PHASE 2 PROJECT

GROUP MEMBERS

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BUSINESS STAKEHOLDER

The real estate agency

BUSINESS PROBLEM

A real estate agency wants to analyze the factors that influence the prices of houses in order to provide accurate pricing estimates to their clients. The agency aims to understand the relationship between various features of a house, such as the number of rooms, living area, basement area, overall quality, and other relevant factors, and how they affect the sale price.

The clients being, homeowners and potential house buyers have difficulty in making informed decisions regarding property investments, to make this decision, understanding the factors influencing housing prices in a specific area is necessary.

OBJECTIVES

REAL ESTATE AGENCY

- To identify the locations with the highest sales prices.
- To identify how seasonal trends affect sales.
- To predict prices of houses depending on the features.

Importing the necessary libraries that will be used to perform analysis on our data

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy import stats
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```python
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import StandardScaler
data = pd.read_csv('kc_house_data.csv')
areas = pd.read_csv('deliverylocations.csv')
```

Defining functions to load and view the data

```python
# loading data

def desription_data(data):
    data = pd.read_csv(data)
    print("\n.............Info:................")
    print(data.info())
    print("\n.............Describe:..............")
    print(data.describe())
    print("\n.............Head:................")
    print(data.head())

desription_data('kc_house_data.csv')
```

```
.............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
```

```
None

.............Describe:...............
                 id         price      bedrooms     bathrooms  
sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000  
21597.000000   
mean   4.580474e+09  5.402966e+05      3.373200      2.115826   
2080.321850   
std    2.876736e+09  3.673681e+05      0.926299      0.768984   
918.106125   
min    1.000102e+06  7.800000e+04      1.000000      0.500000   
370.000000   
25%    2.123049e+09  3.220000e+05      3.000000      1.750000   
1430.000000   
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   
1910.000000   
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   
2550.000000   
max    9.900000e+09  7.700000e+06     33.000000      8.000000   
13540.000000   

           sqft_lot        floors    sqft_above      yr_built  
yr_renovated  \
count  2.159700e+04  21597.000000  21597.000000  21597.000000  
17755.000000   
mean   1.509941e+04      1.494096   1788.596842   1970.999676  
83.636778   
std    4.141264e+04      0.539683    827.759761     29.375234  
399.946414   
min    5.200000e+02      1.000000    370.000000   1900.000000  
0.000000   
25%    5.040000e+03      1.000000   1190.000000   1951.000000  
0.000000   
50%    7.618000e+03      1.500000   1560.000000   1975.000000  
0.000000   
75%    1.068500e+04      2.000000   2210.000000   1997.000000  
0.000000   
max    1.651359e+06      3.500000   9410.000000   2015.000000  
2015.000000   

            zipcode           lat          long  sqft_living15  
sqft_lot15  
count  21597.000000  21597.000000  21597.000000   21597.000000  
21597.000000  
mean   98077.951845     47.560093   -122.213982    1986.620318  
12758.283512  
std       53.513072      0.138552      0.140724     685.230472  
27274.441950  
min    98001.000000     47.155900   -122.519000     399.000000  
```

```
651.000000
25%    98033.000000     47.471100   -122.328000    1490.000000
5100.000000
50%    98065.000000     47.571800   -122.231000    1840.000000
7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000
10083.000000
max    98199.000000     47.777600   -121.315000    6210.000000
871200.000000

.............Head:.................
           id        date     price  bedrooms  bathrooms  sqft_living
\
0  7129300520  10/13/2014  221900.0         3       1.00         1180

1  6414100192   12/9/2014  538000.0         3       2.25         2570

2  5631500400   2/25/2015  180000.0         2       1.00          770

3  2487200875   12/9/2014  604000.0         4       3.00         1960

4  1954400510   2/18/2015  510000.0         3       2.00         1680


   sqft_lot  floors waterfront  view  ...          grade sqft_above  \
0      5650     1.0        NaN  NONE  ...      7 Average       1180
1      7242     2.0         NO  NONE  ...      7 Average       2170
2     10000     1.0         NO  NONE  ...  6 Low Average        770
3      5000     1.0         NO  NONE  ...      7 Average       1050
4      8080     1.0         NO  NONE  ...         8 Good       1680

   sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
0            0.0     1955           0.0    98178  47.5112 -122.257
1          400.0     1951        1991.0    98125  47.7210 -122.319
2            0.0     1933           NaN    98028  47.7379 -122.233
3          910.0     1965           0.0    98136  47.5208 -122.393
4            0.0     1987           0.0    98074  47.6168 -122.045

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 21 columns]
```

Null values

Looking at the information above we can see only three columns have missing values, that is; "waterfront", "view" and "yr_renovated". Every house has its own unique features and not all are the same. Some houses contain certain features while others lack them. Since this is real world data, we can account for missing values in "waterfront" and "view" columns by saying not all houses are build the same and those lacking the two features have caused our data on the two columns to be inconsitent with the rest of the other columns. The "yr_renovated" column can also be accounted for by saying not all houses undergo renovation. Houses build earlier might need renovation but recent houses do not require renovation hence the missing values in the column

```
# Using mode to impute missing values
# Python function to impute missing values

def replace_missing_with_mode(data, column_name):
    mode_value = data[column_name].mode().iloc[0]
    data[column_name].fillna(mode_value, inplace =True)

# columns to be imputed
replace_missing_with_mode(data,'view')
replace_missing_with_mode(data, 'waterfront')

# Changing our date from object to datetime data type
data['date'] = pd.to_datetime(data['date'])
```

After checking for null values, we check for any duplicated values in the data.

```
# Checking for duplicated values in our data
data.duplicated().sum()

0

# drop the rows in sqft_basement with a '?'
data= data.drop(data[data.sqft_basement == '?'].index)
```

Creating a new column 'Grade_1' that stores our new 'grade' column after getting rid of the string 'grade' and converting it to a numeric datatype

```
data["Grade_1"] = data["grade"].str.split().apply(lambda x: x[0])
# Convert the Grade1 column to an integer.
data["Grade_1"] = pd.to_numeric(data["Grade_1"])
```

Converting the categorical columns to numerical data types

We are converting the following categorical data "Waterfront", "View" and "grade" into numerical data types.

```
data['view_1'] = data['view'].replace({'NONE': 0,'FAIR':1,'AVERAGE':
2,'GOOD':3, 'EXCELLENT':4})
data['waterfront_1'] = data['waterfront'].replace({'YES': 0, 'NO':1})
data['condition1'] = data['condition'].replace({'Poor': 0,
'Fair':1,'Average':2,'Good':3,'Very Good':4})
```

Since we have already replaced the strings in our categorical data with numeric values we can drop the original columns

```
data.drop(columns = ['waterfront', 'view', 'grade','condition', ],
inplace= True)
```

```
data.dtypes
```

```
id                         int64
date              datetime64[ns]
price                    float64
bedrooms                   int64
bathrooms                float64
sqft_living                int64
sqft_lot                   int64
floors                   float64
sqft_above                 int64
sqft_basement             object
yr_built                   int64
yr_renovated             float64
zipcode                    int64
lat                      float64
long                     float64
sqft_living15              int64
sqft_lot15                 int64
Grade_1                    int64
view_1                     int64
waterfront_1               int64
condition1                 int64
dtype: object
```

Delivery locations (zip codes) data

```
# Create a new dataframe with two columns for zip codes and cities
new_areas = pd.DataFrame(columns=['Zip Code', 'City'])

# Iterate over the original dataframe and extract zip codes and cities
for i in range(len(areas.columns)):
    # Skip the columns that are not zip codes
    if i % 2 != 0:
        continue
    # Extract the zip codes and cities from each pair of columns
```

