In [1]:

```
pip install pillow
```

```
Requirement already satisfied: pillow in c:\users\rani_\anaconda6\lib\site
-packages (9.4.0)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:

```
from IPython.display import Image
```

In [3]:

```
Image ("Images/Home builder.jpg" , width=1000, height=500)
```

Out[3]:

KING COUNTY HOUSE SALES ANALYSIS REPORT

Author: Sneha Bhaskar

Date: 24 September 2023

Overview

This project analyzes the King County House Sales Dataset to answer the business case question of what type of housing features to focus when building a house and selling in King County Washington, United States. Utilizing the OSEMN framework for data science, the most valuable feature for a Pro Home Builder Company would be living area square footage and zip code. Zip codes provide contextual information about

property values, local demand, and building regulations, allowing builders to choose locations and tailor their designs to specific demographics strategically. On the other hand, square footage directly influences construction costs, selling price, design considerations, building grade improvements, and the house price rises as well.

Business Problem

The Pro Home Builder Company aims to construct residences in King County Washington, and wants to identify which housing features/areas to focus on for maximum profitability. By understanding which amenities significantly influence home prices, the company can make data-driven choices on the types of houses to build in order to optimize profits

Import standard packages

In [4]:

```
import pandas as pd #data manipulation and analysis. Can create data frames, filter data,
import numpy as np #numerical python library for array manipulation, math functions etc.
import seaborn as sns #data visualization library based on Matplotlib, with higher-level

import matplotlib.pyplot as plt #2D plotting lib.
plt.style.use("ggplot") #changes the default style of Matplotlib plots to ggplot.

from statsmodels.formula.api import ols #ordinary least square (OLS) is a regression mode
import statsmodels.api as sm #statsmodel includes various statistical tests, models and f
from statsmodels.stats.outliers_influence import variance_inflation_factor #a measure to
import scipy.stats as stats #statistical functions from the SciPy lib, which builds on Nu
from sklearn.linear_model import LinearRegression  #linear model
from sklearn.model_selection import train_test_split #function for splitting datasets int
from sklearn.metrics import mean_squared_error #function for computing the mean squarred
from sklearn.preprocessing import OneHotEncoder #preprocessing technique to convert categ
from sklearn.model_selection import cross_val_score #function for evaluating a model usin
from sklearn.model_selection import KFold #K-Fold cross validator
from itertools import combinations #itertools is used for generating all possible combina
```

Kings County House Dataset

In [5]:

```
df = pd.read_csv ('Data/kc_house_data.csv')
df
```

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	w
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0	
1	6414100192	12/09/2014	538000	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0	
3	2487200875	12/09/2014	604000	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0	
...	...	...	...	...	...	...	...	...	
21592	263000018	5/21/2014	360000	3	2.50	1530	1131	3.0	
21593	6600060120	2/23/2015	400000	4	2.50	2310	5813	2.0	
21594	1523300141	6/23/2014	402101	2	0.75	1020	1350	2.0	
21595	291310100	1/16/2015	400000	3	2.50	1600	2388	2.0	
21596	1523300157	10/15/2014	325000	2	0.75	1020	1076	2.0	

21597 rows × 21 columns

In [6]:

```
#check for duplicates
df.duplicated(keep = False).sum()
```

Out[6]:

```
0
```

In [7]:

```
#date range for this dataset
df['date'] = pd.to_datetime(df['date'], format='%m/%d/%Y')
is_sorted = df['date'].is_monotonic_increasing
date_range = pd.date_range(start=df['date'].min(), end=df['date'].max())
print(date_range)
```

```
DatetimeIndex(['2014-05-02', '2014-05-03', '2014-05-04', '2014-05-05',
               '2014-05-06', '2014-05-07', '2014-05-08', '2014-05-09',
               '2014-05-10', '2014-05-11',
               ...
               '2015-05-18', '2015-05-19', '2015-05-20', '2015-05-21',
               '2015-05-22', '2015-05-23', '2015-05-24', '2015-05-25',
               '2015-05-26', '2015-05-27'],
              dtype='datetime64[ns]', length=391, freq='D')
```

OBTAIN

This step involves understanding stakeholder requirements, gathering information on the problem, and finally sourcing data we think will be necessary for solving this problem

In [8]:

```
#Removing columns that is not required from this dataframe for our business problem
df.drop(['id'], axis= 1, inplace = True)
df.head()
```

Out[8]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
0	2014-10-13	221900	3	1.00	1180	5650	1.0	NaN	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	

In [9]:

```
print("The number of rows is",df.shape[0])
print('The number of columns is',df.shape[1])
```

```
The number of rows is 21597
The number of columns is 20
```

SCRUB

This step focuses on cleaning the data, which involves handling missing values, removing outliers, and converting data types and many more. Data cleaning is crucial because the quality of data affects the quality of the final model produced

In [10]:

```
df.info()
#all of the columns are in integer/float format except "date" and "sqft_basement" are in
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  int64
 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  float64
 8   view           21534 non-null  float64
 9   condition      21597 non-null  int64
 10  grade          21597 non-null  int64
 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: datetime64[ns](1), float64(7), int64(11), object(1)
memory usage: 3.3+ MB
```

In [11]:

```
df.describe()
#Bedrooms has an outliers of 33 rooms
#waterfront, condition, grade looks like a categorical data
```

Out[11]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000

In [12]:

```
#check for null values
df.isna().sum()
#waterfront and yr_renovated are the only columns with null values
```

Out[12]:

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

FIll null values for waterfront

In [13]:

```
print(df.waterfront.isnull().sum())
print(df['waterfront'].value_counts())
```

```
2376
0.0    19075
1.0      146
Name: waterfront, dtype: int64
```

In [14]:

```
print('Mean = ',df['waterfront'].mean())
print('Median = ',df['waterfront'].median())
```

```
Mean =  0.007595858696217679
Median =  0.0
```

In [15]:

```
# Replace all the missing values in the waterfront column with the Median
df['waterfront'].fillna(df['waterfront'].median(), inplace=True)
df['waterfront'].isnull().sum()
```

Out[15]:

```
0
```

In [16]:

```
df
```

Out[16]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	
21592	2014-05-21	360000	3	2.50	1530	1131	3.0	0.0	0.0	
21593	2015-02-23	400000	4	2.50	2310	5813	2.0	0.0	0.0	
21594	2014-06-23	402101	2	0.75	1020	1350	2.0	0.0	0.0	
21595	2015-01-16	400000	3	2.50	1600	2388	2.0	0.0	0.0	
21596	2014-10-15	325000	2	0.75	1020	1076	2.0	0.0	0.0	

21597 rows × 20 columns

Create a new column to replace the yr_renovated where 1 = Renovated and 0 = Not renovated

In [17]:

```
df.yr_renovated.mean()
```

Out[17]:

```
83.6367783722895
```

In [18]:

```
df.yr_renovated.median()
```

Out[18]:

```
0.0
```

In [19]:

```
df.yr_renovated.fillna(df.yr_renovated.median(),inplace=True)
df.yr_renovated.isnull().sum()
```

Out[19]:

```
0
```

In [20]:

```
df['renovated'] = np.where(df['yr_renovated'] == 0, 0, 1)
```

In [21]:

```
#drop the "yr_rnovated" colum
df.drop('yr_renovated',axis=1, inplace = True)
```

In [22]:

```
df
```

Out[22]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	
21592	2014-05-21	360000	3	2.50	1530	1131	3.0	0.0	0.0	
21593	2015-02-23	400000	4	2.50	2310	5813	2.0	0.0	0.0	
21594	2014-06-23	402101	2	0.75	1020	1350	2.0	0.0	0.0	
21595	2015-01-16	400000	3	2.50	1600	2388	2.0	0.0	0.0	
21596	2014-10-15	325000	2	0.75	1020	1076	2.0	0.0	0.0	

21597 rows × 20 columns

In [23]:

```
df.renovated.value_counts()
```

Out[23]:

```
0    20853
1      744
Name: renovated, dtype: int64
```

Clean "Sqft_Basement" column by replacing '?' with 0 and converting the data type from object ot float

In [24]:

```
df.sqft_basement.value_counts()
```

Out[24]:

```
0       12826
?         454
600       217
500       209
700       208
         ...
1920        1
3480        1
2730        1
2720        1
248         1
Name: sqft_basement, Length: 304, dtype: int64
```

In [25]:

```
#replace the '?' in the besement column with 0
df['sqft_basement'] = df['sqft_basement'].replace(to_replace='?', value='0.0')
```

In [26]:

```
df.sqft_basement.value_counts()
```

Out[26]:

```
0       12826
0.0       454
600       217
500       209
700       208
         ...
1920        1
3480        1
2730        1
2720        1
248         1
Name: sqft_basement, Length: 304, dtype: int64
```

In [27]:

```
#convert the data type of 'sqft_basement' from object to float
df['sqft_basement'] = df['sqft_basement'].astype(float)
```

In [28]:

```
#confirm we don't have any null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype         
---  ------         --------------  -----         
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  int64         
 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     21597 non-null  float64       
 8   view           21534 non-null  float64       
 9   condition      21597 non-null  int64         
 10  grade          21597 non-null  int64         
 11  sqft_above     21597 non-null  int64         
 12  sqft_basement  21597 non-null  float64       
 13  yr_built       21597 non-null  int64         
 14  zipcode        21597 non-null  int64         
 15  lat            21597 non-null  float64       
 16  long           21597 non-null  float64       
 17  sqft_living15  21597 non-null  int64         
 18  sqft_lot15     21597 non-null  int64         
 19  renovated      21597 non-null  int32         
dtypes: datetime64[ns](1), float64(7), int32(1), int64(11)
memory usage: 3.2 MB
```

In [29]:

```
#check the data statistics
df.describe()
```

Out[29]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000

PRICE

In [30]:

```
# Check price distribution
df['price'].div(1000000).hist(color = "yellow")
plt.title('Price Distribution');
plt.xlabel('Price - in Millions :) ');
plt.ylabel('Number of Houses');

#the majority of houses are below the price of 2 million
```

In [31]:

```
#reduce the data to only houses equal to or below 1.5 million
df_og = df.copy()
# remove houses above 1.5 million, boolean mask
df = df[df['price'] <= 1500000]
```

In [32]:

```
# RECHECK price distribution
df['price'].div(1000000).hist(color = "yellow")
plt.title('Price Distribution');
plt.xlabel('Price - in Millions :) ');
plt.ylabel('Number of Houses');
```

Majority of the houses are in between 0.3 - 0.5 price range

BEDROOMS

In [33]:

```
# Plot bedrooms as categorical - ordinal
df['bedrooms'].value_counts().sort_index().plot(kind = 'bar', color = "lightcyan")
plt.xticks(rotation = 0);
plt.title('Bedroom Distribution');
plt.xlabel('Number of Bedrooms');
plt.ylabel('Number of Houses');
```

In [34]:

```
#reduce the data to only bedrooms equal to or below 6
df_og = df.copy()
# remove bedrooms  above 6, boolean mask
df = df[df['bedrooms'] <=6]
```

In [35]:

```
# Plot bedrooms as categorical - ordinal
df['bedrooms'].value_counts().sort_index().plot(kind = 'bar', color = "lightcyan")
plt.xticks(rotation = 0);
plt.title('Bedroom Distribution');
plt.xlabel('Number of Bedrooms');
plt.ylabel('Number of Houses');

#by removings the 33 outliers for bedrooms , its summarises that houses with 3 or 4 bedro
```

Houses with 3 or 4 bedrooms are the most common in the dataset

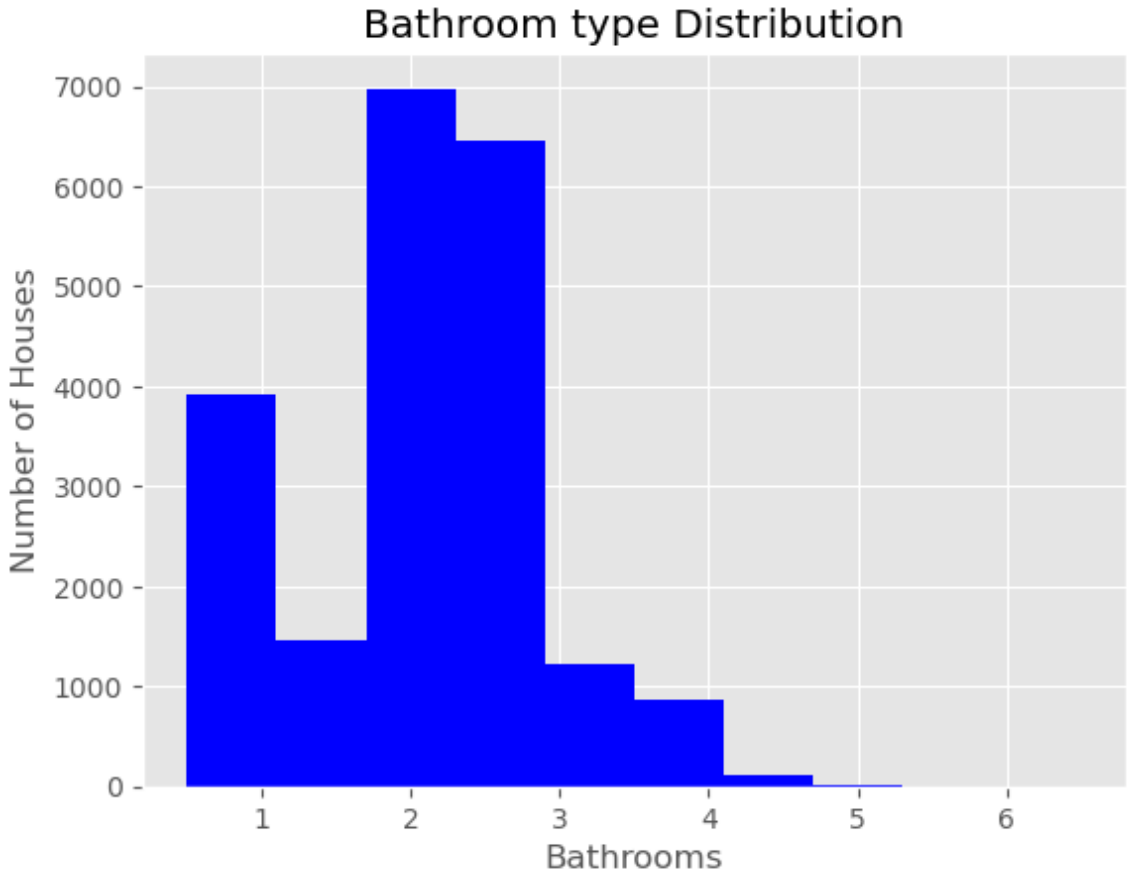
In [36]:

```
sns.boxplot(x = df['bedrooms'], color = "lightcyan");

#Boxplot shows are normal distribution
```

BATHROOMS

In [37]:

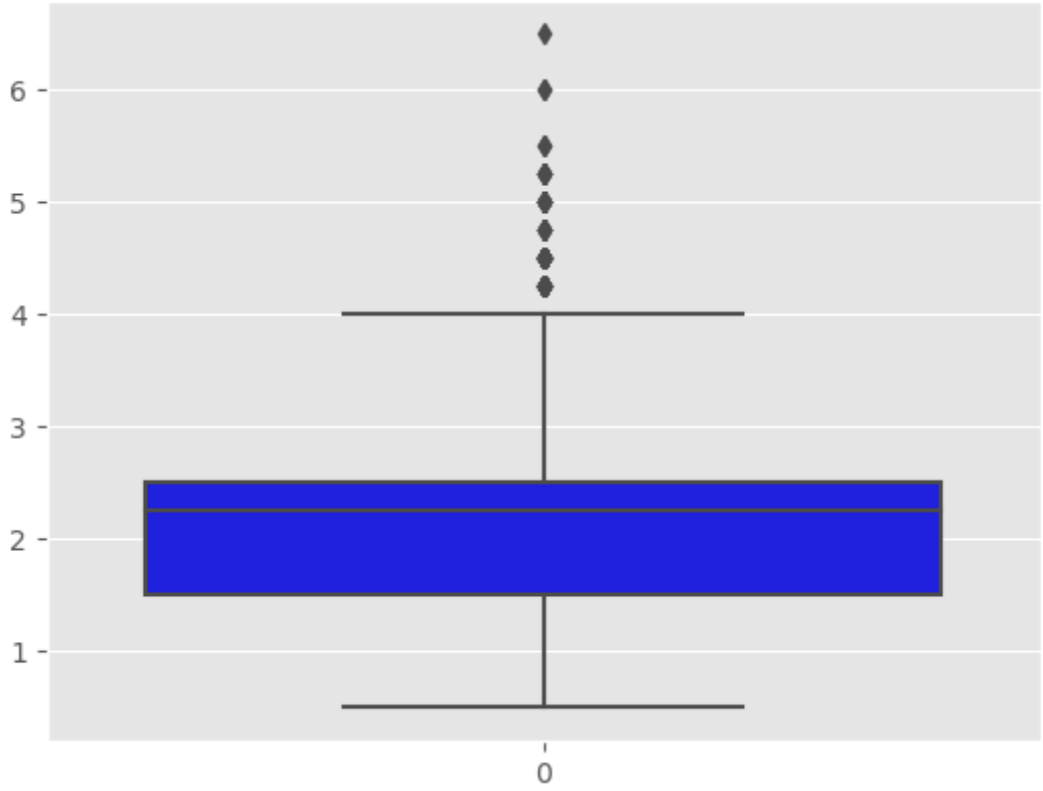
```
# Check bathroom types distribution
df['bathrooms'].hist(color = "BLUE")
plt.title('Bathroom type Distribution');
plt.xlabel('Bathrooms');
plt.ylabel('Number of Houses');
```



There appears to be an outlier and most of the houses have 2 or 3 bathrooms

In [38]:

```
# Boxplot to detect outliers
sns.boxplot(df['bathrooms'], color = "BLUE");

