Kings County House Sales

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Business Understanding

Overview

Real estate developers in King County, Washington are interested in identifying factors that influence the sale price of homes in King County, as well as developing models to predict the sale price of homes based on these factors. To address this challenge, we undertook a data science project to develop a model that could accurately predict the sale price of homes in the region.

Our analysis involved the examination of over 21,000 house sale transactions that occurred between May 2014 and May 2015. Using advanced machine learning techniques, we developed a progression of multiple models that outperformed the baseline model we initially used. These models allowed us to identify the key features that drive property prices, including location, size, condition, and various other factors. This information can be used to optimize the design and marketing of new properties, identify investment opportunities, and make data-driven decisions about the development and sale of properties.

Business Problem

The real estate developers in King County, Washington are facing a significant challenge in identifying the key factors that influence the sale of houses in the region. The developers need to identify these features that affect its sale price to make informed investment decisions and improve their construction process from start to finish. However, identifying this is a challenging task due to the large volume of data to be analyzed, including interdependent and correlated variables. Therefore, data science modeling techniques such as feature engineering and regression analysis are necessary to identify the most influential factors that drive property prices.

By leveraging these insights, the developers can improve their construction process and build homes that are more attractive to buyers, leading to increased sales and profits. Additionally, the insights can help developers understand the competitive landscape of the market, identify emerging trends and opportunities, and develop more effective marketing strategies to improve sales further. Ultimately, our work will contribute to the growth and development of the region's real estate market, leading to economic growth in the area.

Problem Questions

- Which house features have the highest influence on the price?
- How does the size of the property influence the sale price of homes in King County?
- How does the house neighborhood affect the prices?
- How accurately can we predict the sale price of homes in King County based on the available features?

Data Undestanding

The King County House Sales dataset contains information on over 21,000 home sales in King County, Washington, USA between May 2014 and May 2015. The dataset includes a variety of features such as the number of bedrooms and bathrooms, the size of the property, the location of the property, and various other attributes that may influence the sale price of a home.

We began by importing the relevant libraries and set the appropriate alias for each.

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.metrics import mean_absolute_error
import folium
import plotly.express as px

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

Read in the data from King County House Sales from a file named `kc_house_data.csv` and store it as a DataFrame named `data` . Preview the Dataframe to ensure it was loaded correctly.

In [2]:
```
def load_data(filepath):
    """Loads the dataset from the specified file
    path and returns a pandas DataFrame."""
    if filepath.endswith('.csv'):
        return pd.read_csv(filepath)
    if filepath.endswith('.md'):
        df = pd.read_csv(filepath, sep='-', skiprows=2, skipinitialspace=True)
        return df
```

In [3]:
```
# Load data
data = load_data('data/kc_house_data.csv')

# Preview of the dataframe
data.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_a
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	

5 rows × 21 columns

Description of the columns:

In [4]:
```
load_data('data\column_names.md')
```

Out[4]:

	* `date`	Date house was sold
0	* `price`	Sale price (prediction target)
1	* `bedrooms`	Number of bedrooms
2	* `bathrooms`	Number of bathrooms
3	* `sqft_living`	Square footage of living space in the home
4	* `sqft_lot`	Square footage of the lot
5	* `floors`	Number of floors (levels) in house
6	* `waterfront`	Whether the house is on a waterfront
7	* Includes Duwamish, Elliott Bay, Puget Sound,...	NaN
8	* `view`	Quality of view from house
9	* Includes views of Mt. Rainier, Olympics, Cas...	NaN
10	* `condition`	How good the overall condition of the house is...
11	* See the [King County Assessor Website](https...	NaN
12	* `grade`	Overall grade of the house. Related to the con...
13	* See the [King County Assessor Website](https...	NaN
14	* `sqft_above`	Square footage of house apart from basement
15	* `sqft_basement`	Square footage of the basement
16	* `yr_built`	Year when house was built
17	* `yr_renovated`	Year when house was renovated
18	* `zipcode`	ZIP Code used by the United States Postal Service
19	* `lat`	Latitude coordinate
20	* `long`	Longitude coordinate
21	* `sqft_living15`	The square footage of interior housing living ...
22	* `sqft_lot15`	The square footage of the land lots of the nea...

Check the descriptive statistics that summarize the central tendency, dispersion and shape of the dataset's distribution, excluding NaN values.

In [5]:
```
# Check the summary statistics
data.describe()
```

Out[5]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	2159
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	197
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	2
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	190
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	195
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	197
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	199
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	201

Use the `.info()` method to get a quick overview of the dataset such as column names, datatypes and missing entries.

In [6]:

```python
# Dataset overview
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
```

Data Preparation

Preparation of the data involved answering the following questions:

- Does this data contain missing values?
- Are there any outliers?
- Does this data contain any duplicates?
- Are the values in the expected datatype?
- What is the correlation between various features?
- Do the categorical values require One-Hot encoding?
- Does the dataset require any transformation?

Missing Values

Check the columns for missing values.

In [7]:

```python
# Checking for missing values
def check_missing_values(df):
    """
    This function takes a pandas DataFrame as input and returns
    a dictionary with the column names as keys
    and the number of missing values in each column as values.
    """
    missing_values = df.isnull().sum()
    return missing_values[missing_values > 0].sort_values(ascending=False)
check_missing_values(data)
```

Out[7]:

```
yr_renovated    3842
waterfront      2376
view              63
dtype: int64
```

Duplicates

A function was created that takes in a dataset and returns count of duplicate rows as True and count of non-duplicate rows as False.

In [8]:

```python
# Create a function that checks for duplicates values
def check_duplicates(column):
    return column.duplicated().value_counts()
```

In [9]:
```
check_duplicates(data)
```

Out[9]:
```
False    21597
dtype: int64
```

Missing Values

The `waterfront` column is a categorical column. The column has 2 unique values, 'YES' and 'NO' with 2376 missing values. As this is a fairly number of the total records, we shall be replacing the missing values with the mode of the column. The mode of the column is 'NO'. Therefore, we shall be replacing the missing values with 'NO'.

In [10]:
```
def fill_missing_values(df, column):
    '''Replace missing values with the mode'''
    df[column] = df[column].fillna(df[column].mode()[0])
```

In [11]:
```
# Fill the missing values with the mode of the column(waterfront)
fill_missing_values(data, 'waterfront')
```

The `view` column is a categorical column. With 63 missing values, . As this is a small number of the total records, we shall be replacing the records with mode,in this case 'NONE'.

In [12]:
```
# Fill the missing values with the mode of the column(view)
fill_missing_values(data, 'view')
```

The `yr renovated` column is a numerical column with 3842 missing values. Futhermore, majority of the data in the records were zero. This could either be suggesting that the homes have never been renovated or that the data is erroneous. As there is no ideal way of dealing with these values, it would be best to drop the entire column.

In [13]:
```
# Drop the yr_renovated column
data = data.drop(['yr_renovated'], axis=1)
```

Invalid Data

The `sqft_basement` column contains some rows with **?** as a value. We replace this with **0.0**.

In [14]:
```
# Convert all the ? values to 0.0 like we did for the other columns.
# Then convert the values from strings to int

