(school_df: pd.DataFrame, api_key:str) -> pd.DataFrame:
    """
    This function takes a DataFrame containing school name and state as input and returns a DataFrame
    containing the latitude and longitude of the school.

    Inputs:
    school_df: pandas dataframe
    api_key: string


    Output:
    school_df: pandas dataframe with new latitude and longitude columns

    """
    # Adding new columns to dataframe to store lat and long
    school_df['school_lat'] = None
    school_df['school_long'] = None
    for i in range(len(school_df)):
        school_name = school_df.iloc[i]['School']
        school_state = school_df.iloc[i]['school_state']
        # Make a GET request to the API
        url = f"https://maps.googleapis.com/maps/api/geocode/json?address={school_name},+{school_state}&key={api_key}"
        response = requests.get(url)

        # Parse the JSON response
        data = json.loads(response.text)

        # Extract the latitude and longitude from the response
        school_lat = data['results'][0]['geometry']['location']['lat']
        school_long = data['results'][0]['geometry']['location']['lng']

        school_df.at[i,'school_lat'] = school_lat
        school_df.at[i,'school_long'] = school_long
    return school_df
```

In [94]:
```
school_lat_long_df = get_school_lat_long(king_county_schools_df, api_key)
school_lat_long_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 3 to 15
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   School                   16 non-null     object
 1   Type                     16 non-null     object
 2   Grades                   16 non-null     object
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher     16 non-null     object
 5   Reviews                  16 non-null     object
 6   District                 16 non-null     object
 7   rating_score             16 non-null     int32
 8   rating                   16 non-null     object
 9   school_address           16 non-null     object
 10  school_city              16 non-null     object
 11  school_state             16 non-null     object
 12  school_zip               16 non-null     object
 13  school_id                16 non-null     int64
 14  school_lat               16 non-null     object
 15  school_long              16 non-null     object
dtypes: float64(1), int32(1), int64(1), object(13)
memory usage: 2.7+ KB
```

In [95]:
```
school_lat_long_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 3 to 15
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   School                   16 non-null     object
 1   Type                     16 non-null     object
 2   Grades                   16 non-null     object
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher     16 non-null     object
 5   Reviews                  16 non-null     object
 6   District                 16 non-null     object
 7   rating_score             16 non-null     int32
 8   rating                   16 non-null     object
 9   school_address           16 non-null     object
 10  school_city              16 non-null     object
 11  school_state             16 non-null     object
 12  school_zip               16 non-null     object
 13  school_id                16 non-null     int64
 14  school_lat               16 non-null     object
 15  school_long              16 non-null     object
dtypes: float64(1), int32(1), int64(1), object(13)
memory usage: 2.7+ KB
```

In [96]:
```
school_lat_long_df.head(11)
```

Out[96]:

	School	Type	Grades	Total students enrolled	Students per teacher	Reviews	District	rating_score	rating	school_address	school_city	school_state	school_zip	sc
3	Skyline High School	Public district	9-12	2169.00	25:1	21 Reviews	Issaquah School District	10	Above average	1122 228th Avenue Southeast	Sammamish	WA	98075	
4	Sunny Hills Elementary School	Public district	K-5	732.00	18:1	11 Reviews	Issaquah School District	9	Above average	3200 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	
5	Discovery Elementary School	Public district	PK-5	686.00	18:1	6 Reviews	Issaquah School District	9	Above average	2300 228TH AVE SE	ISSAQUAH	WA	98075	
2	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027	
6	Fall City Elementary School	Public district	K-5	544.00	19:1	8 Reviews	Snoqualmie Valley School District	8	Above average	33314 Southeast 42nd Street	Fall City	WA	98024	
7	Cascade Ridge Elementary School	Public district	K-5	487.00	17:1	6 Reviews	Issaquah School District	8	Above average	2020 Trossachs Boulevard Southeast	Sammamish	WA	98075	
8	Creekside Elementary School	Public district	K-5	723.00	18:1	14 Reviews	Issaquah School District	8	Above average	20777 Southeast 16th Street	Sammamish	WA	98075	
9	Issaquah High School	Public district	9-12	2417.00	26:1	23 Reviews	Issaquah School District	8	Above average	700 2nd Avenue Southeast	Issaquah	WA	98027	
10	Pine Lake Middle School	Public district	6-8	943.00	24:1	13 Reviews	Issaquah School District	8	Above average	3095 Issaquah-Pine Lake Road Southeast	Sammamish	WA	98075	
11	Endeavour Elementary School	Public district	K-5	598.00	19:1	9 Reviews	Issaquah School District	8	Above average	26205 Southeast Issaquah-Fall City Road	Issaquah	WA	98029	
0	Grand Ridge Elementary School	Public district	K-5	747.00	19:1	8 Reviews	Issaquah School District	7	Above average	1739 Northeast Park Drive	Issaquah	WA	98029	

In [97]:
```
school_lat_long_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 3 to 15