#there are handfull of outliers above 4
```

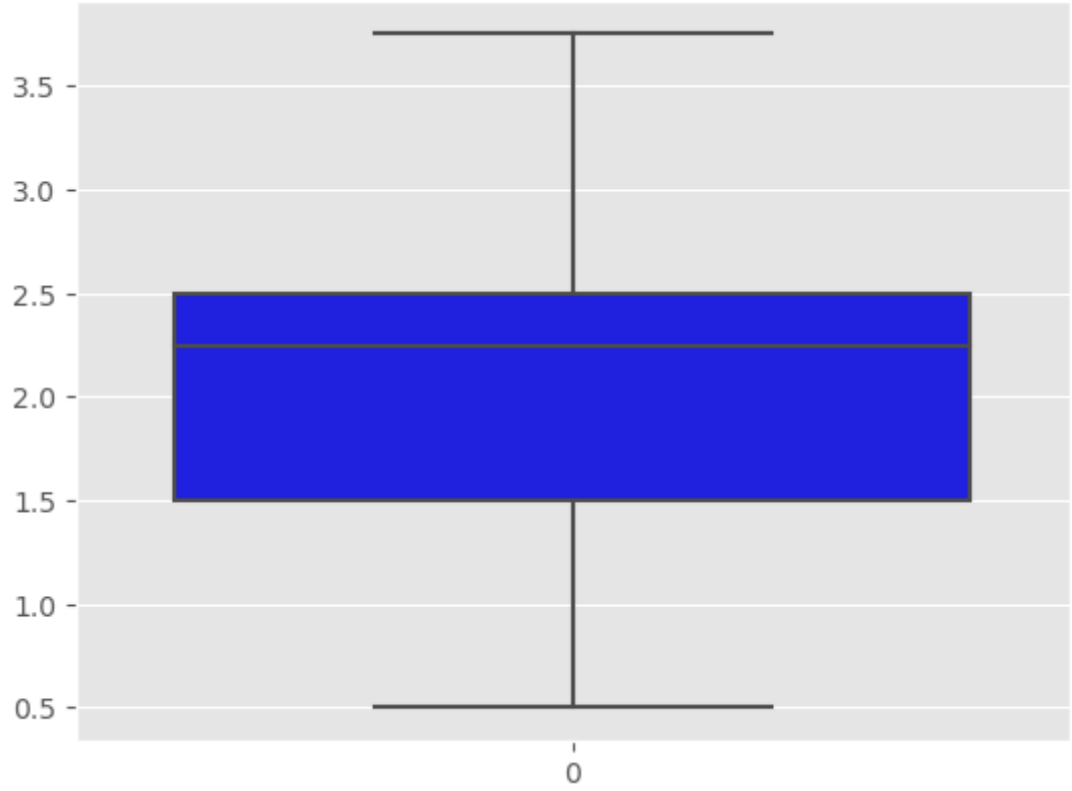


In [39]:

```
# Drop houses that have more than 4 bathrooms
df = df[df['bathrooms'] < 4]
```

In [40]:

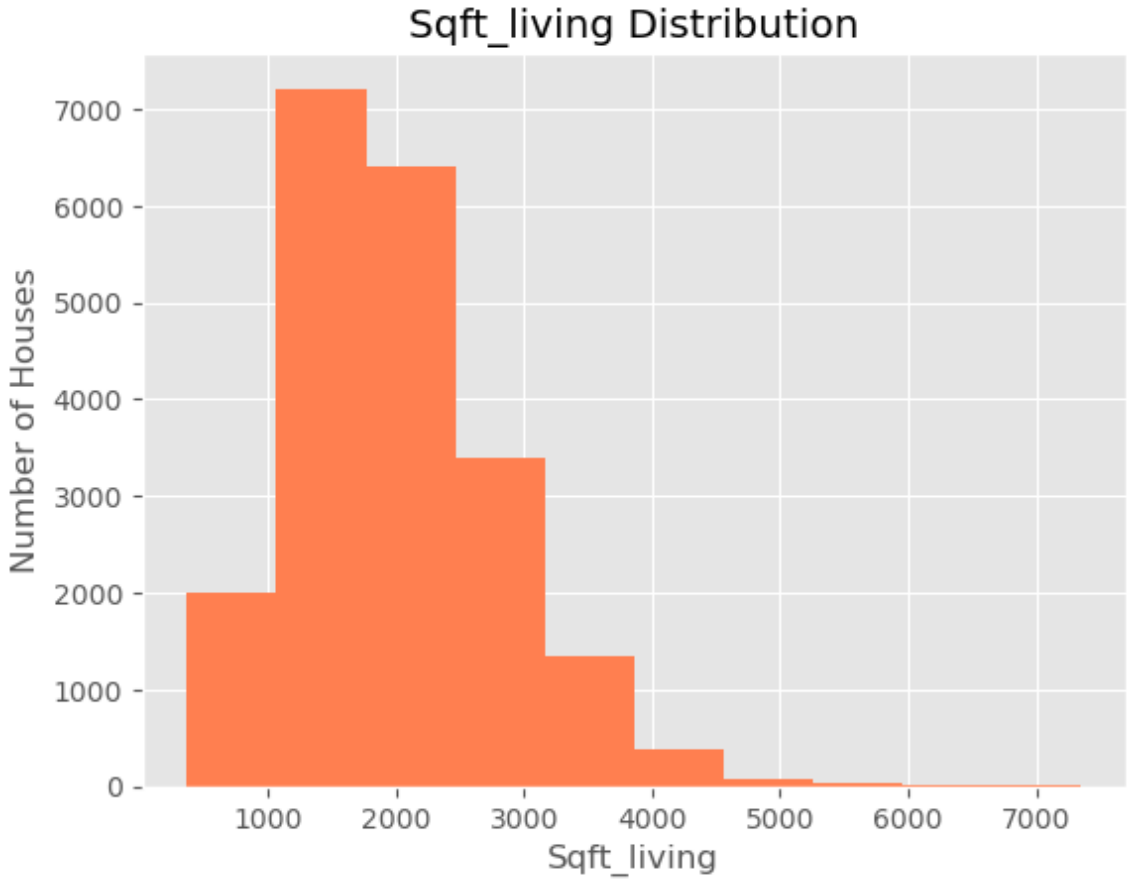
```
# Boxplot to detect outliers
sns.boxplot(df['bathrooms'], color = "BLUE");

#Boxplot shows are normal distribution
```



SQFT_LIVING

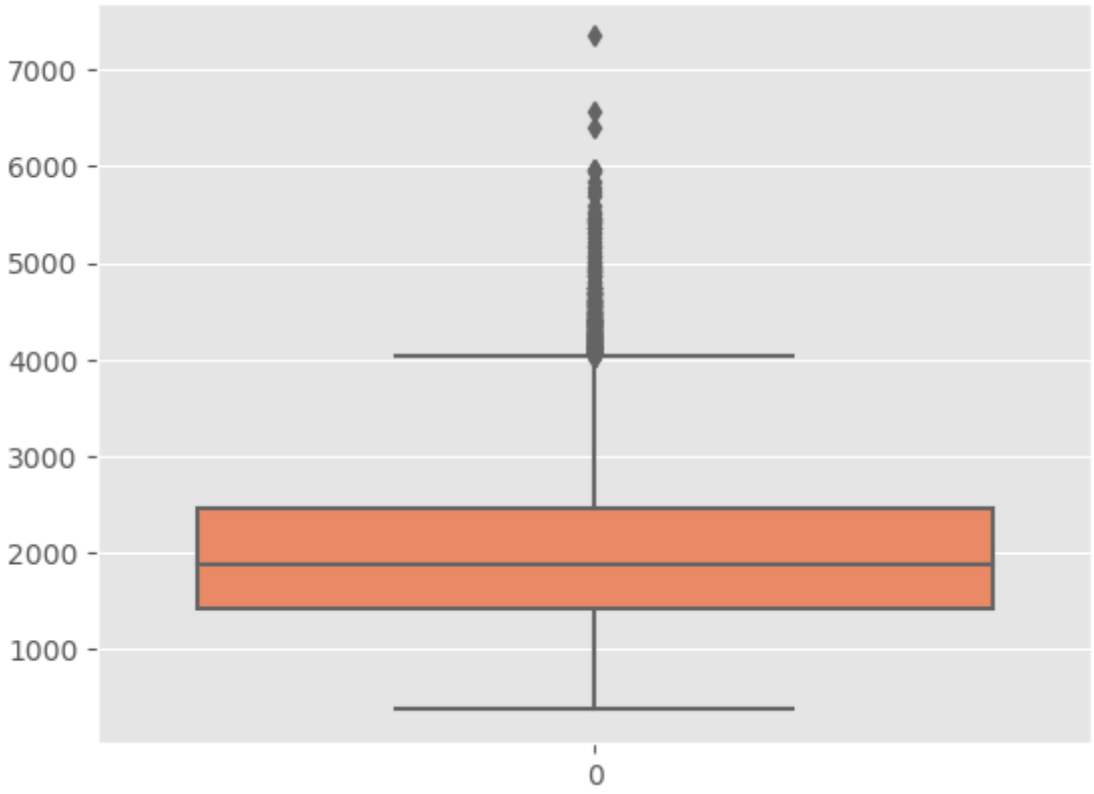
In [41]:

```
# Check sqft_living distribution
df['sqft_living'].hist(color = "coral")
plt.title('Sqft_living Distribution');
plt.xlabel('Sqft_living');
plt.ylabel('Number of Houses');
```



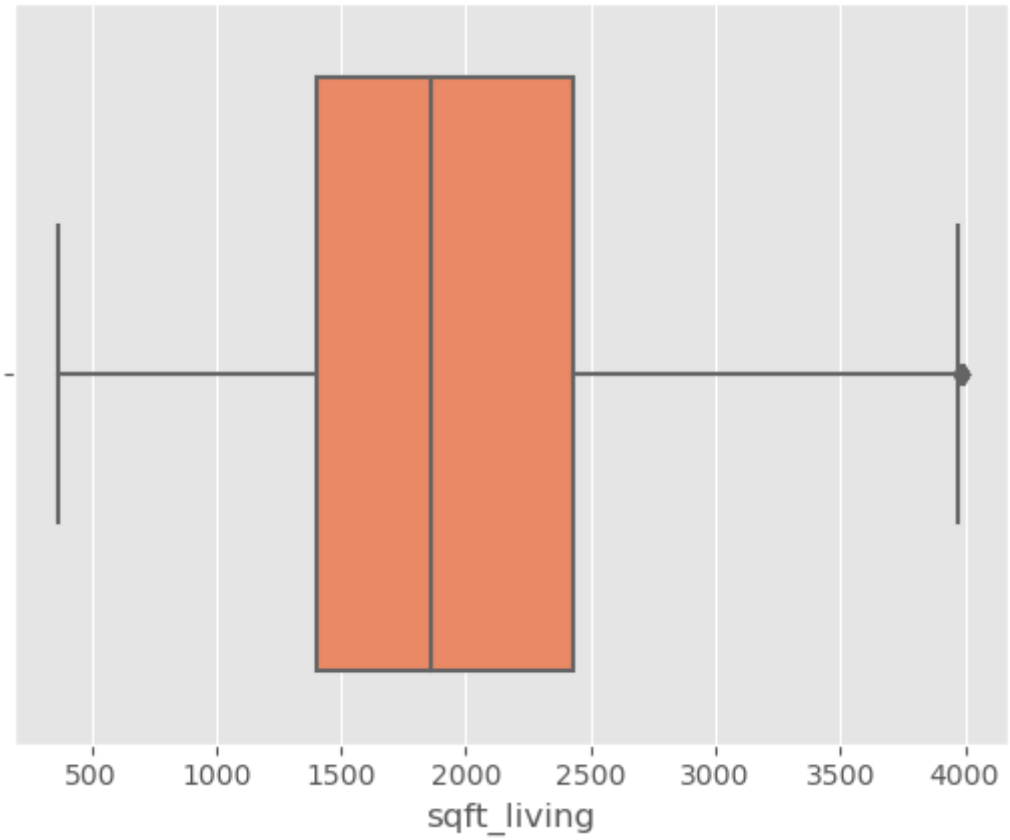
In [42]:

```
# Box plot for outliers
#There are outliers above 4000 sqft_living.
sns.boxplot(df['sqft_living'], color = "coral");
```



In [43]:

```
# Drop outliers in sqft_living
df = df[df['sqft_living'] < 4000]
sns.boxplot(x = df['sqft_living'], color = "coral");
```

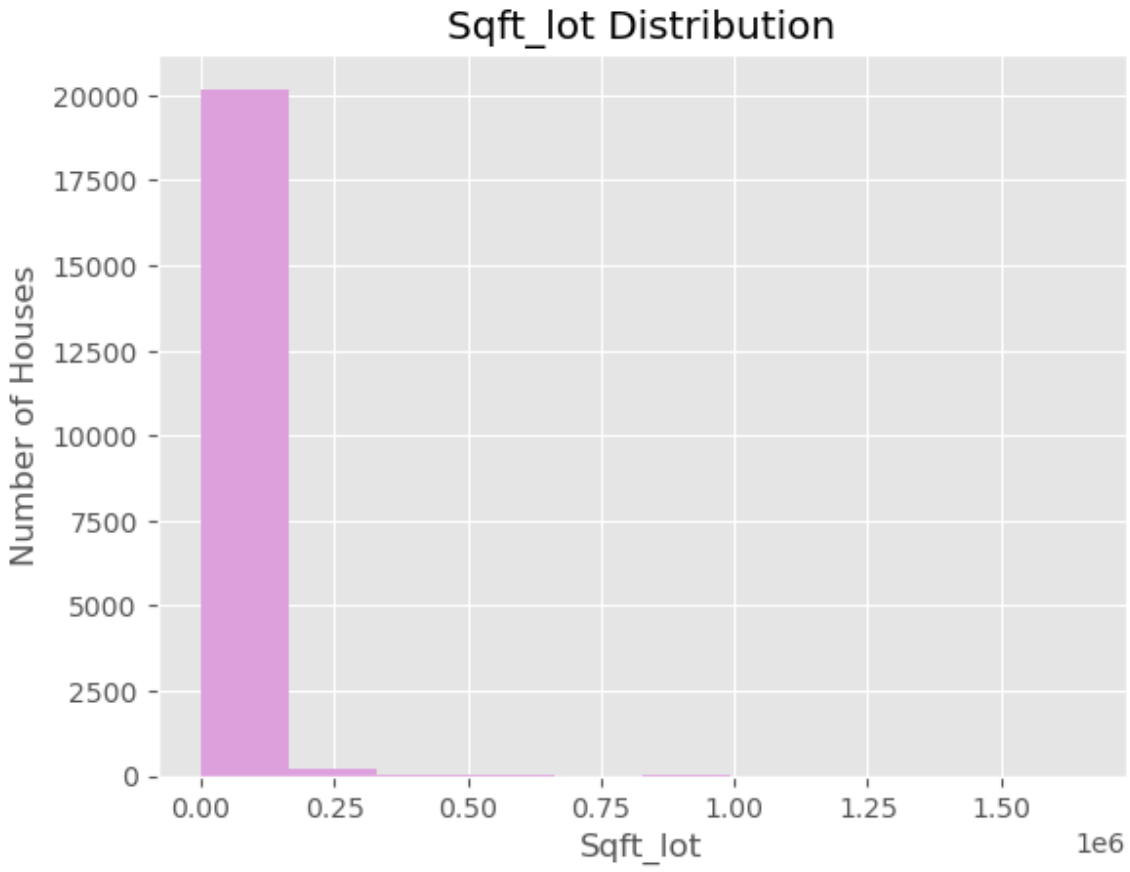


1500 - 2500 sqft_living is most commonly observed footage of the house in this dataset

SQFT_LOT

In [44]:

```
# Check sqft_lot distribution
df['sqft_lot'].hist(color = "plum")
plt.title('Sqft_lot Distribution');
plt.xlabel('Sqft_lot');
plt.ylabel('Number of Houses');
```



In [45]:

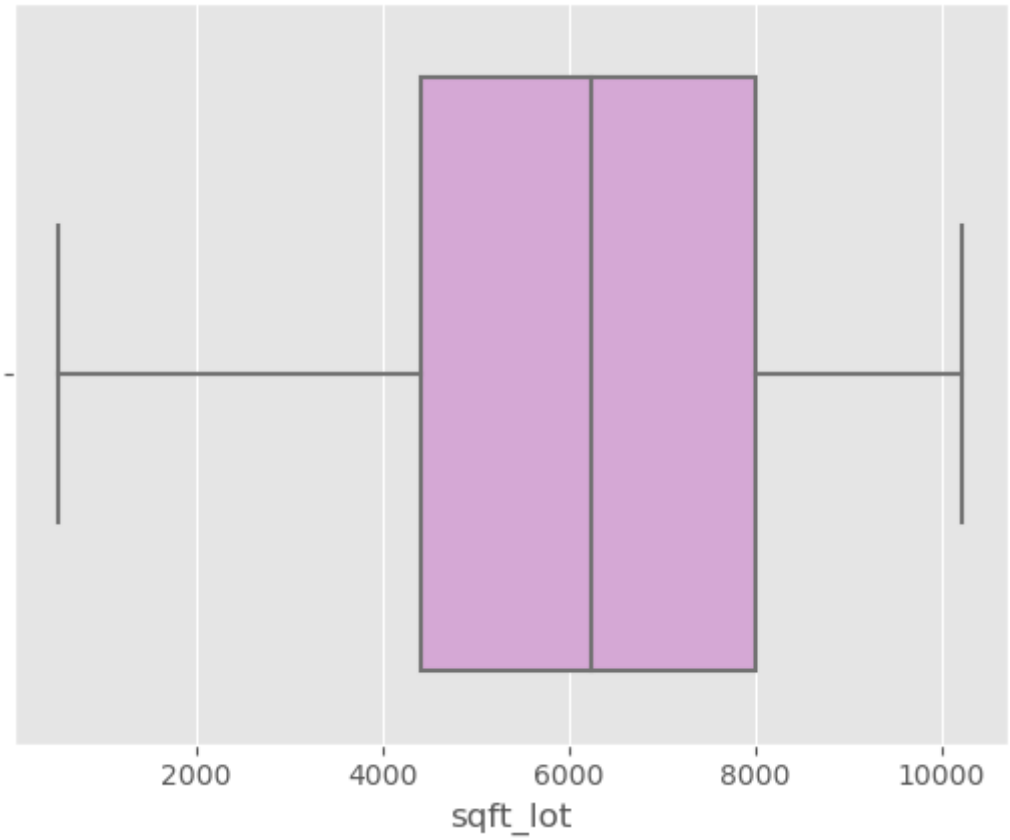
```
df.describe()
```

Out[45]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	2.044600e+04	20446.000000	20446.000000	20446.000000	2.044600e+04	20446.000000
mean	4.872377e+05	3.310036	2.033735	1954.156705	1.399462e+04	1.472684
std	2.327866e+05	0.850293	0.676472	724.038899	3.766160e+04	0.536808
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000
25%	3.150000e+05	3.000000	1.500000	1400.000000	5.000000e+03	1.000000
50%	4.380000e+05	3.000000	2.000000	1860.000000	7.500000e+03	1.000000
75%	6.050000e+05	4.000000	2.500000	2430.000000	1.023275e+04	2.000000
max	1.500000e+06	6.000000	3.750000	3990.000000	1.651359e+06	3.500000

In [46]:

```
# Drop houses that are above the 75 percentile
df = df[df['sqft_lot'] < 1.023275e+04]
sns.boxplot(x = df['sqft_lot'], color = "plum");
```

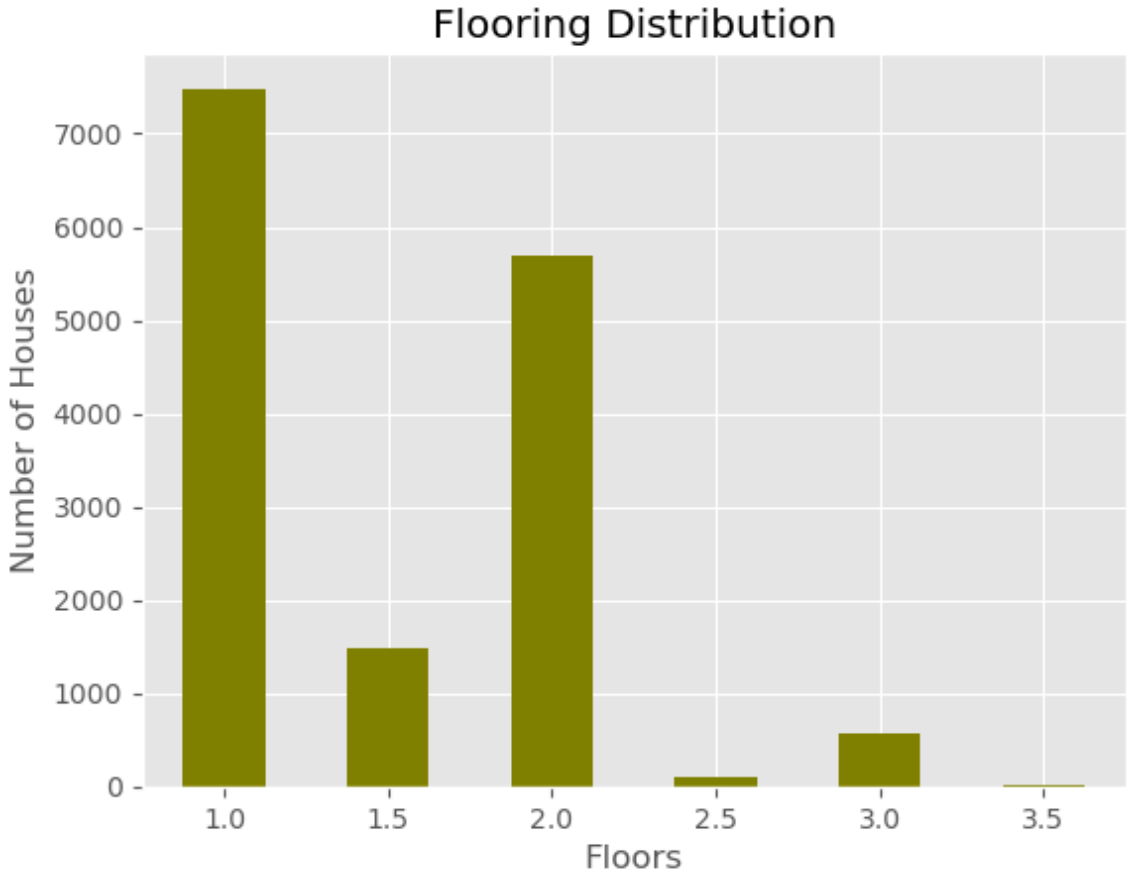


The majority of houses have between 4000 and 8000 sqft_lot.

FLOORS

In [47]:

```
# Plot a bar chart to check distribution of flooring
df['floors'].value_counts().sort_index().plot(kind = 'bar', color = "OLIVE")
plt.xticks(rotation = 0)
plt.title('Flooring Distribution');
plt.xlabel('Floors');
plt.ylabel('Number of Houses');
```

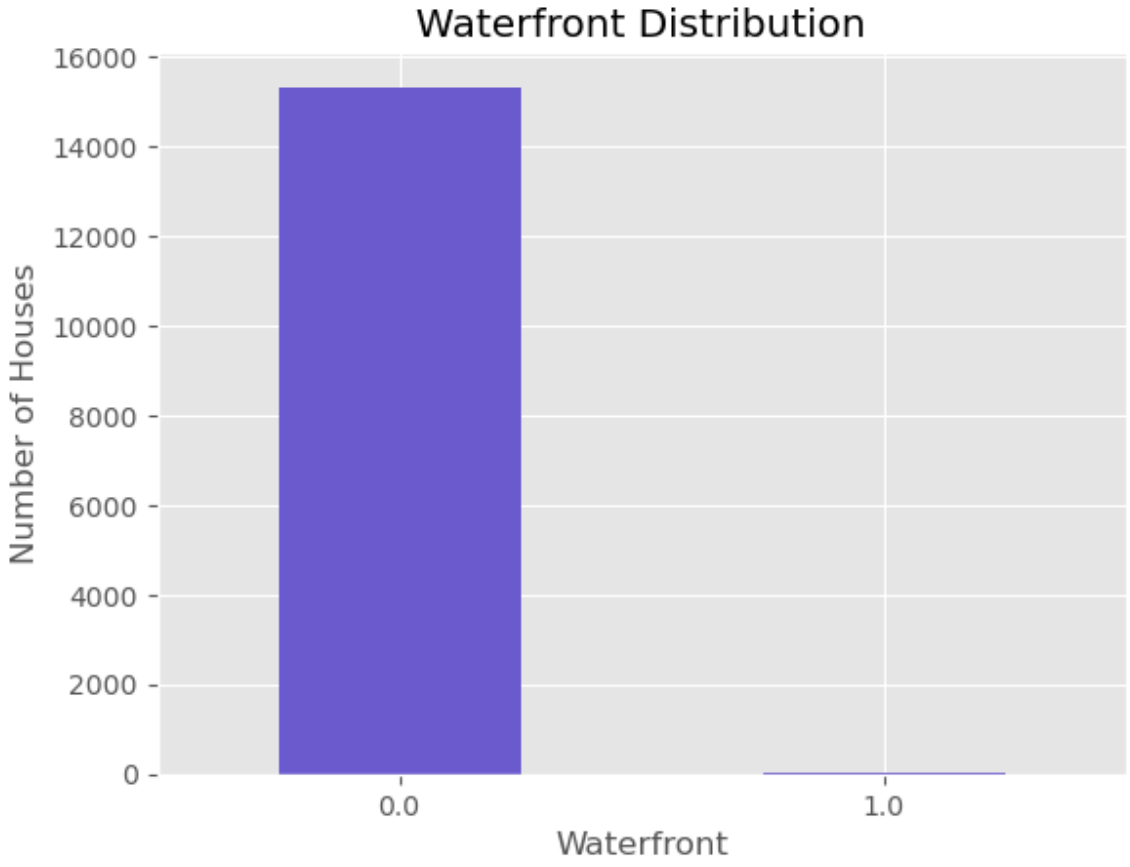


Most houses have either 1 or 2 floors.

WATERFRONT

In [48]:

```
# Plot a bar chart for waterfront
df['waterfront'].value_counts().sort_index().plot(kind = 'bar', color = "slateblue")
plt.xticks(rotation = 0)
plt.title('Waterfront Distribution');
plt.xlabel('Waterfront');
plt.ylabel('Number of Houses');
```



Waterfront is categorical as it has two categories. Also, the majority of the homes are not waterfront. 99% of houses do not have waterfront.

In [49]:

```
#checking data types
df.dtypes
```

Out[49]:

```
date             datetime64[ns]
price                     int64
bedrooms                  int64
bathrooms               float64
sqft_living               int64
sqft_lot                  int64
floors                  float64
waterfront              float64
view                    float64
condition                 int64
grade                     int64
sqft_above                int64
sqft_basement           float64
yr_built                  int64
zipcode                   int64
lat                     float64
long                    float64
sqft_living15             int64
sqft_lot15                int64
renovated                 int32
dtype: object
```

EXPLORE

After cleaning the data, I then explore it to understand its structure, trends, and patterns. This typically involves generating descriptive statistics, and visualizing the data using various kinds of plots. The goal is to gain insights that will help you when modeling.

Identify categorical variables

In [50]:

```
df
```

Out[50]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	
21592	2014-05-21	360000	3	2.50	1530	1131	3.0	0.0	0.0	
21593	2015-02-23	400000	4	2.50	2310	5813	2.0	0.0	0.0	
21594	2014-06-23	402101	2	0.75	1020	1350	2.0	0.0	0.0	
21595	2015-01-16	400000	3	2.50	1600	2388	2.0	0.0	0.0	
21596	2014-10-15	325000	2	0.75	1020	1076	2.0	0.0	0.0	

15334 rows × 20 columns

In [51]:

```
#fill out NaN values for Zipcode
df.zipcode.mean()
df.zipcode.median()
df.zipcode.fillna(df.zipcode.median(),inplace=True)
df.zipcode.isnull().sum()
```

Out[51]:

```
0
```

In [52]:

```
df.tail()
```

Out[52]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
21592	2014-05-21	360000	3	2.50	1530	1131	3.0	0.0	0.0	
21593	2015-02-23	400000	4	2.50	2310	5813	2.0	0.0	0.0	
21594	2014-06-23	402101	2	0.75	1020	1350	2.0	0.0	0.0	
21595	2015-01-16	400000	3	2.50	1600	2388	2.0	0.0	0.0	
21596	2014-10-15	325000	2	0.75	1020	1076	2.0	0.0	0.0	

In [53]:

```
df.reset_index(drop = True)
```

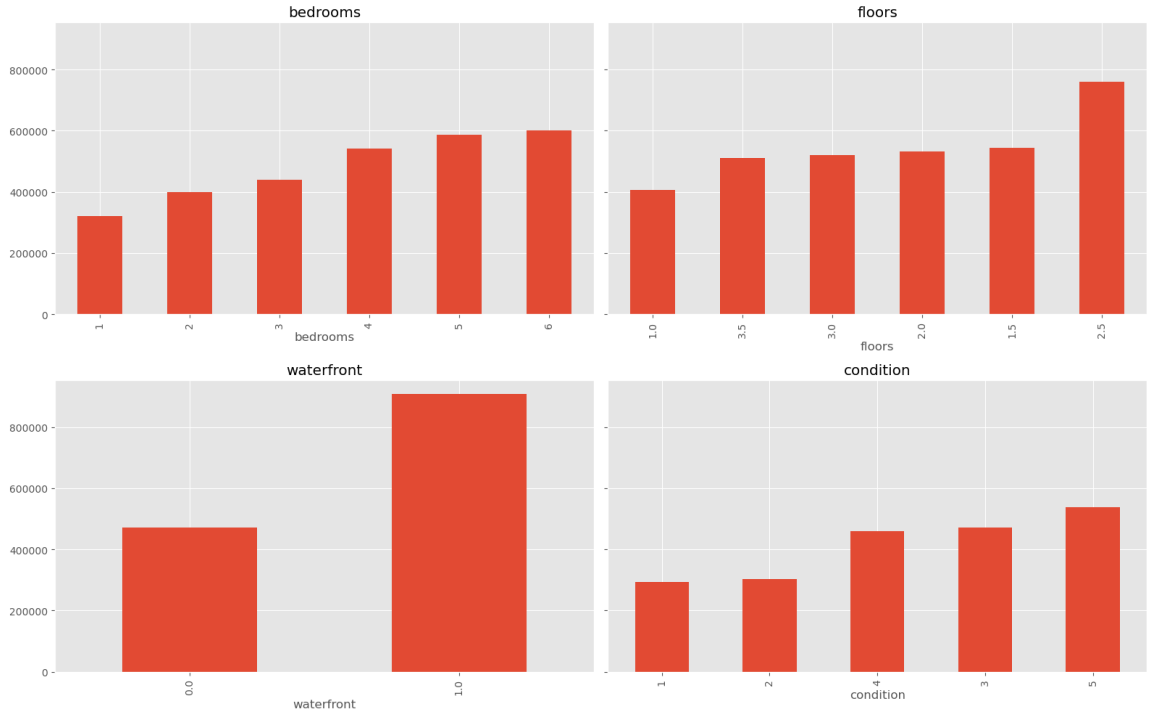
Out[53]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	
15329	2014-05-21	360000	3	2.50	1530	1131	3.0	0.0	0.0	
15330	2015-02-23	400000	4	2.50	2310	5813	2.0	0.0	0.0	
15331	2014-06-23	402101	2	0.75	1020	1350	2.0	0.0	0.0	
15332	2015-01-16	400000	3	2.50	1600	2388	2.0	0.0	0.0	
15333	2014-10-15	325000	2	0.75	1020	1076	2.0	0.0	0.0	

15334 rows × 20 columns

In [54]:

```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(16,10), sharey=True)

cat = ['bedrooms', 'floors', 'waterfront', 'condition']

for col, ax in zip(cat, axes.flatten()):
    (df.groupby(col)                # group values together by column of interest
         .mean(numeric_only=True)['price']        # take the mean of the saleprice for ea
         .sort_values()             # sort the groups in ascending order
         .plot
         .bar(ax=ax))               # create a bar graph on the ax

    ax.set_title(col)               # Make the title the name of the column

fig.tight_layout()
```



In [55]:

```
from sklearn.preprocessing import OneHotEncoder
import pandas as pd

# creating instance of one-hot-encoder
encoder = OneHotEncoder(drop='first')

# Assume df[cat] contains the categorical columns of your original dataframe
# perform one-hot encoding on cat list
encoder_df = pd.DataFrame(encoder.fit_transform(df[cat]).toarray())

# update column names
cols = []
for x in encoder.get_feature_names_out():
    if 'x0' in x:
        cols.append(x.replace('x0', 'bedrooms'))
    elif 'x1' in x:
        cols.append(x.replace('x1', 'floors'))
    elif 'x2' in x:
        cols.append(x.replace('x2', 'waterfront'))
    elif 'x3' in x:
        cols.append(x.replace('x3', 'condition'))
    else:
        cols.append(x)

# set encoder_df columns equal cols
encoder_df.columns = cols

# merge one-hot encoded columns back with original DataFrame
df_ohe = df.join(encoder_df)

# view final df
print(df_ohe.head())
```

```
        date   price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
\
0 2014-10-13  221900         3       1.00         1180      5650     1.0
1 2014-12-09  538000         3       2.25         2570      7242     2.0
2 2015-02-25  180000         2       1.00          770     10000     1.0
3 2014-12-09  604000         4       3.00         1960      5000     1.0
4 2015-02-18  510000         3       2.00         1680      8080     1.0

   waterfront  view  condition  ...  floors_1.5  floors_2.0  floors_2.5  \
0         0.0   0.0          3  ...         0.0         0.0         0.0
1         0.0   0.0          3  ...         0.0         1.0         0.0
2         0.0   0.0          3  ...         0.0         0.0         0.0
3         0.0   0.0          5  ...         0.0         0.0         0.0
4         0.0   0.0          3  ...         0.0         0.0         0.0

   floors_3.0  floors_3.5  waterfront_1.0  condition_2  condition_3  \
0         0.0         0.0             0.0          0.0          1.0
1         0.0         0.0             0.0          0.0          1.0
2         0.0         0.0             0.0          0.0          1.0
3         0.0         0.0             0.0          0.0          0.0
4         0.0         0.0             0.0          0.0          1.0

   condition_4  condition_5
0          0.0          0.0
1          0.0          0.0
2          0.0          0.0
3          0.0          1.0
4          0.0          0.0

[5 rows x 35 columns]
```

In [56]:

```
df_ohe.head()
```

Out[56]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	

5 rows × 35 columns

In [57]:

```
new_cols = []
for x in df_ohe:
    new_cols.append(x.replace(".", "_"))
df_ohe.columns = new_cols
df_ohe.head()
```

Out[57]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	

5 rows × 35 columns

In [58]:

```
# Drop categorical features to avoid redundancy
df_ohe.drop((cat), axis=1, inplace=True)
```

Converting date to age of the house sold

In [59]:

```
# Change date dtype to datetime
df['date'] = pd.to_datetime(df['date'])

df['date'].min()
```

Out[59]:

```
Timestamp('2014-05-02 00:00:00')
```

In [60]:

```
# check dtypes
df.dtypes
```

Out[60]:

```
date             datetime64[ns]
price                     int64
bedrooms                  int64
bathrooms               float64
sqft_living               int64
sqft_lot                  int64
floors                  float64
waterfront              float64
view                    float64
condition                 int64
grade                     int64
sqft_above                int64
sqft_basement           float64
yr_built                  int64
zipcode                   int64
lat                     float64
long                    float64
sqft_living15             int64
sqft_lot15                int64
renovated                 int32
dtype: object
```

In [61]:

```
# Create new column 'age at sold' by subtracting 'date' and 'yr_built'
age_at_sold = df['date'].dt.year - df['yr_built']
df['age_at_sold'] = age_at_sold
df.head()
```

Out[61]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
0	2014-10-13	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	2014-12-09	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2015-02-25	180000	2	1.00	770	10000	1.0	0.0	0.0	
3	2014-12-09	604000	4	3.00	1960	5000	1.0	0.0	0.0	
4	2015-02-18	510000	3	2.00	1680	8080	1.0	0.0	0.0	

5 rows × 21 columns

age_at_sold = New column is now a continuous feature.

In [62]:

```
# Drop columns 'date'
df.drop('date', axis=1, inplace=True)
```

In [63]:

```
df
```

Out[63]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	..
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

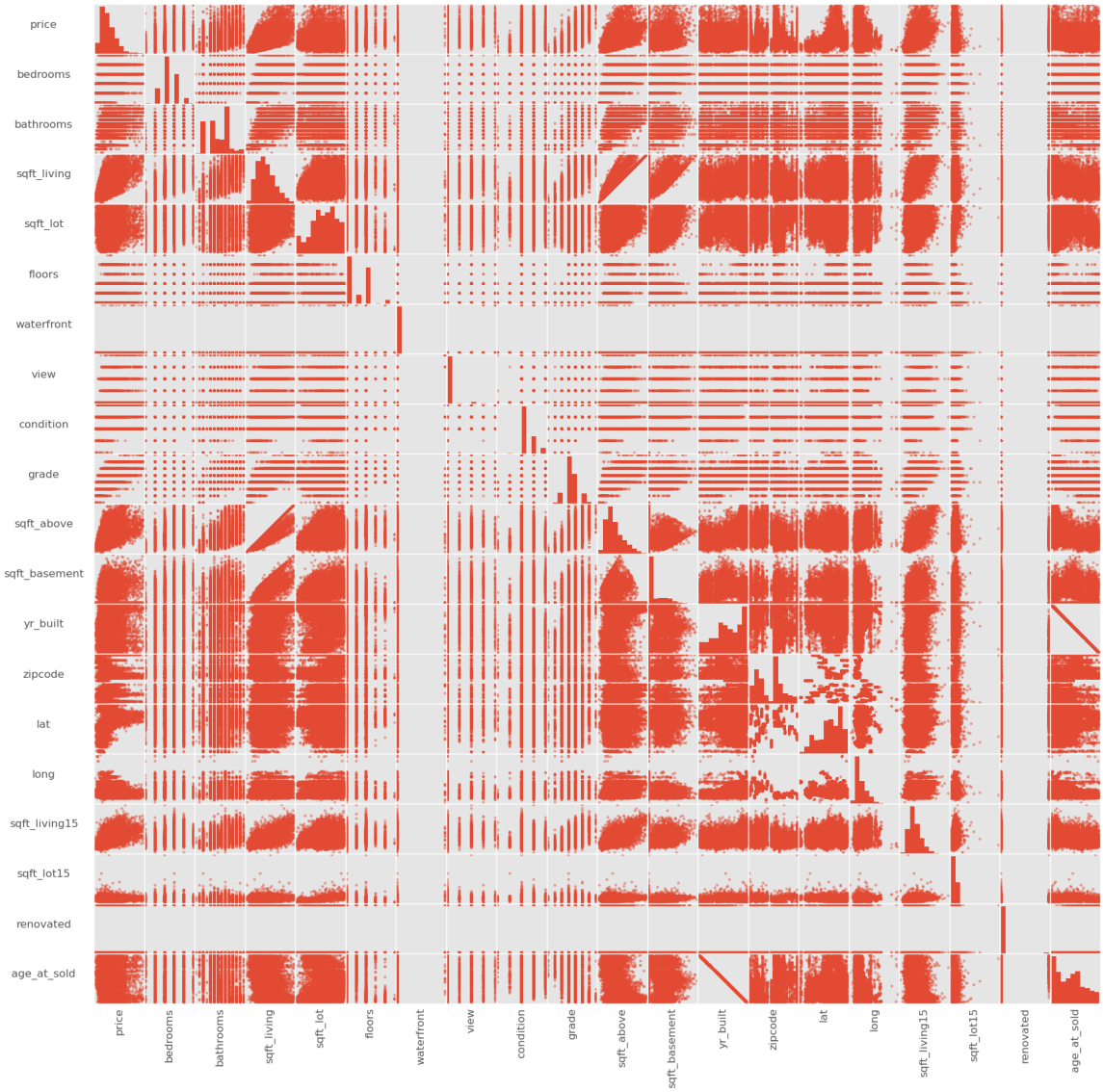
15334 rows × 20 columns

Check for multicollinearity

Scatter matrix

In [64]:

```
sm = pd.plotting.scatter_matrix(df, figsize=[20, 20]);

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

#Hide all ticks
[s.set_xticks(()) for s in sm.reshape(-1)]
[s.set_yticks(()) for s in sm.reshape(-1)]

plt.show()
```



Correlation matrix

In [65]:

```
#Correlation matrix
df.corr(numeric_only=True)
```

Out[65]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
price	1.000000	0.270020	0.401291	0.582435	-0.091096	0.258474	0.062988
bedrooms	0.270020	1.000000	0.484538	0.628025	0.230280	0.159391	-0.026551
bathrooms	0.401291	0.484538	1.000000	0.701893	-0.092625	0.533343	-0.009154
sqft_living	0.582435	0.628025	0.701893	1.000000	0.171210	0.343853	-0.006088
sqft_lot	-0.091096	0.230280	-0.092625	0.171210	1.000000	-0.449486	0.007880
floors	0.258474	0.159391	0.533343	0.343853	-0.449486	1.000000	0.003375
waterfront	0.062988	-0.026551	-0.009154	-0.006088	0.007880	0.003375	1.000000
view	0.288403	0.031689	0.082679	0.160663	0.024788	-0.004820	0.200719
condition	0.062857	0.015076	-0.152621	-0.069797	0.143082	-0.284153	0.008267
grade	0.600733	0.325391	0.608525	0.670470	-0.047194	0.487685	-0.006307
sqft_above	0.456314	0.507400	0.626796	0.840791	0.136252	0.537249	-0.007722
sqft_basement	0.269508	0.262739	0.194036	0.365580	0.077200	-0.294297	0.002646
yr_built	-0.033115	0.165549	0.555123	0.328073	-0.089224	0.523722	-0.016596
zipcode	0.058303	-0.169524	-0.225719	-0.192169	-0.245899	-0.083009	0.017435
lat	0.443162	-0.075943	-0.041972	-0.005617	-0.191920	0.022036	-0.005560
long	-0.030962	0.168526	0.263014	0.264305	0.219901	0.150705	-0.005365
sqft_living15	0.483158	0.403860	0.519489	0.728039	0.199125	0.275359	0.010680
sqft_lot15	-0.096889	0.180471	-0.089923	0.132528	0.832437	-0.394623	0.051694
renovated	0.107844	0.003951	0.026586	0.031777	-0.014106	-0.006285	0.029324
age_at_sold	0.033206	-0.165735	-0.555538	-0.328501	0.089285	-0.523947	0.016707

In [66]:

```
#Return True for positive or negative correlations that are bigger than 0.75 in the corre
abs(df.corr(numeric_only=True)) > 0.75
```

Out[66]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
price	True	False	False	False	False	False	False	False	
bedrooms	False	True	False	False	False	False	False	False	
bathrooms	False	False	True	False	False	False	False	False	
sqft_living	False	False	False	True	False	False	False	False	
sqft_lot	False	False	False	False	True	False	False	False	
floors	False	False	False	False	False	True	False	False	
waterfront	False	False	False	False	False	False	True	False	
view	False	False	False	False	False	False	False	True	
condition	False	False	False	False	False	False	False	False	
grade	False	False	False	False	False	False	False	False	
sqft_above	False	False	False	True	False	False	False	False	
sqft_basement	False	False	False	False	False	False	False	False	
yr_built	False	False	False	False	False	False	False	False	
zipcode	False	False	False	False	False	False	False	False	
lat	False	False	False	False	False	False	False	False	
long	False	False	False	False	False	False	False	False	
sqft_living15	False	False	False	False	False	False	False	False	
sqft_lot15	False	False	False	False	True	False	False	False	
renovated	False	False	False	False	False	False	False	False	
age_at_sold	False	False	False	False	False	False	False	False	

Now, include stack and zip to create a more robust solution that will return the variable pairs from the correlation matrix that have correlations over .75, but less than 1.

In [67]:

```
df1 = df.corr(numeric_only=True).abs().stack().reset_index().sort_values(0, ascending=Fal


df1['pairs'] = list(zip(df1.level_0, df1.level_1))

df1.set_index(['pairs'], inplace = True)

df1.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
df1.columns = ['cc']

df1.drop_duplicates(inplace=True)

df1[(df1.cc>.75) & (df1.cc<1)]
```

Out[67]:

	cc
pairs	
(age_at_sold, yr_built)	0.999890
(sqft_above, sqft_living)	0.840791
(sqft_lot, sqft_lot15)	0.832437

There are three sets of variales that are highly correlated.

- age_at_sold with yr_built
- sqft_above with sqft_living
- sqft_lot15 with sqft_lot).

Did not removed any variables yet

Heatmap

In [68]:

```
# View columns
df.columns
```

Out[68]:

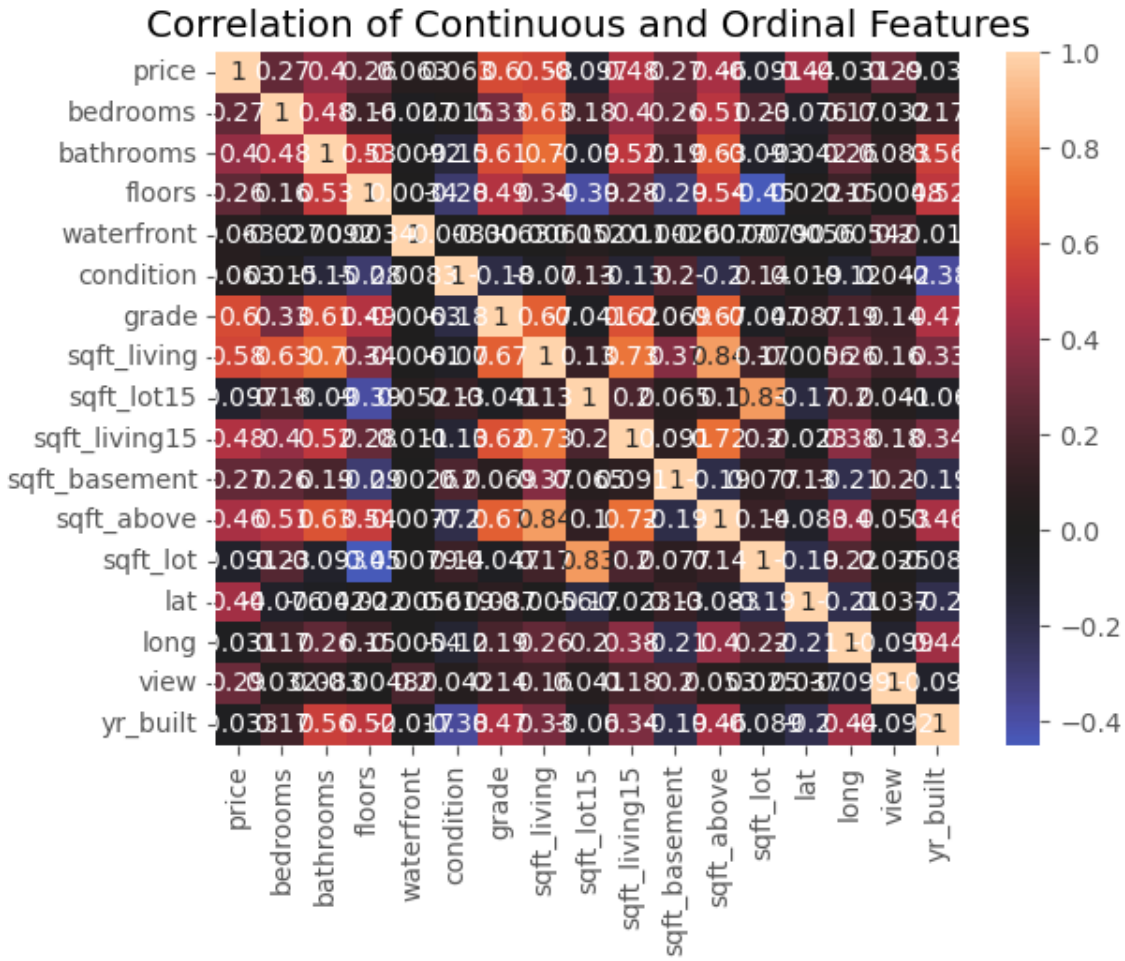
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floor
s',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long', 'sqft_living
15',
       'sqft_lot15', 'renovated', 'age_at_sold'],
      dtype='object')
```

In [69]:

```
# Create a list of continuous and ordinal categorical features
cont_ordinal = ['price', 'bedrooms', 'bathrooms', 'floors', 'waterfront', 'condition', 'g
```

In [70]:

```
# Correlation heat map with continuous and ordinal features
corr = df[cont_ordinal].corr()
sns.heatmap(corr, center=0, annot=True).set_title('Correlation of Continuous and Ordinal
```



In [71]:

```
df
```

Out[71]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	..
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

15334 rows × 20 columns

Can see a correlatation between (sqft_above, sqft_living) is 0.840791 and (sqft_lot15, sqft_lot) is 0.83243

Double checking for null values

In [72]:

```
df
```

Out[72]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	..
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

15334 rows × 20 columns

In [73]:

```
#check for null values
df.isnull().sum()
```

Out[73]:

```
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront        0
view             43
condition         0
grade             0
sqft_above        0
sqft_basement     0
yr_built          0
zipcode           0
lat               0
long              0
sqft_living15     0
sqft_lot15        0
renovated         0
age_at_sold       0
dtype: int64
```

In [74]:

```
#view has 43 null values
df['view'].value_counts()
```

Out[74]:

```
0.0    14249
2.0      550
3.0      221
1.0      190
4.0       81
Name: view, dtype: int64
```

In [75]:

```
df['view'].mean()
```

Out[75]:

```
0.1489111241907004
```

In [76]:

```
df['view'].median()
```

Out[76]:

```
0.0
```

In [77]:

```
df['view'].fillna(df['view'].median(),inplace=True)
```

In [78]:

```
df.view.isnull().sum()
```

Out[78]:

```
0
```

MODEL

The modeling phase involves selecting appropriate algorithms to analyze the data. This phase usually involves training and testing a model.

MODEL 1

In [79]:

```
df
```

Out[79]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	..
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

15334 rows × 20 columns

In [80]:

```
train, test = train_test_split(df, random_state = 150)
train.head()
```

Out[80]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
16187	447000	2	1.00	720	7500	1.0	0.0	2.0	3
6767	809000	4	1.75	1790	8372	1.0	0.0	0.0	4
17872	217000	2	1.00	720	4760	1.0	0.0	0.0	5
20242	778983	4	2.50	2490	5647	2.0	0.0	0.0	3
5748	387000	2	2.25	1230	1280	2.0	0.0	0.0	3

In [81]:

```
# Create model function to fit a linear regression that includes rmse
def model1(train, test):

  target = 'price'
  x_cols = list(train.columns)
  x_cols.remove('price')

  predictors = '+'.join(x_cols)
  formula = target + '~' + predictors
  model = ols(formula=formula, data=train).fit()

  # RMSE
  train_err = (mean_squared_error(train['price'], model.predict(train)))**0.5
  test_err = (mean_squared_error(test['price'], model.predict(test)))**0.5

  print("Train RMSE: ", train_err)
  print("Test RMSE: ", test_err, '\n')

  return model
```

In [82]:

```
model1(train, test).summary()
```

```
Train RMSE:  122255.66801937918
Test RMSE:  121587.4592701153
```

Out[82]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.706
Model:	OLS	**Adj. R-squared:**	0.706
Method:	Least Squares	**F-statistic:**	1452.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:01	**Log-Likelihood:**	-1.5103e+05
No. Observations:	15035	**AIC:**	3.021e+05
Df Residuals:	14980	**BIC:**	3.022e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.992e+07	5.56e+06	-8.978	0.000	-6.08e+07	-3.9e+07
bedrooms	-1.414e+04	1810.270	-7.813	0.000	-1.77e+04	-1.06e+04
bathrooms	2.456e+04	2915.238	8.425	0.000	1.88e+04	3.03e+04
sqft_living	118.0345	18.503	6.379	0.000	81.766	154.303
sqft_lot	-6.1074	0.923	-6.617	0.000	-7.917	-4.298
floors	7886.2621	3564.781	2.212	0.027	898.684	1.49e+04
waterfront	7.259e+05	1.77e+04	40.999	0.000	6.91e+05	7.61e+05
view	4.287e+04	2094.430	20.470	0.000	3.88e+04	4.7e+04
condition	2.709e+04	1978.907	13.688	0.000	2.32e+04	3.1e+04
grade	8.953e+04	1926.123	46.485	0.000	8.58e+04	9.33e+04
sqft_above	-3.3708	18.502	-0.182	0.855	-39.638	32.897
sqft_basement	-13.4485	18.286	-0.735	0.462	-49.292	22.395
yr_built	2.031e+04	2444.861	8.305	0.000	1.55e+04	2.51e+04
zipcode	-288.1826	28.728	-9.987	0.000	-343.495	-206.87
lat	5.616e+05	9316.830	60.277	0.000	5.43e+05	5.8e+05
long	-1.137e+04	1.22e+04	-5.040	0.000	-1.58e+04	-6.95e+04
sqft_living15	40.8444	3.442	11.866	0.000	34.097	47.592
sqft_lot15	-4.3054	0.761	-5.661	0.000	-5.796	-2.815
renovated	2.917e+04	6905.832	4.224	0.000	1.56e+04	4.27e+04
age_at_sold	2.246e+04	2444.023	9.190	0.000	1.77e+04	2.73e+04

Omnibus:	2292.811	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7785.939
Skew:	0.995	**Prob(JB):**	0.00
Kurtosis:	6.506	**Cond. No.**	4.80e+08

Notes:

Initial model has a **R-squared of 0.706** suggests that the model explains a significant portion (70.6%) of the variance in the dependent variable, which often means that the model could be useful for predictions. However this can be improved !

A **skewness value of 0.995** is a moderate positive skew, suggesting that there are somewhat more low values and fewer high values, and the "tail" of the distribution stretches more towards the right (higher values).

A **kurtosis value of 6.506** is greater than 3, indicating a leptokurtic distribution. This suggests that the dataset has more extreme values, or outliers, than we would expect from a normal distribution. It implies that the tails of the distribution are relatively heavy, and that data points are more likely to be found far from the mean compared to a normally distributed dataset.