data['sqft_basement'] = data["sqft_basement"].replace({"?": '0.0'})
data['sqft_basement'] = data['sqft_basement'].astype(float)
```

In [15]:
```
# Convert the date column to datetime data type
data['date'] = pd.to_datetime(data['date'])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 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     21597 non-null  object
 9   view           21597 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  float64
 14  yr_built       21597 non-null  int64
 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(6), int64(9), object(4)
memory usage: 3.3+ MB
```

Univariate Analysis

In this section, we'll explore each column in the dataset to see the distributions of features. The main two parts in this section are:

> - Categorical Columns
> - Numerical Columns

Categorical Columns

There are 5 Categorical Columns in the dataset that we shall be analysing:

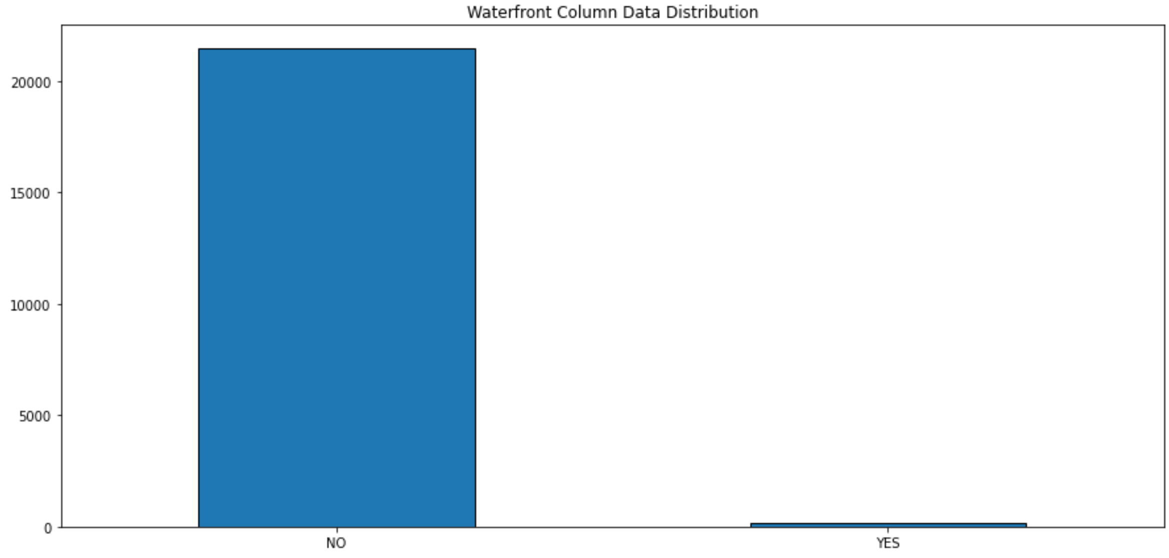
- `waterfront`
- `view`
- `condition`
- `grade`
- `zipcode`

In [16]:
```
# Function to visualise the data in the columns
def plot_data(df, col, title):
    ''' Plots the value counts of a column in a dataframe
    as a bar chart
    '''
    df[col].value_counts().plot(kind='bar', figsize=(15, 7),
                                edgecolor='black')
    plt.title(title)
    plt.xticks(rotation=0)
```

Waterfront

The `waterfront` column shows the house has a waterfront or not.

In [17]:
```
# Visualise the data distribution
plot_data(data, 'waterfront', 'Waterfront Column Data Distribution')
```

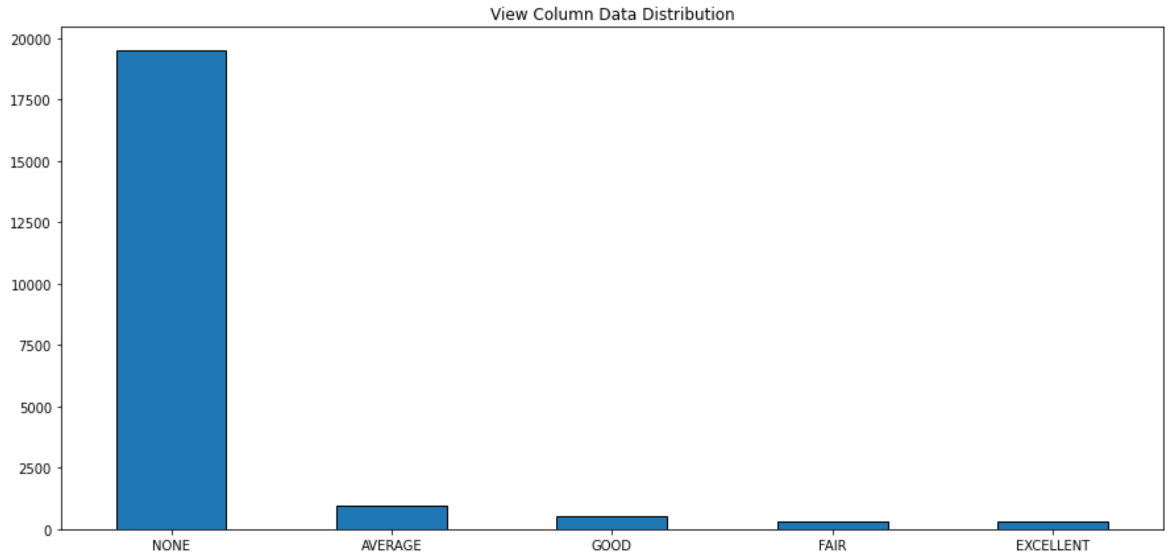


The distribution above shows that most of the houses in the dataset are not on a waterfront.

The view

The `view` shows whether a house has a view or not, and if it has, what quality of view.

In [18]:
```
# Visualise the data distribution
plot_data(data, 'view', 'View Column Data Distribution')
```

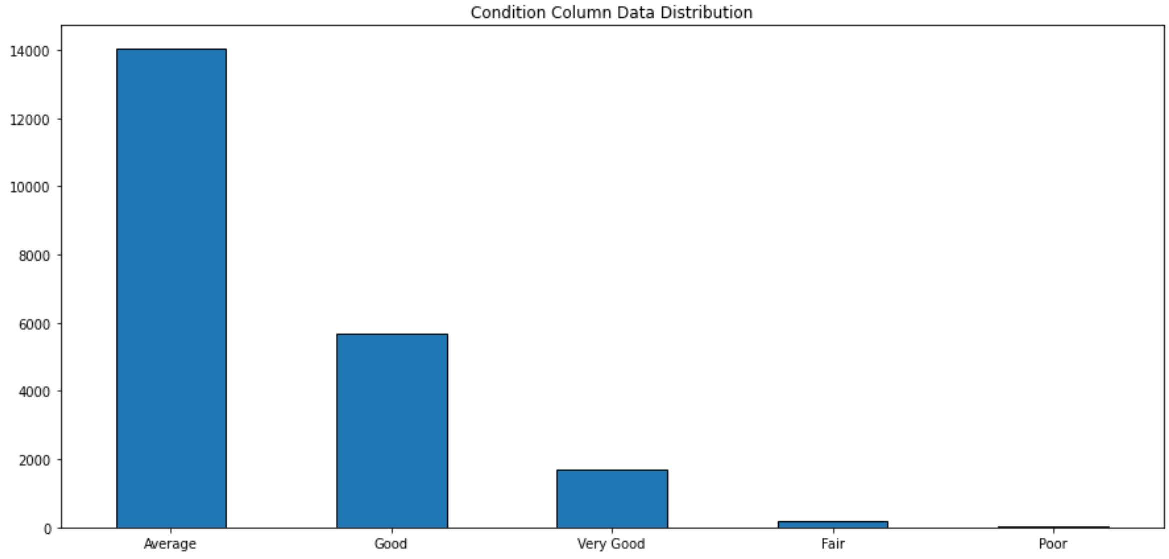


In the distribution above, we see that majority of the houses in the dataset don't have a view. Very few houses have an excellent view.

Condition

The condition column identifies the condition of the house.

In [19]:
```
# Visualise the data distribution
plot_data(data, 'condition', 'Condition Column Data Distribution')
```

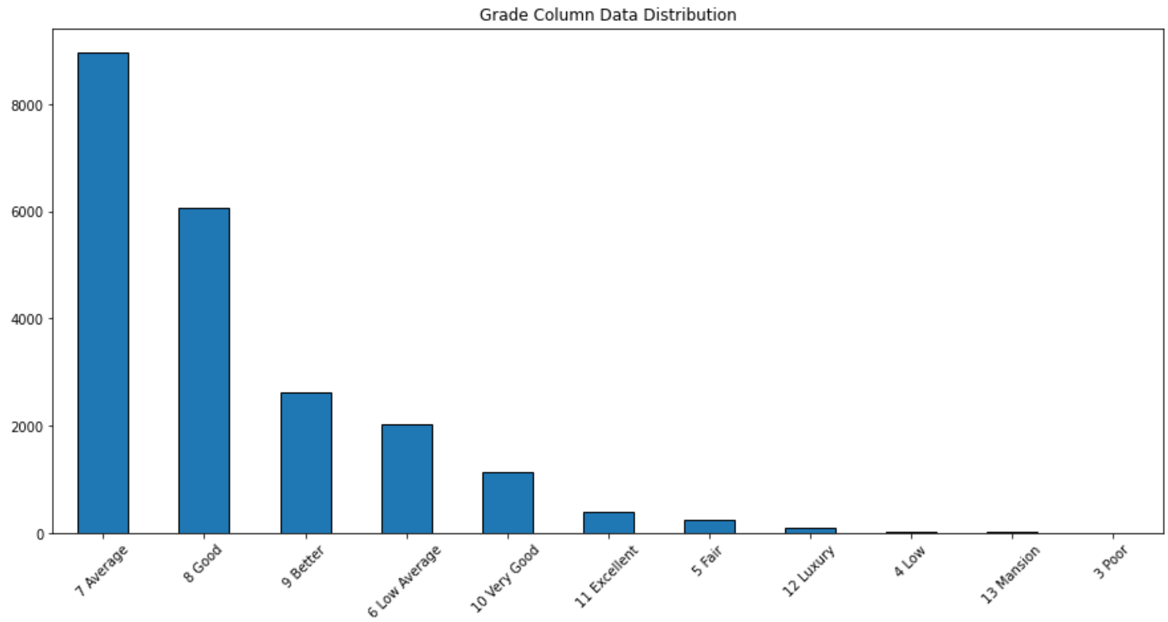


From the distribution above, we can see that most of the houses in the dataset are in average condition. The number of houses in **average** condition is nearly 14,000. The number of houses in **good** condition is nearly 6,000. The number of houses in **very good** condition is nearly 2,000.The number of houses in **fair** condition and **poor** condition are way below 2,000.

Grade

The grade column identifies the quality of construction and design of the house. The grade represents the construction quality of improvements. Grades run from grade 1 to 13.

In [20]:
```
# Visualise the data distribution
plot_data(data, 'grade', 'Grade Column Data Distribution')
plt.xticks(rotation=45);
```

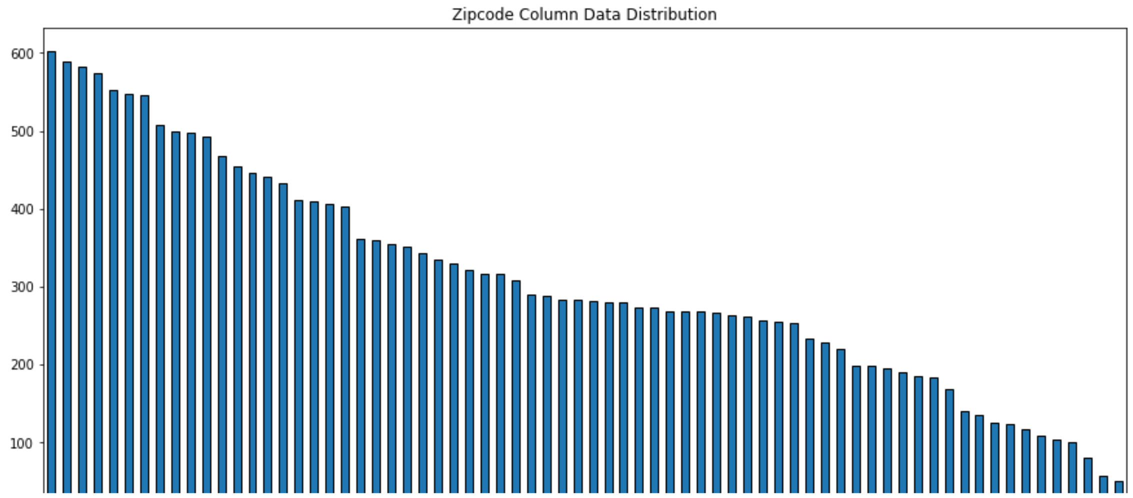


From the distribution above, we see that the houses in this dataset range from grades 3-13. The column is however not evenly distributed as we can see majority of the houses with a grade of 7 (Average), and 8 (Good).

Zipcode

The zipcode column identifies the zipcode area the house is in.

In [21]:
```
# Visualise the data distribution
plot_data(data, 'zipcode', 'Zipcode Column Data Distribution')
plt.xticks(rotation=70);
```



From the distribution above, we see that the zipcode with the most houses is 98103. The zipcode with the least houses is 98039. Unlike the other categorical columns, we see more evenly distributed data in this column.

Numeric Columns

There are 11 Numerical Columns in the dataset that we shall be analysing:

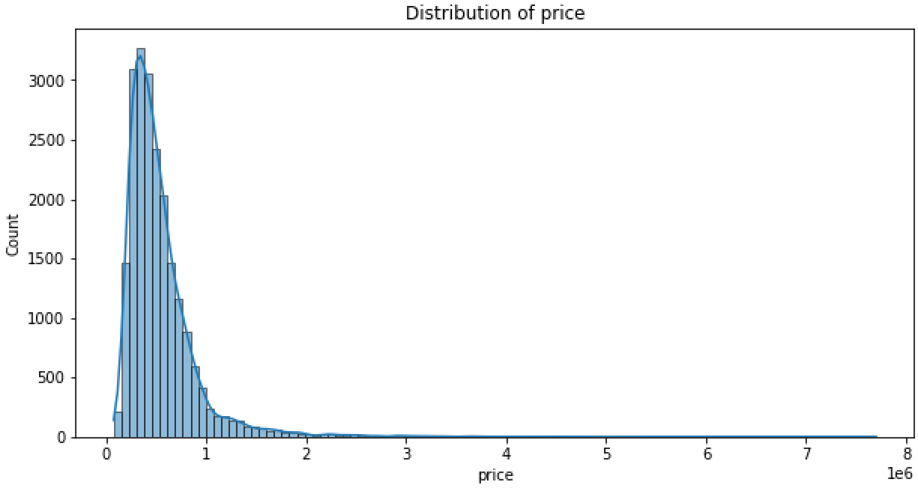
- `price`
- `bedrooms`
- `bathrooms`
- `sqft_living`
- `sqft_lot`
- `floors`
- `sqft_above`
- `sqft_basement`
- `yr_built`
- `lat`
- `long`

In [22]:
```
# Function to visualise the distribution of numerical columns
def plot_distribution(df, col, bins):
    """
    Plot the distribution of a numeric column in a pandas DataFrame.

