Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Data understanding

In [1]:

```
# Importing relevant libraries
import pandas as pd
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
import seaborn as sns
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
import statsmodels.api as sm
from sklearn.metrics import r2_score, mean_squared_error
import folium
from datetime import datetime
pd.options.display.float_format = '{:.2f}'.format
```

Loading the Dataset

In [2]:

```
kc_data= pd.read_csv('data/kc_house_data.csv')
kc_data.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wate
0	7129300520	10/13/2014	221900.00	3	1.00	1180	5650	1.00	
1	6414100192	12/9/2014	538000.00	3	2.25	2570	7242	2.00	
2	5631500400	2/25/2015	180000.00	2	1.00	770	10000	1.00	
3	2487200875	12/9/2014	604000.00	4	3.00	1960	5000	1.00	
4	1954400510	2/18/2015	510000.00	3	2.00	1680	8080	1.00	

5 rows × 21 columns

In [3]:

```
#getting basic information about the data
kc_data.info()
```

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

The dataset has 21 columns:

- 6 categorical and 15 numerical columns.
- It has as a total of 21597 rows, the columns with a non null count of less than 21597 show existence of some missing values

In [4]:

```
#getting general summary statistics  on the data
kc_data.describe()
```

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sq
count	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	
mean	4580474287.77	540296.57	3.37	2.12	2080.32	15099.41	1.49	
std	2876735715.75	367368.14	0.93	0.77	918.11	41412.64	0.54	
min	1000102.00	78000.00	1.00	0.50	370.00	520.00	1.00	
25%	2123049175.00	322000.00	3.00	1.75	1430.00	5040.00	1.00	
50%	3904930410.00	450000.00	3.00	2.25	1910.00	7618.00	1.50	
75%	7308900490.00	645000.00	4.00	2.50	2550.00	10685.00	2.00	
max	9900000190.00	7700000.00	33.00	8.00	13540.00	1651359.00	3.50	

Data Pre-processing

Involves manipulation, dropping or cleaning of data before it is used in order to ensure or enhance performance.

Identifying and dealing with missing values

In [5]:

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

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

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

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

    return missing


missing_data = missing_values(kc_data)
missing_data
```

Out[5]:

	Missing Values	Percentage(%)
yr_renovated	3842	0.18
waterfront	2376	0.11
view	63	0.00

- The threshold on how to deal with missing values commonly used is 50% and also depends on the specific column. The percentages of missing values are very low for the specific columns so we can replace.
- The percentage of the missing values for waterfront column(11.00%), view column(0.29%) and year renovated column(17.70%) are less than 50% , so we can replace them.
- Checking the year renovated column we may assume the missing value is because the house was never renovated, maybe the house did not have a view or a waterfront also for the other two columns hence we can Fill them with zeros.
- Since the missing values in the 3 columns are categorical and are a small percentage of the columns, replacing them with mode won`t skew the data nor give false conclusions

In [6]:

```
def filling_missing_values(data, columns):
    missing = missing_values(data) # store the output of missing_values function
    for col in columns:
        if col in missing.index: # check if column has missing values
            data[col] = data[col].fillna(data[col].mode()[0]) # fill missing values
    return data
filling_missing_values(kc_data, ['waterfront','yr_renovated','view'])

kc_data.isna().sum()
```

Out[6]:

```
id               0
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
```

Duplicates

In [7]:

```
def check_duplicates(data):
    """
    A simple function to check for duplicates in a given dataset.
    """
    duplicates = data.duplicated().sum()
    return duplicates
check_duplicates(kc_data)
```

Out[7]:

```
0
```

There are no duplicates in the data.

Checking duplicated id

In [8]:

```
duplicates_id = kc_data[kc_data.duplicated(subset=['id'], keep=False)]
duplicates_id
```

Out[8]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
93	6021501535	7/25/2014	430000.00	3	1.50	1580	5000	1.00
94	6021501535	12/23/2014	700000.00	3	1.50	1580	5000	1.00
313	4139480200	6/18/2014	1380000.00	4	3.25	4290	12103	1.00
314	4139480200	12/9/2014	1400000.00	4	3.25	4290	12103	1.00
324	7520000520	9/5/2014	232000.00	2	1.00	1240	12092	1.00
...	...	...	...	...	...	...	...	...
20654	8564860270	3/30/2015	502000.00	4	2.50	2680	5539	2.00
20763	6300000226	6/26/2014	240000.00	4	1.00	1200	2171	1.50
20764	6300000226	5/4/2015	380000.00	4	1.00	1200	2171	1.50
21564	7853420110	10/3/2014	594866.00	3	3.00	2780	6000	2.00
21565	7853420110	5/4/2015	625000.00	3	3.00	2780	6000	2.00

353 rows × 21 columns

- The id column shows the unique identifier for a house.
- While there are duplicated ids of a house the prices and dates (of sale) of the house were different- hence why there were no duplicated rows- meaning the duplicated ids represent a house that was sold multiple times

Data inconsistencies

In [9]:

```
def print_value_counts(df):
    for column in df.columns:
        # Print the column name
        print("Value counts for {} column:".format(column))
        # Print the value counts for the column
        print(df[column].value_counts())
        # Add a separator for clarity
        print("="*30)

print_value_counts(kc_data)
```

```
Value counts for id column:
795000620     3
8910500150    2
7409700215    2
1995200200    2
9211500620    2
             ..
3649100387    1
2767603649    1
1446403617    1
5602000275    1
1523300157    1
Name: id, Length: 21420, dtype: int64
==============================
Value counts for date column:
6/23/2014    142
6/25/2014    131
6/26/2014    131
7/8/2014     127
```

In [10]:

```
def find_inconsistent_data(df):
    # Identify potential data inconsistencies
    inconsistent_bedrooms = df[(df['bedrooms'] == 10) | (df['bedrooms'] == 11) | (d
    inconsistent_bathrooms = df[(df['bathrooms'] == 7) | (df['bathrooms'] == 8)]

    # Concatenate the inconsistent data into a single DataFrame
    inconsistent_data = pd.concat([inconsistent_bedrooms, inconsistent_bathrooms])
inconsistent_data = find_inconsistent_data(kc_data)
inconsistent_data
```

The square foot basement column has a placeholder value,?.

In [11]:

```
def place_holders(data, column):
    inconsistent = data[data[column] == '?']
    data[column].replace('?', 0.0, regex=False, inplace=True)

place_holders(kc_data, 'sqft_basement')
```

- When the number of bedrooms is greater than 10, the value in the sqft_living and sqft_lot a too little to match to that record meaning there is most likely an error in data entry. Therefore it`s best drop that column
- It has 454 placeholder values, dropping the would mean loss of valuable data in the other columns

- The placeholder would have most likely have been used to show that the house has no basement, we can therefore replace these placeholder values with the mode ie 0
- The placeholder values constitute 2% of the column so imputing the data won't skew the data
- We noticed that sqft_basement feature was categorica (object type) instead of numerical so we have to change it

In [12]:

```
#changing the data type of the column because it contains numerical values
kc_data['sqft_basement']=kc_data['sqft_basement'].astype(float)
```

Outliers

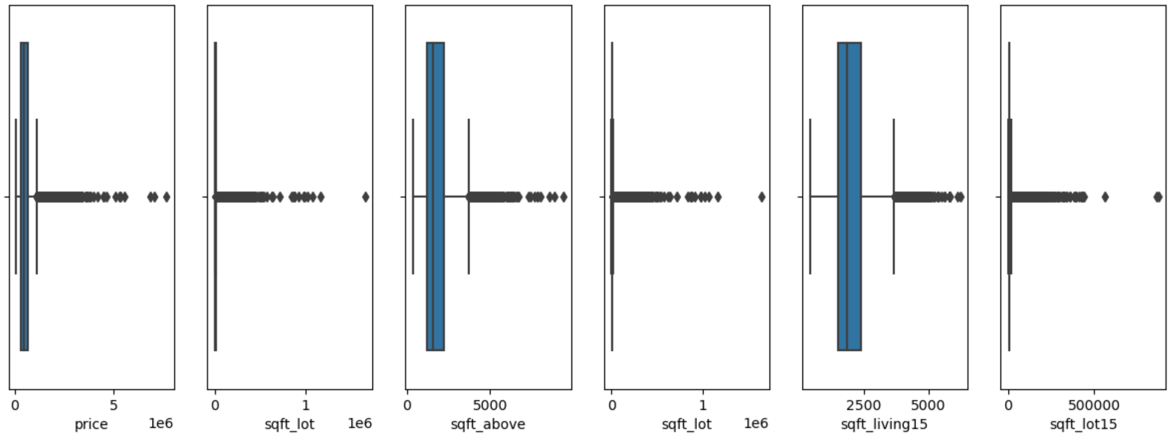
In [13]:

```
def check_outliers(data, columns):
    fig, axes = plt.subplots(nrows=1, ncols=len(columns), figsize=(15,5))
    for i, column in enumerate(columns):
        # Use interquartile range (IQR) to find outliers for the specified column
        q1 = data[column].quantile(0.25)
        q3 = data[column].quantile(0.75)
        iqr = q3 - q1
        print("IQR for {} column: {}".format(column, iqr))

        # Determine the outliers based on the IQR
        outliers = (data[column] < q1 - 1.5 * iqr) | (data[column] > q3 + 1.5 * iqr
        print("Number of outliers in {} column: {}".format(column, outliers.sum()))

        # Create a box plot to visualize the distribution of the specified column
        sns.boxplot(data=data, x=column, ax=axes[i])
    plt.show()
```

In [14]:

```
check_outliers(kc_data, ['price', 'sqft_lot', 'sqft_above','sqft_lot','sqft_living1
```