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   School                   16 non-null     object
 1   Type                     16 non-null     object
 2   Grades                   16 non-null     object
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher     16 non-null     object
 5   Reviews                  16 non-null     object
 6   District                 16 non-null     object
 7   rating_score             16 non-null     int32
 8   rating                   16 non-null     object
 9   school_address           16 non-null     object
 10  school_city              16 non-null     object
 11  school_state             16 non-null     object
 12  school_zip               16 non-null     object
 13  school_id                16 non-null     int64
 14  school_lat               16 non-null     object
 15  school_long              16 non-null     object
dtypes: float64(1), int32(1), int64(1), object(13)
memory usage: 2.7+ KB
```

In [98]:
```
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20131 entries, 7129300520 to 1523300157
Data columns (total 68 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   price                20131 non-null  float64
 1   bedrooms             20131 non-null  int64  
 2   sqft_living          20131 non-null  int64  
 3   lat                  20131 non-null  float64
 4   long                 20131 non-null  float64
 5   view_EXCELLENT       20131 non-null  uint8  
 6   view_GOOD            20131 non-null  uint8  
 7   view_NONE            20131 non-null  uint8  
 8   zipcode_98004        20131 non-null  uint8  
 9   zipcode_98005        20131 non-null  uint8  
 10  zipcode_98006        20131 non-null  uint8  
 11  zipcode_98007        20131 non-null  uint8  
 12  zipcode_98008        20131 non-null  uint8  
 13  zipcode_98010        20131 non-null  uint8  
 14  zipcode_98019        20131 non-null  uint8  
 15  zipcode_98022        20131 non-null  uint8  
 16  zipcode_98023        20131 non-null  uint8  
 17  zipcode_98024        20131 non-null  uint8  
 18  zipcode_98027        20131 non-null  uint8  
 19  zipcode_98029        20131 non-null  uint8  
 20  zipcode_98033        20131 non-null  uint8  
 21  zipcode_98034        20131 non-null  uint8  
 22  zipcode_98038        20131 non-null  uint8  
 23  zipcode_98039        20131 non-null  uint8  
 24  zipcode_98040        20131 non-null  uint8  
 25  zipcode_98045        20131 non-null  uint8  
 26  zipcode_98052        20131 non-null  uint8  
 27  zipcode_98053        20131 non-null  uint8  
 28  zipcode_98056        20131 non-null  uint8  
 29  zipcode_98059        20131 non-null  uint8  
 30  zipcode_98065        20131 non-null  uint8  
 31  zipcode_98072        20131 non-null  uint8  
 32  zipcode_98074        20131 non-null  uint8  
 33  zipcode_98075        20131 non-null  uint8  
 34  zipcode_98102        20131 non-null  uint8  
 35  zipcode_98103        20131 non-null  uint8  
 36  zipcode_98105        20131 non-null  uint8  
 37  zipcode_98106        20131 non-null  uint8  
 38  zipcode_98107        20131 non-null  uint8  
 39  zipcode_98108        20131 non-null  uint8  
 40  zipcode_98109        20131 non-null  uint8  
 41  zipcode_98112        20131 non-null  uint8  
 42  zipcode_98115        20131 non-null  uint8  
 43  zipcode_98116        20131 non-null  uint8  
 44  zipcode_98117        20131 non-null  uint8  
 45  zipcode_98118        20131 non-null  uint8  
 46  zipcode_98119        20131 non-null  uint8  
 47  zipcode_98122        20131 non-null  uint8  
 48  zipcode_98125        20131 non-null  uint8  
 49  zipcode_98126        20131 non-null  uint8  
 50  zipcode_98133        20131 non-null  uint8  
 51  zipcode_98136        20131 non-null  uint8  
 52  zipcode_98144        20131 non-null  uint8  
 53  zipcode_98146        20131 non-null  uint8  
 54  zipcode_98155        20131 non-null  uint8  
 55  zipcode_98166        20131 non-null  uint8  
 56  zipcode_98177        20131 non-null  uint8  
 57  zipcode_98178        20131 non-null  uint8  
 58  zipcode_98199        20131 non-null  uint8  
 59  grade_11 Excellent   20131 non-null  uint8  
 60  grade_12 Luxury      20131 non-null  uint8  
 61  grade_4 Low          20131 non-null  uint8  
 62  grade_5 Fair         20131 non-null  uint8  
 63  grade_6 Low Average  20131 non-null  uint8  
 64  grade_7 Average      20131 non-null  uint8  
 65  grade_8 Good         20131 non-null  uint8  
 66  grade_9 Better       20131 non-null  uint8  
 67  waterfront_YES       20131 non-null  uint8  
dtypes: float64(3), int64(2), uint8(63)
memory usage: 2.1 MB
```

In [99]:
```
grouped_schools = school_lat_long_df.groupby(['Grades', 'School']).sum()
grouped_schools
```

Out[99]:

Grades	School	Total students enrolled	rating_score	school_id
6-8	Beaver Lake Middle School	852.00	7	16
	Issaquah Middle School	988.00	7	15
	Pacific Cascade Middle School	2000.00	14	16
	Pine Lake Middle School	943.00	8	11
9-12	Issaquah High School	4834.00	16	13
	Skyline High School	2169.00	10	4
K-5	Cascade Ridge Elementary School	487.00	8	8
	Creekside Elementary School	723.00	8	9
	Endeavour Elementary School	598.00	8	12
	Fall City Elementary School	544.00	8	7
	Grand Ridge Elementary School	1494.00	14	14
	Sunny Hills Elementary School	732.00	9	5
PK-5	Discovery Elementary School	686.00	9	6

In [100]:
```
import pandas as pd
from geopy.distance import geodesic