```
    zip_codes = areas.iloc[:, i]
    cities = areas.iloc[:, i + 1]
    # Append the zip codes and cities to the new dataframe
    new_areas = new_areas.append(pd.DataFrame({'Zip Code': zip_codes,
'City': cities}), ignore_index=True)

# Print the new dataframe
print(new_areas)
```

```
    Zip Code         City
0      98001       Algona
1      98001       Auburn
2      98001  Federal Way
3      98002       Auburn
4      98003  Federal Way
..       ...          ...
447      NaN          NaN
448      NaN          NaN
449      NaN          NaN
450      NaN          NaN
451      NaN          NaN

[452 rows x 2 columns]
```

```
new_areas.isnull().sum()
new_areas.dropna()
```

```
    Zip Code         City
0      98001       Algona
1      98001       Auburn
2      98001  Federal Way
3      98002       Auburn
4      98003  Federal Way
..       ...          ...
404    98593        Vader
405    98595     Westport
406    98596     Chehalis
407    98596      Winlock
408    98597         Yelm

[409 rows x 2 columns]
```

```
#renaming to match our first data set
new_areas = new_areas.rename(columns={"Zip Code": "zipcode"})
new_areas
```

```
    zipcode         City
0     98001       Algona
1     98001       Auburn
2     98001  Federal Way
3     98002       Auburn
```

```
4     98003  Federal Way
..      ...          ...
447     NaN          NaN
448     NaN          NaN
449     NaN          NaN
450     NaN          NaN
451     NaN          NaN

[452 rows x 2 columns]
```

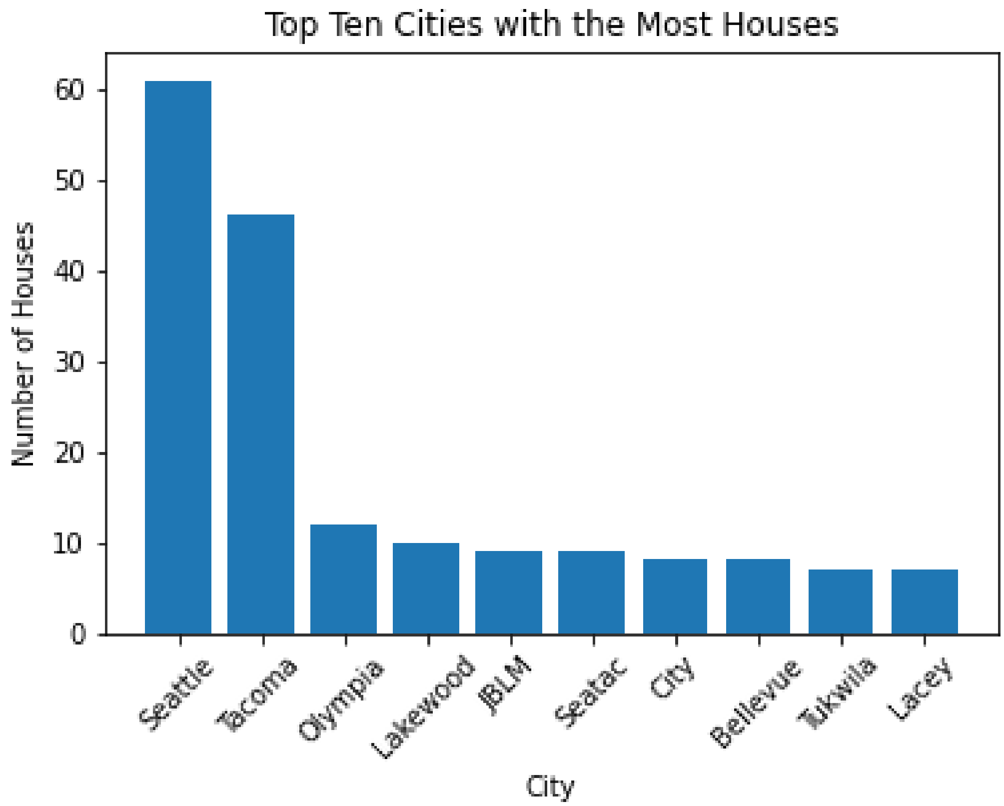
```
#merging our data sets
new_areas['zipcode'] = new_areas['zipcode'].astype(str)
data['zipcode'] = new_areas['zipcode'].astype(str)


merged_data = pd.merge(new_areas, data , on='zipcode')
merged_data
```

```
     zipcode    City          id        date      price  bedrooms  
bathrooms  \
0      98001  Algona  7129300520  10/13/2014   221900.0         3   
1.00   
1      98001  Algona  6414100192   12/9/2014   538000.0         3   
2.25   
2      98001  Algona  5631500400   2/25/2015   180000.0         2   
1.00   
3      98001  Auburn  7129300520  10/13/2014   221900.0         3   
1.00   
4      98001  Auburn  6414100192   12/9/2014   538000.0         3   
2.25   
...      ...     ...         ...         ...        ...       ...   
...   
2405     nan     NaN  1049010390   3/19/2015   505000.0         3   
2.00   
2406     nan     NaN  7905370390   10/9/2014   475000.0         5   
2.50   
2407     nan     NaN  4140090240   11/5/2014   520000.0         3   
2.25   
2408     nan     NaN  4055700030    5/2/2015  1450000.0         3   
4.50   
2409     nan     NaN  3775300030  12/31/2014   333500.0         3   
1.75   

      sqft_living  sqft_lot  floors  ...  yr_built yr_renovated  
lat  \
0            1180      5650     1.0  ...      1955          0.0  
47.5112   
1            2570      7242     2.0  ...      1951       1991.0  
47.7210   
2             770     10000     1.0  ...      1933          NaN  
```

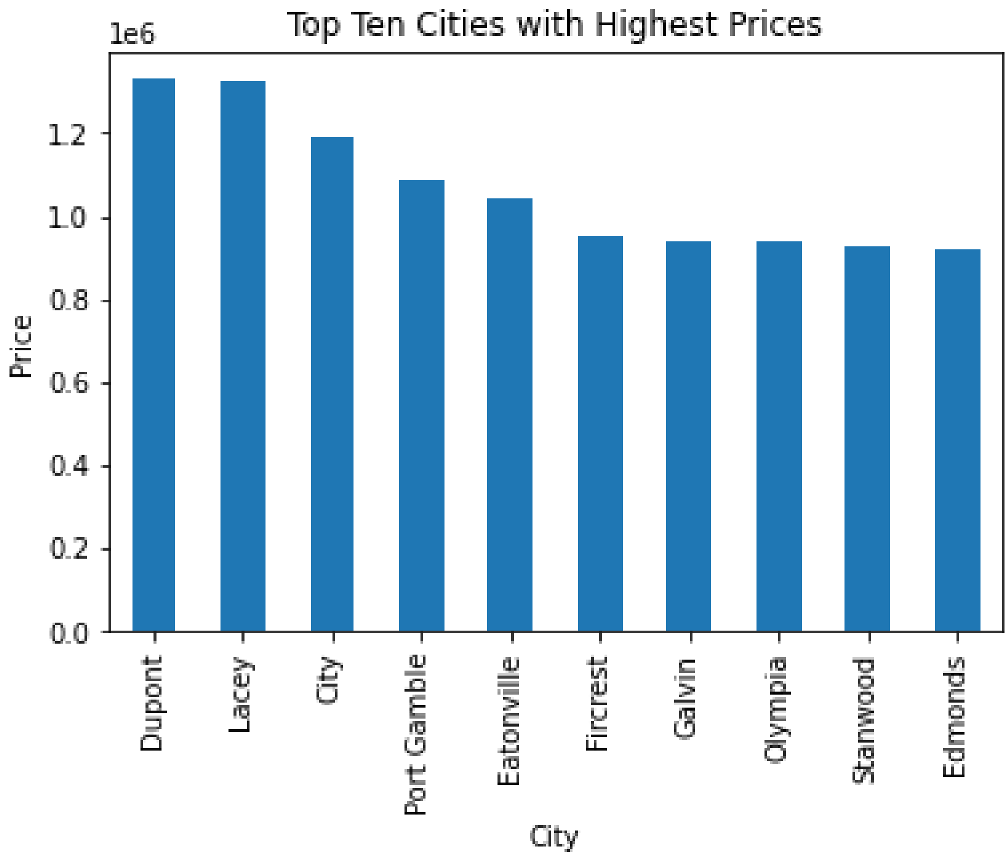
```
47.7379
3             1180      5650     1.0  ...       1955          0.0
47.5112
4             2570      7242     2.0  ...       1951       1991.0
47.7210
...            ...       ...     ...  ...        ...          ...       .
..
2405          1260      5460     1.0  ...       1972          0.0
47.7355
2406          2340      7200     1.0  ...       1975          0.0
47.7206
2407          2590      9263     1.0  ...       1977          0.0
47.7691
2408          3970     24920     2.0  ...       1977          NaN
47.7183
2409          1220      9732     1.0  ...       1965          0.0
47.7736