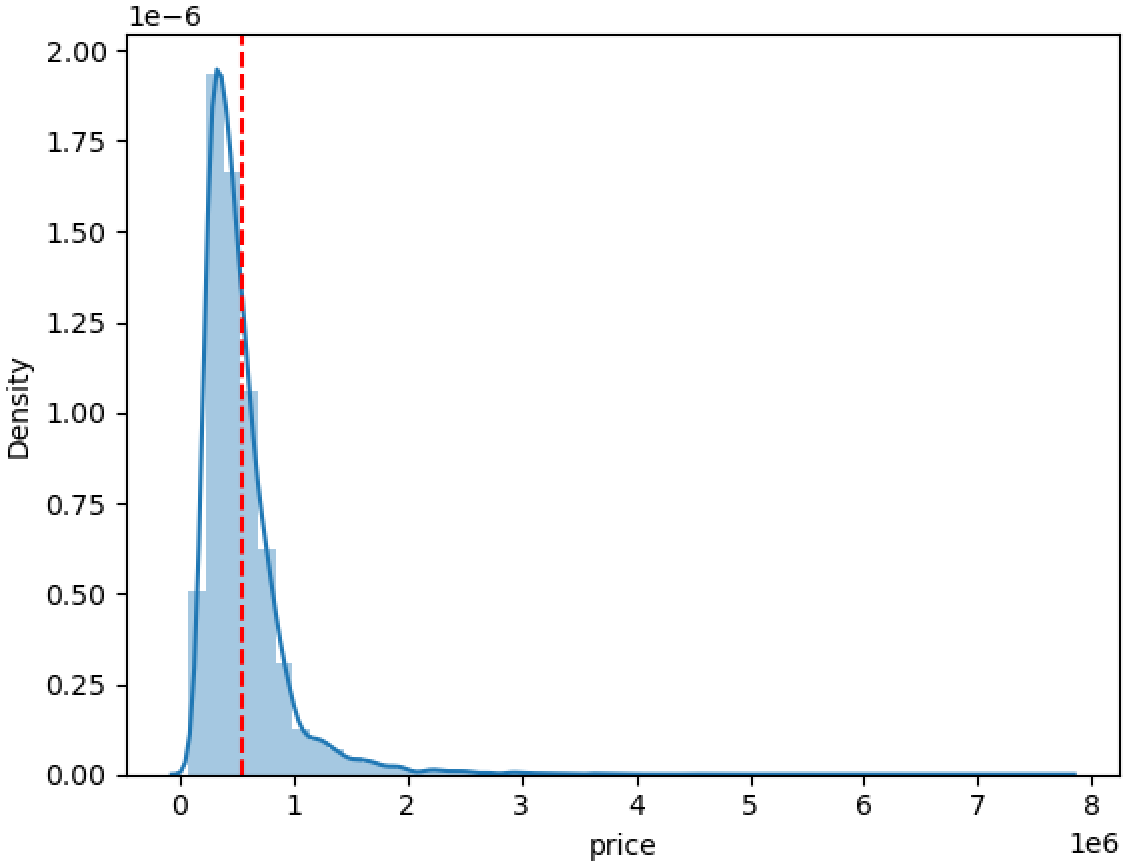
```
IQR for price column: 323000.0
Number of outliers in price column: 1158
IQR for sqft_lot column: 5645.0
Number of outliers in sqft_lot column: 2419
IQR for sqft_above column: 1020.0
Number of outliers in sqft_above column: 610
IQR for sqft_lot column: 5645.0
Number of outliers in sqft_lot column: 2419
IQR for sqft_living15 column: 870.0
Number of outliers in sqft_living15 column: 543
IQR for sqft_lot15 column: 4983.0
Number of outliers in sqft_lot15 column: 2188
```



In [15]:

```
sns.distplot(kc_data['price'])
mean = kc_data['price'].mean()
plt.axvline(x=mean, color='r', linestyle='--')
plt.show()
```

```
/home/pk/anaconda3/lib/python3.9/site-packages/seaborn/distributions.p
y:2619: FutureWarning: `distplot` is a deprecated function and will be
removed in a future version. Please adapt your code to use either `dis
plot` (a figure-level function with similar flexibility) or `histplot`
(an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



The data has outliers but we cannot eliminate the outliers because they actually provide valuable information

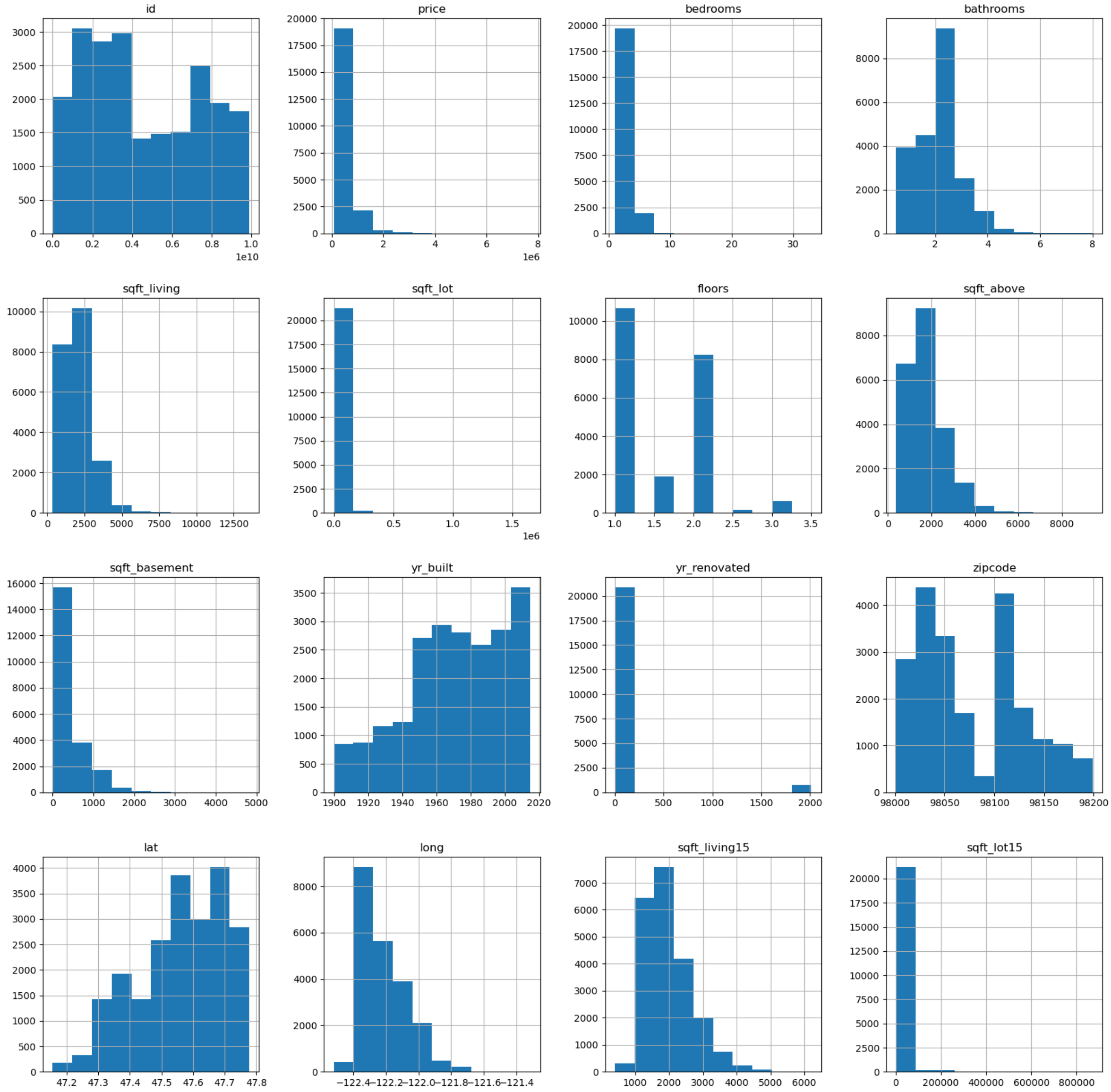
Exploratory Data Analysis

Univariate EDA

Checking for the distribution of individual columns

In [16]:

```
kc_data.hist(figsize=(20,20));
```

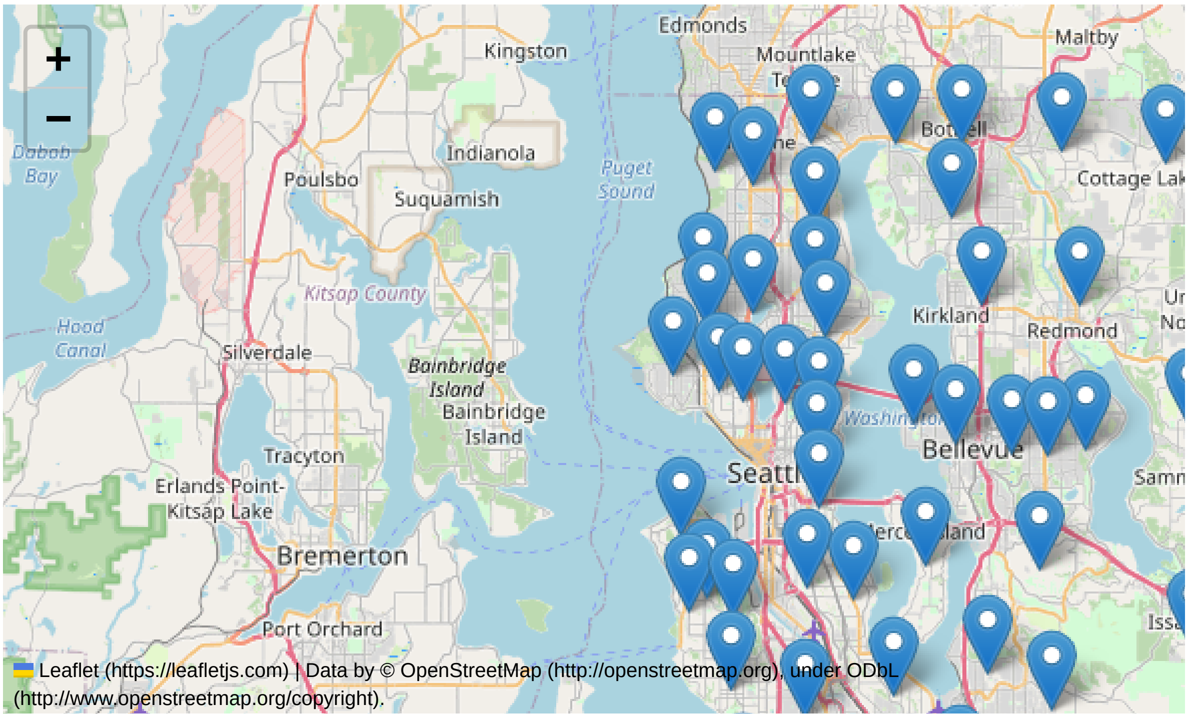


Checking for the location of our house sales

In [17]:

```
# Group the data by zipcode and calculate the mean latitude and longitude
zipcode_data = kc_data.groupby('zipcode').agg({'lat': 'mean', 'long': 'mean'}).rese

# Create a map centered at the mean latitude and longitude of all the zipcodes
m = folium.Map(location=[kc_data['lat'].mean(), kc_data['long'].mean()], zoom_start

# Add markers for each zipcode
for _, row in zipcode_data.iterrows():
    folium.Marker(location=[row['lat'], row['long']], popup=row['zipcode']).add_to(

# Display the map
m
```

Out[17]:

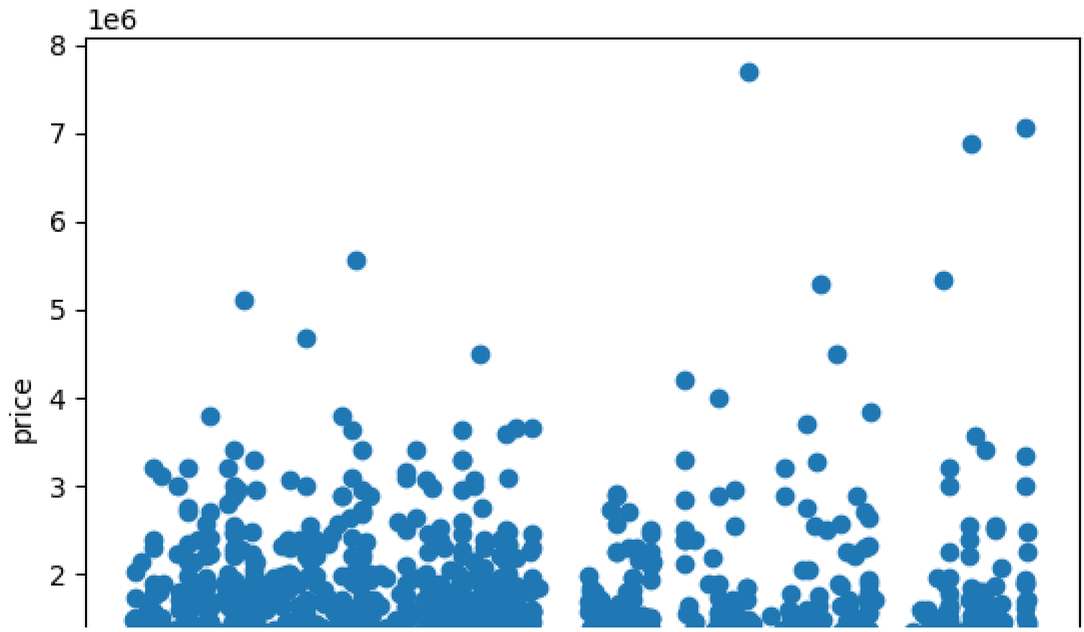


Bivariate EDA

- Checking for the relationship between variables.
- Our bivariate EDA involves checking for relationship between various features and the price

In [18]:

```
specific_col = 'price'
for col in kc_data.columns:
    if col != specific_col:
        plt.scatter(kc_data[col], kc_data[specific_col])
        plt.xlabel(col)
        plt.ylabel(specific_col)
        plt.show()
```



From the above visualizations we can see that the following features have the most linear relationship with price

- sqft_living
- sqft_above
- sqft_living15
- sqft_basement

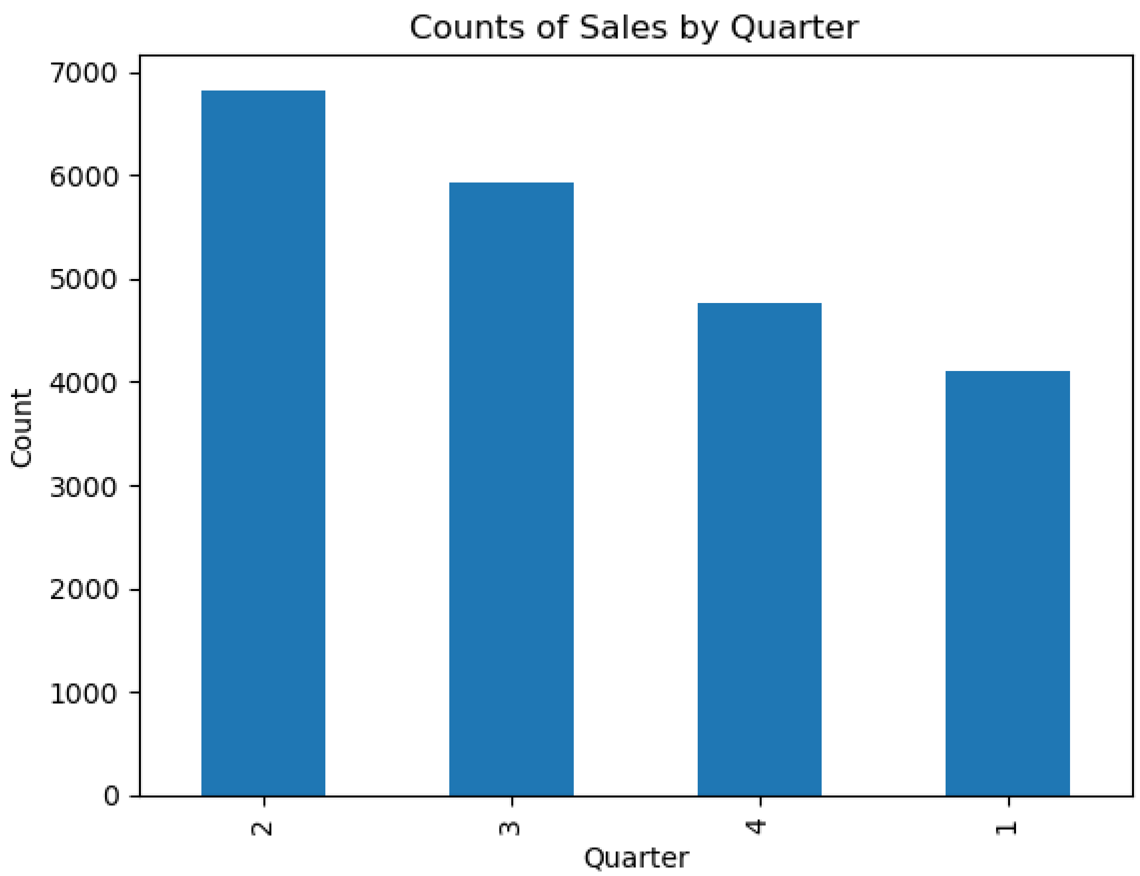
What is the peak and low seasons for house sales?

In [19]:

```
kc_quarter =kc_data.copy()
```

In [20]:

```
def plot_quarter_counts(data):
    dates = pd.to_datetime(data['date'], format='%m/%d/%Y')
    dates_column = dates.dt.quarter
    # get the counts for each quarter
    quarter_counts = dates_column.value_counts()
    quarter_counts.plot.bar()
    # plot a bar chart of the quarter counts
    plt.title('Counts of Sales by Quarter')
    plt.xlabel('Quarter')
    plt.ylabel('Count')
    plt.show()