def distance_between_home_school(homes_df: pd.DataFrame, schools_df: pd.DataFrame) -> pd.DataFrame:
    # Create an empty column for the distance to closest school
    homes_df["distance_to_school"] = None
    homes_df["closest_school_id"] = None
    homes_df["closest_school_name"] = None
    # Iterate through each home and find the closest school
    for i, home in homes_df.iterrows():
        min_distance = float("inf")
        closest_school_id = None
        closest_school_name = None
        for j, school in schools_df.iterrows():
            distance = geodesic((home["lat"], home["long"]), (school["school_lat"], school["school_long"])).miles
            if distance < min_distance:
                min_distance = distance
                closest_school_id = school["school_id"]
                closest_school_name = school["School"]
        homes_df.at[i, "distance_to_school"] = min_distance
        homes_df.at[i, "closest_school_id"] = closest_school_id
        homes_df.at[i, "closest_school_name"] = closest_school_name
    return homes_df
```

In [101]:
```
school_lat_long_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16 entries, 3 to 15
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   School                  16 non-null     object
 1   Type                    16 non-null     object
 2   Grades                  16 non-null     object
 3   Total students enrolled  16 non-null     float64
 4   Students per teacher    16 non-null     object
 5   Reviews                 16 non-null     object
 6   District                16 non-null     object
 7   rating_score            16 non-null     int32
 8   rating                  16 non-null     object
 9   school_address          16 non-null     object
 10  school_city             16 non-null     object
 11  school_state            16 non-null     object
 12  school_zip              16 non-null     object
 13  school_id               16 non-null     int64
 14  school_lat              16 non-null     object
 15  school_long             16 non-null     object
dtypes: float64(1), int32(1), int64(1), object(13)
memory usage: 2.7+ KB
```

In [102]:
```
final_df.head(20)
```

Out[102]:

id	price	bedrooms	sqft_living	lat	long	view_EXCELLENT	view_GOOD	view_NONE	zipcode_98004	zipcode_98005	...	zipcode_9819
7129300520	221900.00	3	1180	47.51	-122.26	0	0	1	0	0	...	
6414100192	538000.00	3	2570	47.72	-122.32	0	0	1	0	0	...	
5631500400	180000.00	2	770	47.74	-122.23	0	0	1	0	0	...	
2487200875	604000.00	4	1960	47.52	-122.39	0	0	1	0	0	...	
1954400510	510000.00	3	1680	47.62	-122.05	0	0	1	0	0	...	
1321400060	257500.00	3	1715	47.31	-122.33	0	0	1	0	0	...	
2008000270	291850.00	3	1060	47.41	-122.31	0	0	0	0	0	...	
2414600126	229500.00	3	1780	47.51	-122.34	0	0	1	0	0	...	
3793500160	323000.00	3	1890	47.37	-122.03	0	0	1	0	0	...	
1736800520	662500.00	3	3560	47.60	-122.14	0	0	1	0	0	...	
9212900260	468000.00	2	1160	47.69	-122.29	0	0	1	0	0	...	