         long  sqft_living15  sqft_lot15  Grade_1  view_1
waterfront_1  \
0    -122.257           1340        5650        7     0.0
NaN
1    -122.319           1690        7639        7     0.0
1.0
2    -122.233           2720        8062        6     0.0
1.0
3    -122.257           1340        5650        7     0.0
NaN
4    -122.319           1690        7639        7     0.0
1.0
...       ...            ...         ...      ...     ...             ..
.
2405 -122.180           1510        5460        7     0.0
1.0
2406 -122.211           1930        7221        7     0.0
1.0
2407 -122.262           2580        9450        8     0.0
1.0
2408 -122.258           2610       13838       10     2.0
1.0
2409 -122.214           1630       10007        7     0.0
1.0

      condition1
0              2
1              2
2              2
3              2
4              2
```

```
...          ...
2405           2
2406           2
2407           4
2408           2
2409           2

[2410 rows x 22 columns]
```

```
merged_data.isnull().sum()
#dropping the rows with null values
new_data = merged_data.dropna()

def create_bar_graph(data):
    # Count the occurrences of each city
    city_counts = data['City'].value_counts()

    # Select the top ten cities
    top_cities = city_counts.head(10)

    # Create a bar graph
    plt.bar(top_cities.index, top_cities.values)
    plt.xlabel('City')
    plt.ylabel('Number of Houses')
    plt.title('Top Ten Cities with the Most Houses')
    plt.xticks(rotation=45)
    plt.show()


# Example usage:
create_bar_graph(new_data)
```




```
city_prices = new_data.groupby('City')['price'].mean()

# Select the top ten cities with the highest mean prices
top_ten_cities = city_prices.nlargest(10)

# Create a bar graph
top_ten_cities.plot(kind='bar', xlabel='City', ylabel='Price',
title='Top Ten Cities with Highest Prices')

# Show the plot
plt.show()
```



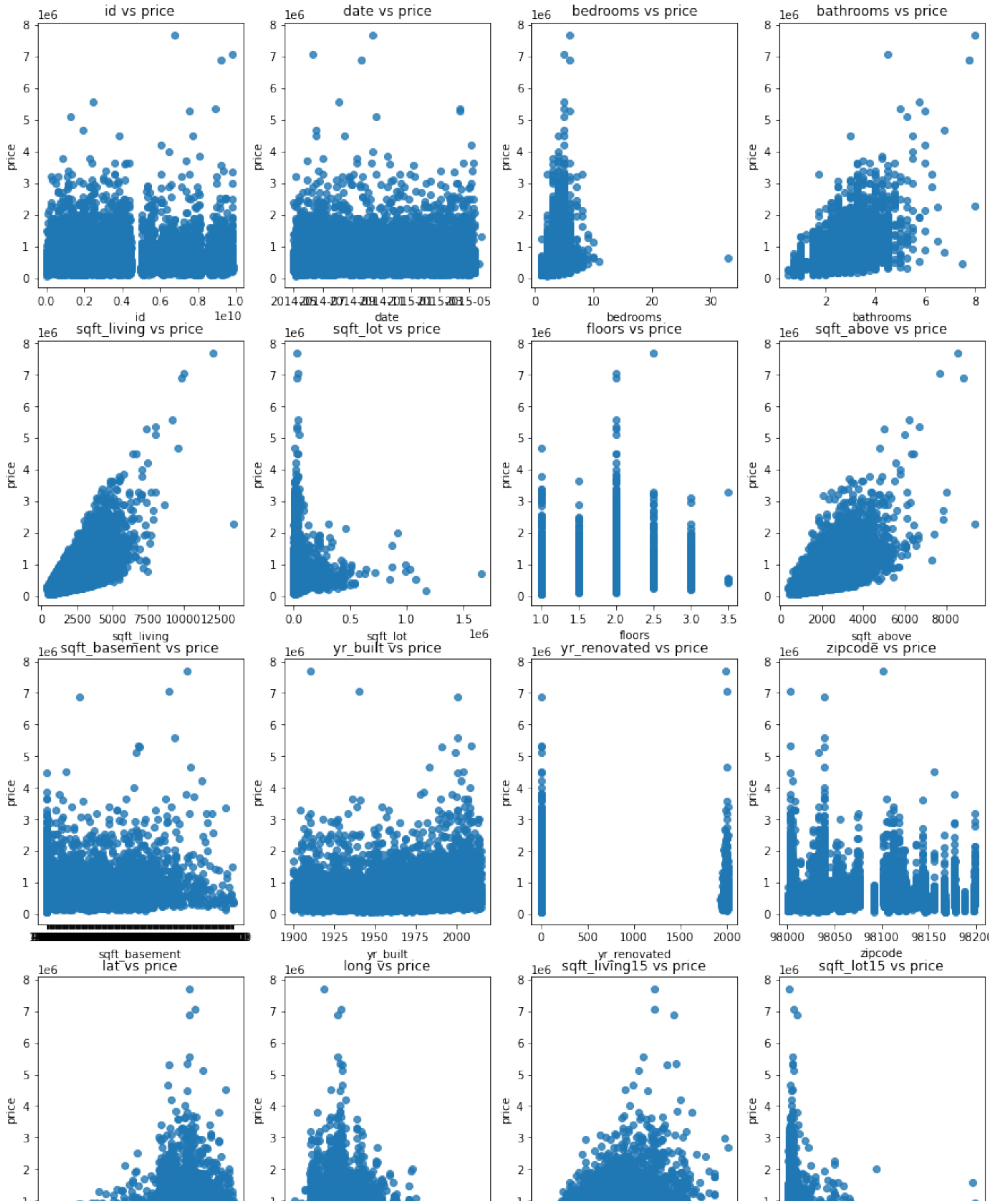
Data visualization

Now we have checked for abnormalities in the data, we can go ahead and plot the data to explore the distribution, relationships and patterns in the data. This will also help us in identifying outliers and trends.