MODEL 2 - Remove features with p_value less than 0.05

In [83]:

```
print(train.columns)
print(test.columns)
```

```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floor
s',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long', 'sqft_living
15',
       'sqft_lot15', 'renovated', 'age_at_sold'],
      dtype='object')
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floor
s',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long', 'sqft_living
15',
       'sqft_lot15', 'renovated', 'age_at_sold'],
      dtype='object')
```

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.8e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [84]:

```
# Code from the Appendix Lab: Modeling Your Data
# remove features with p_value less than 0.05
model2 = model1(train, test).summary()
p_table = model2.tables[1]
p_table = pd.DataFrame(p_table.data)
p_table.columns = p_table.iloc[0]
p_table = p_table.drop(0)
p_table = p_table.set_index(p_table.columns[0])
p_table['P>|t|'] = p_table['P>|t|'].astype(float)
sig = list(p_table[p_table['P>|t|'] < 0.05].index)
sig.remove('Intercept')
print("Total # features: ", len(p_table))
print("Total significant features", len(sig))
p_table.head()
```

```
Train RMSE:  122255.66801937918
Test RMSE:  121587.4592701153

Total # features:  20
Total significant features 17
```

Out[84]:

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.992e+07	5.56e+06	-8.978	0.0	-6.08e+07	-3.9e+07
bedrooms	-1.414e+04	1810.270	-7.813	0.0	-1.77e+04	-1.06e+04
bathrooms	2.156e+04	2917.233	7.389	0.0	1.58e+04	2.73e+04
sqft_living	118.0345	18.503	6.379	0.0	81.766	154.303
sqft_lot	-6.1074	0.923	-6.617	0.0	-7.917	-4.298

In [85]:

```
# Gathering together significant features
train, test = train[sig+['price']], test[sig+['price']]
```

In [86]:

```
# Applying only features with a p_value less than 0.05
model2 = model1(train, test)
model2.summary()
```

```
Train RMSE:  122284.7267523019
Test RMSE:  121596.23044719924
```

Out[86]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.706
Model:	OLS	**Adj. R-squared:**	0.706
Method:	Least Squares	**F-statistic:**	1623.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:02	**Log-Likelihood:**	-1.5103e+05
No. Observations:	11500	**AIC:**	3.021e+05
Df Residuals:	11482	**BIC:**	3.022e+05
Df Model:	17		
Covariance Type:	nonrobust		

Removing features with p_value less than 0.05 which was for sqft_above and sqft_basement. There Was'nt that much difference in the model 2 compared to model 1

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.914e+07	5.55e+06	-8.854	0.000	-6e+07	-3.83e+07
bedrooms	-1.415e+04	1810.415	-7.815	0.000	-1.77e+04	-1.06e+04
bathrooms	2.036e+04	2867.004	7.100	0.000	1.47e+04	2.6e+04
sqft_living	110.7889	3.496	31.688	0.000	103.936	117.642
sqft_lot	-5.7416	0.908	-6.322	0.000	-7.522	-3.961
floors	1.189e+04	3066.633	3.876	0.000	5875.209	1.79e+04
waterfront	3.261e+05	3.77e+04	8.653	0.000	2.52e+05	4e+05
view	4.227e+04	2075.824	20.361	0.000	3.82e+04	4.63e+04
condition	2.664e+04	1968.122	13.537	0.000	2.28e+04	3.05e+04
grade	8.989e+04	1919.873	46.823	0.000	8.61e+04	9.37e+04
yr_built	2.031e+04	2445.193	8.306	0.000	1.55e+04	2.51e+04
zipcode	-263.7018	28.731	-9.178	0.000	-320.020	-207.384
lat	5.595e+05	9266.046	60.377	0.000	5.41e+05	5.78e+05
long	-5.612e+04	1.19e+04	-4.699	0.000	-7.95e+04	-3.27e+04
sqft_living15	42.2596	3.382	12.495	0.000	35.630	48.889
sqft_lot15	-4.3441	0.760	-5.712	0.000	-5.835	-2.853
renovated	2.914e+04	6906.844	4.220	0.000	1.56e+04	4.27e+04
age_at_sold	2.246e+04	2444.354	9.190	0.000	1.77e+04	2.73e+04

Omnibus:	2296.870	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7827.477
Skew:	0.995	**Prob(JB):**	0.00
Kurtosis:	6.518	**Cond. No.**	4.79e+08

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

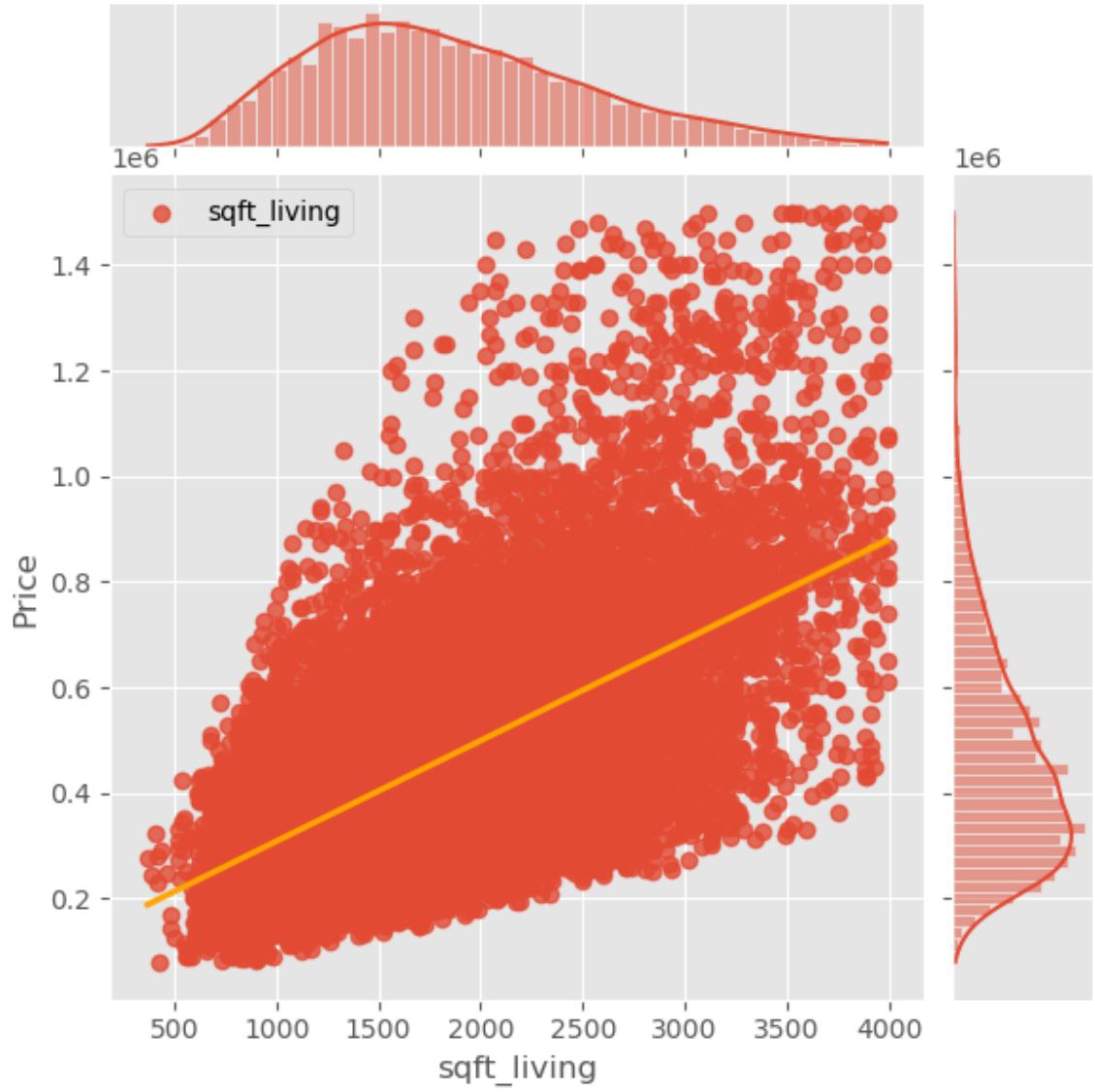
[2] The condition number is large, 4.79e+08. This might indicate that there are strong multicollinearity or other numerical problems.

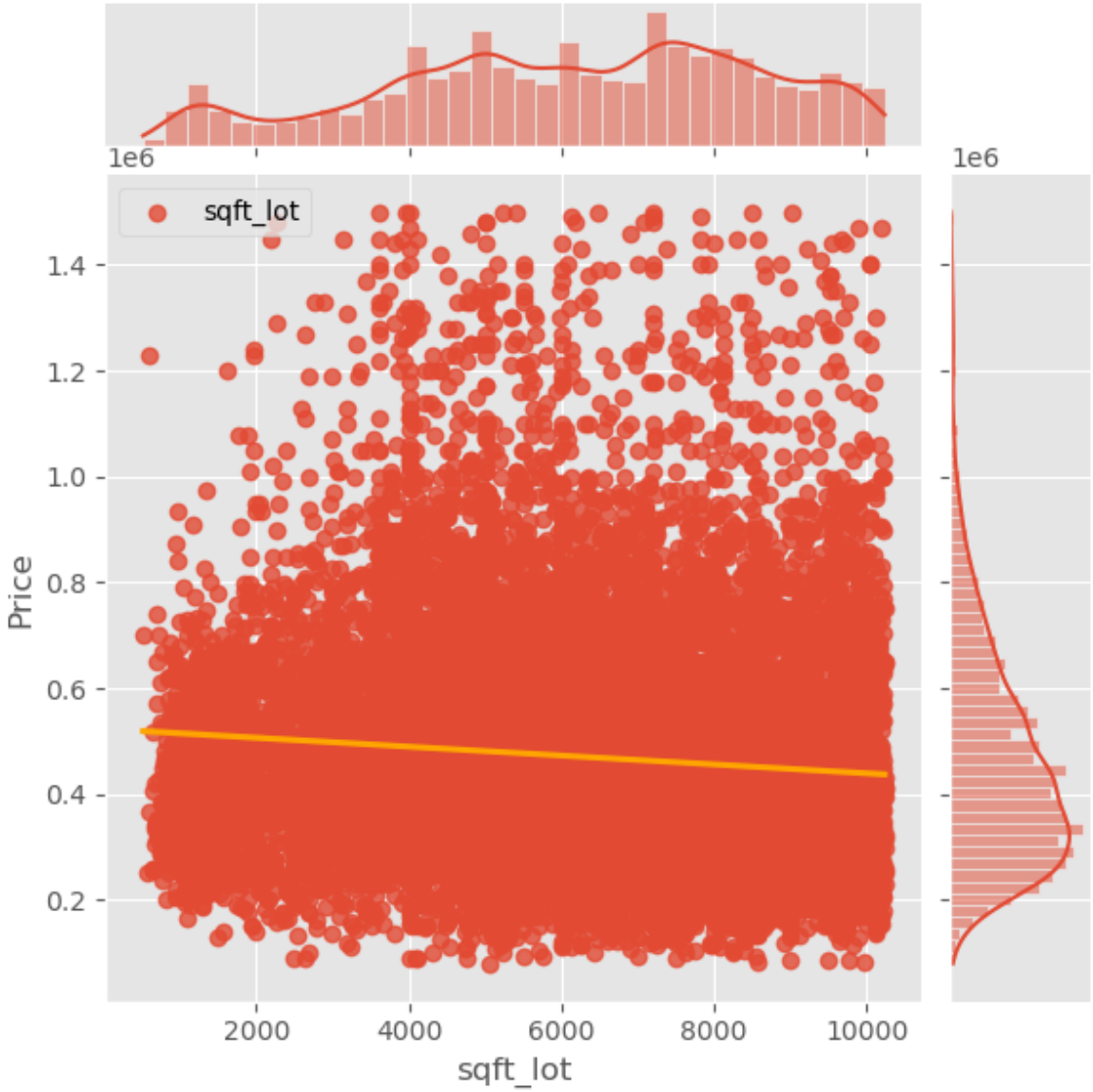
Check assumptions

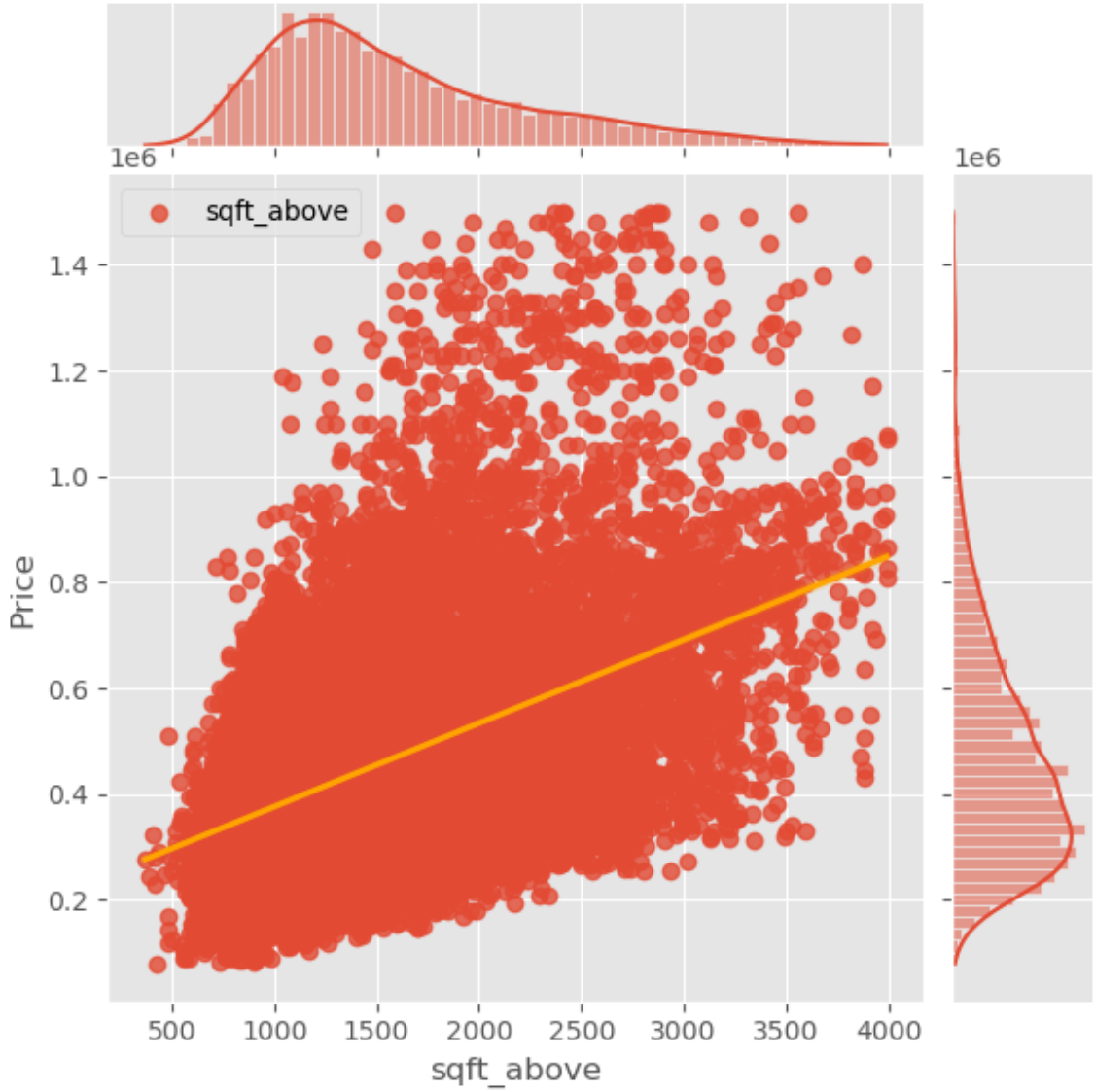
Prepare Continuous Data for Modeling: Checking Linearity

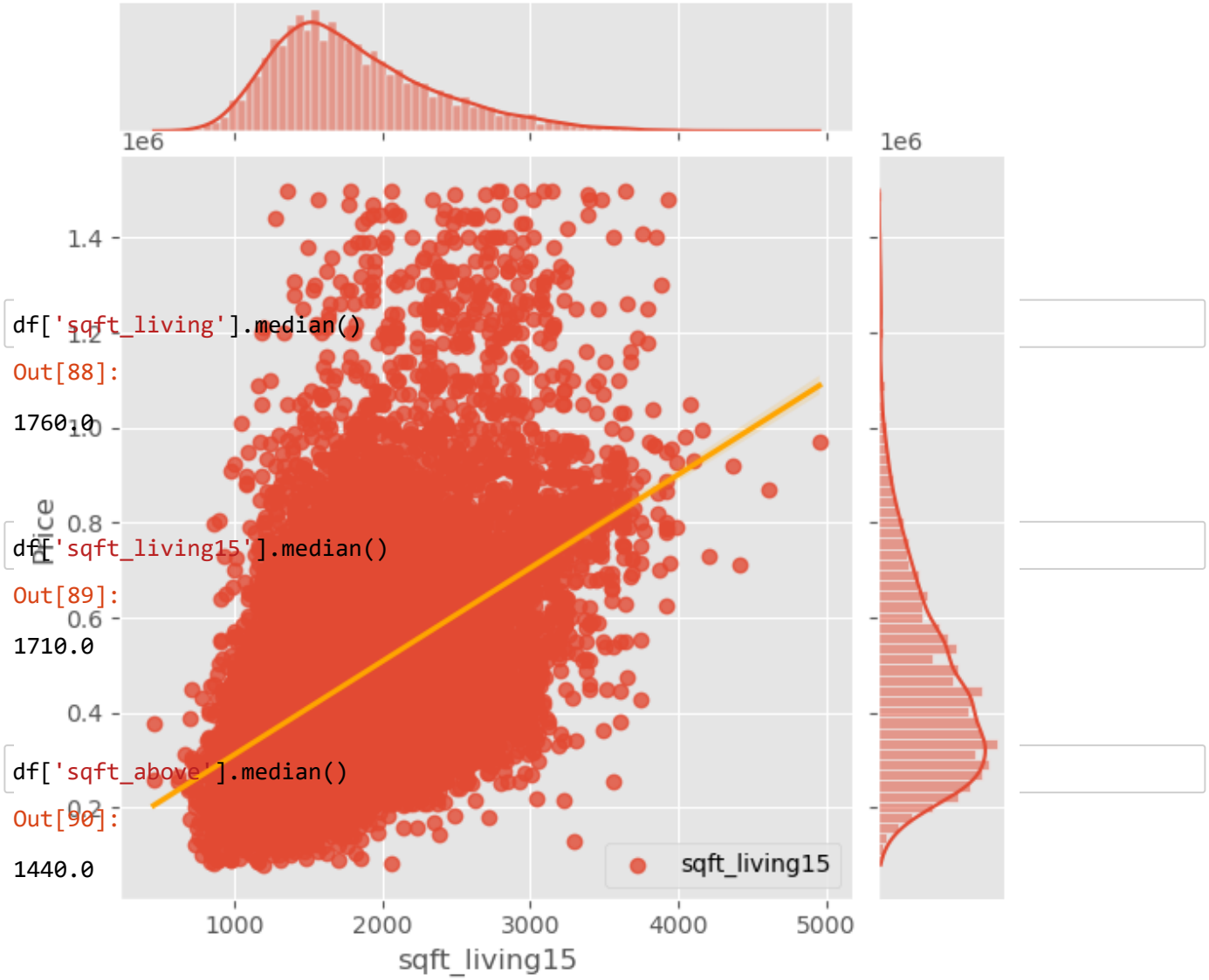
In [87]:

```
# Select and visualize continuous data (data that can take any value)
continuous = ['sqft_living','sqft_lot','sqft_above','sqft_living15','sqft_lot15']

for column in continuous:
    sns.jointplot(x=column, y="price", data=df, kind='reg', label=column,joint_kws={'line

# Set y-axis label
    plt.ylabel('Price')

    plt.legend()
    plt.show()
```




1e6
1e6
sqft_lot
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Price
2000
4000
6000
8000
10000
sqft_lot


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




```
df['sqft_living'].median()
```

Out[88]:

1760.0

```
df['sqft_living15'].median()
```

Out[89]:

1710.0

```
df['sqft_above'].median()
```

Out[90]:

1440.0

sqft_living, sqft_living15 , sqft_above all have a positive linear relationship with our target variable (price). Since continuous predictors have high multicolinearity (as addressed previously) I will use only sqft_living and sqft_living15