114101516	310000.00	3	1430	47.76	-122.23	0	0	1	0	0	...	
6054650070	400000.00	3	1370	47.61	-122.05	0	0	1	0	0	...	
1175000570	530000.00	5	1810	47.67	-122.39	0	0	1	0	0	...	
9297300055	650000.00	4	2950	47.57	-122.38	0	1	0	0	0	...	
1875500060	395000.00	3	1890	47.73	-121.96	0	0	1	0	0	...	
6865200140	485000.00	4	1600	47.66	-122.34	0	0	1	0	0	...	
16000397	189000.00	2	1200	47.31	-122.21	0	0	1	0	0	...	
7983200060	230000.00	3	1250	47.33	-122.31	0	0	1	0	0	...	
6300500875	385000.00	4	1620	47.70	-122.34	0	0	1	0	0	...	

20 rows × 68 columns

In [103]:
```
test_df = distance_between_home_school(final_df, school_lat_long_df)
```

In [104]:
```
test_df.head(100)
```

Out[104]:

id	price	bedrooms	sqft_living	lat	long	view_EXCELLENT	view_GOOD	view_NONE	zipcode_98004	zipcode_98005	...	grade_4 Low	gra
7129300520	221900.00	3	1180	47.51	-122.26	0	0	1	0	0	...	0	
6414100192	538000.00	3	2570	47.72	-122.32	0	0	1	0	0	...	0	
5631500400	180000.00	2	770	47.74	-122.23	0	0	1	0	0	...	0	
2487200875	604000.00	4	1960	47.52	-122.39	0	0	1	0	0	...	0	
1954400510	510000.00	3	1680	47.62	-122.05	0	0	1	0	0	...	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
5200100125	555000.00	3	1980	47.68	-122.37	0	0	1	0	0	...	0	
7214720075	699950.00	3	2190	47.77	-122.08	0	0	1	0	0	...	0	
6197800045	290000.00	3	1210	47.44	-122.18	0	0	1	0	0	...	0	
1328310370	375000.00	3	2340	47.44	-122.13	0	0	1	0	0	...	0	
546000875	460000.00	3	1670	47.69	-122.38	0	0	1	0	0	...	0	

100 rows × 71 columns

In [105]:
```
grouped_distance_to_school = test_df.loc[:, ["price", "closest_school_name", "bedrooms"
                                             ,"distance_to_school"]]
grouped_distance_to_school.head(20)
```

Out[105]:

id	price	closest_school_name	bedrooms	distance_to_school
7129300520	221900.00	Skyline High School	3	10.71
6414100192	538000.00	Issaquah High School	3	12.45
5631500400	180000.00	Issaquah High School	2	10.64
2487200875	604000.00	Fall City Elementary School	4	16.23
1954400510	510000.00	Grand Ridge Elementary School	3	1.30
1321400060	257500.00	Skyline High School	3	20.29
2008000270	291850.00	Skyline High School	3	15.52
2414600126	229500.00	Fall City Elementary School	3	14.00
3793500160	323000.00	Skyline High School	3	10.65
1736800520	662500.00	Fall City Elementary School	3	3.83
9212900260	468000.00	Fall City Elementary School	2	12.54
114101516	310000.00	Issaquah High School	3	9.41
6054650070	400000.00	Grand Ridge Elementary School	3	1.05
1175000570	530000.00	Fall City Elementary School	5	16.29
9297300055	650000.00	Fall City Elementary School	4	14.65
1875500060	395000.00	Grand Ridge Elementary School	3	9.41
6865200140	485000.00	Fall City Elementary School	4	13.92
16000397	189000.00	Skyline High School	2	17.03
7983200060	230000.00	Skyline High School	3	18.39
6300500875	385000.00	Issaquah High School	4	14.00

In [106]:
```
def plot_closest_schools_price(df:pd.DataFrame) -> sns.barplot:
    """
    Plot bar graph of disance to closest school vs price