```
y = data["price"]
X = data.drop("price", axis = 1)

def scatter_plots(y, X):
    plots = X.shape[1]
    cols = 4
    rows = (plots + cols - 1) // cols

    fig, axes = plt.subplots(rows, cols, figsize=(15, 5 * rows))
    fig.suptitle(f"Scatter plot of Independent variables vs {y.name}")

    for i, ax in enumerate(axes.flat):
        if i < plots:
            x_col_name = X.columns[i]
            ax.scatter(X.iloc[:, i], y, alpha=0.8)
```

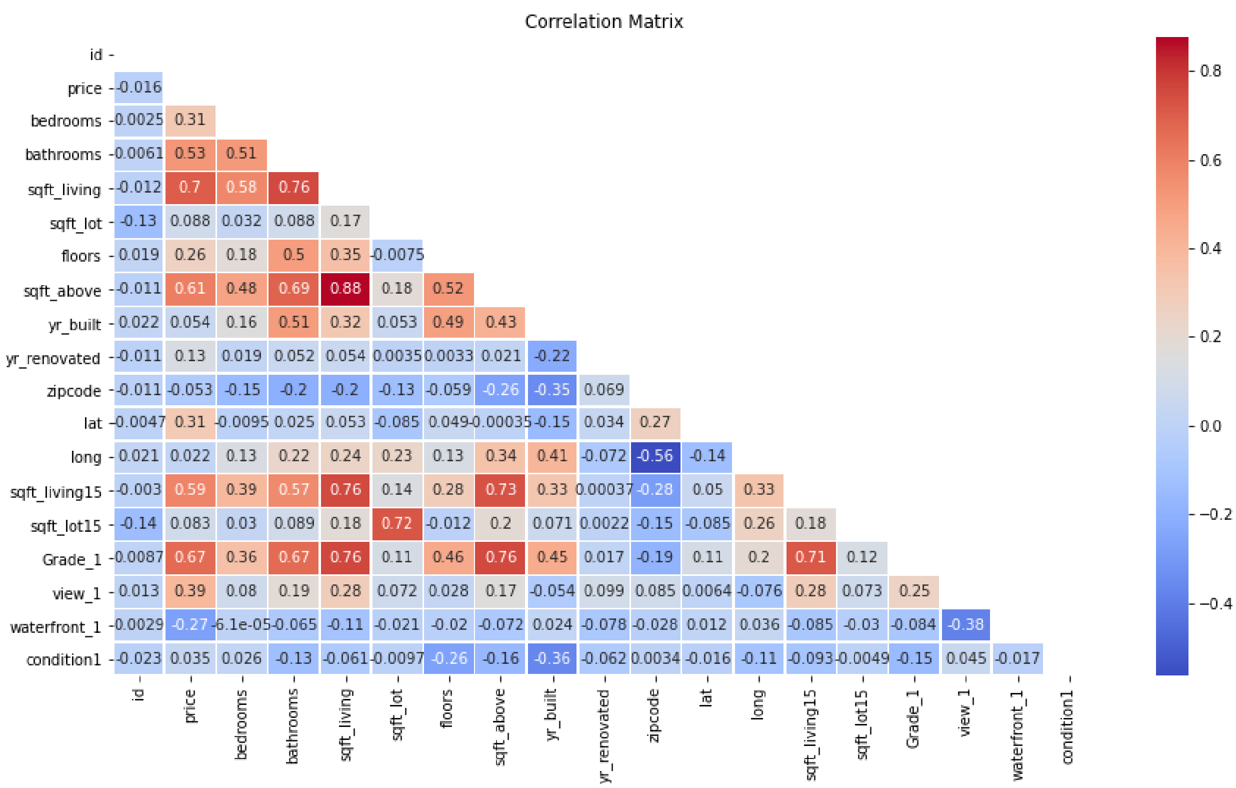
```
            ax.set_xlabel(x_col_name)
            ax.set_ylabel(y.name)
            ax.set_title(f"{x_col_name} vs {y.name}")




# Run the function
scatter_plots(y, X)
```

Scatter plot of Independent variables vs price



Relationship between our independent variables and the dependent variable("price")

```
#correlation
columns_to_test = data.columns

# computing the correlation matrix
correlation_matrix = data[columns_to_test].corr()
matrix = np.triu(np.ones_like(correlation_matrix, dtype = bool))
one_sided_correlation = correlation_matrix.mask(matrix)

# using heatmap to visualize the correlation
plt.figure(figsize=(15, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=0.5, mask = matrix)
plt.title(f'Correlation Matrix')
plt.show()
```



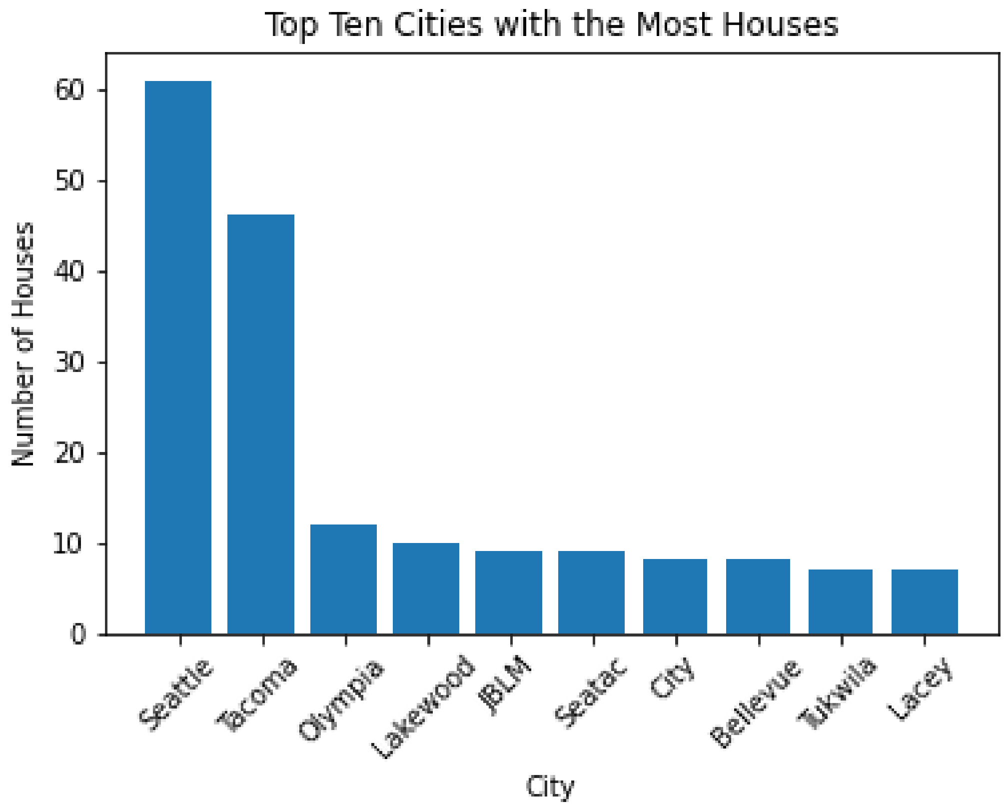
Correlation of our columns against the target("price)

```
def correlation(df):

    return data.corr()['price'].sort_values()