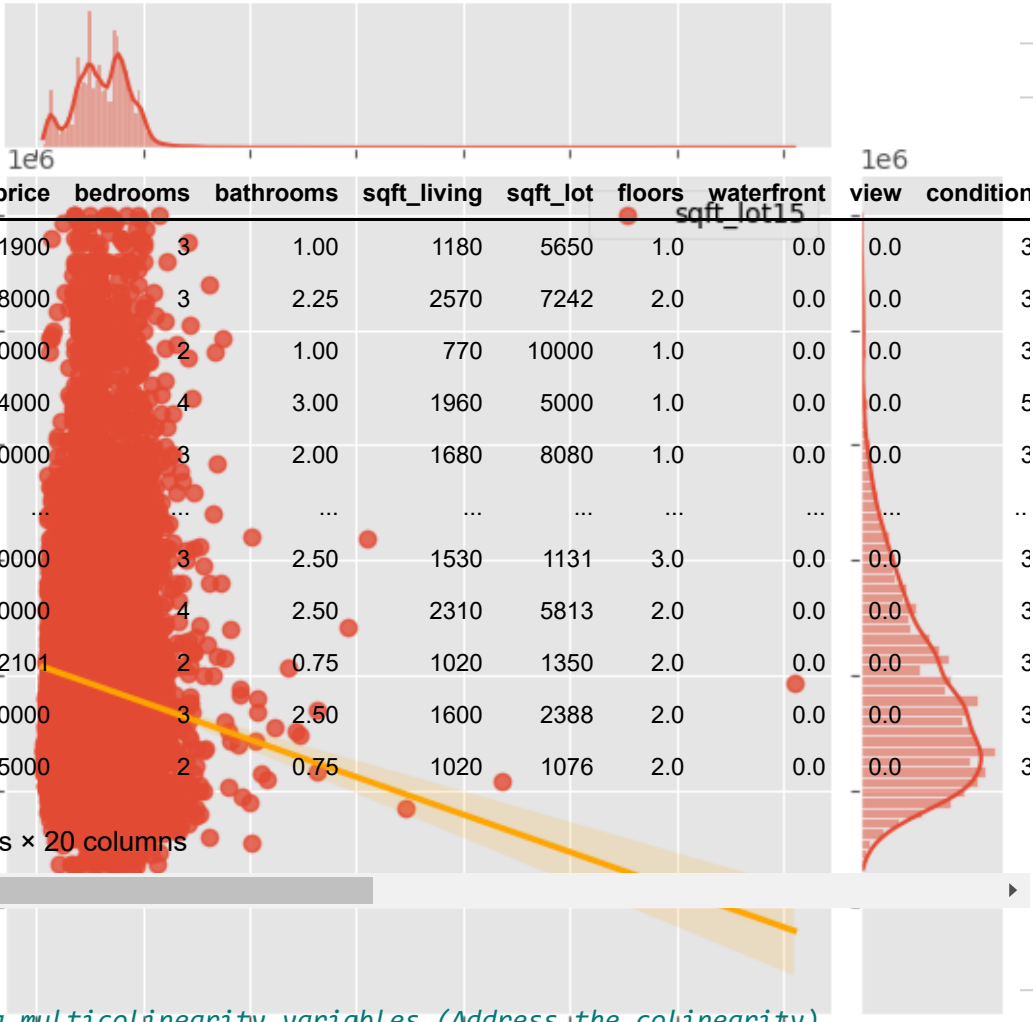
MODEL 3 - addressed multicollinearity

```
df
```

Out[91]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	...
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

15334 rows × 20 columns




```
#Removing multicolinearity variables (Address the colinearity)
df.drop(['sqft_above','sqft_lot15','age_at_sold'], axis= 1, inplace = True)
df.head()
```

Out[92]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gr
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3	
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3	
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3	
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5	
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3	

In [93]:

```
train, test = train_test_split(df, random_state = 150)
train.head()
```

Out[93]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
16187	447000	2	1.00	720	7500	1.0	0.0	2.0	3
6767	809000	4	1.75	1790	8372	1.0	0.0	0.0	4
17872	217000	2	1.00	720	4760	1.0	0.0	0.0	5
20242	778983	4	2.50	2490	5647	2.0	0.0	0.0	3
5748	387000	2	2.25	1230	1280	2.0	0.0	0.0	3

In [94]:

```
# Create model function to fit a linear regression that includes rmse
def model(train, test):

  target = 'price'
  x_cols = list(train.columns)
  x_cols.remove('price')

  predictors = '+'.join(x_cols)
  formula = target + '~' + predictors
  model = ols(formula=formula, data=train).fit()

  # RMSE
  train_err = (mean_squared_error(train['price'], model.predict(train)))**0.5
  test_err = (mean_squared_error(test['price'], model.predict(test)))**0.5

  print("Train RMSE: ", train_err)
  print("Test RMSE: ", test_err, '\n')

  return model
```

In [95]:

```
model(train, test).summary()
```

```
Train RMSE:  122874.48068419255
Test RMSE:  122673.49484315024
```

Out[95]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.703
Model:	OLS	**Adj. R-squared:**	0.703
Method:	Least Squares	**F-statistic:**	1701.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:09	**Log-Likelihood:**	-1.5100e+05
No. Observations:	11500	**AIC:**	3.022e+05
Df Residuals:	11483	**BIC:**	3.023e+05
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.424e+06	2.53e+06	-1.747	0.081	-9.39e+06	5.4e+05
bedrooms	-1.404e+04	1818.999	-7.719	0.000	-1.76e+04	-1.05e+04
bathrooms	2.194e+04	2926.184	7.498	0.000	1.62e+04	2.77e+04
sqft_living	115.4947	3.902	29.602	0.000	107.847	123.142
sqft_lot	-9.8514	0.641	-15.367	0.000	-11.108	-8.595
floors	8499.5620	3547.739	2.396	0.017	1545.388	1.55e+04
waterfront	3.196e+05	3.79e+04	8.444	0.000	2.45e+05	3.94e+05
view	4.301e+04	2102.288	20.457	0.000	3.89e+04	4.71e+04
condition	2.568e+04	1982.959	12.950	0.000	2.18e+04	2.96e+04
grade	8.942e+04	1934.990	46.210	0.000	8.56e+04	9.32e+04
sqft_basement	-10.7853	4.406	-2.448	0.014	-19.422	-2.149
yr_built	-2178.2131	57.930	-37.600	0.000	-2291.767	-2064.659
zipcode	-262.4633	28.869	-9.091	0.000	-319.052	-205.874
lat	5.596e+05	9353.707	59.826	0.000	5.41e+05	5.78e+05
long	-5.99e+04	1.22e+04	-4.902	0.000	-8.39e+04	-3.59e+04
sqft_living15	38.4202	3.437	11.180	0.000	31.684	45.156
renovated	2.545e+04	6923.065	3.676	0.000	1.19e+04	3.9e+04

Omnibus:	2260.095	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7467.245
Skew:	0.989	**Prob(JB):**	0.00
Kurtosis:	6.416	**Cond. No.**	2.17e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.17e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

After addressing the colinearity and droping 'sqft_above','sqft_lot15', 'age_at_sold' columns there was'nt any improvement in terms of R2 square instead there was a reduction in 0.003

A skewness value of 0.989 suggests a moderately right-skewed distribution. This means:

- Most of the data points are concentrated on the left side of the distribution.
- The tail of the distribution extends more towards the right, not the left.
- The mean is typically greater than the median in a positively skewed distribution.

Kurtosis of 6.416 is leptokurtic, meaning it has fatter tails and a sharper peak compared to a normal distribution. This would suggest:

- The data set has a higher propensity for outliers or extreme values than does a normal distribution.
- The distribution is more "peaked" than a normal distribution, implying that data points are more concentrated around the mean.

NO SIGNIFICANT DIFFERENCES WERE FOUND IN MODEL 3 FROM MODEL 1 AFTER ADDRESSING THE MULTICOLLINEARITY

Log transformation and normalisation only in continuous data

In [96]:

```
df
```

Out[96]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900	3	1.00	1180	5650	1.0	0.0	0.0	3
1	538000	3	2.25	2570	7242	2.0	0.0	0.0	3
2	180000	2	1.00	770	10000	1.0	0.0	0.0	3
3	604000	4	3.00	1960	5000	1.0	0.0	0.0	5
4	510000	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	..
21592	360000	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	400000	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	402101	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	400000	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	325000	2	0.75	1020	1076	2.0	0.0	0.0	3

15334 rows × 17 columns

In [97]:

```
df.describe()
```

Out[97]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	1.533400e+04	15334.000000	15334.000000	15334.000000	15334.000000	15334.000000
mean	4.721766e+05	3.262880	2.007125	1857.591626	6097.929829	1.504695
std	2.240077e+05	0.852576	0.687194	684.015787	2427.995819	0.553630
min	8.000000e+04	1.000000	0.500000	370.000000	520.000000	1.000000
25%	3.090000e+05	3.000000	1.500000	1340.000000	4400.000000	1.000000
50%	4.250000e+05	3.000000	2.000000	1760.000000	6250.000000	1.500000
75%	5.847125e+05	4.000000	2.500000	2290.000000	8007.500000	2.000000
max	1.500000e+06	6.000000	3.750000	3990.000000	10232.000000	3.500000

MODEL 4 - USING LOG TRANSFORMATION FOR CONTINUOUS DATA

In [98]:

```
outcome = 'price'
x_cols = ['sqft_living','sqft_lot','sqft_living15','sqft_basement']
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[98]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.398
Model:	OLS	**Adj. R-squared:**	0.398
Method:	Least Squares	**F-statistic:**	2534.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:09	**Log-Likelihood:**	-2.0677e+05
No. Observations:	15334	**AIC:**	4.136e+05
Df Residuals:	15329	**BIC:**	4.136e+05
Df Model:	4		
Covariance Type:	nonrobust		

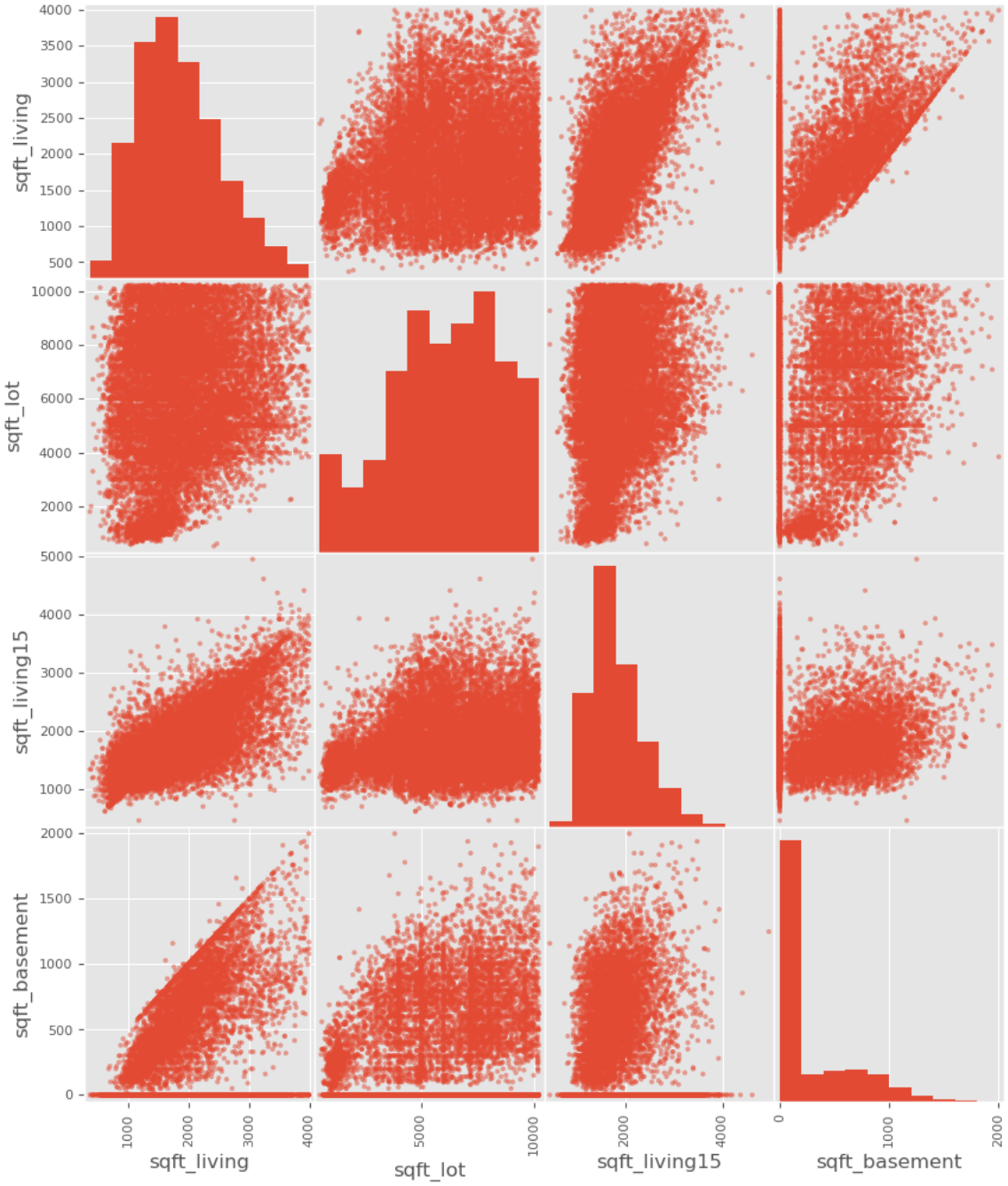
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.644e+05	5554.947	29.595	0.000	1.54e+05	1.75e+05
sqft_living	141.8809	3.330	42.602	0.000	135.353	148.409
sqft_lot	-19.7057	0.591	-33.336	0.000	-20.864	-18.547
sqft_living15	81.6155	3.901	20.922	0.000	73.969	89.262
sqft_basement	65.2759	4.186	15.595	0.000	57.071	73.480

Omnibus:	2414.066	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5066.425
Skew:	0.946	**Prob(JB):**	0.00
Kurtosis:	5.087	**Cond. No.**	2.78e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.78e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [99]:

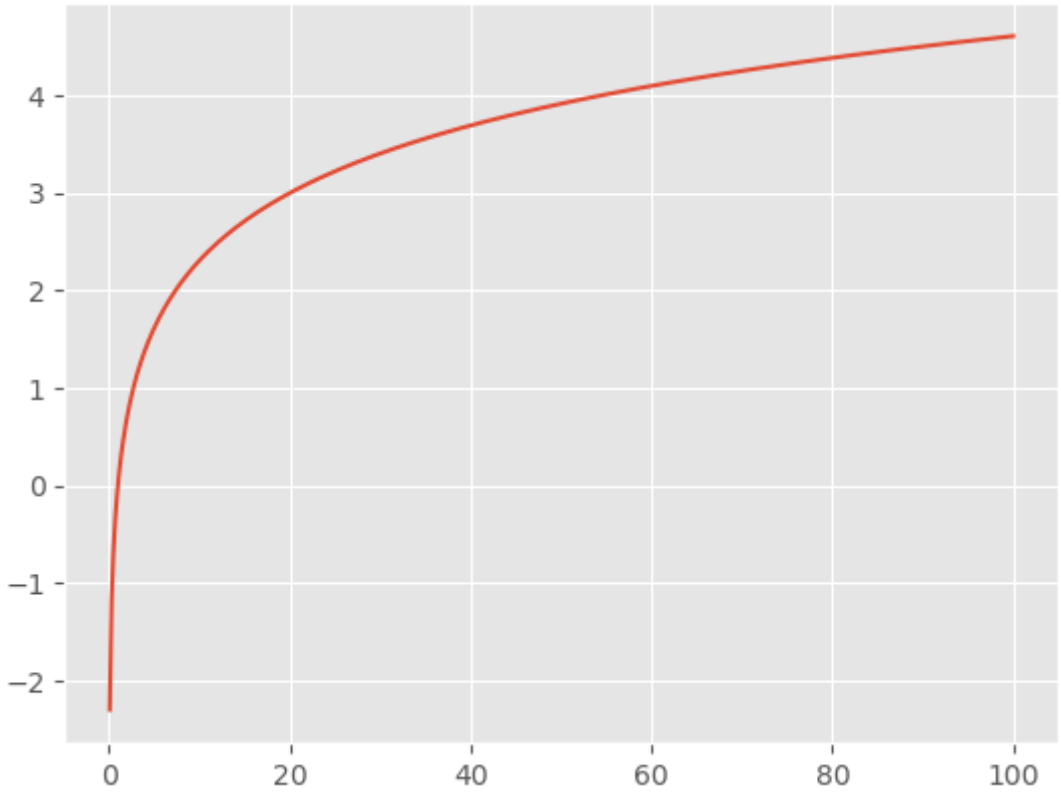
```
pd.plotting.scatter_matrix(df[x_cols], figsize=(10,12));
```



In [100]:

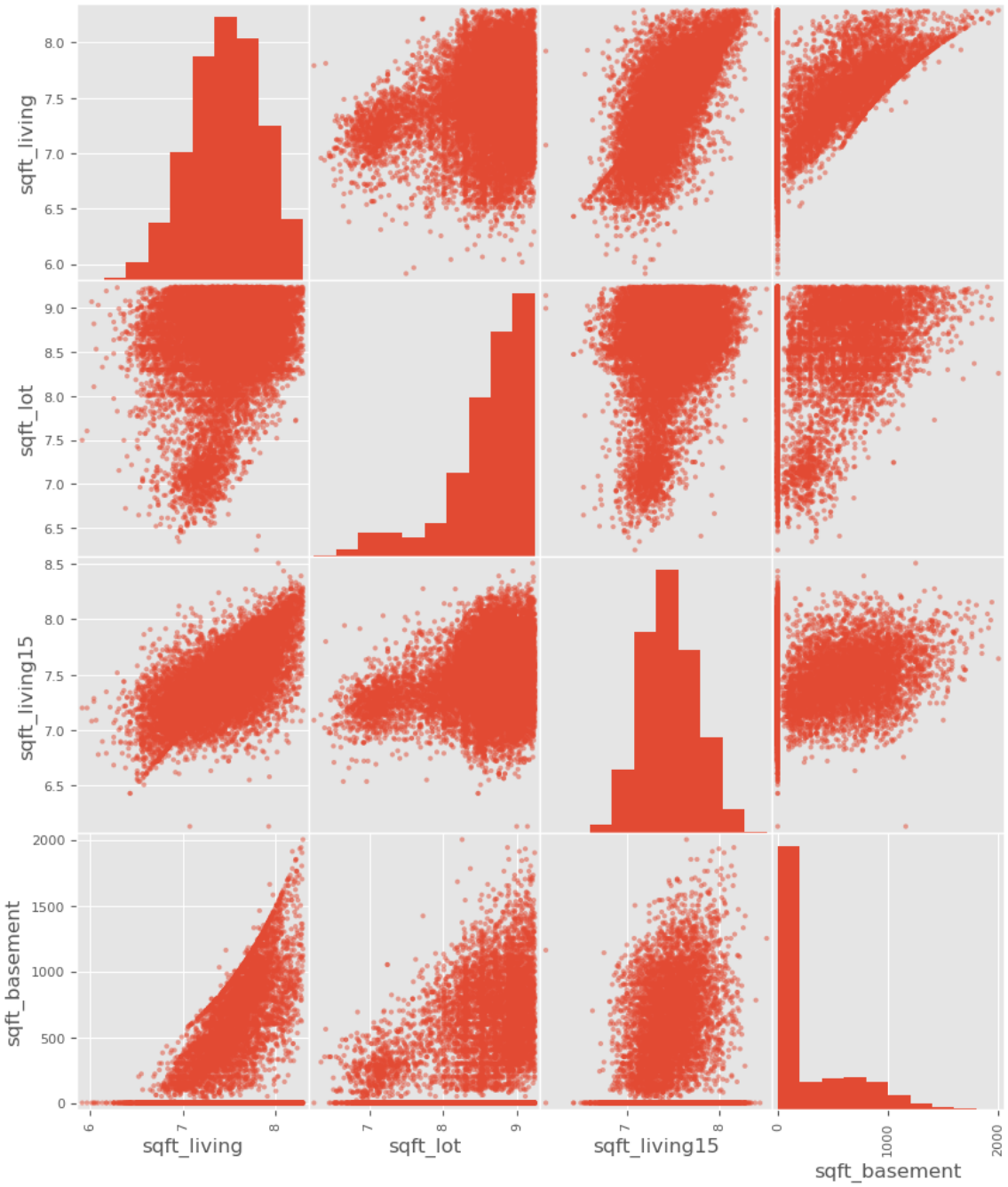
```
x = np.linspace(start=-100, stop=100, num=10**3)
y = np.log(x)
plt.plot(x, y);
```