    Inputs:
    df: pandas dataframe
    Output:
    bar plot
    """
    # Create plot variables
    prices = np.array(df.price)
    closest_schools = np.array(df.distance_to_school)
    median_price = np.median(prices)
    median_distance = np.median(closest_schools)

    # Create plot labels
    x_label = "Sale Price (Millions of Dollars)"
    y_label = "Distance to Closest School (miles)"
    title = "Affect of Distance to Above Average Schools on Sale Price in King County Homes"

    # Create a palette that highlights the top 5 sale price values as a function of the closest distance to an
    # above average school
    clrs = ['grey' if (x < median_price) else 'blue' for x in prices]
    # Set up plot figure size
    plt.figure(figsize = (14,10))

    # Plot bar using input of bedrooms, price, index and palette
    ax = sns.barplot(x = prices, y = closest_schools, palette = clrs, estimator = np.median, orient = 'h')
    # Setup titles and axes labels
    ax.set_title(title, weight='bold').set_fontsize('20')
    ax.set_ylabel(y_label, fontsize='16', weight='bold')
    ax.set_xlabel(x_label, fontsize='16', weight='bold')
```

In [107]:
```
grouped_distance_to_school = pd.DataFrame(grouped_distance_to_school)
grouped_distance_to_school.drop_duplicates(inplace = True)
grouped_distance_to_school.head(20)
```

Out[107]:

id	price	closest_school_name	bedrooms	distance_to_school
7129300520	221900.00	Skyline High School	3	10.71
6414100192	538000.00	Issaquah High School	3	12.45
5631500400	180000.00	Issaquah High School	2	10.64
2487200875	604000.00	Fall City Elementary School	4	16.23
1954400510	510000.00	Grand Ridge Elementary School	3	1.30
1321400060	257500.00	Skyline High School	3	20.29
2008000270	291850.00	Skyline High School	3	15.52
2414600126	229500.00	Fall City Elementary School	3	14.00
3793500160	323000.00	Skyline High School	3	10.65