correlation(data)
```

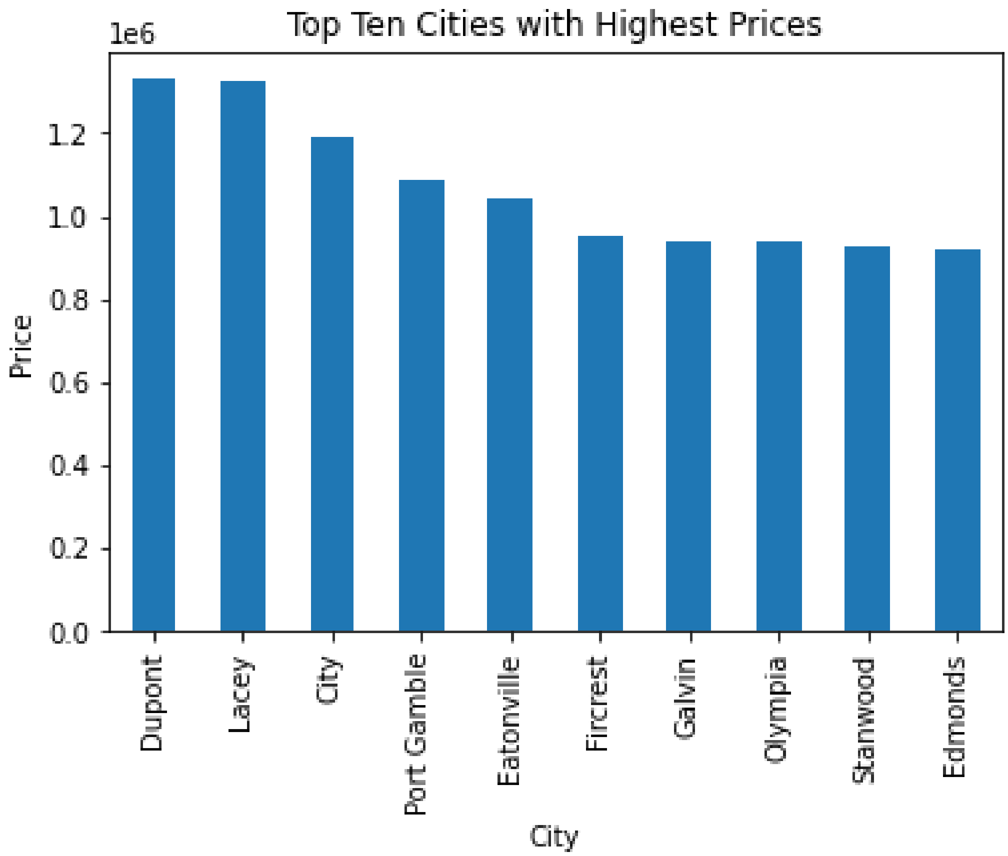
```
waterfront_1    -0.265969
zipcode         -0.053166
id              -0.015796
long             0.022101
condition1       0.035290
yr_built         0.054459
sqft_lot15       0.083192
sqft_lot         0.087937
yr_renovated     0.128227
floors           0.256355
lat              0.306507
bedrooms         0.309204
view_1           0.394885
bathrooms        0.525889
sqft_living15    0.586415
sqft_above       0.605143
Grade_1          0.667738
sqft_living      0.702328
price            1.000000
Name: price, dtype: float64
```

Analyzing price and location

```
def create_bar_graph(data):
    # Count the occurrences of each city
    city_counts = data['City'].value_counts()

    # Select the top ten cities
    top_cities = city_counts.head(10)

    # Create a bar graph
    plt.bar(top_cities.index, top_cities.values)
    plt.xlabel('City')
    plt.ylabel('Number of Houses')
    plt.title('Top Ten Cities with the Most Houses')
    plt.xticks(rotation=45)
    plt.show()


# Example usage:
create_bar_graph(new_data)
```




```
city_prices = new_data.groupby('City')['price'].mean()

# Select the top ten cities with the highest mean prices
top_ten_cities = city_prices.nlargest(10)

# Create a bar graph
top_ten_cities.plot(kind='bar', xlabel='City', ylabel='Price',
title='Top Ten Cities with Highest Prices')

# Show the plot
plt.show()
```



Analyzing seasonal trends in prices

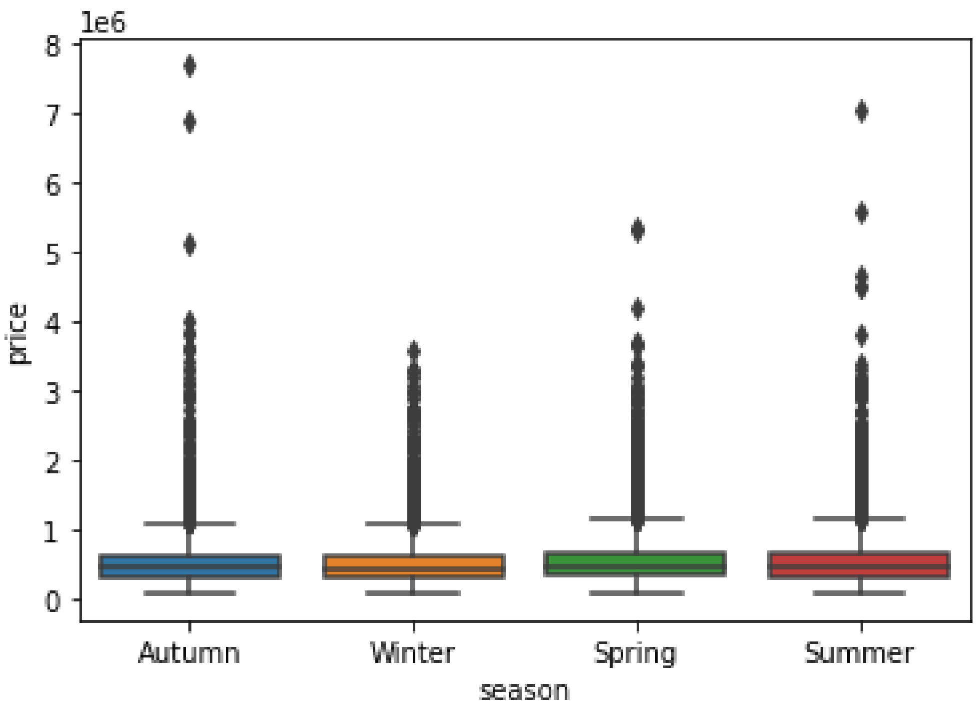
```
# Creating a function to map months to seasons
def get_season(date):
    if date.month in [3,4,5]:
        return 'Spring'
    elif date.month in [6,7,8]:
        return 'Summer'
    elif date.month in [9,10,11]:
        return 'Autumn'
    else:
        return 'Winter'

# Applying the function to the 'date' column to create a 'season'
column
data['season'] = data['date'].apply(get_season)
data[['date', 'season']]
```

	date	season
0	2014-10-13	Autumn
1	2014-12-09	Winter
2	2015-02-25	Winter
3	2014-12-09	Winter

```
4      2015-02-18  Winter
...           ...     ...
21592 2014-05-21  Spring
21593 2015-02-23  Winter
21594 2014-06-23  Summer
21595 2015-01-16  Winter
21596 2014-10-15  Autumn

[21597 rows x 2 columns]
```

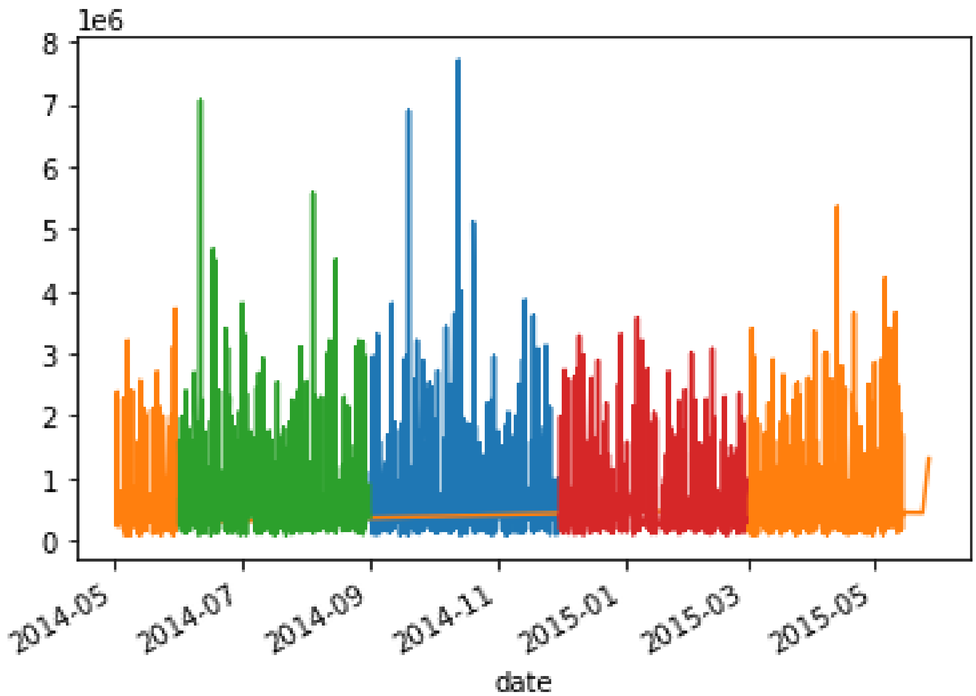
Creating a boxplot of price segmented by season to view differences in price distribution by season.