```
C:\Users\rani_\AppData\Local\Temp\ipykernel_20364\762412792.py:2: RuntimeW
arning: invalid value encountered in log
  y = np.log(x)
```



In [101]:

```
non_normal = ['sqft_living','sqft_lot','sqft_living15']
for feat in non_normal:
    df[feat] = df[feat].map(lambda x: np.log(x))
pd.plotting.scatter_matrix(df[x_cols], figsize=(10,12));
```



In [102]:

```
outcome = 'price'
x_cols = ['sqft_living','sqft_lot','sqft_living15','sqft_basement']
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[102]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.362
Model:	OLS	**Adj. R-squared:**	0.361
Method:	Least Squares	**F-statistic:**	2170.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:15	**Log-Likelihood:**	-2.0722e+05
No. Observations:	15334	**AIC:**	4.145e+05
Df Residuals:	15329	**BIC:**	4.145e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.884e+06	4.02e+04	-46.863	0.000	-1.96e+06	-1.8e+06
sqft_living	2.24e+05	5952.604	37.623	0.000	2.12e+05	2.36e+05
sqft_lot	-7.83e+04	2710.864	-28.885	0.000	-8.36e+04	-7.3e+04
sqft_living15	1.798e+05	7254.859	24.789	0.000	1.66e+05	1.94e+05
sqft_basement	68.8601	4.277	16.099	0.000	60.476	77.244

Omnibus:	2590.857	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5385.142
Skew:	1.011	**Prob(JB):**	0.00
Kurtosis:	5.083	**Cond. No.**	1.25e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.25e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Comparing OLS regression results before and after log transformation for continuous data

- The R-squared is 0.398 for the first model and 0.362 for the second, which means the model explains around 47-45% of the variability in price.
- The variable sqft_basement seems to be not statistically significant in both models (high p-value).
- Both models suffer from non-normality in the residuals, as evidenced by the Omnibus and JB tests.
- The condition number (Cond. No.) is lower in the second model, which might imply less multicollinearity.

- The increase in skewness from 0.946 to 1.011 indicates that the distribution has become more positively skewed, suggesting more frequent higher values in the dataset.
- The increase in kurtosis from 5.467 to 5.083 suggests that the distribution has become more "tailed,"

INTERPRET

The final step is interpreting the results of the models.

Summary of Models

- Model 1 -> R- SQUARE = 0.706 , Number of Features = 19 , Best Model = ✅ No change in data except dropped one column (ID)
- Model 2 -> R- SQUARE = 0.706 , Number of Features = 17 , Best Model = ✅ Removed P-value greater than 0.05 for 3 column (sqft_above and sqft_basement)
- Model 3 -> R- SQUARE = 0.703 , Number of Features = 17 , Best Model = ✅ Addressed multicollinearity and compared to Model 1
- Model 4 -> R- SQUARE = 0.362 , Number of Features = 5 , Best Model = ❌ Applied Log transformation only for continuous data

ANOTHER APPROACH !

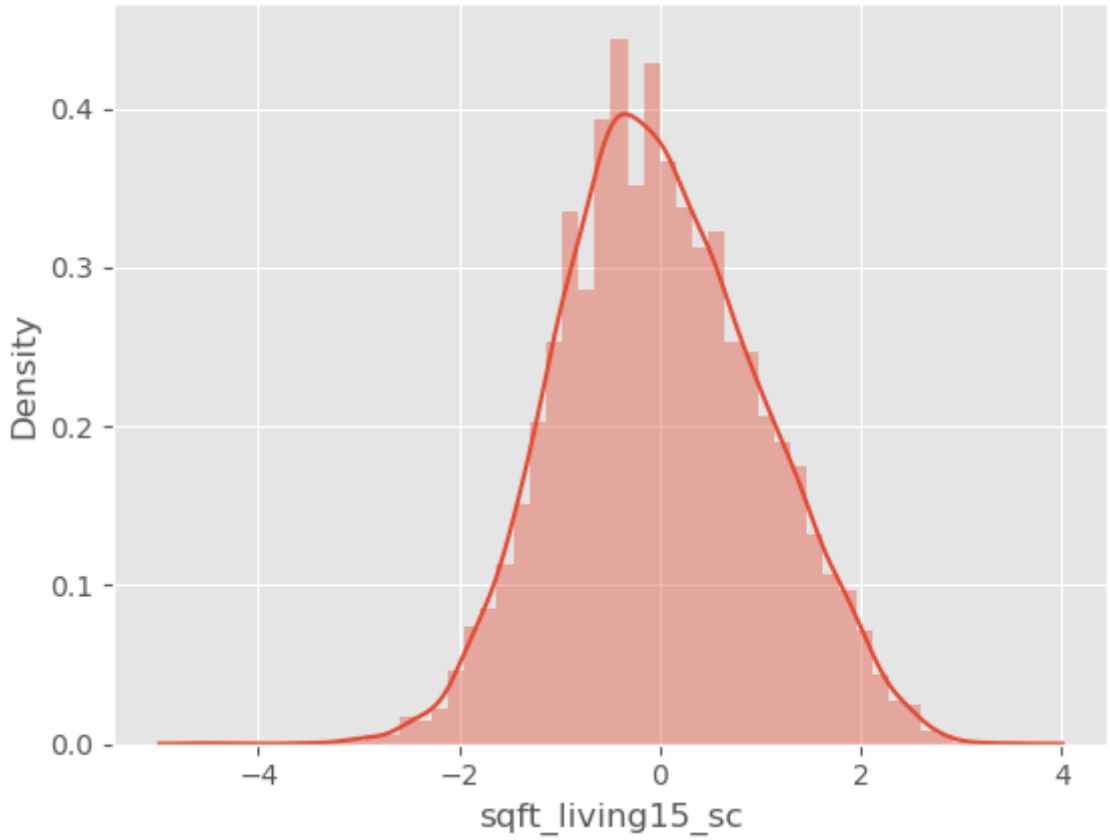
Let's first Standardize the variables

MODEL 5 Using selected variables

In [103]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
col_df = df['sqft_living15'].values.reshape(-1,1)
scale_df = scaler.fit_transform(col_df)
df['sqft_living15_sc'] = scale_df.flatten()

x = df['sqft_living15_sc']
ax = sns.distplot(x)
```

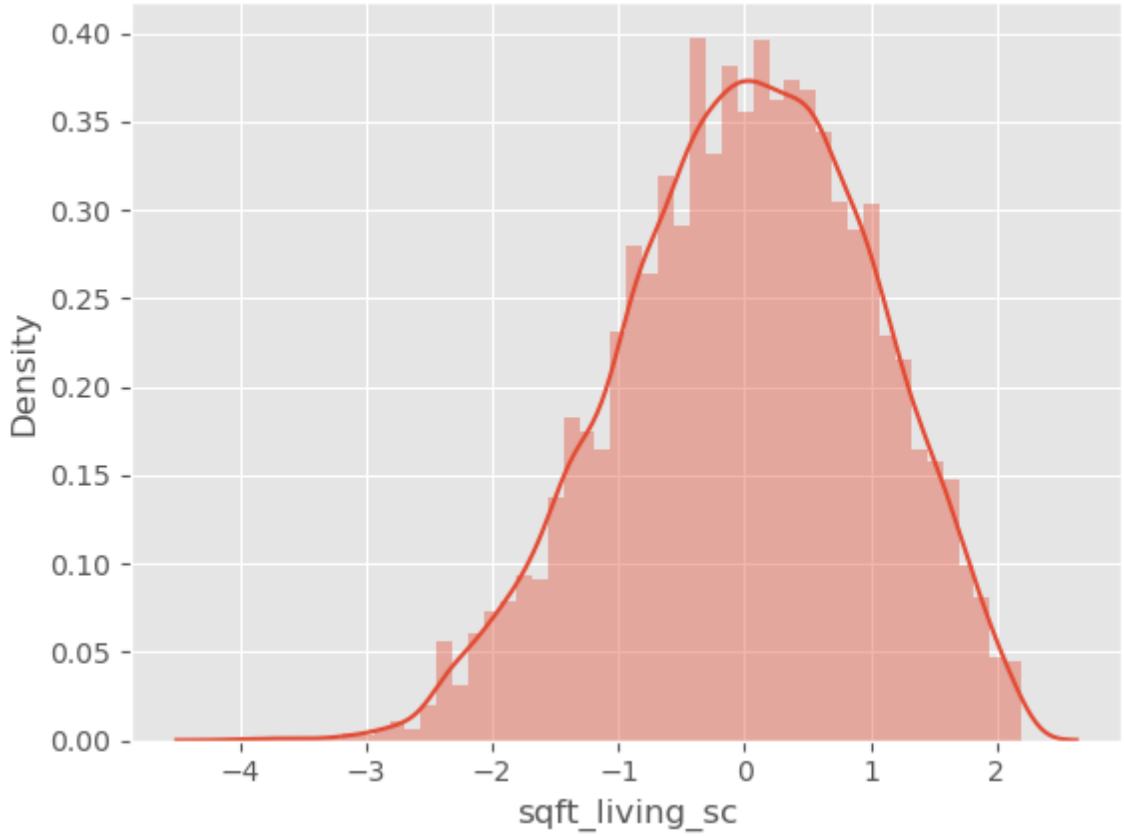
```
C:\Users\rani_\AppData\Local\Temp\ipykernel_20364\1073268049.py:8: UserWar
ning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function wi
th
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://
gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  ax = sns.distplot(x)
```



In [104]:

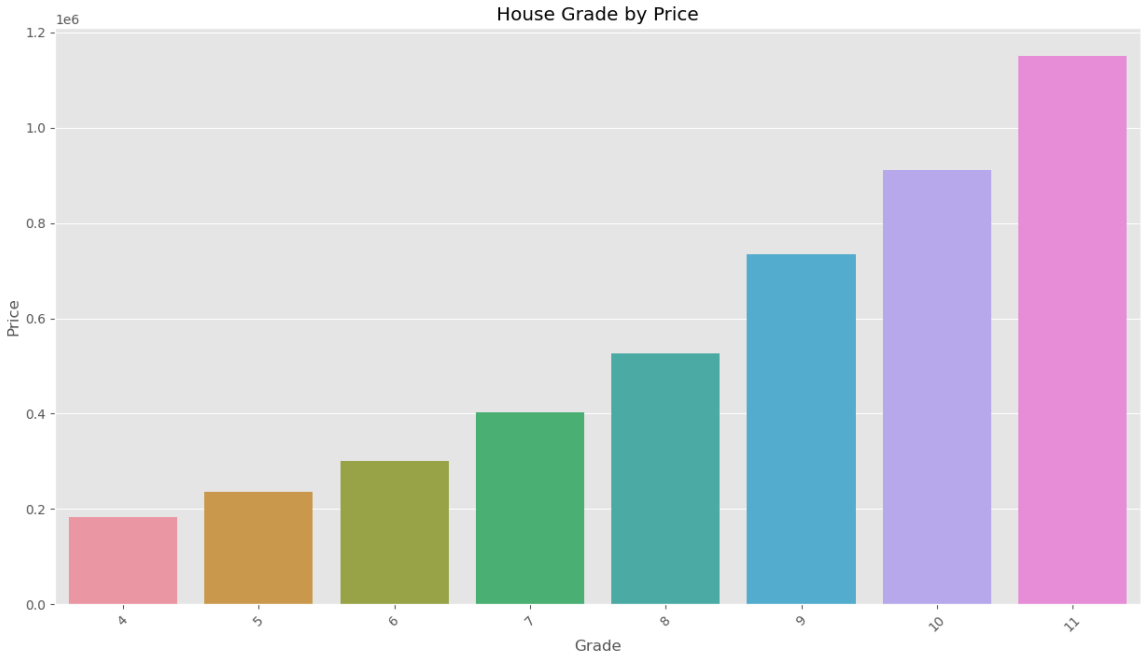
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
col_df = df['sqft_living'].values.reshape(-1,1)
scale_df = scaler.fit_transform(col_df)
df['sqft_living_sc'] = scale_df.flatten()

x = df['sqft_living_sc']
ax = sns.distplot(x)
```

```
C:\Users\rani_\AppData\Local\Temp\ipykernel_20364\896630809.py:8: UserWarn
ing:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function wi
th
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://
gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  ax = sns.distplot(x)
```



In [105]:

```
plt.figure(figsize=(15, 8))
sns.barplot(x='grade', y='price', data=df, errorbar=None)
plt.xticks(rotation=45)
plt.xlabel('Grade')
plt.ylabel('Price')
plt.title('House Grade by Price')
plt.show()
```



Building grade:

Represents the construction quality of improvements. Grades run from grade 1 to 13. Generally defined as:

1-3 Falls short of minimum building standards. Normally cabin or inferior structure.

4 Generally older, low quality construction. Does not meet code.

5 Low construction costs and workmanship. Small, simple design.

6 Lowest grade currently meeting building code. Low quality materials and simple designs.

7 Average grade of construction and design. Commonly seen in plats and older sub-divisions.

8 Just above average in construction and design. Usually better materials in both the exterior and interior finish work.

9 Better architectural design with extra interior and exterior design and quality.

10 Homes of this quality generally have high quality features. Finish work is better and more design quality is seen in the floor plans. Generally have a larger square footage.

11 Custom design and higher quality finish work with added amenities of solid woods, bathroom fixtures and more luxurious options.

12 Custom design and excellent builders. All materials are of the highest quality and all conveniences are present.

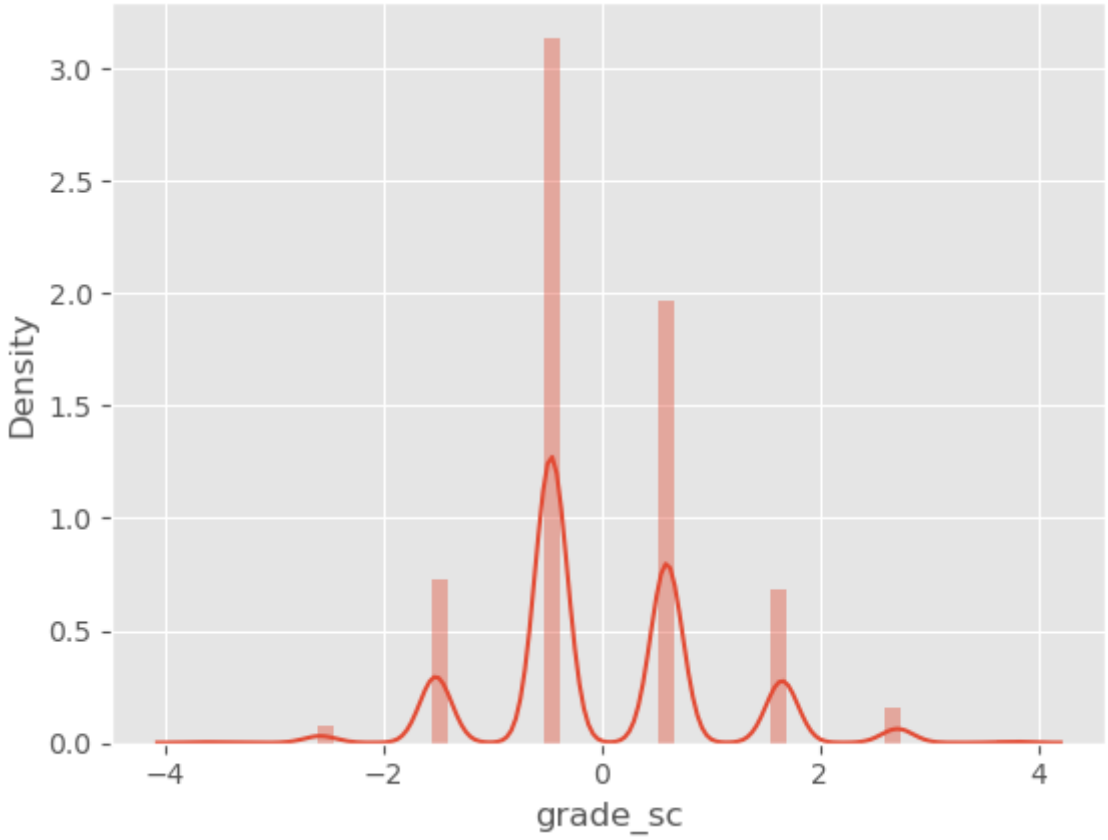
13 Generally custom designed and built. Mansion level. Large amount of highest quality cabinet work, wood

The visualization above shows that when the building grade improves, the house price rises as well. We can see in the bar plot that the mean house price for a home with a grade of 11 is far above other grades. While the building grade of 4 falls short of minimum building standards based on the King County grading system.