1736800520	662500.00	Fall City Elementary School	3	3.83
9212900260	468000.00	Fall City Elementary School	2	12.54
114101516	310000.00	Issaquah High School	3	9.41
6054650070	400000.00	Grand Ridge Elementary School	3	1.05
1175000570	530000.00	Fall City Elementary School	5	16.29
9297300055	650000.00	Fall City Elementary School	4	14.65
1875500060	395000.00	Grand Ridge Elementary School	3	9.41
6865200140	485000.00	Fall City Elementary School	4	13.92
16000397	189000.00	Skyline High School	2	17.03
7983200060	230000.00	Skyline High School	3	18.39
6300500875	385000.00	Issaquah High School	4	14.00

In [108]:
```
grouped_distance_to_school.sort_values("price", ascending = False)
```

Out[108]:

id	price	closest_school_name	bedrooms	distance_to_school
644200040	1000000.00	Fall City Elementary School	5	6.03
3343301910	1000000.00	Fall City Elementary School	5	7.00
5426300060	1000000.00	Fall City Elementary School	3	8.29
7605800050	1000000.00	Fall City Elementary School	3	4.92
6669000070	1000000.00	Fall City Elementary School	4	6.50
...	...	...	...	...
1623049041	82500.00	Skyline High School	2	12.86
3883800011	82000.00	Fall City Elementary School	3	14.58
3028200080	81000.00	Skyline High School	2	13.71
8658300340	80000.00	Discovery Elementary School	1	5.04
40000362	78000.00	Skyline High School	2	12.24

20111 rows × 4 columns

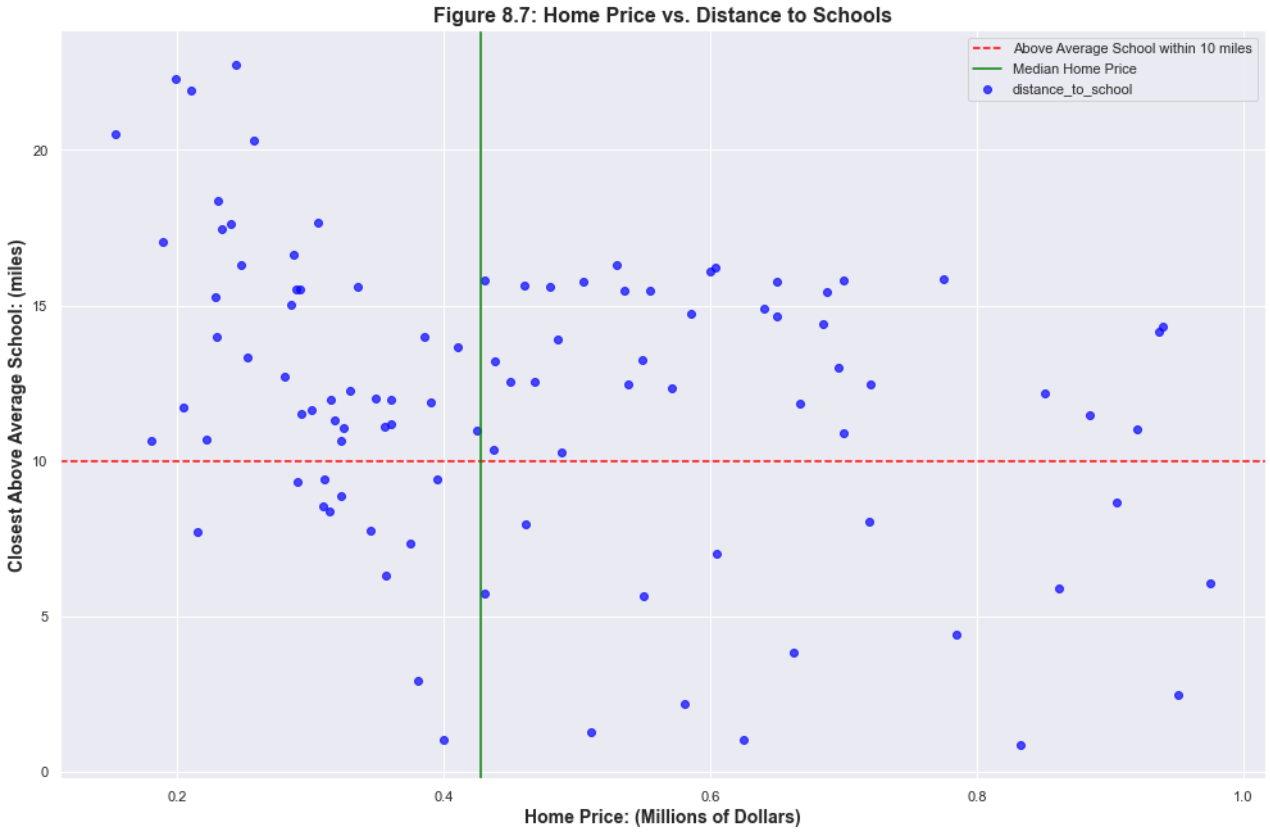
In [109]:
```
grouped_distance_to_school.describe()
```

Out[109]:

	price	bedrooms
count	20111.00	20111.00
mean	467889.18	3.32
std	196533.08	0.88
min	78000.00	1.00
25%	314500.00	3.00
50%	434500.00	3.00
75%	594000.00	4.00
max	1000000.00	8.00

In [110]:
```
# Create a scatter plot
# Set up theme
sns.set_theme(style="darkgrid", palette="Set2")
data = grouped_distance_to_school.head(100)
prices = np.array(data.price)/1000000
y_values = np.array(data.distance_to_school)
median_price = np.median(prices)