```
sns.boxplot(x='season', y='price', data=data);
```



Making a timeseries plot of price over time, colored by season to see seasonal patterns.

```
data.set_index('date').groupby('season')['price'].plot();
```



Calculating summary statistics (mean, median, std dev) for price grouped by season to quantify differences.

```
data.groupby('season')['price'].agg([np.mean, np.median, np.std])
```

	mean	median	std
season			
Autumn	531276.474881	443725.0	378513.665722
Spring	552782.763271	465000.0	367075.050556
Summer	546719.464286	455000.0	368925.606702
Winter	519613.645467	430000.0	348171.543129

```
# Extract price by season into separate dataframes
spring = data[data['season'] == 'Spring']['price']
summer = data[data['season'] == 'Summer']['price']
fall = data[data['season'] == 'Autumn']['price']
winter = data[data['season'] == 'Winter']['price']

# Perform ANOVA test
f_val, p_val = stats.f_oneway(spring, summer, fall, winter)

print(f_val, p_val)

# Interpret results
alpha = 0.05
if p_val < alpha:
  print("We reject the null hypothesis")
  print("There is a statistically significant difference in price by
```

```
season")
else:
  print("We fail to reject the null hypothesis")
  print("There is no statistically significant difference in price by 
season")
```

```
8.082642416374668 2.2312373653979034e-05
We reject the null hypothesis
There is a statistically significant difference in price by season
```

In this case; these are the hypotheses.

Null hypothesis:

There is no difference in the mean price across the seasons. The season has no effect on price.

H0: μspring = μsummer = μfall = μwinter

Alternative hypothesis:

There is a difference in mean price for at least one season compared to the others. The season has an effect on price.

H1: At least one μ season ≠ μ other seasons

Where μseason is the population mean price for that season.

So in summary: Null hypothesis (H0): The seasons all have an equal effect on mean price (no difference). Alternative hypothesis (H1): At least two seasons have a statistically significant difference in their effect on mean price. If we reject H0 based on a small ANOVA p-value, we would conclude there is a significant difference in price by season. Failing to reject H0 means we cannot say there is a seasonal effect.

Linear Regression

Since we now have a better understanding of the correlation between our target("price") and our features("independent variables"), we proceed to building regression models to further understand the magnitude our features have on price and predict whether this model can give us accurate house prices when fitted with the said features. We will explore a few features from our data set which we have investigated and come to a conclusion that they have a significance on our target.Steps involved here are as follows;

1. Feature Selection
2. Model Selection
3. Model training
4. Model evaluation
5. Model interpretation
6. Model validation and testing
7. **feature engineering

1.Feature selection

Here we just choose the endogenous and exogenous variables. First we will select for the baseline model then after we shall add features to see if it improves and evaluate it.

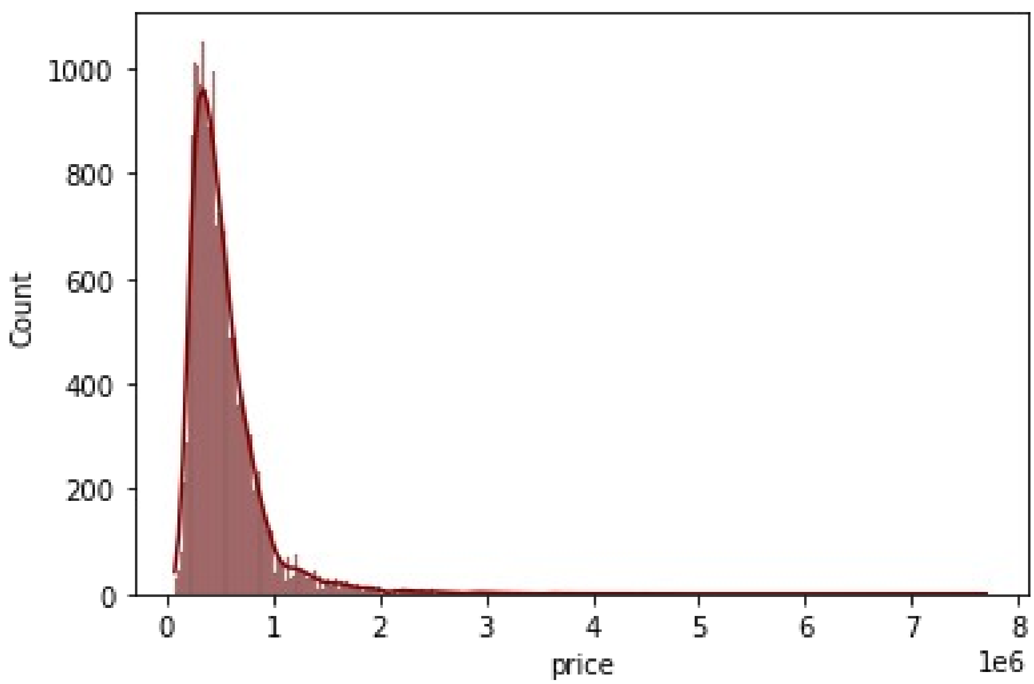
```
y= data["price"]
X = data["sqft_living"]
```

2. Building a baseline model

Creating a baseline model for our regression model

First we visualize the target(price) column in order to understand the distribution

```
sns.histplot(data["price"], color="maroon", kde=True)
plt.show();
```



The distribution of our data seems to a have a longer right tail than the left tail. This indicates a positive skewness in our target meaning the mean is greater than the median. This may have impact on our model since linear regression, assume that the target variable follows a normal distribution, so significant skewness can be problematic.

Splitting our data into train and test sets

First we split the data into test set and training set. We will use the "train_test_split" function from scikit-learn library to split our data.

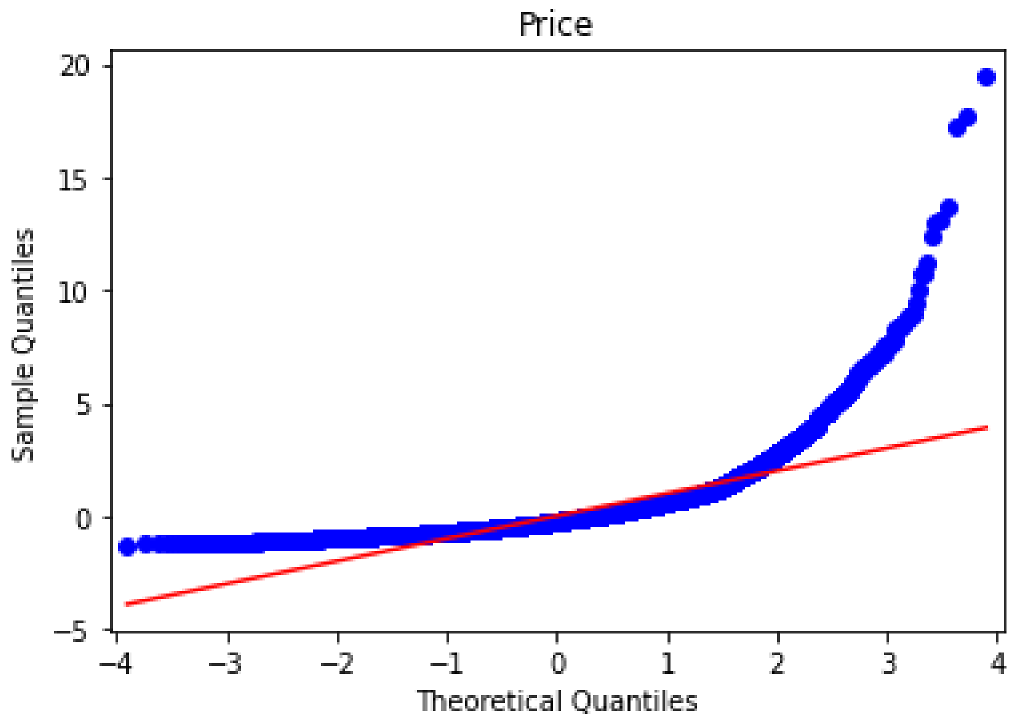
```
#importing scikit-learn library
from sklearn.model_selection import train_test_split
#defining a function for splitting data into train and test sets
def split(X, y):
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)
    return X_train, X_test, y_train, y_test