    Parameters:
        dataframe (pandas.DataFrame): The DataFrame containing the column to plot.
        column (str): The name of the column to plot.

    Returns:
        None
    """
    plt.figure(figsize=(10, 5))
    sns.histplot(data=data, x=col, bins=bins, edgecolor='black', kde=True)
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.title(f'Distribution of {col}')
    plt.show()
```

Price

The price column identifies the price of the house.

In [23]:
```
# Visualise the data distribution
plot_distribution(data, 'price', 100)
```

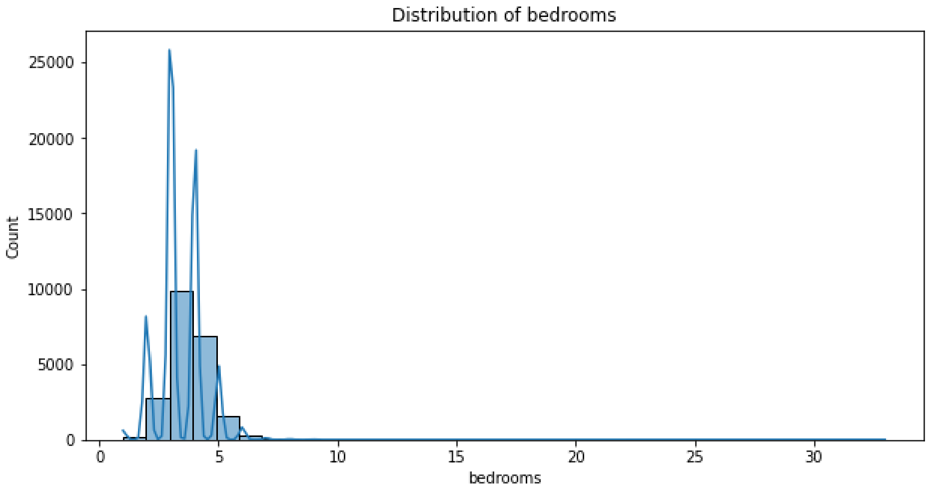


From the distribution above, we see that the price column is skewed to the right. The maximum price of a house in the dataset is 7,700,000 and the minimum price of a house in the dataset is 78,000.

Bedrooms

The bedrooms column identifies the number of bedrooms in the house.

In [24]:
```
# Visualise the data distribution
plot_distribution(data, 'bedrooms',33)
```



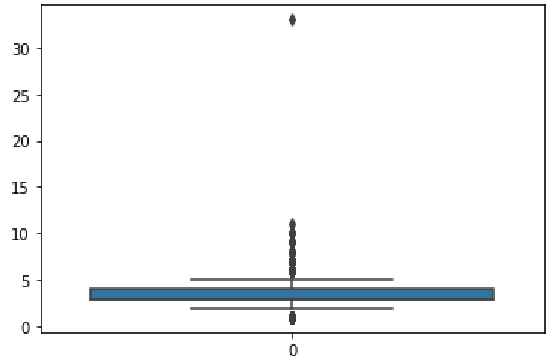
The bedroom column distribution is skewed with most houses having less than five bedrooms.The most common number of bedrooms is 3. The minimum number of bedrooms in a house in the dataset is 1, and the maximum number of bedrooms in a house in the dataset is 33.

Futher investigation of outliers:

In [25]:
```
# Checking for outliers
def check_outliers(column):
    return sns.boxplot(column)
```

In [26]:
```
check_outliers(data['bedrooms'])
```

Out[26]: <AxesSubplot: >



Dropping extreme outliers:

In [27]:
```
# Drop values above 9
data = data[~data['bedrooms'].between(10, 33)]
```

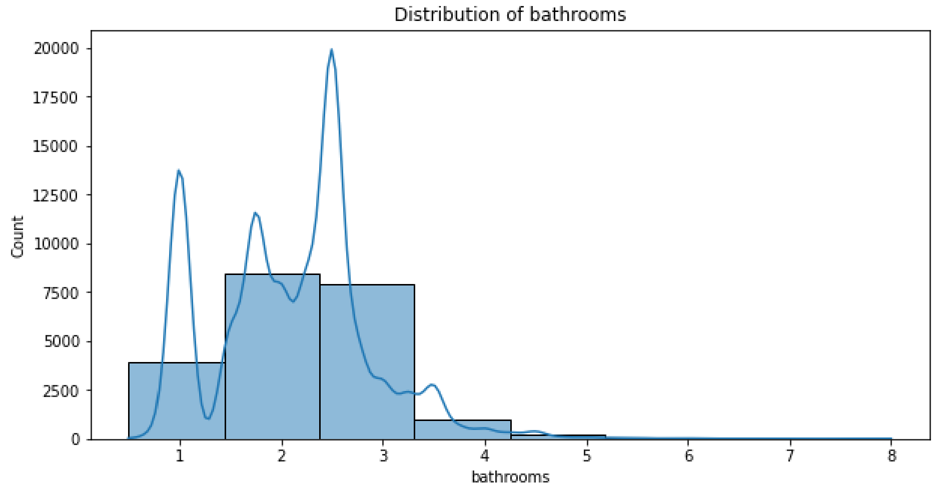
In [28]:
```
data['bedrooms'].value_counts()
```

Out[28]:
```
3    9824
4    6882
2    2760
5    1601
6     272
1     196
7      38
8      13
9       6
Name: bedrooms, dtype: int64
```

Bathrooms

The bathrooms column identifies the number of bathrooms in the house.

In [29]:
```
# Visualise the data distribution
plot_distribution(data, 'bathrooms', 8)
```

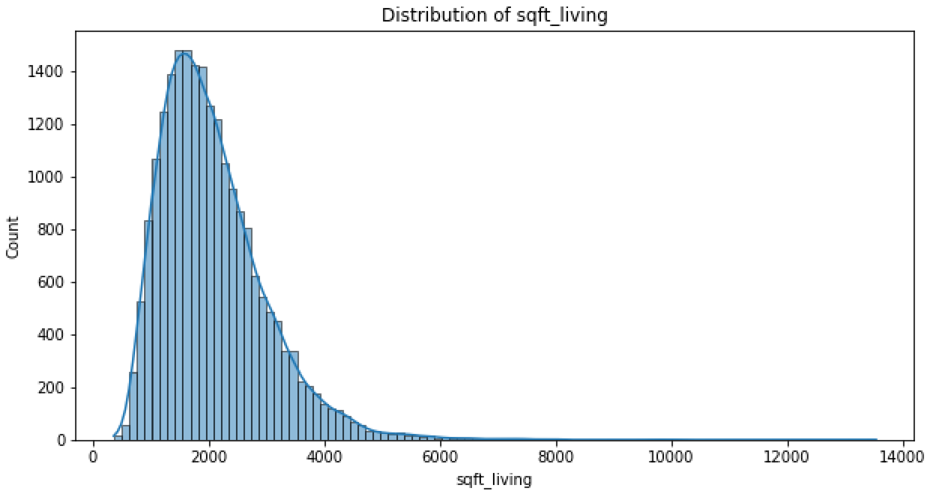


From the distribution above we can see that the bathroom column is not skewed. The minimum number of bathrooms in a house in the dataset is 0.5, and the maximum number of bathrooms in a house in the dataset is 8. The most common number of bathrooms in a house in the dataset is 2.

Sqft Living

The sqft living column identifies the square footage of the house.

In [30]:
```
# Visualise the data distribution
plot_distribution(data, 'sqft_living', 100)
```

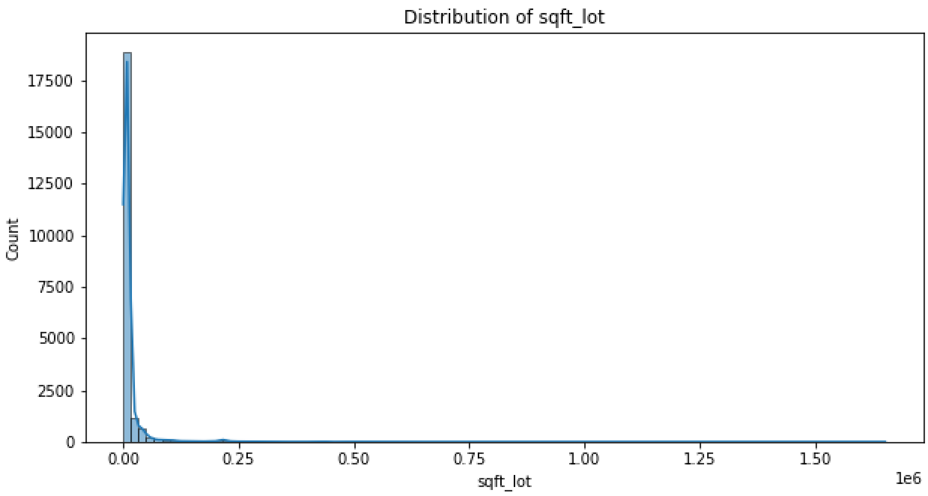


From the distribution above, we can see that the sqft living column is skewed to the right. This means that the mean square footage of the homes is greater than the median. The minimum square footage of a house in the dataset is 370, and the maximum square footage of a house in the dataset is 13,540. The mean square footage of a house in the dataset is 2080.

Sqft Lot

> The `sqft lot` column identifies the square footage of the lot.

In [31]:
```
# Visualise the data distribution
plot_distribution(data, 'sqft_lot', 100)
```

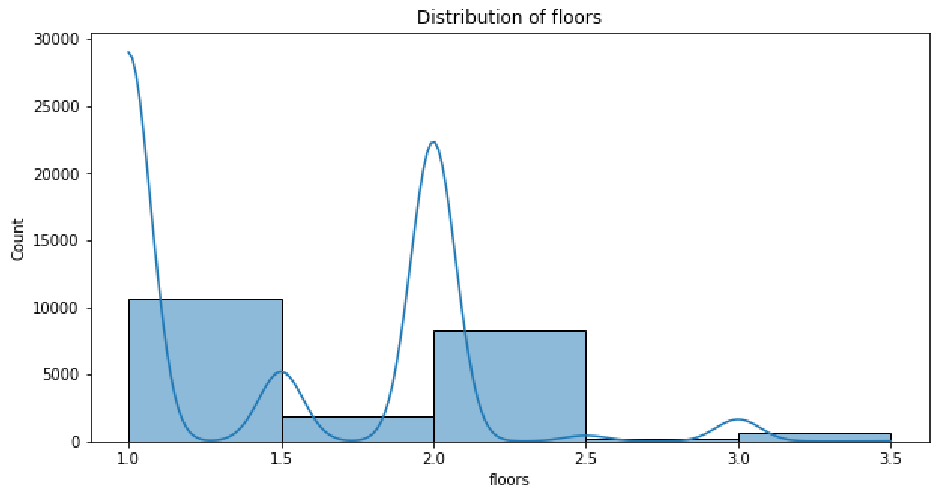


From the distribution above, we can see that the data is skewed to the right. This is because the mean is greater than the median. The minimum lot square footage is 520, the maximium lot square footage is 1,651,359.

Floors

> `floors` column identifies the number of floors in the house.

In [32]:
```
# Visualise the data distribution
plot_distribution(data, 'floors', 5)
```

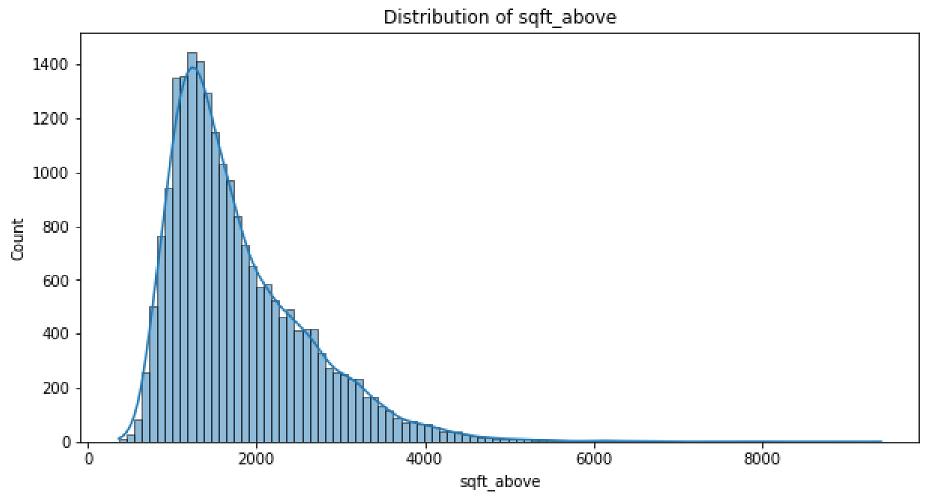


From the distributions above, majority of the homes in the data set have 1 floor. The minimum number of floors in a house is 1, and the maximum number of floors in a house is 3.5.

Sqft Above

> The `sqft above` column identifies the square footage of the house above the ground.

In [33]:
```
# Visualise the data distribution
plot_distribution(data, 'sqft_above',100)
```



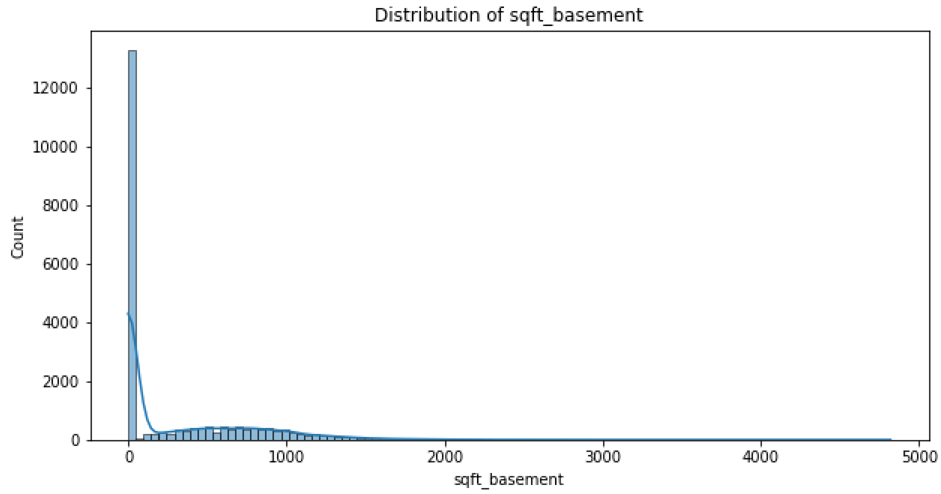
From the distribution above, the data is skewed to the right. This means that mean of sqft_above is greater than the median. The minimum is 370sqft and the maximum is 9410sqft.

Sqft Basement

> The `sqft basement` column identifies the square footage of the basement of the house.

In [34]:

```
# Visualise the data distribution
plot_distribution(data, 'sqft_basement', 100)
```



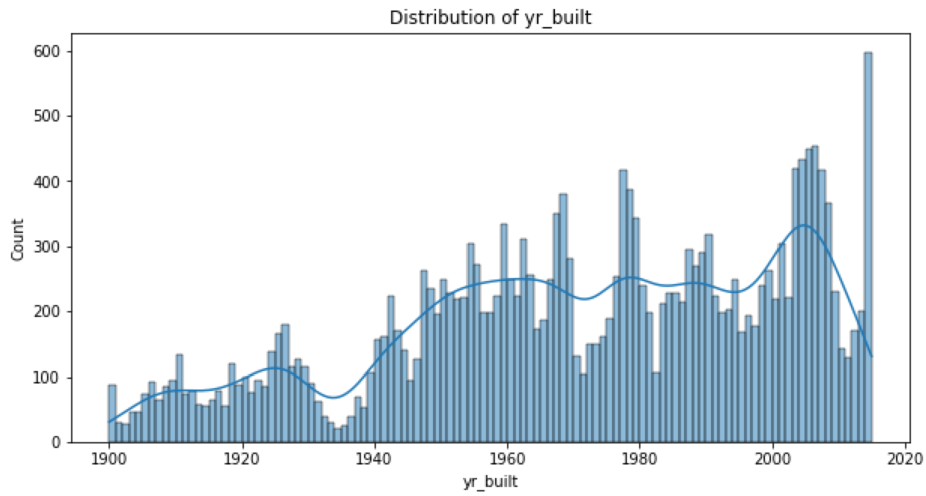
From the distribution above, the data is not clearly distributed with most houses having no basement.

Yr Built

> The `yr_built` column identifies the year the house was built.

In [35]:

```
# Visualise the data distribution
plot_distribution(data, 'yr_built', 115)
```

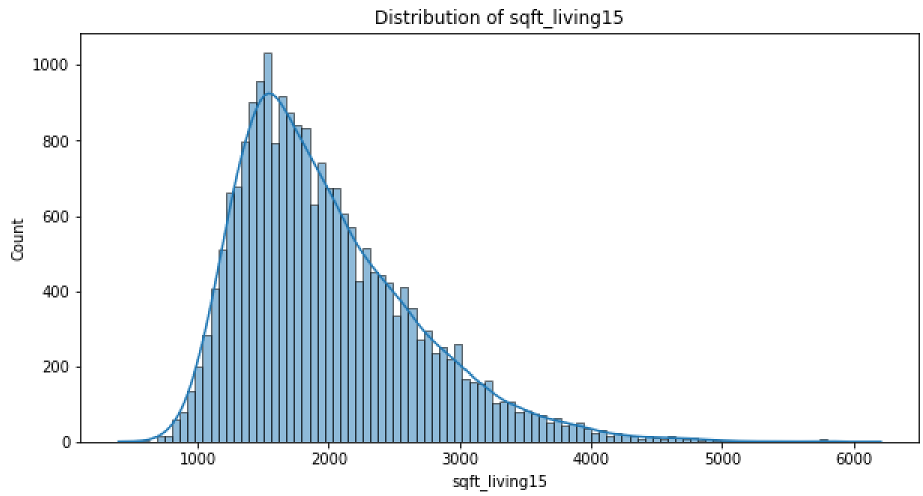


From the distributions above we can see that the the oldest house in the dataset was built in 1900, and the newest house in the dataset was built in 2015. The mean year the houses in the dataset were built is 1971.

Sqft Living15

> The `sqft_living15` square footage of interior housing living space for the nearest 15 neighbors

In [36]:
```python
# Visualise the data distribution
plot_distribution(data, 'sqft_living15', 100)
```

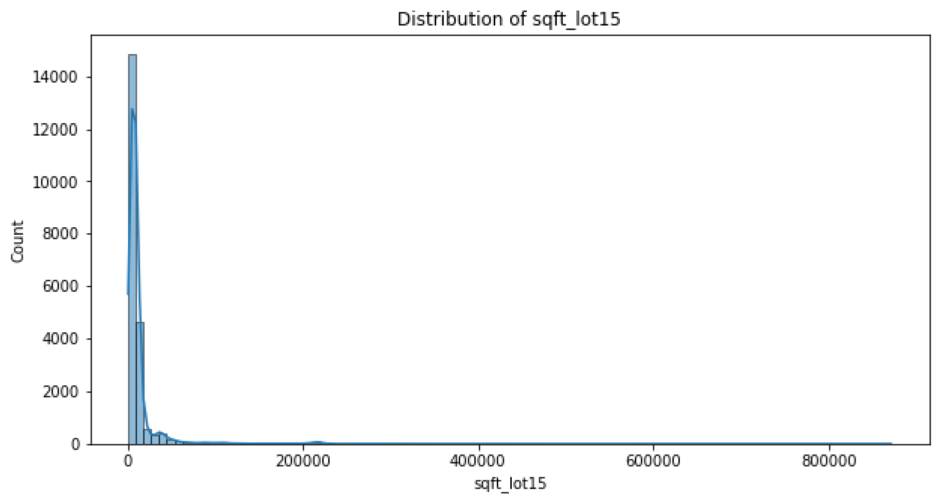


From the distribution plot, we can see that the data is skewed to the right. This means that the mean value is greater than the median. The minimum value of the nearest 15 neighbors is 399sqft, and the maximum of the nearest 15 neighbors is 6,210sqft. The mean of the nearest 15 neighbors is 1987sqft.

Sqft Lot15

> The `sqft_lot15` column represents the square footage of the land lots for the nearest 15 neighbors.

In [37]:
```python
# Visualise the data distribution
plot_distribution(data, 'sqft_lot15', 100)
```



From the distribution plot, data is skewed to the right. The minimum value of the nearest 15 neighbors is 651sqft, and the maximum value of the nearest 15 neighbors is 871,200ft. The mean value of the nearest 15 neighbors is 12758sqft.

Lat & Long

> The `lat` column identifies the latitude of the house. The `long` column identifies the longitude of the house.

In [38]:
```
# create a mapbox scatter plot that shows the location of the houses
fig = px.scatter_mapbox(
    data,  # DataFrame
    lat='lat',
    lon='long',
    width=600,  # Width of map
    height=600,  # Height of map
    color='price',
    hover_data=["price"],  # Display price when hovering mouse over house
)

fig.update_layout(mapbox_style="open-street-map")
fig.show()
```

Linear Transformations

We converted sq_ft units of area to sq_m to make the output more interpretable to our stakeholders.

In [39]:
```
# Function to convert sq_ft to sq_m
def convert_sqft_to_sqm(df, columns):
    # Define a conversion factor from sqft to sqm
    sqft_to_sqm = 0.092903