# Set up plot
fig, ax = plt.subplots(figsize = (15, 10))
ax.scatter(x = prices, y = "distance_to_school", data = data, alpha=0.7, color="blue")
ax.set_title("Figure 8.7: Home Price vs. Distance to Schools", weight = 'bold').set_fontsize('16')
ax.set_xlabel("Home Price: (Millions of Dollars)", fontsize = 14, weight = 'bold')
ax.set_ylabel("Closest Above Average School: (miles)", fontsize = 14, weight = 'bold');
ax.ticklabel_format(style = "plain")

# Add horizontal line
ax.axhline(y = 10, color = 'red', linestyle = '--', label = 'Above Average School within 10 miles')
ax.axvline(x = median_price, color = 'green', linestyle = '-', label = "Median Home Price")
ax.legend()
```

Out[110]: <matplotlib.legend.Legend at 0x13199204550>



Analyzing this scatterplot, I notice that there are **zero Above Average schools for homes with Sale Prices of 200K dollars**, there are is a small cluster of homes that have sale prices between **210 K dollars and 1 Million dollars that are within 10 miles of an above average school**. Finally the majority of homes that are within 5 miles of an Above Average school are between *the median price (467,889.18 dollars) and 800K dollars*.

9 Insights

It seems as though truncating the data to limit the maximum home price to 1 million dollars, removing features that were highly correlated like:

- sqft_above
- sqft_living15
- bathrooms
- sqft_lot
- sqft_lot15

Allowed for fitting an initial linear regression model to my data that yielded an R-squared value that explained 36.5% of the variance in the sale price of homes in the King County dataset.

Addressing duplicates, using dummies to encode categorical data and removed high p-value features allowed a revised model that included multiple variables that produced a model with an R-squared value that explaine 81.0% of the variance in the sale price of homes in the King County dataset.

It seems that it is better to purchase homes 2, 4,and 5 bedrooms as they have sale prices that are greater than the median. It also seems better to purchase a home at or above the median sale price if you have school aged children as there is a larger cluster of homes at or above the median sale price that are between 5 and 10 miles of an Above Average school.

10 Recommendations

I have the following recommendations:

Curate a set of listings using the interactive map that are a **between 2 and 5 bedroom homes**.

Use the interactive map to narrow down homes that have a **minimum sale price of 470K dollars**.

Show families **homes that and are within 10 miles of an Above Average school**. This will allow Landing Pad to reach a broader set of home owners who are within our target market.