plot_quarter_counts(kc_quarter)
```



We can see that:

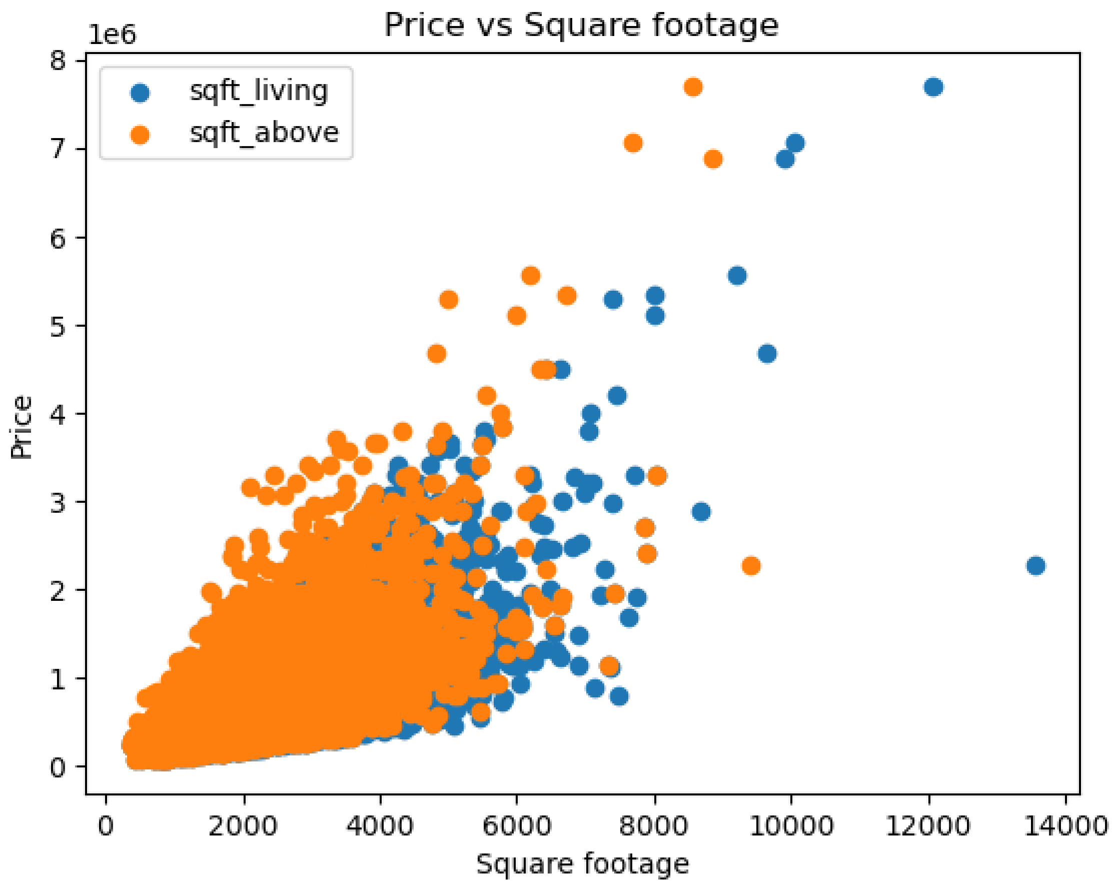
- The highest number of house sales are made in the second quarter of the year (Q2: April 1 - June 30) which fall in the Spring season
- The lowest number of house sales are made in the first quarter of the year (Q1: January 1 - March 31) which fall mostly in the Winter season

Multivariate Visualizations

We took the features with the most linear relationship to the price and then visualize them together

In [21]:

```
plt.scatter(kc_data['sqft_living'], kc_data['price'], label='sqft_living')
plt.scatter(kc_data['sqft_above'], kc_data['price'], label='sqft_above')
plt.xlabel('Square footage')
plt.ylabel('Price')
plt.title('Price vs Square footage')
plt.legend()
plt.show()
```



The data points of sqft_living and sqft_above lie close together and they show a strong positive linear relationship with the price

In [22]:

```
plt.scatter(kc_data['sqft_living'], kc_data['price'], label='sqft_living')
plt.scatter(kc_data['sqft_above'], kc_data['price'], label='sqft_above')
plt.scatter(kc_data['sqft_living15'], kc_data['price'], label='sqft_living15')
plt.scatter(kc_data['sqft_basement'], kc_data['price'], label='sqft_basement')
plt.xlabel('Square footage')
plt.ylabel('Price')
plt.title('Price vs Square footage')
plt.legend()
plt.show()
```

The data points of sqft_living, sqft_above, sqft_living15 and sqft_basement lie close together and they show a strong positive linear relationship with the price

Feature Engineering

Extracting the year from date sold

In [23]:

```
#converting date column from categorical (object) to numerical (int64)
kc_data['date'] = pd.to_datetime(kc_data['date'], format='%m/%d/%Y')
#Extract the year and create a new column
kc_data['year'] = kc_data['date'].dt.year
kc_data.drop('date', axis=1, inplace=True)
```

Creating a new column named Age

The date (year) of the sale and the year built can be used to obtain the age of the house

In [24]:

```
#creating new column age
kc_data['age']= kc_data['year']-kc_data['yr_built']
kc_data['age']
```

Out[24]:

```
0        59
1        63
2        82
3        49
4        28
         ..
21592     5
21593     1
21594     5
21595    11
21596     6
Name: age, Length: 21597, dtype: int64
```

- Since we have obtained the age of the house we can drop the year and yr_built columns.
- We drop the id of the house since it`s not in the modelling

In [25]:

```
#dropping the columns year, yr_built, id
kc_data.drop(['year','yr_built', 'id'],axis=1, inplace=True )
```

In [26]:

```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64  
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64  
 4   sqft_lot       21597 non-null  int64  
 5   floors         21597 non-null  float64
 6   waterfront     21597 non-null  object 
 7   view           21597 non-null  object 
 8   condition      21597 non-null  object 
 9   grade          21597 non-null  object 
 10  sqft_above     21597 non-null  int64  
 11  sqft_basement  21597 non-null  float64
 12  yr_renovated   21597 non-null  float64
 13  zipcode        21597 non-null  int64  
 14  lat            21597 non-null  float64
 15  long           21597 non-null  float64
 16  sqft_living15  21597 non-null  int64  
 17  sqft_lot15     21597 non-null  int64  
 18  age            21597 non-null  int64  
dtypes: float64(7), int64(8), object(4)
memory usage: 3.1+ MB
```

In [27]:

```
kc_data.describe()
```

Out[27]:

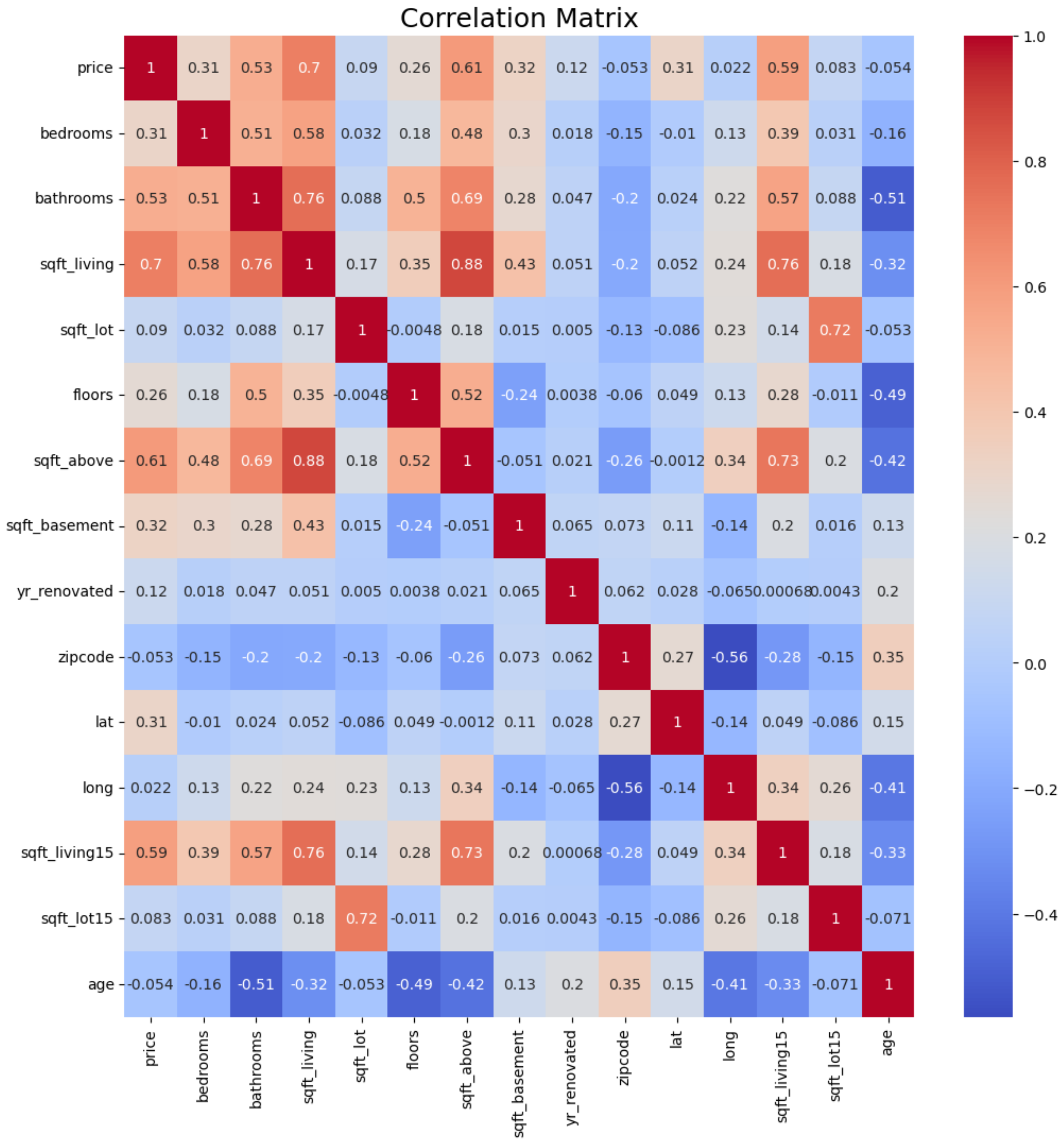
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_b
count	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	
mean	540296.57	3.37	2.12	2080.32	15099.41	1.49	1788.60	
std	367368.14	0.93	0.77	918.11	41412.64	0.54	827.76	
min	78000.00	1.00	0.50	370.00	520.00	1.00	370.00	
25%	322000.00	3.00	1.75	1430.00	5040.00	1.00	1190.00	
50%	450000.00	3.00	2.25	1910.00	7618.00	1.50	1560.00	
75%	645000.00	4.00	2.50	2550.00	10685.00	2.00	2210.00	
max	7700000.00	33.00	8.00	13540.00	1651359.00	3.50	9410.00	

The data doesn't have missing values, duplicates or placeholder values and all the columns are in their correct datatypes

Correlations

In [28]:

```
corr_matrix = kc_data.corr()
fig, ax = plt.subplots(figsize=(12,12))   # Set the figure size to 12 inches by 12
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', ax=ax)
plt.title('Correlation Matrix', fontsize=18)
plt.show()
```



Multicollinearity

How does each independent variable relate with the other

In [29]:

```
df=kc_data.corr().abs().stack().reset_index().sort_values(0, ascending=False)

# zip the variable name columns (Which were only named level_0 and level_1 by defau
df['pairs'] = list(zip(df.level_0, df.level_1))

# set index to pairs
df.set_index(['pairs'], inplace = True)

#d rop level columns
df.drop(columns=['level_1', 'level_0'], inplace = True)

# rename correlation column as cc rather than 0
df.columns = ['cc']

# drop duplicates. This could be dangerous i
df[(df.cc>.75) & (df.cc <1)]
```

Out[29]:

pairs	cc
(sqft_above, sqft_living)	0.88
(sqft_living, sqft_above)	0.88
(sqft_living15, sqft_living)	0.76
(sqft_living, sqft_living15)	0.76
(bathrooms, sqft_living)	0.76
(sqft_living, bathrooms)	0.76

- The above pairs are the most highly collerated to each other.
- Therefore adding all those variables will bring about multicollinearity in the model so we will drop some of them.

In [30]:

```
kc_data.drop(['sqft_above', 'sqft_living15', 'bathrooms'], axis=1, inplace=True)
```

In [31]:

```
kc_data.drop(['lat', 'long', 'zipcode'], axis=1, inplace=True)
```

One hot encoding

In [32]:

```
kc_data['yr_renovated']= kc_data['yr_renovated'].apply(lambda x: 1 if x>0 else 0 )
kc_data['yr_renovated'].value_counts()
```

Out[32]:

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

In [33]:

```
#one hot encoding waterfront,view and condition
kc_transform = pd.get_dummies(kc_data, columns=["waterfront",'view','condition'])
kc_transform = kc_transform.drop(["condition_Poor",'view_NONE','waterfront_NO'], ax
kc_transform
```

Out[33]:

	price	bedrooms	sqft_living	sqft_lot	floors	grade	sqft_basement	yr_renovated
0	221900.00	3	1180	5650	1.00	7 Average	0.00	0
1	538000.00	3	2570	7242	2.00	7 Average	400.00	1
2	180000.00	2	770	10000	1.00	6 Low Average	0.00	0
3	604000.00	4	1960	5000	1.00	7 Average	910.00	0
4	510000.00	3	1680	8080	1.00	8 Good	0.00	0
...	...	...	...	...	...	...	...	...
21592	360000.00	3	1530	1131	3.00	8 Good	0.00	0
21593	400000.00	4	2310	5813	2.00	8 Good	0.00	0
21594	402101.00	2	1020	1350	2.00	7 Average	0.00	0
21595	400000.00	3	1600	2388	2.00	8 Good	0.00	0
21596	325000.00	2	1020	1076	2.00	7 Average	0.00	0

21597 rows × 19 columns

The reference categories for view will be None, for waterfront will be No and for condition will be poor condition

Label Encoding

In [34]:

```
#Convert grade column to numeric using label encoding
label_encoder = LabelEncoder()
kc_transform['grade'] = label_encoder.fit_transform(kc_transform['grade'])
kc_transform['grade'].value_counts()
```

Out[34]:

```
8     8974
9     6065
10    2615
7     2038
0     1134
1      399
6      242
2       89
5       27
3       13
4        1
Name: grade, dtype: int64
```

In [35]:

```
kc_transform.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   price               21597 non-null  float64
 1   bedrooms            21597 non-null  int64  
 2   sqft_living         21597 non-null  int64  
 3   sqft_lot            21597 non-null  int64  
 4   floors              21597 non-null  float64
 5   grade               21597 non-null  int64  
 6   sqft_basement       21597 non-null  float64
 7   yr_renovated        21597 non-null  int64  
 8   sqft_lot15          21597 non-null  int64  
 9   age                 21597 non-null  int64  
 10  waterfront_YES      21597 non-null  uint8  
 11  view_AVERAGE        21597 non-null  uint8  
 12  view_EXCELLENT      21597 non-null  uint8  
 13  view_FAIR           21597 non-null  uint8  
 14  view_GOOD           21597 non-null  uint8  
 15  condition_Average   21597 non-null  uint8  
 16  condition_Fair      21597 non-null  uint8  
 17  condition_Good      21597 non-null  uint8  
 18  condition_Very Good  21597 non-null  uint8  
dtypes: float64(3), int64(7), uint8(9)
memory usage: 1.8 MB
```

In [36]:

```
kc_transform.corr()['price'].sort_values(ascending=False)
```

Out[36]:

```
price                1.00
sqft_living          0.70
sqft_basement        0.32
bedrooms             0.31
view_EXCELLENT       0.30
waterfront_YES       0.26
floors               0.26
view_GOOD            0.18
view_AVERAGE         0.15
yr_renovated         0.12
view_FAIR            0.09
sqft_lot             0.09
sqft_lot15           0.08
condition_Very Good  0.06
condition_Average    0.01
condition_Good      -0.03
condition_Fair      -0.05
age                 -0.05
grade               -0.37
Name: price, dtype: float64
```

- Sqft_living has the strongest positive correlation with price
- Sqft_basement, bedrooms and view_EXCELLENT has low positive correlation with price
- Grade, Age and condition have weak negative correlation

Linear Regression

The first model will be that of price and the variable that is highly correlated to it

- We will use an `alpha` of `0.05`
- We used forward filling to determine the best model

We choose to use RMSE as our error based metric because:

- RMSE gives more weight to larger errors than smaller errors.
- RMSE is more sensitive to outliers than other metrics such as MAE
- It is commonly used to compare different models and choose the best performing one.

Baseline model

In [37]:

```
#baseline model
X= kc_transform[['sqft_living']]
y=kc_transform['price']
model=sm.OLS(y, sm.add_constant(X))
results=model.fit()
results.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	13:36:40	**Log-Likelihood:**	-3.0006e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21595	**BIC:**	6.001e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-4.399e+04	4410.023	-9.975	0.000	-5.26e+04	-3.53e+04
sqft_living	280.8630	1.939	144.819	0.000	277.062	284.664

Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [38]:

```
# fit the model
pred_model = LinearRegression()
pred_model.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 261655.00451904474
```

Interpretation

The baseline model is that of square foot living and price since square foot living has the highest correlation to price. The model is statistically significant since the F-statistic p-value is less than 0.05 and it explains 49.3% of the total variation of price.

- An increase of 1 square foot in the living area leads to a price increase of approximately 281.
- The model is off by 261656 in price.

Let's add more predictors to improve the accuracy of this model.

Multiple Linear Regression

In [39]:

```
X= kc_transform[['sqft_living','sqft_basement']]
y=kc_transform['price']
model=sm.OLS(y, sm.add_constant(X))
results=model.fit()
results.summary()
```

Out[39]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	1.051e+04
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	13:36:40	**Log-Likelihood:**	-3.0005e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21594	**BIC:**	6.001e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-4.106e+04	4453.261	-9.220	0.000	-4.98e+04	-3.23e+04
sqft_living	276.6134	2.146	128.920	0.000	272.408	280.819
sqft_basement	20.6946	4.479	4.620	0.000	11.916	29.474

Omnibus:	14754.603	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	538977.524
Skew:	2.807	**Prob(JB):**	0.00
Kurtosis:	26.821	**Cond. No.**	5.75e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.75e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [40]:

```
# fit the model
pred_model1 = LinearRegression()
pred_model1.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model1.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 261525.75896081686
```

Interpretation

- The model is that of square foot living , square foot basement and price.
- The model is statistically significant since the F-statistic p-value is less than 0.05
- The model explains 49.3% of the total variation of price same as the other model showing that adding the square foot basement doesn't improve the model.
- The two coefficients are statistically significant since their t-statistic p values are less than 0.05.
- The model is off by $261525inpricewhichhasreducedfromthepreviousmodel.$ $*Anincreaseof1squarefootinthelivingarealeadstoanincreaseofapproximately$ 276.6 in price.
- An increase of 1 square foot in the basement area leads to an increase of approximately $20.7 in price.

Let's add more predictors to improve the accuracy of this model.

In [41]:

```
X= kc_transform[['sqft_living','sqft_basement','bedrooms','view_EXCELLENT']]
y=kc_transform['price']
model=sm.OLS(y, sm.add_constant(X))
results=model.fit()
results.summary()
```

Out[41]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.539
Model:	OLS	**Adj. R-squared:**	0.539
Method:	Least Squares	**F-statistic:**	6321.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	13:36:41	**Log-Likelihood:**	-2.9902e+05
No. Observations:	21597	**AIC:**	5.980e+05
Df Residuals:	21592	**BIC:**	5.981e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	8.598e+04	6483.583	13.261	0.000	7.33e+04	9.87e+04
sqft_living	296.1099	2.424	122.160	0.000	291.359	300.861
sqft_basement	12.8491	4.298	2.989	0.003	4.424	21.274
bedrooms	-5.144e+04	2258.361	-22.776	0.000	-5.59e+04	-4.7e+04
view_EXCELLENT	5.55e+05	1.44e+04	38.499	0.000	5.27e+05	5.83e+05

Omnibus:	13478.282	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	464463.605
Skew:	2.466	**Prob(JB):**	0.00
Kurtosis:	25.177	**Cond. No.**	1.95e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.95e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [42]:

```
# fit the model
pred_model2 = LinearRegression()
pred_model2.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model2.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 249321.59062795973
```

Interpretation

- The model is that of square foot living , square foot basement, bedrooms, view_EXCELLENT and price.
- The model is statistically significant since the p-value is less than 0.05 and it explains 54% of the total variation of price which has improved from the previous models making our model more accurate.
- The coefficients are statistically significant since their pvalues are less than 0.05.
- The model is off by $249321 inpricewhichhasreducedfromthepreviousmodels. * Anincreaseof 1 squarefootinthelivingarealeadstoanincreaseofapproximately$ 296.11 in price.
- An increase of 1 square foot in the basement area leads to an increase of approximately $12.85 inprice. * Anincreaseof 1 bedroomleadstoandecreaseofapproximately$56090 in price.
- A house with an excellent view compared to that with no view leads to an increase of $552500 in price.