    # Loop through the specified columns and convert the values to sqm
    for column in columns:
        df[column] = df[column] * sqft_to_sqm

    return df
```

In [40]:
```
# Use function to convert sq_ft to sq_m
data = convert_sqft_to_sqm(data, ['sqft_living15', 'sqft_lot',
                                  'sqft_above', 'sqft_basement',
                                  'sqft_lot15', 'sqft_living'])
```

In [41]:
```
def rename_columns(df):
    # Renaming columns using dictionary of old name -> new name
    df = df.rename(columns={
        'sqft_living': 'sqm_living',
        'sqft_lot': 'sqm_lot',
        'sqft_above': 'sqm_above',
        'sqft_basement': 'sqm_basement',
        'sqft_living15': 'sqm_living15',
        'sqft_lot15': 'sqm_lot15'
    })
    return df
```

In [42]:
```
# Rename transformed columns
data = rename_columns(data)
```

In [43]:
```
data
```

Out[43]:

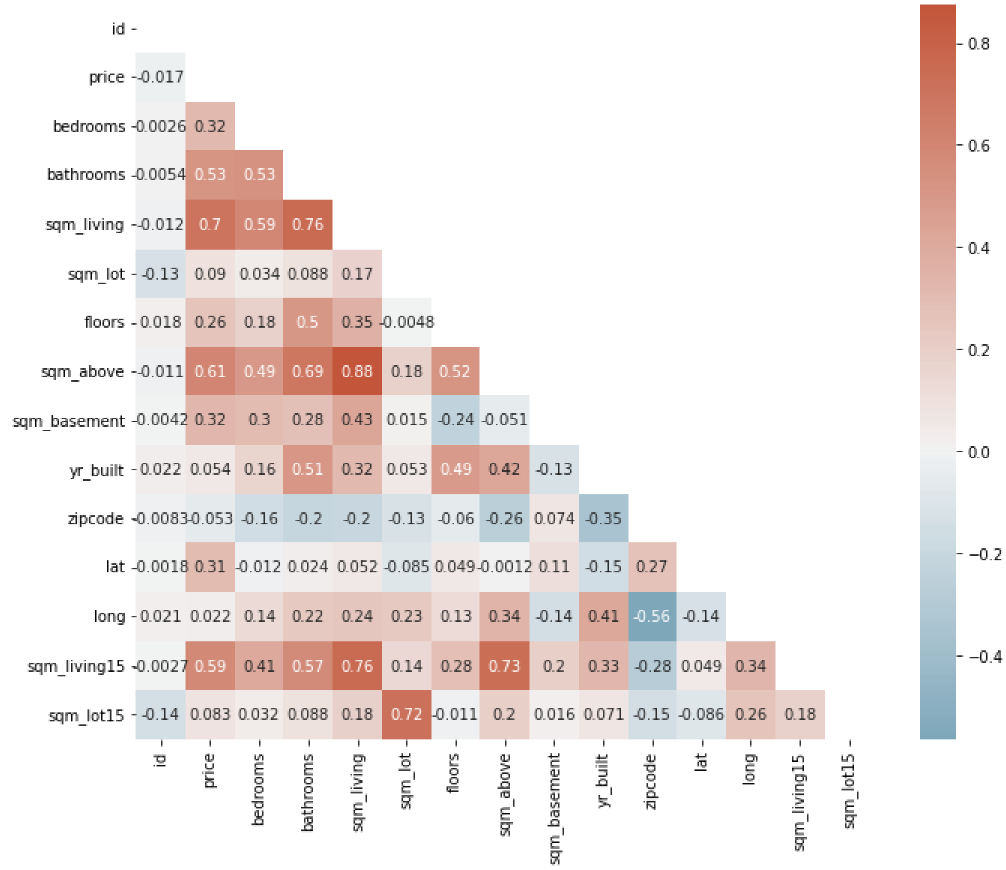
	id	date	price	bedrooms	bathrooms	sqm_living	sqm_lot	floors	waterfront	view	condition	gra
0	7129300520	2014-10-13	221900.0	3	1.00	109.62554	524.901950	1.0	NO	NONE	Average	Avera
1	6414100192	2014-12-09	538000.0	3	2.25	238.76071	672.803526	2.0	NO	NONE	Average	Avera
2	5631500400	2015-02-25	180000.0	2	1.00	71.53531	929.030000	1.0	NO	NONE	Average	6 L Avera
3	2487200875	2014-12-09	604000.0	4	3.00	182.08988	464.515000	1.0	NO	NONE	Very Good	Avera
4	1954400510	2015-02-18	510000.0	3	2.00	156.07704	750.656240	1.0	NO	NONE	Average	8 Gc
...	...	...	...	...	...	...	...	...	...	...	...	
21592	263000018	2014-05-21	360000.0	3	2.50	142.14159	105.073293	3.0	NO	NONE	Average	8 Gc
21593	6600060120	2015-02-23	400000.0	4	2.50	214.60593	540.045139	2.0	NO	NONE	Average	8 Gc
21594	1523300141	2014-06-23	402101.0	2	0.75	94.76106	125.419050	2.0	NO	NONE	Average	Avera
21595	291310100	2015-01-16	400000.0	3	2.50	148.64480	221.852364	2.0	NO	NONE	Average	8 Gc
21596	1523300157	2014-10-15	325000.0	2	0.75	94.76106	99.963628	2.0	NO	NONE	Average	Avera

21592 rows × 20 columns

Correlation Matrix

A correlation matrix was created to visualize the correlations between the different features. A higher figure describes a higher correlation

In [44]:
```
corr = data.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
plt.figure(figsize=(11,9))
sns.heatmap(corr, cmap=sns.diverging_palette(230, 20, as_cmap=True),
            mask = mask, annot=True, center=0);
```



Based on the correlation matrix generated from the dataset, we can see that the most strongly correlated feature with the target column `price` is `sqft_living` with a correlation coefficient of `0.7` . This suggests that there is a strong positive linear relationship between the living area of a house and its price. Houses with larger living areas are likely to have higher prices than those with smaller living areas.

Data Modelling

In this section, we shall use Regression technique. Regression is a statistical method used to estimate the relationship between a dependent variable and one or more independent variables. The goal of regression analysis is to model the relationship between the variables and to use the model to make predictions or to understand the underlying factors that affect the dependent variable. In this case we are trying to estimate the effect that the different features of the homes has on our dependent variable, the price of the homes.

Furthermore, as we are working with multiple features, we will be using multiple linear regression. Multiple linear regression is a regression algorithm that is used to predict the value of a dependent variable based on the value of multiple independent variables (unlike simple linear regression which only uses one independent variable).

Simple Linear Regression

We will use simple linear regression as our baseline model. The regression will be between two variables , the sale price as the dependent variable and the size of living space(sqm) in the home as the independent variable in our model.

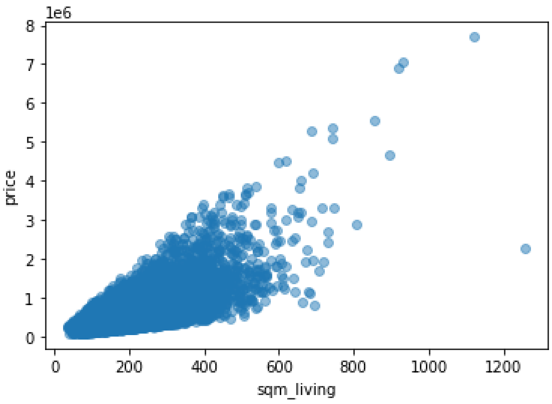
In [45]:
```
corr = data.corr()['price'].sort_values(ascending=False)
corr
```

Out[45]:
```
price            1.000000
sqm_living       0.701929
sqm_above        0.605396
sqm_living15     0.585250
bathrooms        0.525860
sqm_basement     0.320931
bedrooms         0.316939
lat              0.306686
floors           0.256904
sqm_lot          0.089898
sqm_lot15        0.082866
yr_built         0.053914
long             0.022000
id              -0.016690
zipcode         -0.053299
Name: price, dtype: float64
```

We see that the `sqm_living` column has the highest correlation with the `price` column. This is expected since the size of the house is a major factor in determining the price of the house. Let's create a scatter plot to determine the relationship between the `sqm_living` and `price` is linear.

In [46]:
```
def scatter_plot(df, x, y):
    '''Plot a scatter plot'''
    plt.scatter(data[x],data[y], alpha=0.5)
    plt.xlabel(x)
    plt.ylabel(y)
    plt.show()
```

In [47]:
```
# Plot a scatter plot of 'Price' against 'sqft_living'
scatter_plot(data, 'sqm_living', 'price')
```



In [48]:
```
# Assigning values of the variables
X = data[['sqm_living']]
y = data['price']
```

From the scatter plot we identified that the relationship is linear

In [49]:

```
baseline_model = sm.OLS(y, sm.add_constant(X))
baseline_results = baseline_model.fit()
print(baseline_results.summary())
```

```
                            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:                        08:27:49   Log-Likelihood:            -2.9999e+05
No. Observations:               21592   AIC:                         6.000e+05
Df Residuals:                   21590   BIC:                         6.000e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       -4.41e+04   4410.853     -9.998      0.000   -5.27e+04   -3.55e+04
sqm_living  3023.8882     20.882    144.807      0.000    2982.958    3064.819
==============================================================================
Omnibus:                    14794.567   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           542101.232
Skew:                           2.819   Prob(JB):                         0.00
Kurtosis:                      26.891   Cond. No.                         523.
==============================================================================

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

In [50]:

```
# calculate the mean absolute error of our baseline model
y_pred = baseline_results.predict(sm.add_constant(X))
baseline_mae = mean_absolute_error(y, y_pred)
baseline_mae
```

Out[50]: 173829.54414048948

In [51]:

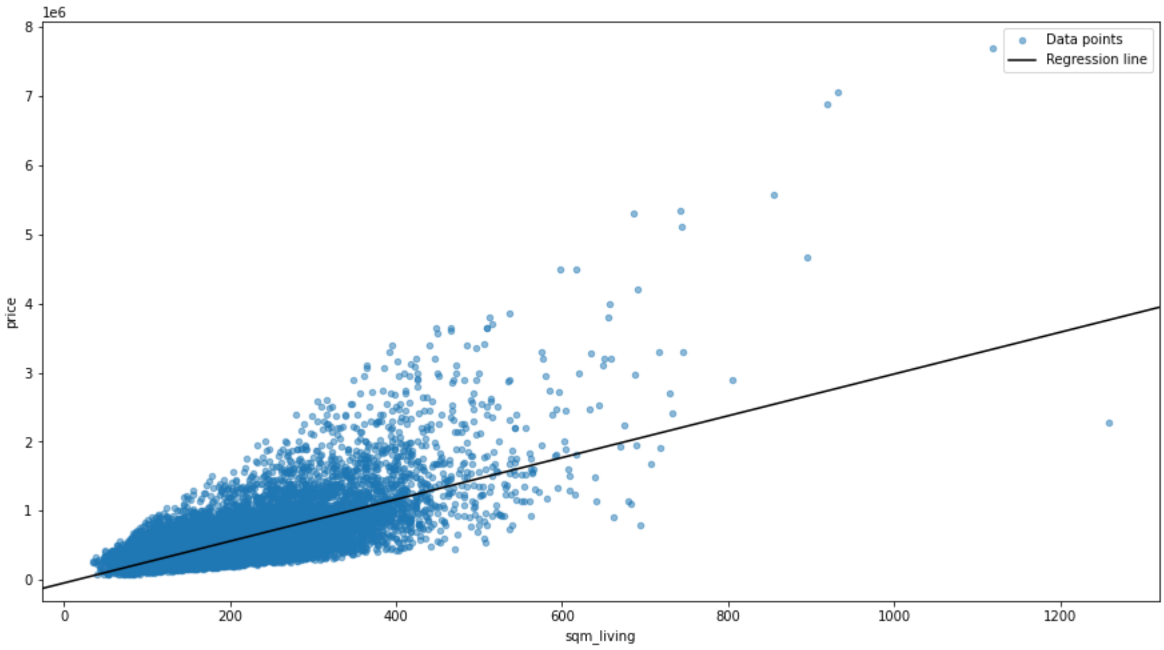
```
from sklearn.metrics import mean_squared_error
baseline_rmse = np.sqrt(mean_squared_error(y, y_pred))
baseline_rmse
```

Out[51]: 261662.72801862823

We want to minimize the difference between the predicted and actual prices, and MAE provides a good measure of how well the model is performing.

In [52]:

```
# Plot partial regression plot for the feature
fig, ax = plt.subplots(figsize=(15,8))
data.plot.scatter(x="sqm_living", y="price", label="Data points", alpha=0.5 ,ax=ax)
sm.graphics.abline_plot(model_results=baseline_results, label="Regression line", ax=ax, color="black")
ax.legend();
```



Baseline Model Evaluation and Interpretation

The baseline model is statistically significant overall, and explains about 49.2% of the variance in price. The model is off by about $173,829

The coefficients for the intercept, `sqm_living` is statistically significant.

- Every increase of 1 in Square meters of living space in the home is associated with an increase of $3023 in the Sale price .

The model is statistically significant except it only explains about 49% variance of our target. However we target to achieve `R-squared` of about 70% and a lower mean absolute error. This informed our decision to build another model.

Multiple Linear Regression Model

> We will now iterate the baseline model by building a multiple linear regression model that will have more than one independent variable.

We will start by creating a new dataframe that will contain all of the features that we want to have in our model. In order to know which variables to keep in our model, we will first look at a correlation matrix. This is done in order to reduce multicollinearity. Multicollinearity is a situation in which two or more independent variables are highly correlated. This can cause problems in the model as it can lead to unstable estimates of the regression coefficients. Therefore, we will be removing the variables that are highly correlated with each other.

In [53]:
```
# Declare X_iterated variables
X_all = data[['bedrooms', 'bathrooms','sqm_living','sqm_living15', 'sqm_lot','floors',
              'view', 'condition', 'grade', 'sqm_above', 'sqm_basement', 'yr_built']]

# Preview the X_iterated dataframe
pd.DataFrame(X_all).head()
```

Out[53]:

	bedrooms	bathrooms	sqm_living	sqm_living15	sqm_lot	floors	view	condition	grade	sqm_above	sqm_basement
0	3	1.00	109.62554	124.49002	524.901950	1.0	NONE	Average	7 Average	109.62554	0.00000
1	3	2.25	238.76071	157.00607	672.803526	2.0	NONE	Average	7 Average	201.59951	37.16120
2	2	1.00	71.53531	252.69616	929.030000	1.0	NONE	Average	6 Low Average	71.53531	0.00000
3	4	3.00	182.08988	126.34808	464.515000	1.0	NONE	Very Good	7 Average	97.54815	84.54173
4	3	2.00	156.07704	167.22540	750.656240	1.0	NONE	Average	8 Good	156.07704	0.00000

Ordinal Encoding

> Ordinal encoding converts each label into integer values and the encoded data represents the sequence of labels

Using the official [King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r), we were able to understand that the values in the `condition` and `grade` columns are ordinal, and have been assigned a value based on the quality of the feature. Therefore, we will be ordinal encoding these columns.

In [54]:

```python
# Create dictionaries for mapping the  numerical valueS
condition_dict = {'Poor': 1, 'Fair': 2, 'Average': 3, 'Good': 4, 'Very Good': 5}
grade_dict = {'3 Poor': 3, '4 Low': 4, '5 Fair': 5, '6 Low Average': 6, '7 Average': 7,
              '8 Good': 8, '9 Better': 9, '10 Very Good': 10, '11 Excellent': 11, '12 Luxury': 12, '13


X_all['condition'] = X_all['condition'].map(condition_dict)
X_all['grade'] = X_all['grade'].map(grade_dict)

# Preview the dataframe
X_all.head()
```

Out[54]:

	bedrooms	bathrooms	sqm_living	sqm_living15	sqm_lot	floors	view	condition	grade	sqm_above	sqm_basement
0	3	1.00	109.62554	124.49002	524.901950	1.0	NONE	3	7	109.62554	0.00000
1	3	2.25	238.76071	157.00607	672.803526	2.0	NONE	3	7	201.59951	37.16120
2	2	1.00	71.53531	252.69616	929.030000	1.0	NONE	3	6	71.53531	0.00000
3	4	3.00	182.08988	126.34808	464.515000	1.0	NONE	5	7	97.54815	84.54173
4	3	2.00	156.07704	167.22540	750.656240	1.0	NONE	3	8	156.07704	0.00000

One Hot Encoding

In order to use a categorical variable in our model, we'll create multiple dummy variables, one for each category of the categorical variable.

In [55]:

```python
#Encoding the categorical columns
X_all = pd.get_dummies(X_all, columns=['view'], drop_first=False)
#Preview the dataframe
X_all
```

Out[55]:

	bedrooms	bathrooms	sqm_living	sqm_living15	sqm_lot	floors	condition	grade	sqm_above	sqm_basement	yr_l
0	3	1.00	109.62554	124.49002	524.901950	1.0	3	7	109.62554	0.00000	
1	3	2.25	238.76071	157.00607	672.803526	2.0	3	7	201.59951	37.16120	
2	2	1.00	71.53531	252.69616	929.030000	1.0	3	6	71.53531	0.00000	
3	4	3.00	182.08988	126.34808	464.515000	1.0	5	7	97.54815	84.54173	
4	3	2.00	156.07704	167.22540	750.656240	1.0	3	8	156.07704	0.00000	
...	...	...	...	...	...	...	...	...	...	...	
21592	3	2.50	142.14159	142.14159	105.073293	3.0	3	8	142.14159	0.00000	
21593	4	2.50	214.60593	170.01249	540.045139	2.0	3	8	214.60593	0.00000	
21594	2	0.75	94.76106	94.76106	125.419050	2.0	3	7	94.76106	0.00000	
21595	3	2.50	148.64480	130.99323	221.852364	2.0	3	8	148.64480	0.00000	
21596	2	0.75	94.76106	94.76106	99.963628	2.0	3	7	94.76106	0.00000	

21592 rows × 16 columns

In the `view` column, we shall be dropping the `NONE` column as the reference column. This will allow us to determine if having a waterfront has any effect on property value

In [56]:

```python
X_all = X_all.drop(['view_NONE'], axis=1)
X_all.columns
```

Out[56]:

```
Index(['bedrooms', 'bathrooms', 'sqm_living', 'sqm_living15', 'sqm_lot',
       'floors', 'condition', 'grade', 'sqm_above', 'sqm_basement', 'yr_built',
       'view_AVERAGE', 'view_EXCELLENT', 'view_FAIR', 'view_GOOD'],
      dtype='object')
```

Check for MultiCollinearity

In [57]:
```
# save absolute value of correlation matrix as a data frame
# converts all values to absolute value
# stacks the row:column pairs into a multindex
# reset the index to set the multindex to seperate columns
# sort values. 0 is the column automatically generated by the stacking

df=X_all.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 default) in a new column named "pairs"
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 if you have variables perfectly
# correlated with variables other than themselves.
# for the sake of exercise, kept it in.
df.drop_duplicates(inplace=True)
```

In [58]:
```
df[(df.cc>.75) & (df.cc <1)]
```

Out[58]:

pairs	cc
(sqm_above, sqm_living)	0.876504
(grade, sqm_living)	0.762978
(sqm_living, sqm_living15)	0.756551
(sqm_above, grade)	0.756183
(sqm_living, bathrooms)	0.755697

Using .75 as a cutoff, (sqm_living, sqm_above) and (sqm_living15, sqm_living) are highly correlated with correlation coefficients of 0.856068 and 0.758043, respectively. We are going to retain `sqm_living` since the rest have a lower correlation with the target variable(price)