#splitting the data by calling the function
X_train, X_test, y_train, y_test = split(X,y)
```

In the train_test_split function we have is used above, we have split 80% of the data into training set and 20% of the data into test set.

In the next cell we are going to build a baseline model using the y_train and x_train variables. To do that we import statsmodels library which is a powerful library for statistical modelling and is similar to the sci-kit learn module

```
#importing statsmodels
import statsmodels.api as sm

#function to create models and print the summary
model = sm.OLS(y_train, sm.add_constant(X_train))
results = model.fit()
results.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.495
Model:                            OLS   Adj. R-squared:
0.495
Method:                 Least Squares   F-statistic:
1.655e+04
Date:                Thu, 26 Oct 2023   Prob (F-statistic):
0.00
Time:                        01:44:37   Log-Likelihood:            -
2.3497e+05
No. Observations:               16914   AIC:
4.700e+05
Df Residuals:                   16912   BIC:
4.700e+05
Df Model:                           1

Covariance Type:            nonrobust
```

```
==============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       -4.448e+04   4960.688     -8.966      0.000   -5.42e+04   -3.48e+04
sqft_living   280.1781      2.178    128.639      0.000     275.909     284.447
==============================================================================
Omnibus:                    11863.674   Durbin-Watson:                   2.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           453836.272
Skew:                           2.904   Prob(JB):                         0.00
Kurtosis:                      27.703   Cond. No.                     5.62e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.62e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""

import scipy.stats as stats

# Generate a Q-Q plot
sm.qqplot(data["price"], line='s', fit=True, dist=stats.norm, loc=0, scale=1)
plt.title('Price')
plt.show()
```



Wonderful! We now have our baseline model and from it we can interpret its metrics

Interpretation

Looking at the summary above, we can see that the regression line we found was

price = sqft_living285.8630 - 43,990

The model is statistically significant overall, with an F-statistic p-value well below 0.05. The model explains about 50% of the variance in price. The model `const` and `sqft_living` coefficients are both statistically significant, with t-statistic p-values well below 0.05. If a house had 0 sqft of living , we would expect price to be about -43,990 dollars. For each increase of 1 sqft in the living , we see an associated increase in price of about 280 dollars.

We now have our baseline model which we created using the train sets obtained from splitting our data. To analyze our model further we will predict our target("price") using the trained model then compare metrics to determine if our model is efficient or we need to adjust it. We also check if our model is under fitted or over fitted. To perform comparisson we will import another module from sci-kit learn

```
#predicting the dependent varible
X_test = sm.add_constant(X_test)
y_pred = results.predict(X_test)

#defining a function to calculate metrics for our prediction model
def calculate_regression_metrics(y_test, y_pred):
    metrics = {}
```

```
    # Calculate Mean Absolute Error (MAE)
    metrics['MAE'] = mean_absolute_error(y_test, y_pred)

    # Calculate Mean Squared Error (MSE)
    metrics['MSE'] = mean_squared_error(y_test, y_pred)

    # Calculate R-squared (coefficient of determination)
    metrics['R-squared'] = r2_score(y_test, y_pred)

    return metrics

metrics = calculate_regression_metrics(y_test, y_pred)
print(metrics)
```

```
{'MAE': 177033.87791345723, 'MSE': 70202650031.35713, 'R-squared': 0.48779757847019767}
```

Comparison of our baseline model against the prediction model

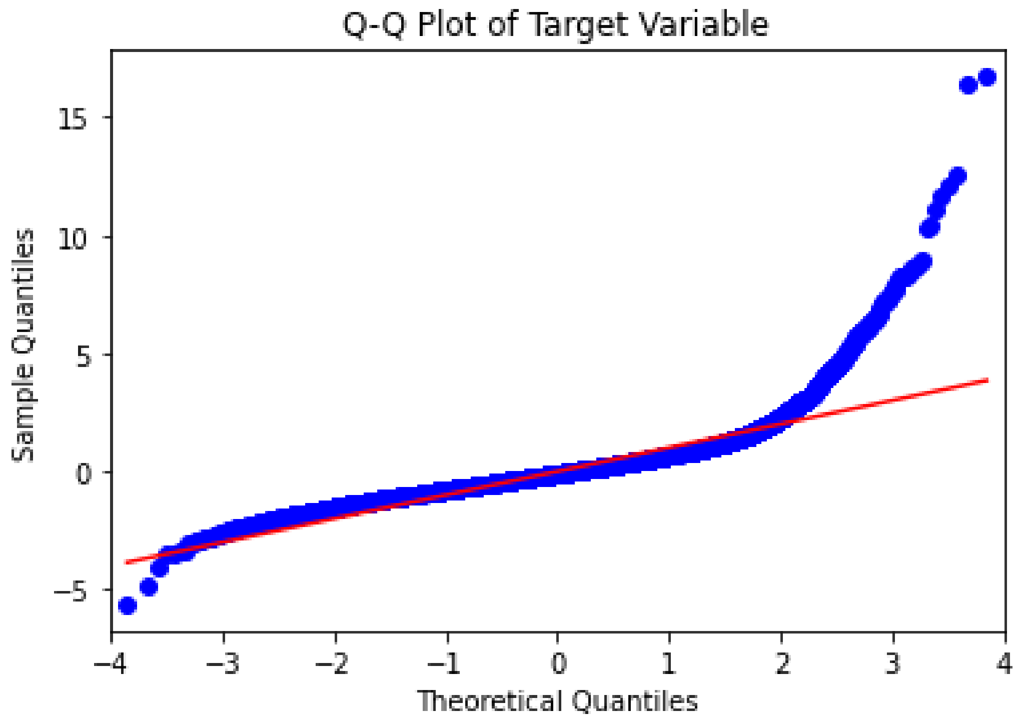
R-squared

Comparing the r-squared values from the test model and and the prediction model we can note a difference. Our train model has a R-squared value of almost 50% while our test model has a value of almost 48%. This means our baseline model is good ...

Residuals

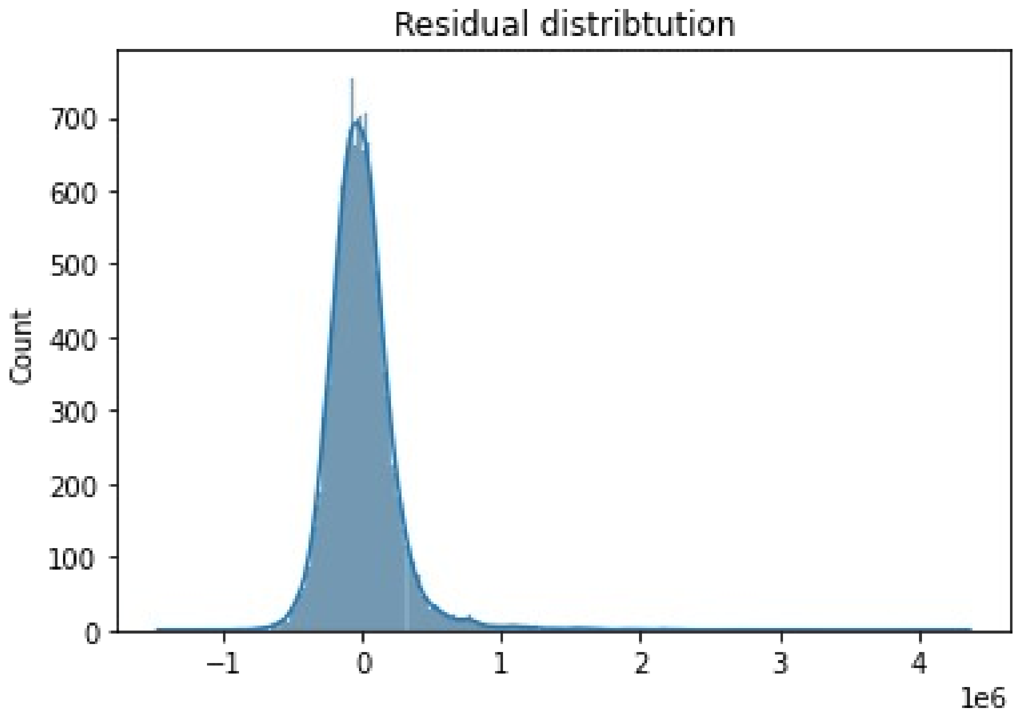
Residuals are the difference between the true values and the values predicted by our model. We visualize to understand the distribution and also check if it meets the assumption of linearity; that is normal distribution