In [106]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
col_df = df['grade'].values.reshape(-1,1)
scale_df = scaler.fit_transform(col_df)
df['grade_sc'] = scale_df.flatten()

x = df['grade_sc']
ax = sns.distplot(x)
```

```
C:\Users\rani_\AppData\Local\Temp\ipykernel_20364\3865672094.py:8: UserWar
ning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function wi
th
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://
gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  ax = sns.distplot(x)
```



In [107]:

```
f = 'price~grade_sc+sqft_living_sc+sqft_living15_sc'
model = ols(formula=f, data=df).fit()
model.summary()
```

Out[107]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.404
Model:	OLS	**Adj. R-squared:**	0.404
Method:	Least Squares	**F-statistic:**	3460.
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:16	**Log-Likelihood:**	-2.0670e+05
No. Observations:	15334	**AIC:**	4.134e+05
Df Residuals:	15330	**BIC:**	4.134e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4.722e+05	1397.045	337.982	0.000	4.69e+05	4.75e+05
grade_sc	9.106e+04	1934.308	47.075	0.000	8.73e+04	9.48e+04
sqft_living_sc	5.414e+04	2178.768	24.848	0.000	4.99e+04	5.84e+04
sqft_living15_sc	1.245e+04	2050.301	6.073	0.000	8432.070	1.65e+04

Omnibus:	2142.294	**Durbin-Watson:**	1.961
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3825.446
Skew:	0.914	**Prob(JB):**	0.00
Kurtosis:	4.628	**Cond. No.**	2.88

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

We can see that after standardization of our selected features our model performed poorly than before COMPARING TO MODEL 1 AND 2.

In [108]:

```
#include the zipcode column to the model
#zipcodes have no numerical significance in our data,this variable is treated as categori
f = 'price~grade_sc+sqft_living_sc+sqft_living15_sc+C(zipcode)'
model = ols(formula=f, data=df).fit()
model.summary()
```

Out[108]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.775
Model:	OLS	**Adj. R-squared:**	0.774
Method:	Least Squares	**F-statistic:**	730.7
Date:	Sat, 23 Sep 2023	**Prob (F-statistic):**	0.00
Time:	19:00:16	**Log-Likelihood:**	-1.9922e+05
No. Observations:	15334	**AIC:**	3.986e+05
Df Residuals:	15261	**BIC:**	3.991e+05
Df Model:	72		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.625e+05	7103.962	36.951	0.000	2.49e+05	2.76e+05
C(zipcode)[T.98002]	5.112e+04	1.09e+04	4.684	0.000	2.97e+04	7.25e+04
C(zipcode)[T.98003]	1.568e+04	1.05e+04	1.496	0.135	-4859.404	3.62e+04
C(zipcode)[T.98004]	5.824e+05	1.3e+04	44.957	0.000	5.57e+05	6.08e+05
C(zipcode)[T.98005]	3.531e+05	1.68e+04	21.022	0.000	3.2e+05	3.86e+05
C(zipcode)[T.98006]	3.047e+05	1.01e+04	30.143	0.000	2.85e+05	3.25e+05
C(zipcode)[T.98007]	2.585e+05	1.31e+04	19.750	0.000	2.33e+05	2.84e+05
C(zipcode)[T.98008]	2.603e+05	1.03e+04	25.320	0.000	2.4e+05	2.8e+05
C(zipcode)[T.98010]	1.201e+05	2.1e+04	5.713	0.000	7.89e+04	1.61e+05
C(zipcode)[T.98011]	1.485e+05	1.16e+04	12.824	0.000	1.26e+05	1.71e+05
C(zipcode)[T.98014]	1.754e+05	2.61e+04	6.716	0.000	1.24e+05	2.27e+05
C(zipcode)[T.98019]	8.871e+04	1.32e+04	6.704	0.000	6.28e+04	1.15e+05
C(zipcode)[T.98022]	4.537e+04	1.21e+04	3.756	0.000	2.17e+04	6.9e+04
C(zipcode)[T.98023]	-6358.3963	8958.869	-0.710	0.478	-2.39e+04	1.12e+04
C(zipcode)[T.98024]	2.03e+05	3.44e+04	5.894	0.000	1.35e+05	2.7e+05
C(zipcode)[T.98027]	2.324e+05	1.04e+04	22.337	0.000	2.12e+05	2.53e+05
C(zipcode)[T.98028]	1.328e+05	1.1e+04	12.094	0.000	1.11e+05	1.54e+05
C(zipcode)[T.98029]	2.22e+05	9600.360	23.121	0.000	2.03e+05	2.41e+05
C(zipcode)[T.98030]	6114.1759	1.03e+04	0.591	0.555	-1.42e+04	2.64e+04
C(zipcode)[T.98031]	1.473e+04	1.02e+04	1.444	0.149	-5267.858	3.47e+04
C(zipcode)[T.98032]	2.38e+04	1.31e+04	1.812	0.070	-1942.272	4.95e+04
C(zipcode)[T.98033]	3.812e+05	9588.995	39.753	0.000	3.62e+05	4e+05
C(zipcode)[T.98034]	1.966e+05	8827.053	22.277	0.000	1.79e+05	2.14e+05
C(zipcode)[T.98038]	3.113e+04	8686.068	3.584	0.000	1.41e+04	4.82e+04
C(zipcode)[T.98039]	7.727e+05	4.09e+04	18.900	0.000	6.93e+05	8.53e+05
C(zipcode)[T.98040]	4.959e+05	1.37e+04	36.144	0.000	4.69e+05	5.23e+05
C(zipcode)[T.98042]	2.313e+04	9058.715	2.553	0.011	5372.175	4.09e+04

C(zipcode)[T.98045]	1.039e+05	1.47e+04	7.090	0.000	7.52e+04	1.33e+05
C(zipcode)[T.98052]	2.617e+05	8974.764	29.158	0.000	2.44e+05	2.79e+05
C(zipcode)[T.98053]	2.593e+05	1.02e+04	25.526	0.000	2.39e+05	2.79e+05
C(zipcode)[T.98055]	6.24e+04	1.01e+04	6.187	0.000	4.26e+04	8.22e+04
C(zipcode)[T.98056]	1.284e+05	9293.634	13.814	0.000	1.1e+05	1.47e+05
C(zipcode)[T.98058]	4.18e+04	9278.424	4.506	0.000	2.36e+04	6e+04
C(zipcode)[T.98059]	9.91e+04	9680.914	10.237	0.000	8.01e+04	1.18e+05
C(zipcode)[T.98065]	1.366e+05	9873.457	13.839	0.000	1.17e+05	1.56e+05
C(zipcode)[T.98070]	2.178e+05	3.83e+04	5.684	0.000	1.43e+05	2.93e+05
C(zipcode)[T.98072]	1.553e+05	1.32e+04	11.779	0.000	1.29e+05	1.81e+05
C(zipcode)[T.98074]	2.289e+05	1.03e+04	22.321	0.000	2.09e+05	2.49e+05
C(zipcode)[T.98075]	2.562e+05	1.14e+04	22.428	0.000	2.34e+05	2.79e+05
C(zipcode)[T.98077]	1.958e+05	2.94e+04	6.670	0.000	1.38e+05	2.53e+05
C(zipcode)[T.98092]	-2.162e+04	1.01e+04	-2.141	0.032	-4.14e+04	-1823.879
C(zipcode)[T.98102]	4.568e+05	1.32e+04	34.676	0.000	4.31e+05	4.83e+05
C(zipcode)[T.98103]	3.563e+05	8381.081	42.511	0.000	3.4e+05	3.73e+05
C(zipcode)[T.98105]	4.529e+05	1.04e+04	43.502	0.000	4.33e+05	4.73e+05
C(zipcode)[T.98106]	1.529e+05	9394.093	16.273	0.000	1.34e+05	1.71e+05
C(zipcode)[T.98107]	3.46e+05	9727.831	35.569	0.000	3.27e+05	3.65e+05
C(zipcode)[T.98108]	1.432e+05	1.06e+04	13.448	0.000	1.22e+05	1.64e+05
C(zipcode)[T.98109]	4.861e+05	1.29e+04	37.791	0.000	4.61e+05	5.11e+05
C(zipcode)[T.98112]	5.221e+05	1.02e+04	51.053	0.000	5.02e+05	5.42e+05
C(zipcode)[T.98115]	3.574e+05	8433.391	42.374	0.000	3.41e+05	3.74e+05
C(zipcode)[T.98116]	3.401e+05	9326.051	36.469	0.000	3.22e+05	3.58e+05
C(zipcode)[T.98117]	3.505e+05	8492.311	41.278	0.000	3.34e+05	3.67e+05
C(zipcode)[T.98118]	2.031e+05	8627.299	23.542	0.000	1.86e+05	2.2e+05
C(zipcode)[T.98119]	4.721e+05	1.09e+04	43.368	0.000	4.51e+05	4.93e+05
C(zipcode)[T.98122]	3.463e+05	9578.762	36.153	0.000	3.28e+05	3.65e+05
C(zipcode)[T.98125]	2.214e+05	9086.817	24.363	0.000	2.04e+05	2.39e+05
C(zipcode)[T.98126]	2.429e+05	9151.685	26.537	0.000	2.25e+05	2.61e+05
C(zipcode)[T.98133]	1.795e+05	8766.169	20.479	0.000	1.62e+05	1.97e+05
C(zipcode)[T.98136]	2.958e+05	9832.800	30.085	0.000	2.77e+05	3.15e+05
C(zipcode)[T.98144]	2.885e+05	9244.885	31.202	0.000	2.7e+05	3.07e+05
C(zipcode)[T.98146]	1.523e+05	1.01e+04	15.115	0.000	1.33e+05	1.72e+05
C(zipcode)[T.98148]	8.49e+04	1.71e+04	4.969	0.000	5.14e+04	1.18e+05
C(zipcode)[T.98155]	1.762e+05	9384.587	18.779	0.000	1.58e+05	1.95e+05
C(zipcode)[T.98166]	1.338e+05	1.19e+04	11.222	0.000	1.1e+05	1.57e+05
C(zipcode)[T.98168]	9.239e+04	1.07e+04	8.611	0.000	7.14e+04	1.13e+05
C(zipcode)[T.98177]	2.499e+05	1.07e+04	23.277	0.000	2.29e+05	2.71e+05
C(zipcode)[T.98178]	9.114e+04	1.02e+04	8.949	0.000	7.12e+04	1.11e+05

C(zipcode)[T.98188]	6.384e+04	1.29e+04	4.951	0.000	3.86e+04	8.91e+04
C(zipcode)[T.98198]	6.585e+04	1.03e+04	6.382	0.000	4.56e+04	8.61e+04
C(zipcode)[T.98199]	4.074e+05	9532.378	42.741	0.000	3.89e+05	4.26e+05
grade_sc	4.668e+04	1267.898	36.818	0.000	4.42e+04	4.92e+04
sqft_living_sc	7.548e+04	1357.667	55.597	0.000	7.28e+04	7.81e+04
sqft_living15_sc	2.532e+04	1362.295	18.584	0.000	2.26e+04	2.8e+04

Omnibus:	4323.067	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	22074.428
Skew:	1.270	**Prob(JB):**	0.00
Kurtosis:	8.301	**Cond. No.**	108.

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

Validate Model using theTrain-Test- Split

In [109]:

```
from sklearn.model_selection import train_test_split
X = df.drop('price', axis=1)
y = df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42
```

In [110]:

```
df_train = pd.DataFrame(X_train, columns = X.columns)
df_train['price'] = y_train
df_test = pd.DataFrame(X_test, columns = X.columns)
df_test['price'] = y_test
```

In [111]:

```
from sklearn.metrics import r2_score
y_hat_test = model.predict(df_test)
r2_score(y_test, y_hat_test)
```

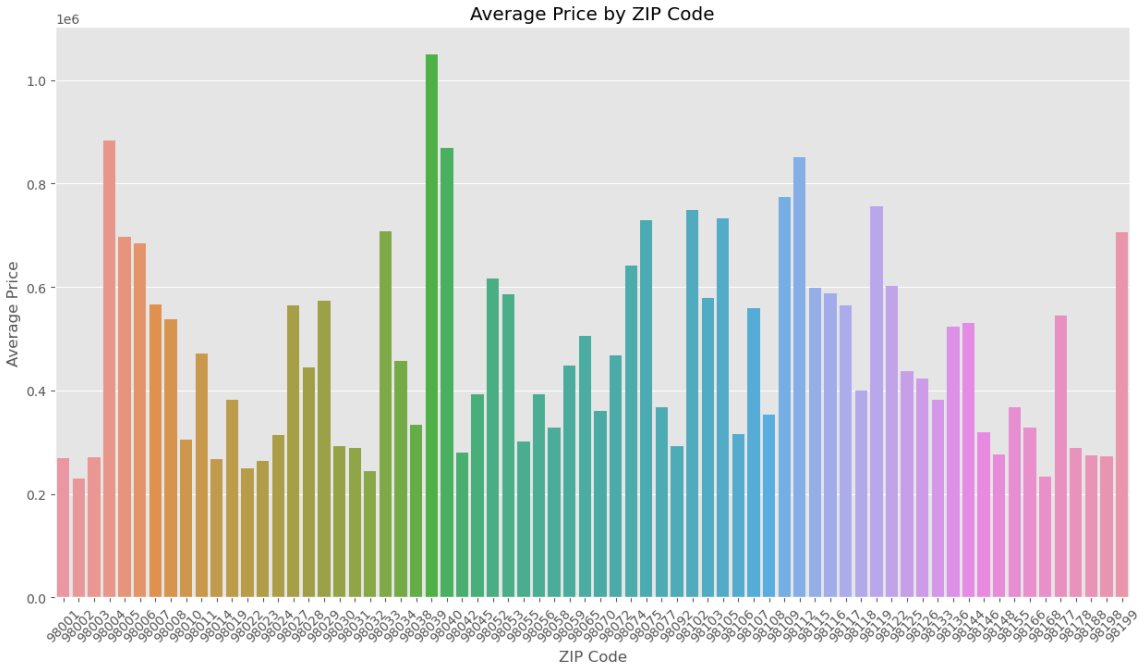
Out[111]:

```
0.768252174841723
```

Visual data to figure out the average price per zip codes

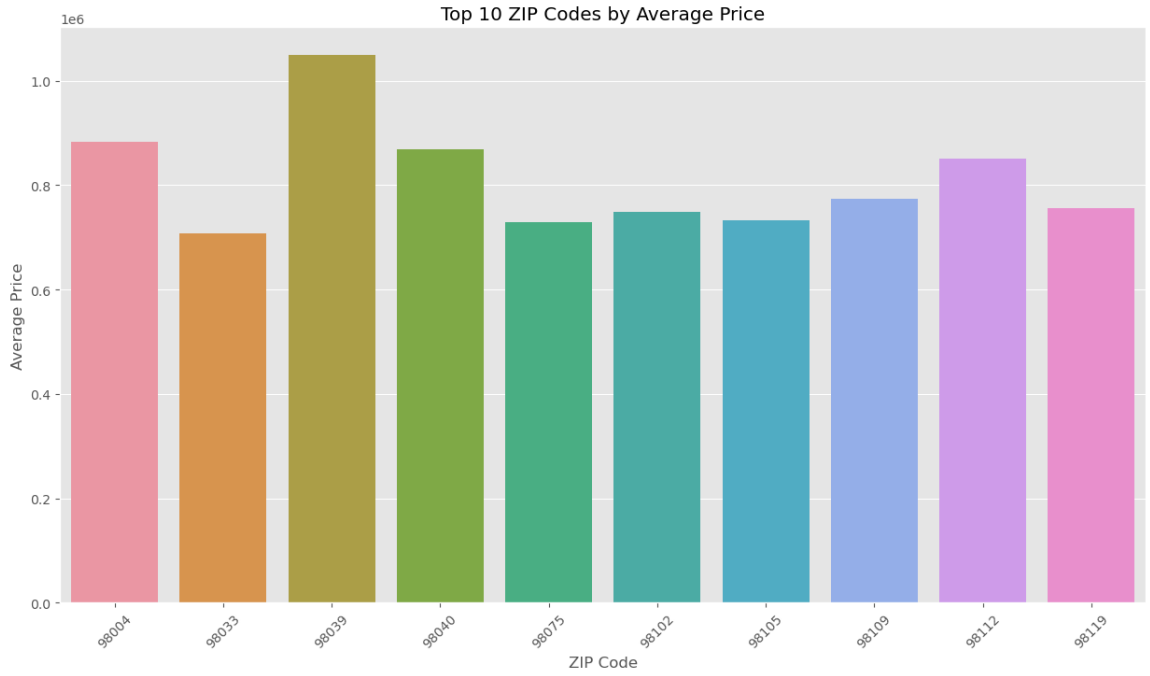
In [112]:

```
plt.figure(figsize=(15, 8))
sns.barplot(x='zipcode', y='price', data=df, errorbar=None)
plt.xticks(rotation=45)
plt.xlabel('ZIP Code')
plt.ylabel('Average Price')
plt.title('Average Price by ZIP Code')
plt.show()
```



In [113]:

```
# Calculate the average price for each ZIP code
avg_price_per_zip = df.groupby('zipcode')['price'].mean().reset_index()

# Sort ZIP codes by average price in descending order and take top 10
top_10_zip = avg_price_per_zip.sort_values('price', ascending=False).head(10)

# Plotting
plt.figure(figsize=(15, 8))
sns.barplot(x='zipcode', y='price', data=top_10_zip, errorbar=None)
plt.xticks(rotation=45)
plt.xlabel('ZIP Code')
plt.ylabel('Average Price')
plt.title('Top 10 ZIP Codes by Average Price')
plt.show()
```



Analysis Summary:

Upon conducting multiple regression analyses, the fifth model demonstrated a robust R-squared value of 0.775, signifying that approximately 78% of the variability in home prices within King County can be explained by the predictors in the model. Notably, the postal code emerged as one of the most significant determinants influencing property valuation. Additional variables that were positively correlated with property prices include:

- Living Space Square Footage
- Building Grade, as per the King County Grading System
- Average Interior Square Footage of the Nearest 15 Residences

Strategic Recommendations for a Pro Home Builder Company:

To optimize the profitability and marketability of residential properties in King County, the following strategies are recommended:

- Strategic Location Selection: Prioritize property acquisition in high-value zip codes to benefit from the area's intrinsically higher property valuations.
- Optimize Living Space: Expand the square footage of the living area to align with the positive correlation observed between living space and property value.
- Quality of Construction: Employ premium-quality building materials and construction techniques to secure the highest possible building grade according to the King County Grading System. This will not only enhance the property's intrinsic value but also its appeal to potential buyers.
- Neighborhood Composition: Opt for land parcels where the surrounding 15 residences have a higher average interior square footage. This is indicative of a neighborhood's overall property value and can positively influence the value of the new development.

By implementing these targeted strategies, housing development firms can substantially increase