In [59]:
```
X_all.drop(['sqm_above','sqm_living15'], axis=1, inplace=True)
```

In [60]:
```
iterated_model = sm.OLS(y, sm.add_constant(X_all))
iterated_results = iterated_model.fit()
print(iterated_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.646
Model:                            OLS   Adj. R-squared:                  0.646
Method:                 Least Squares   F-statistic:                     3030.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        08:27:52   Log-Likelihood:            -2.9611e+05
No. Observations:               21592   AIC:                         5.922e+05
Df Residuals:                   21578   BIC:                         5.924e+05
Df Model:                          13
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           6.409e+06   1.32e+05     48.484      0.000    6.15e+06    6.67e+06
bedrooms       -4.495e+04   2154.018    -20.866      0.000   -4.92e+04   -4.07e+04
bathrooms        4.91e+04   3516.680     13.962      0.000    4.22e+04     5.6e+04
sqm_living      1861.8235     38.254     48.670      0.000    1786.843    1936.804
sqm_lot           -2.6355      0.399     -6.608      0.000      -3.417      -1.854
floors          2.666e+04   3764.167      7.083      0.000    1.93e+04     3.4e+04
condition       1.793e+04   2492.129      7.193      0.000     1.3e+04    2.28e+04
grade           1.237e+05   2194.879     56.340      0.000    1.19e+05    1.28e+05
sqm_basement      15.7356     48.191      0.327      0.744     -78.722     110.193
yr_built       -3673.1712     67.947    -54.059      0.000   -3806.352   -3539.990
view_AVERAGE    5.543e+04   7425.426      7.465      0.000    4.09e+04       7e+04
view_EXCELLENT   4.91e+05   1.28e+04     38.441      0.000    4.66e+05    5.16e+05
view_FAIR       1.119e+05   1.23e+04      9.131      0.000    8.79e+04    1.36e+05
view_GOOD       1.269e+05   1.01e+04     12.524      0.000    1.07e+05    1.47e+05
==============================================================================
Omnibus:                    16586.849   Durbin-Watson:                   1.978
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1254573.573
Skew:                           3.102   Prob(JB):                         0.00
Kurtosis:                      39.824   Cond. No.                     3.70e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.7e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [61]:
```
# Calculate the mean absolute error of our iterated model
y_pred = iterated_results.predict(sm.add_constant(X_all))
iterated_mae = mean_absolute_error(y,y_pred)
iterated_mae
```

Out[61]: 140692.204515442

In [62]:
```
# The mean absolute error values of the baseline model and iterated_model
print("Baseline Model Mean Absolute Error: ", baseline_mae)
print("Iterated Model Mean Absolute Error:", iterated_mae)


# The adjusted R-squared values of the baseline model and iterated model
print("Baseline Model Adjusted R-squared: ", baseline_results.rsquared_adj)
print("Iterated Model Adjusted R-squared: ", iterated_results.rsquared_adj)
```

```
Baseline Model Mean Absolute Error:  173829.54414048948
Iterated Model Mean Absolute Error: 140692.204515442
Baseline Model Adjusted R-squared:  0.4926808087361043
Iterated Model Adjusted R-squared:  0.6458660832294414
```

Overall the model performed better. From the model results, we can see that the model is statistically significant and it explains 64.5% of the variance in the data compared to the 49.2% in the baseline model. Furthermore, the model is off by about $140694 compared to the $173824 in the baseline model. This is a significant improvement.

In [63]:
```
results_df = pd.concat([iterated_results.params, iterated_results.pvalues], axis =1)
results_df.columns = ['coefficient','p-value']
results_df
```

Out[63]:

	coefficient	p-value
const	6.408900e+06	0.000000e+00
bedrooms	-4.494520e+04	9.673014e-96
bathrooms	4.910154e+04	4.109894e-44
sqm_living	1.861823e+03	0.000000e+00
sqm_lot	-2.635470e+00	3.991863e-11
floors	2.666171e+04	1.453689e-12
condition	1.792535e+04	6.555596e-13
grade	1.236595e+05	0.000000e+00
sqm_basement	1.573565e+01	7.440282e-01
yr_built	-3.673171e+03	0.000000e+00
view_AVERAGE	5.542823e+04	8.668392e-14
view_EXCELLENT	4.909560e+05	0.000000e+00
view_FAIR	1.118657e+05	7.354961e-20
view_GOOD	1.269046e+05	7.327627e-36

All of the coefficients are statistically significant.

`bedrooms` : a one-unit increase in the number of bedrooms is associated with a decrease of $ 44,945.2 in home price.

`bathrooms` : a one-unit increase in the number of bathrooms is associated with an increase of $49,101.5 in home price.

`sqm_living` : a one-unit increase in square metre of living space is associated with an increase of $1,861.8 in home price.

`sqm_lot` : a one-unit increase in square metre of the lot size is associated with a decrease of $2.635 in home price.

`floors` : a one-unit increase in the number of floors is associated with an increase of $26,661.7 in home price.

`condition` : a one-unit increase in the condition rating of the home is associated with an increase of $17,925.4 in home price.

`grade` : a one-unit increase in the grade rating of the home is associated with an increase of $123,659.5 in home price.

`sqm_basement` : a one-unit increase in the square metre of the basement is associated with an increase of $15.736 in home price.

`yr_built` : a one-unit increase in the year the home was built is associated with a decrease of $3,673.2 in home price.

`view_EXCELLENT` : having an EXCELLENT view is associated with an increase of $490,956.0 in home price. This suggests that excellent views are highly desirable and tend to increase the price of a home.

`view_GOOD` : having a GOOD view is associated with an increase of $126,904.6 in home price.

`view_FAIR` : having a FAIR view is associated with an increase of $118,657.0 in home price.

`view_AVERAGE` : having an AVERAGE view is associated with an increase of $55,4282.3 in home price.

Second Multiple Linear Regression Model

In [64]:
```
# Declare X_iterated variables
iterable = data[['bathrooms','sqm_living', 'sqm_lot',
              'sqm_basement', 'yr_built', 'zipcode']]

# Preview the X_iterated dataframe
pd.DataFrame(iterable).head()
```

Out[64]:

	bathrooms	sqm_living	sqm_lot	sqm_basement	yr_built	zipcode
0	1.00	109.62554	524.901950	0.00000	1955	98178
1	2.25	238.76071	672.803526	37.16120	1951	98125
2	1.00	71.53531	929.030000	0.00000	1933	98028
3	3.00	182.08988	464.515000	84.54173	1965	98136
4	2.00	156.07704	750.656240	0.00000	1987	98074

In [65]:
```
data['zipcode'].value_counts()
```

Out[65]:
```
98103    601
98038    589
98115    583
98052    574
98117    553
        ...
98102    104
98010    100
98024     80
98148     57
98039     50
Name: zipcode, Length: 70, dtype: int64
```

We chose `98103` as our reference category since it has the highest number of value counts.

In [66]:
```
iterable = pd.get_dummies(iterable, columns=['zipcode'])
iterable = iterable.drop('zipcode_98103', axis = 1)
#Preview the dataframe
iterable
```

Out[66]:

	bathrooms	sqm_living	sqm_lot	sqm_basement	yr_built	zipcode_98001	zipcode_98002	zipcode_98003	zipcode_98(
0	1.00	109.62554	524.901950	0.00000	1955	0	0	0	
1	2.25	238.76071	672.803526	37.16120	1951	0	0	0	
2	1.00	71.53531	929.030000	0.00000	1933	0	0	0	
3	3.00	182.08988	464.515000	84.54173	1965	0	0	0	
4	2.00	156.07704	750.656240	0.00000	1987	0	0	0	
...	...	...	...	...	...	...	...	...	
21592	2.50	142.14159	105.073293	0.00000	2009	0	0	0	
21593	2.50	214.60593	540.045139	0.00000	2014	0	0	0	
21594	0.75	94.76106	125.419050	0.00000	2009	0	0	0	
21595	2.50	148.64480	221.852364	0.00000	2004	0	0	0	
21596	0.75	94.76106	99.963628	0.00000	2008	0	0	0	

21592 rows × 74 columns

In [67]:
```
iterated_model2 = sm.OLS(y, sm.add_constant(iterable))
iterated_results2 = iterated_model2.fit()
print(iterated_results2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.736
Model:                            OLS   Adj. R-squared:                  0.735
Method:                 Least Squares   F-statistic:                     811.7
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        08:27:53   Log-Likelihood:            -2.9293e+05
No. Observations:               21592   AIC:                         5.860e+05
Df Residuals:                   21517   BIC:                         5.866e+05
Df Model:                          74                                         
Covariance Type:            nonrobust                                         
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const          1.774e+06   1.17e+05     15.118      0.000    1.54e+06       2e+06
bathrooms      1.641e+04   2929.362      5.603      0.000    1.07e+04    2.22e+04
sqm_living     2813.4898     26.608    105.739      0.000    2761.336    2865.643
sqm_lot           2.9292      0.367      7.977      0.000       2.209       3.649
sqm_basement   -663.3922     38.149    -17.389      0.000    -738.168    -588.617
yr_built       -838.7064     60.961    -13.758      0.000    -958.194    -719.218
zipcode_98001 -3.546e+05   1.27e+04    -27.905      0.000    -3.8e+05    -3.3e+05
zipcode_98002 -3.401e+05   1.55e+04    -21.951      0.000    -3.7e+05    -3.1e+05
zipcode_98003 -3.461e+05   1.38e+04    -25.164      0.000   -3.73e+05   -3.19e+05
zipcode_98004  4.629e+05   1.33e+04     34.779      0.000    4.37e+05    4.89e+05
zipcode_98005 -2.094e+04   1.66e+04     -1.262      0.207   -5.35e+04    1.16e+04
zipcode_98006  -1.84e+04   1.17e+04     -1.574      0.115   -4.13e+04    4511.079
zipcode_98007  -9.42e+04   1.77e+04     -5.312      0.000   -1.29e+05   -5.94e+04
zipcode_98008 -4.759e+04   1.37e+04     -3.479      0.001   -7.44e+04   -2.08e+04
zipcode_98010 -2.889e+05   2.06e+04    -14.044      0.000   -3.29e+05   -2.49e+05
zipcode_98011 -2.318e+05   1.57e+04    -14.786      0.000   -2.63e+05   -2.01e+05
zipcode_98014 -2.621e+05    1.9e+04    -13.791      0.000   -2.99e+05   -2.25e+05
zipcode_98019 -2.861e+05   1.59e+04    -17.952      0.000   -3.17e+05   -2.55e+05
zipcode_98022 -3.285e+05   1.48e+04    -22.128      0.000   -3.58e+05   -2.99e+05
zipcode_98023 -3.667e+05   1.16e+04    -31.722      0.000   -3.89e+05   -3.44e+05
zipcode_98024 -2.056e+05   2.28e+04     -9.022      0.000    -2.5e+05   -1.61e+05
zipcode_98027 -1.728e+05   1.23e+04    -14.041      0.000   -1.97e+05   -1.49e+05
zipcode_98028 -2.255e+05   1.37e+04    -16.436      0.000   -2.52e+05   -1.99e+05
zipcode_98029 -1.208e+05   1.33e+04     -9.087      0.000   -1.47e+05   -9.47e+04
zipcode_98030 -3.547e+05   1.42e+04    -24.936      0.000   -3.83e+05   -3.27e+05
zipcode_98031 -3.414e+05   1.39e+04    -24.578      0.000   -3.69e+05   -3.14e+05
zipcode_98032 -3.403e+05   1.86e+04    -18.264      0.000   -3.77e+05   -3.04e+05
zipcode_98033  4.557e+04    1.2e+04      3.784      0.000     2.2e+04    6.92e+04
zipcode_98034 -1.298e+05   1.13e+04    -11.519      0.000   -1.52e+05   -1.08e+05
zipcode_98038 -3.347e+05   1.12e+04    -29.781      0.000   -3.57e+05   -3.13e+05
zipcode_98039  1.023e+06    2.8e+04     36.485      0.000    9.68e+05    1.08e+06
zipcode_98040  2.528e+05   1.38e+04     18.256      0.000    2.26e+05     2.8e+05
zipcode_98042 -3.457e+05   1.14e+04    -30.454      0.000   -3.68e+05   -3.23e+05
zipcode_98045 -2.496e+05   1.51e+04    -16.515      0.000   -2.79e+05    -2.2e+05
zipcode_98052 -1.072e+05   1.12e+04     -9.566      0.000   -1.29e+05   -8.53e+04
zipcode_98053 -1.508e+05   1.26e+04    -12.002      0.000   -1.75e+05   -1.26e+05
zipcode_98055 -3.064e+05   1.39e+04    -22.003      0.000   -3.34e+05   -2.79e+05
zipcode_98056  -2.44e+05   1.22e+04    -19.930      0.000   -2.68e+05    -2.2e+05
zipcode_98058 -3.218e+05   1.19e+04    -27.125      0.000   -3.45e+05   -2.99e+05
zipcode_98059 -2.743e+05   1.19e+04    -23.079      0.000   -2.98e+05   -2.51e+05
zipcode_98065 -2.826e+05   1.35e+04    -20.888      0.000   -3.09e+05   -2.56e+05
zipcode_98070 -1.735e+05   1.94e+04     -8.947      0.000   -2.11e+05   -1.35e+05
zipcode_98072 -1.888e+05    1.4e+04    -13.530      0.000   -2.16e+05   -1.61e+05
zipcode_98074 -1.428e+05   1.21e+04    -11.791      0.000   -1.67e+05   -1.19e+05
zipcode_98075 -1.379e+05    1.3e+04    -10.635      0.000   -1.63e+05   -1.13e+05
zipcode_98077  -2.17e+05   1.58e+04    -13.739      0.000   -2.48e+05   -1.86e+05
zipcode_98092 -3.817e+05   1.29e+04    -29.541      0.000   -4.07e+05   -3.56e+05
zipcode_98102  1.863e+05   2.01e+04      9.274      0.000    1.47e+05    2.26e+05
zipcode_98105  1.478e+05   1.47e+04     10.023      0.000    1.19e+05    1.77e+05
zipcode_98106 -2.066e+05   1.29e+04    -15.965      0.000   -2.32e+05   -1.81e+05
zipcode_98107  1.762e+04   1.39e+04      1.265      0.206   -9684.284    4.49e+04
zipcode_98108 -2.296e+05   1.59e+04    -14.467      0.000   -2.61e+05   -1.99e+05
zipcode_98109   1.88e+05   1.97e+04      9.542      0.000    1.49e+05    2.27e+05
zipcode_98112    2.9e+05    1.4e+04     20.785      0.000    2.63e+05    3.17e+05
zipcode_98115 -5137.2933    1.1e+04     -0.467      0.641   -2.67e+04    1.64e+04
zipcode_98116 -8897.3337    1.3e+04     -0.686      0.492   -3.43e+04    1.65e+04
zipcode_98117 -1.437e+04   1.11e+04     -1.289      0.198   -3.62e+04    7485.252
zipcode_98118 -1.701e+05   1.14e+04    -14.898      0.000   -1.92e+05   -1.48e+05
zipcode_98119   1.72e+05   1.59e+04     10.787      0.000    1.41e+05    2.03e+05
zipcode_98122  1.278e+04   1.35e+04      0.945      0.345   -1.37e+04    3.93e+04
zipcode_98125 -1.288e+05   1.21e+04    -10.607      0.000   -1.53e+05   -1.05e+05
zipcode_98126 -1.259e+05   1.27e+04     -9.927      0.000   -1.51e+05   -1.01e+05
zipcode_98133 -1.769e+05   1.15e+04    -15.341      0.000   -1.99e+05   -1.54e+05
zipcode_98136 -4.197e+04    1.4e+04     -3.000      0.003   -6.94e+04   -1.46e+04
zipcode_98144 -4.717e+04   1.28e+04     -3.684      0.000   -7.23e+04   -2.21e+04
zipcode_98146 -2.119e+05   1.36e+04    -15.605      0.000   -2.38e+05   -1.85e+05
zipcode_98148 -2.878e+05   2.62e+04    -10.981      0.000   -3.39e+05   -2.36e+05
```