Let's add more predictors to improve the accuracy of this model.

In [43]:

```
X= kc_transform[['sqft_living','sqft_basement','bedrooms','view_EXCELLENT', 'waterf
y=kc_transform['price']
model=sm.OLS(y, sm.add_constant(X))
results=model.fit()
results.summary()
```

Out[43]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.550
Model:	OLS	**Adj. R-squared:**	0.550
Method:	Least Squares	**F-statistic:**	4394.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	13:36:41	**Log-Likelihood:**	-2.9877e+05
No. Observations:	21597	**AIC:**	5.976e+05
Df Residuals:	21590	**BIC:**	5.976e+05
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.564e+04	7399.575	8.871	0.000	5.11e+04	8.01e+04
sqft_living	288.7641	2.700	106.937	0.000	283.471	294.057
sqft_basement	23.3275	4.796	4.864	0.000	13.927	32.728
bedrooms	-4.946e+04	2234.583	-22.134	0.000	-5.38e+04	-4.51e+04
view_EXCELLENT	3.455e+05	1.72e+04	20.129	0.000	3.12e+05	3.79e+05
waterfront_YES	5.445e+05	2.49e+04	21.874	0.000	4.96e+05	5.93e+05
floors	1.697e+04	3756.029	4.519	0.000	9611.470	2.43e+04

Omnibus:	13080.999	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	416972.977
Skew:	2.384	**Prob(JB):**	0.00
Kurtosis:	23.991	**Cond. No.**	3.74e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.74e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [44]:

```
# fit the model
pred_model3 = LinearRegression()
pred_model3.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model3.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 246489.82517730806
```

Interpretation

- The model is that of square foot living , square foot basement, bedrooms, view_EXCELLENT, waterfront_yes ,floors and price.
- The model is statistically significant since the F-statistic p-value is less than 0.05 and it explains 55% of the total variation of price which has improved from the previous models making our model more accurate.
- The coefficients are statistically significant since their t-statistic p values are less than 0.05.
- The model is off by $246200 in price which has reduced from the previous models. * An increase of 1 square foot in the living area leads to an increase of approximately$ 288.76 in price.
- An increase of 1 square foot in the basement area leads to an increase of approximately $23.33 in price. * An increase of 1 bedroom leads to decrease of approximately$ 49460 in price.
- A house with an excellent view compared to that with no view leads to an increase of an $345500 in price. * A house on a waterfront compared to that not on a waterfront leads to an increase in 54 * An increase of one more floor in a house leads to an increase of$ 16970 in price.

Let's add more predictors to improve the accuracy of this model.

In [45]:

```
X= kc_transform[['sqft_living','sqft_basement','bedrooms','view_EXCELLENT',
                 'waterfront_YES','floors','grade','age','condition_Fair']]
y=kc_transform['price']
model=sm.OLS(y, sm.add_constant(X))
results=model.fit()
results.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.598
Model:	OLS	**Adj. R-squared:**	0.598
Method:	Least Squares	**F-statistic:**	3572.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	13:36:42	**Log-Likelihood:**	-2.9754e+05
No. Observations:	21597	**AIC:**	5.951e+05
Df Residuals:	21587	**BIC:**	5.952e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1290.9624	1.1e+04	-0.117	0.907	-2.29e+04	2.03e+04
sqft_living	285.8478	2.814	101.574	0.000	280.332	291.364
sqft_basement	13.7330	4.623	2.970	0.003	4.671	22.795
bedrooms	-4.325e+04	2136.247	-20.246	0.000	-4.74e+04	-3.91e+04
view_EXCELLENT	3.049e+05	1.62e+04	18.780	0.000	2.73e+05	3.37e+05
waterfront_YES	5.096e+05	2.35e+04	21.658	0.000	4.63e+05	5.56e+05
floors	8.064e+04	3781.025	21.329	0.000	7.32e+04	8.81e+04
grade	-1.951e+04	747.873	-26.092	0.000	-2.1e+04	-1.8e+04
age	2626.9890	64.029	41.028	0.000	2501.487	2752.491
condition_Fair	-7.913e+04	1.8e+04	-4.394	0.000	-1.14e+05	-4.38e+04

Omnibus:	12894.735	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	471213.634
Skew:	2.288	**Prob(JB):**	0.00
Kurtosis:	25.421	**Cond. No.**	3.74e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.74e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [46]:

```
# fit the model
pred_model4 = LinearRegression()
pred_model4.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model4.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 232835.86406326134
```

- On adding the variables that are lowly correlated to price , the model's accuracy improved to 59.9% and the RMSE has reduced to 232835.
- So let's try adding all the variables and see how the model performs.
- Before adding square foot lot and lot15 we need to log transform them

Log Transformation

In [47]:

```
kc_copy= kc_transform.copy()

kc_copy["log(sqft_lot)"] = np.log(kc_copy["sqft_lot"])

# Visually inspect raw vs. transformed values
kc_copy[["sqft_lot", "log(sqft_lot)"]]
```

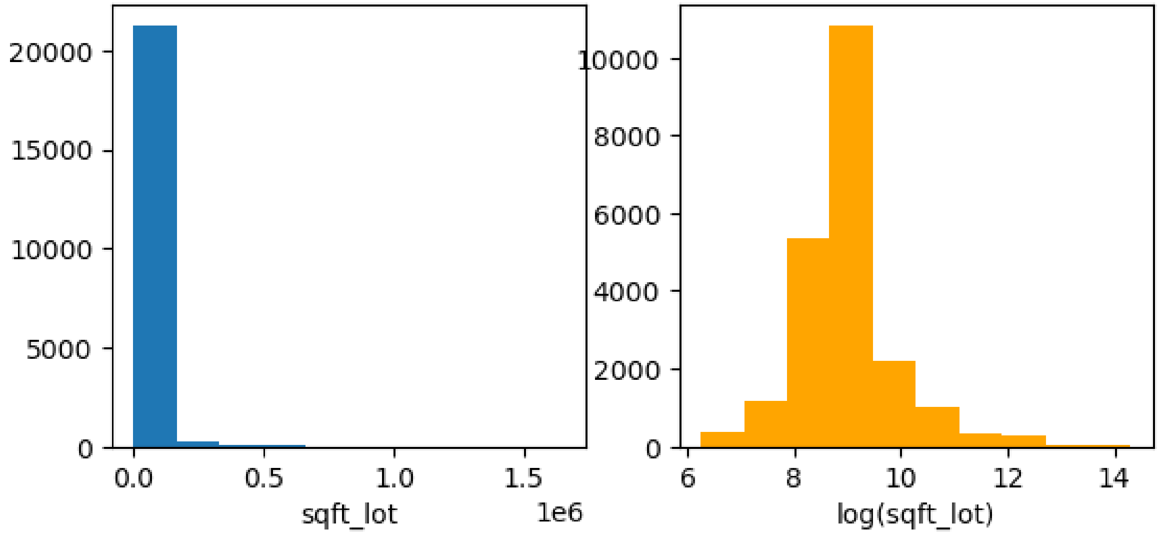
Out[47]:

	sqft_lot	log(sqft_lot)
0	5650	8.64
1	7242	8.89
2	10000	9.21
3	5000	8.52
4	8080	9.00
...	...	...
21592	1131	7.03
21593	5813	8.67
21594	1350	7.21
21595	2388	7.78
21596	1076	6.98

21597 rows × 2 columns

In [48]:

```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(7,3))
ax1.hist(kc_copy["sqft_lot"])
ax1.set_xlabel("sqft_lot")
ax2.hist(kc_copy["log(sqft_lot)"], color="orange")
ax2.set_xlabel("log(sqft_lot)");
```



In [49]:

```
kc_copy["log(sqft_lot15)"] = np.log(kc_copy["sqft_lot15"])

# Visually inspect raw vs. transformed values
kc_copy[["sqft_lot15", "log(sqft_lot15)"]]
```

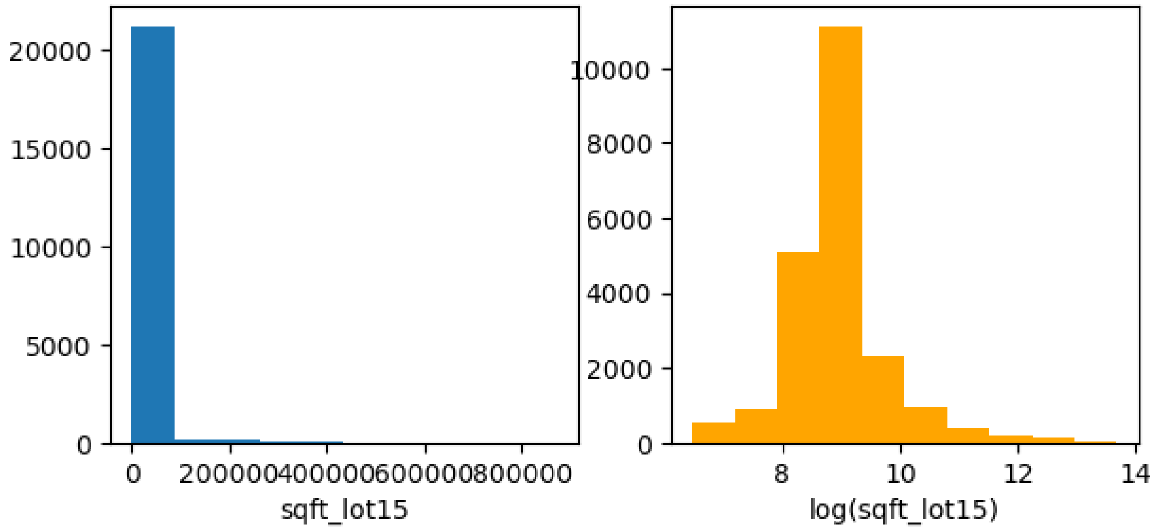
Out[49]:

	sqft_lot15	log(sqft_lot15)
0	5650	8.64
1	7639	8.94
2	8062	8.99
3	5000	8.52
4	7503	8.92
...	...	...
21592	1509	7.32
21593	7200	8.88
21594	2007	7.60
21595	1287	7.16
21596	1357	7.21

21597 rows × 2 columns

In [50]:

```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(7,3))
ax1.hist(kc_copy["sqft_lot15"])
ax1.set_xlabel("sqft_lot15")
ax2.hist(kc_copy["log(sqft_lot15)"], color="orange")
ax2.set_xlabel("log(sqft_lot15)");
```



In [51]:

```
kc_copy.drop(['sqft_lot15',"sqft_lot"],axis=1, inplace= True)
```

Before Transformation

In [52]:

```
X = kc_transform.drop('price', axis=1)
y = kc_transform['price']
X = sm.add_constant(X)
model1 = sm.OLS(y, X)
results1 = model1.fit()
print(results1.summary())
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:                  price   R-squared:
0.610
Model:                            OLS   Adj. R-squared:
0.610
Method:                 Least Squares   F-statistic:
1878.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):
0.00
Time:                        13:36:43   Log-Likelihood:             -2.
9721e+05
No. Observations:               21597   AIC:
5.945e+05
Df Residuals:                   21578   BIC:
5.946e+05
Df Model:                          18
Covariance Type:            nonrobust
======================================================================
=================
                          coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-----------------
const               -7.298e+04    4.4e+04     -1.658      0.097   -1.5
9e+05    1.33e+04
bedrooms            -4.242e+04   2124.382    -19.969      0.000   -4.6
6e+04   -3.83e+04
sqft_living           282.8626      2.889     97.895      0.000     27
7.199     288.526
sqft_lot               -0.0503      0.054     -0.925      0.355      -
0.157       0.056
floors               7.215e+04   3813.828     18.919      0.000    6.4
7e+04    7.96e+04
grade               -1.971e+04    738.685    -26.676      0.000   -2.1
2e+04   -1.83e+04
sqft_basement          -8.0449      4.641     -1.734      0.083     -1
7.141       1.051
yr_renovated         5.957e+04   8993.484      6.623      0.000    4.1
9e+04    7.72e+04
sqft_lot15             -0.6520      0.083     -7.854      0.000      -
0.815      -0.489
age                  2195.5491     69.357     31.656      0.000    205
9.605    2331.493
waterfront_YES       4.837e+05    2.32e+04     20.817      0.000    4.3
8e+05    5.29e+05
view_AVERAGE         8.942e+04   7762.987     11.518      0.000    7.4
2e+04    1.05e+05
view_EXCELLENT        3.38e+05    1.61e+04     20.980      0.000    3.0
6e+05     3.7e+05
```

```
view_FAIR              1.39e+05   1.28e+04     10.817      0.000     1.1
4e+05    1.64e+05
view_GOOD             1.568e+05   1.06e+04     14.761      0.000     1.3
6e+05    1.78e+05
condition_Average     1.025e+05   4.28e+04      2.396      0.017     1.8
6e+04    1.86e+05
condition_Fair        4.676e+04   4.61e+04      1.014      0.311    -4.3
6e+04    1.37e+05
condition_Good        1.182e+05   4.28e+04      2.762      0.006     3.4
3e+04    2.02e+05
condition_Very Good  1.593e+05    4.3e+04      3.702      0.000     7.4
9e+04    2.44e+05
======================================================================
========
Omnibus:                    13117.463   Durbin-Watson:
1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            51
3061.458
Skew:                           2.326   Prob(JB):
0.00
Kurtosis:                      26.420   Cond. No.
3.10e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 3.1e+06. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

In [53]:

```
# fit the model
pred_model5 = LinearRegression()
pred_model5.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model5.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 229308.23230450405
```

After Transformation

In [54]:

```
X = kc_copy.drop('price', axis=1)
y = kc_copy['price']
X = sm.add_constant(X)
model1 = sm.OLS(y, X)
results1 = model1.fit()
print(results1.summary())
```

```
                            OLS Regression Results
====================================================================
==========
Dep. Variable:                  price   R-squared:
0.618
Model:                            OLS   Adj. R-squared:
0.617
Method:                 Least Squares   F-statistic:
1936.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):
0.00
Time:                        13:36:44   Log-Likelihood:              -
2.9701e+05
No. Observations:               21597   AIC:
5.941e+05
Df Residuals:                   21578   BIC:
5.942e+05
Df Model:                          18
Covariance Type:            nonrobust
====================================================================
===================
                          coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------
-------------------
const               4.212e+05   4.89e+04      8.608      0.000
3.25e+05    5.17e+05
bedrooms           -4.092e+04   2096.887    -19.516      0.000      -
4.5e+04   -3.68e+04
sqft_living          308.7373      3.132     98.585      0.000
302.599     314.876
floors              3.144e+04   4240.093      7.414      0.000
2.31e+04    3.97e+04
grade              -1.999e+04    731.893    -27.311      0.000     -
2.14e+04   -1.86e+04
sqft_basement        -36.7279      4.803     -7.647      0.000
-46.142     -27.314
yr_renovated        6.311e+04   8914.943      7.079      0.000
4.56e+04    8.06e+04
age                 2154.7781     69.012     31.223      0.000      2
019.509    2290.048
waterfront_YES      5.025e+05    2.3e+04     21.806      0.000
4.57e+05    5.48e+05
view_AVERAGE         9.07e+04   7690.072     11.795      0.000
7.56e+04    1.06e+05
view_EXCELLENT      3.406e+05    1.6e+04     21.342      0.000
3.09e+05    3.72e+05
view_FAIR           1.402e+05   1.27e+04     11.015      0.000
1.15e+05    1.65e+05
view_GOOD           1.599e+05   1.05e+04     15.211      0.000
1.39e+05    1.81e+05
```

```
condition_Average    8.002e+04   4.24e+04      1.887      0.059   -3
108.063    1.63e+05
condition_Fair       4.118e+04   4.57e+04      0.901      0.367   -
4.84e+04    1.31e+05
condition_Good       1.031e+05   4.24e+04      2.431      0.015
2e+04    1.86e+05
condition_Very Good  1.383e+05   4.27e+04      3.243      0.001
5.47e+04    2.22e+05
log(sqft_lot)       -3.868e+04   4480.735     -8.633      0.000   -
4.75e+04   -2.99e+04
log(sqft_lot15)     -1.356e+04   4862.256     -2.789      0.005   -
2.31e+04   -4032.148
======================================================================
==========
Omnibus:                    12884.757   Durbin-Watson:
1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
482700.127
Skew:                           2.278   Prob(JB):
0.00
Kurtosis:                      25.708   Cond. No.
1.42e+05
======================================================================
==========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors
is correctly specified.
[2] The condition number is large, 1.42e+05. This might indicate tha
t there are
strong multicollinearity or other numerical problems.
```

In [55]:

```
# fit the model
pred_model6 = LinearRegression()
pred_model6.fit(X, y)

# predict the values of the dependent variable
y_pred = pred_model6.predict(X)

# calculate the RMSE
rmse = np.sqrt(mean_squared_error(y, y_pred))
print('RMSE:', rmse)
```

```
RMSE: 227171.42435161455
```

Why transform?

- The first model is without the log transformation and the second one is after the log transformation. The second one is better since it explains 61.7% of the total variation in price compared to the first model that explains 61% of the variation in price .
- The RMSE of the second model is also lower thus we'll use the second model.
- Interpreting the second model, some variables are not significant since their p-value is more than 0.05 but we can't drop them because that will mean we'll use them as a reference category and we already have a reference category.

This is our final model.