```
zipcode_98155 -1.858e+05   1.19e+04    -15.682      0.000    -2.09e+05   -1.63e+05
zipcode_98166 -2.213e+05   1.42e+04    -15.597      0.000    -2.49e+05   -1.93e+05
zipcode_98168 -2.918e+05   1.39e+04    -20.964      0.000    -3.19e+05   -2.65e+05
zipcode_98177 -6.838e+04   1.42e+04     -4.818      0.000    -9.62e+04   -4.06e+04
zipcode_98178 -2.814e+05    1.4e+04    -20.063      0.000    -3.09e+05   -2.54e+05
zipcode_98188  -3.22e+05    1.8e+04    -17.910      0.000    -3.57e+05   -2.87e+05
zipcode_98198 -2.934e+05   1.37e+04    -21.373      0.000     -3.2e+05   -2.67e+05
zipcode_98199  9.226e+04   1.32e+04      7.008      0.000     6.65e+04    1.18e+05
==============================================================================
Omnibus:                    21177.585   Durbin-Watson:                   1.978
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2881614.378
Skew:                           4.451   Prob(JB):                         0.00
Kurtosis:                      58.890   Cond. No.                     3.81e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.81e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [68]:
```
# Calculate the mean absolute error of our model
y_pred2 = iterated_results2.predict(sm.add_constant(iterable))
iterated_mae2 = mean_absolute_error(y ,y_pred2)
iterated_mae2
```

Out[68]:
```
109747.2759342834
```

Regression Results

1. Simple Linear Model

The baseline model is statistically significant overall, and explains about 49.2% of the variance in price. Each prediction is off by about $173,829

The coefficient for the intercept, `sqm_living` is statistically significant.

Every increase of 1 in Square meters of living space in the home is associated with an increase of $3023 in the Sale price .

2 .Multiple Linear Model 1

All of the coefficients are statistically significant, and explains about 65% of the variance in price. Each prediction is off by about $ 140,692.20

`bedrooms` : a one-unit increase in the number of bedrooms is associated with a decrease of $ 44,945.2 in home price.

`bathrooms` : a one-unit increase in the number of bathrooms is associated with an increase of $49,101.5 in home price.

`sqm_living` : a one-unit increase in square metre of living space is associated with an increase of $1,861.8 in home price.

`sqm_lot` : a one-unit increase in square metre of the lot size is associated with a decrease of $2.635 in home price.

`floors` : a one-unit increase in the number of floors is associated with an increase of $26,661.7 in home price.

`condition` : a one-unit increase in the condition rating of the home is associated with an increase of $17,925.4 in home price.

`grade` : a one-unit increase in the grade rating of the home is associated with an increase of $123,659.5 in home price.

`sqm_basement` : a one-unit increase in the square metre of the basement is associated with an increase of $15.736 in home price.

`yr_built` : a one-unit increase in the year the home was built is associated with a decrease of $3,673.2 in home price.

`view_EXCELLENT` : having an EXCELLENT view is associated with an increase of $490,956.0 in home price. This suggests that excellent views are highly desirable and tend to increase the price of a home.

`view_GOOD` : having a GOOD view is associated with an increase of $126,904.6 in home price.

`view_FAIR` : having a FAIR view is associated with an increase of $118,657.0 in home price.

`view_AVERAGE` : having an AVERAGE view is associated with an increase of $55,4282.3 in home price.

There was increase of adjusted R-Squared from about 49% in the Baseline Model to about 65% in this model. This was a significant increase but it did not achieve our target of 70%.

3 .Multiple Linear Model 2

Some of the coefficients are not statistically significant, and explains about 74% of the variance in price. Each prediction is off by about $ 109,000

`bathrooms` : a one-unit increase in the number of bathrooms is associated with an increase of $16,410.00 in home price.

`sqm_living` : a one-unit increase in square metre of living space is associated with an increase of $ 2813.50 in home price.

`sqm_lot` : a one-unit increase in square metre of the lot size is associated with a increase of $ 2.9292 in home price.

`sqm_basement` : a one-unit increase in the square metre of the basement is associated with an decrease of $ 663.40 in home price.

`yr_built` : a one-unit increase in the year the home was built is associated with a decrease of $ 838.71 in home price.

`zipcode_98004` : Compared to `zipcode_98103` , `zipcode_98004` has the highest increase of $462,900 in home price.

`zipcode_98092` : Compared to `zipcode_98103` , `zipcode_98092` has the highest decrease of $381,700 in home price.

Conclusion

`Multiple Linear Model 2` was chosen as the final model. This is beacause it explained about *74 %* of the variance in price, about 10% more than Multiple Linear Model 1. It also had a lower Mean Absolute Error, by about $ 32,000.

From the final model, `bathroom` is associated with bringing the highest increase in sale price.

An increase in `sqm_living` count by 1 unit had the second highest associated increase in price.

Compared to `zipcode_98103` , `zipcode_98004` has the highest increase of $462,900 in home price.

When building new houses, The Real Estate Developer should therefore:

- **Increase the number of bathrooms in the houses:** Based on our analysis, increasing the number of bathrooms in the houses has the highest positive association with an increase in home prices. Therefore, it is recommended that Real Estate Developers prioritize adding more bathrooms to the houses they build to increase the value of the properties.
- **Consider the size of the living space (sqm_living) when building houses:** The size of the living space has a significant impact on the price of a house. Therefore, it is suggested that Real Estate Developers should consider the living space size when designing and constructing new houses. Increasing the living space size could lead to a higher selling price of the property.
- **Consider building houses in the postal area of zipcode_98004:** Our analysis suggests that the postal area of zipcode_98004 has the highest increase in home prices compared to other areas. Therefore, it is recommended that Real Estate Developers consider building houses in this area to increase the potential selling price of their properties.

However, it is important to note that our model prediction for house prices has a mean absolute error of approximately $109,000. Therefore, this suggests that the model may not be completely accurate and may require further evaluation and refinement.

Lastly, it is worth mentioning that the study had limitations, primarily due to the presence of missing values. Therefore, future studies may need to consider using a larger dataset to obtain more reliable insights. Overall, we can have confidence in the validity of the results obtained from this study, but further work is necessary to enhance the accuracy of the predictions. A further study may be required with a larger dataset for better insights.