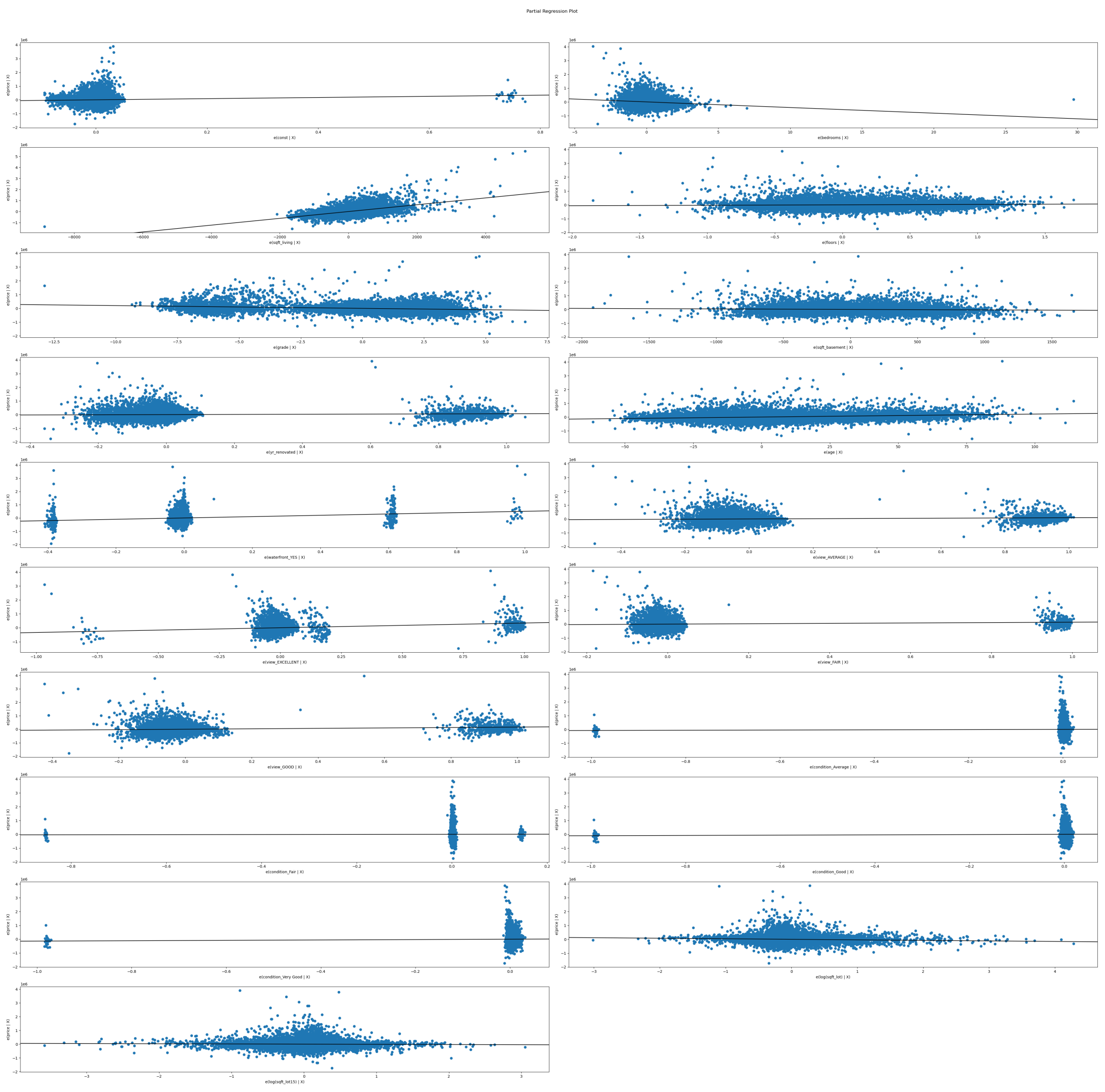
Interpretation

- The model is that of bedrooms, sqft_living, floors, grade,sqft_basement,yr_renovated, age, waterfront_YES, view_AVERAGE,view_EXCELLENT, view_FAIR, view_GOOD, condition_Average,condition_Fair, condition_Good, condition_Very Good,log(sqft_lot), log(sqft_lot15) and price.
- The model is statistically significant since the F-statistic p-value is less than 0.05 and it explains 61.7%% of the total variation of price which has improved from the previous models making our model more accurate.
- Most of the predictor variables are statistically significant apart from condition fair and condition average.
- The model is off by $227171 inpricewhichhasreducedfromthepreviousmodels. * Anincreaseof 1 squarefootinthelivingarealeadstoanincreaseofapproximately$ 308.73 in price.
- An increase of 1 square foot in the basement area leads to a decrease of approximately $36.72 inprice. * Anincreaseof 1 bedroomleadstoandecreaseofapproximately$ 409200 in price.
- A house graded higher by one unit leads to a decrease of approximately $19990 inprice. * Anincreaseof 1 yearintheageofthehouseleadstoanincreaseofapproximately$ 2154. in price.
- Renovating a house leads to an increase of your price by $63110 inprice. * Ahouseonawaterfrontcomparedtothatnotonawaterfrontleadstoanincreasein$ 5025 in price.
- A house with an average view compared to that with no view leads to an increase of an $90700 inprice. * Ahousewithanexcellentviewcomparedtothatwithnoviewleadstoanincreaseofan$ 3 in price.
- A house with a good view compared to that with no view leads to an increase of an $159900 inprice. * Ahousewithafairviewcomparedtothatwithnoviewleadstoanincreaseofan$ 14020 in price.
- An increase of one more floor in a house leads to an increase of $31440 inprice. * Ahouseinanaverageconditioncomparedtothatinpoorconditionleadstoanincreaseo$ in price.
- A house in fair condition compared to that in poor condition leads to an increase of an $41180 inprice. * Ahouseingoodconditioncomparedtothatinpoorconditionleadstoanincreaseofan$ 10 in price.
- A house in very good condition compared to that in poor condition leads to an increase of an $138300 inprice. * Foreachincreaseof 1$ 386.8 in price.
- For each increase of 1% in square foot lot15 there is decrease of $135.6 in price.

In [56]:

```
fig= plt.figure( figsize=(40,40))
sm.graphics.plot_partregress_grid(results1, exog_idx=list(X.columns.values),fig=fig
plt.show()
```

```
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
```



On visualizing the partial regression plots we can see that the predictor variables have a linear relationship with price thus concluding that they are beneficial to our model

Standardizing the model

In [57]:

```
for col in kc_copy:
    kc_copy[col]=(kc_copy[col]-kc_copy[col].mean())/kc_copy[col].std()

X = kc_copy.drop('price', axis=1)
y = kc_copy['price']
X = sm.add_constant(X)
model1 = sm.OLS(y, X)
results1 = model1.fit()
print(results1.summary())
```

```
                            OLS Regression Results
======================================================================
==========
Dep. Variable:                  price   R-squared:
0.618
Model:                            OLS   Adj. R-squared:
0.617
Method:                 Least Squares   F-statistic:
1936.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):
0.00
Time:                        13:36:51   Log-Likelihood:
-20264.
No. Observations:               21597   AIC:
4.057e+04
Df Residuals:                   21578   BIC:
4.072e+04
Df Model:                          18
Covariance Type:            nonrobust
======================================================================
===================
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------------
const           -4.231e-15      0.004  -1.01e-12      1.000
-0.008       0.008
bedrooms           -0.1032      0.005    -19.516      0.000
-0.114      -0.093
sqft_living         0.7716      0.008     98.585      0.000
0.756       0.787
floors              0.0462      0.006      7.414      0.000
0.034       0.058
grade              -0.1254      0.005    -27.311      0.000
-0.134      -0.116
sqft_basement      -0.0440      0.006     -7.647      0.000
-0.055      -0.033
yr_renovated        0.0313      0.004      7.079      0.000
0.023       0.040
age                 0.1723      0.006     31.223      0.000
0.161       0.183
waterfront_YES      0.1121      0.005     21.806      0.000
0.102       0.122
view_AVERAGE        0.0508      0.004     11.795      0.000
0.042       0.059
view_EXCELLENT      0.1115      0.005     21.342      0.000
0.101       0.122
view_FAIR           0.0468      0.004     11.015      0.000
```

```
0.038       0.055
view_GOOD                 0.0660      0.004     15.211      0.000
0.057       0.074
condition_Average         0.1039      0.055      1.887      0.059
-0.004       0.212
condition_Fair            0.0099      0.011      0.901      0.367
-0.012       0.031
condition_Good            0.1235      0.051      2.431      0.015
0.024       0.223
condition_Very Good       0.1014      0.031      3.243      0.001
0.040       0.163
log(sqft_lot)            -0.0950      0.011     -8.633      0.000
-0.117      -0.073
log(sqft_lot15)          -0.0300      0.011     -2.789      0.005
-0.051      -0.009
====================================================================
==========
Omnibus:                     12884.757   Durbin-Watson:
1.985
Prob(Omnibus):                   0.000   Jarque-Bera (JB):
482700.127
Skew:                            2.278   Prob(JB):
0.00
Kurtosis:                       25.708   Cond. No.
31.9
====================================================================
==========

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

In [58]:

```
results1.params.sort_values(ascending=False)
```

Out[58]:

```
sqft_living             0.77
age                     0.17
condition_Good          0.12
waterfront_YES          0.11
view_EXCELLENT          0.11
condition_Average       0.10
condition_Very Good     0.10
view_GOOD               0.07
view_AVERAGE            0.05
view_FAIR               0.05
floors                  0.05
yr_renovated            0.03
condition_Fair          0.01
const                  -0.00
log(sqft_lot15)        -0.03
sqft_basement          -0.04
log(sqft_lot)          -0.09
bedrooms               -0.10
grade                  -0.13
dtype: float64
```

- We can see that square foot living has the highest influence on the price of the house.

- The variables that have a major influence on the price of the house are; square foot living, age of the house,good condition of the house,if the house is on a waterfront and has an excellent view.
- The variables that has the least influence on the price of the house are; grade,number of bedrooms,sqft lot,sqft basement and sqft lot 15.

Conclusion

- The variables that have a major influence on the price of the house are; square foot living, age of the house,good condition of the house,if the house is on a waterfront and has an excellent view.
- The variables that has the least influence on the price of the house are; grade,number of bedrooms,sqft lot,sqft basement and sqft lot 15.

We can also see that:

- The highest number of house sales are made in the second quarter of the year (Q2: April 1 - June 30) which fall in the Spring season
- The lowest number of house sales are made in the first quarter of the year (Q1: January 1 - March 31) which fall mostly in the Winter season

Recommendations

- Revonate their house since this increases the value of the house
- Ensure that the houses are in good condition before putting it into the market for sale
- Increase square footage of living space
- Put up their houses for sale in peak season-Spring

Future work

- Reducing noise in the data to improve the accuracy of our model.
- Additionally investigate certain features, such as constructional/architectural values of the house, to see what trends we could discern from that.