```
# Generate a Q-Q plot
sm.qqplot(results.resid, line='s', fit=True, dist=stats.norm, loc=0, scale=1)
plt.title('Q-Q Plot of baseline residuals')
plt.show()
```



Quantile-quantile plots are used to asses whether a dataset follows a specific theoretical normal distribution. The visual above shows our model residuals almost follow a straight line but then curves at some point. The skewness or outliers in our target might be the cause of this.

```
#ploting histogram to show residuals distribution
sns.histplot(results.resid, bins = "auto", kde = True)
plt.title("Residual distribtution")
plt.show();
```

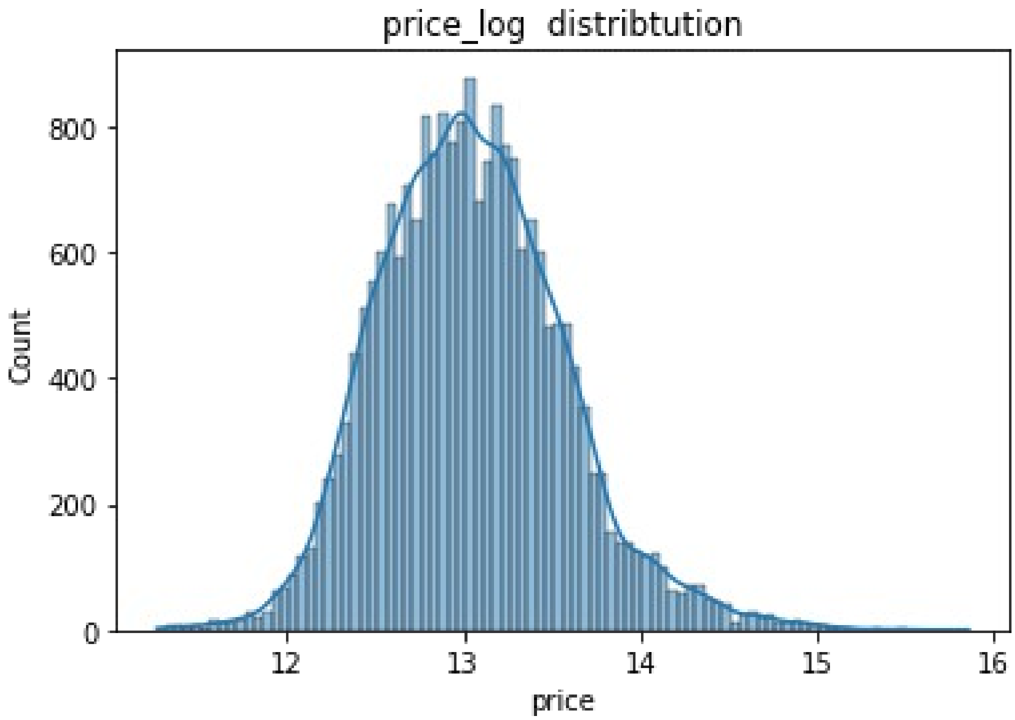


From the above plot we can see that our baseline model residuals have a normal distribution. This meets one of the linearity assumptions of linear regression. Linear models make key assumptions one of which is that the errors or residuals follow a normal distribution. The normality assumption is essential for valid statistical inferences and hypothesis testing. Non-normal residuals can lead to biased parameter estimates, incorrect p-values, and unreliable confidence intervals.

Target transformation

The non-normal distribution shown by the residuals(where it curves above) can be accounted for by the skewness of our target. Transforming the target variable can be an effective approach to make the data more closely approximate a normal distribution. By transforming the target variable, you aim to reduce skewness and make the data more symmetric, thus bringing it closer to a normal distribution. This, in turn, helps the residuals conform more closely to the normality assumption, which is crucial for the validity of the model. We shall log transform our target and see if our residuals will follow a normal distribution.

```
#log transforming the target
y_log = np.log(data["price"])
# visualizing to see its distribution
sns.histplot(y_log, bins = "auto", kde = True)
plt.title("price_log  distribtution")
plt.show();
```



Wonderful! Our target after transformation seems to follow an almost normal distribution. Next we create a model for the transformed target, then we shall visualize the residuals once again to see their distribution. We will also check if it improves our model or not.

Log transformed target model

```
#splitting data into test and train test
split(X, y_log)

##creating a model
log_model = sm.OLS(y_train, sm.add_constant(X_train))
log_results = log_model.fit()
log_results.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                    price   R-squared:
0.484
Model:                              OLS   Adj. R-squared:
0.484
Method:                   Least Squares   F-statistic:
1.586e+04
Date:                  Thu, 26 Oct 2023   Prob (F-statistic):
0.00
```

```
Time:                           01:45:00   Log-Likelihood:
-7525.5
No. Observations:                  16914   AIC:
1.506e+04
Df Residuals:                      16912   BIC:
1.507e+04
Df Model:                              1

Covariance Type:               nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
const          12.2207      0.007   1704.768      0.000      12.207
12.235
sqft_living     0.0004   3.15e-06    125.933      0.000       0.000
0.000
======================================================================
========
Omnibus:                           3.650   Durbin-Watson:
1.980
Prob(Omnibus):                     0.161   Jarque-Bera (JB):
3.629
Skew:                              0.035   Prob(JB):
0.163
Kurtosis:                          3.015   Cond. No.
5.62e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.62e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

Interpreting the results of the model

From the summary above we can see that the regression line we found was

price = sqft_living0.0004 - 12.2207

The model is statistically significant overall, with an F-statistic p-value well below 0.05. The model explains about 48% of the variance in price. The model `const` and `sqft_living` coefficients are both statistically significant, with t-statistic p-values well below 0.05. If a house had 0 sqft of living , we would expect price to be about -12.2207 dollars. For each increase of 1 sqft in the living , we see an associated increase in price of about 0.0004 dollars.

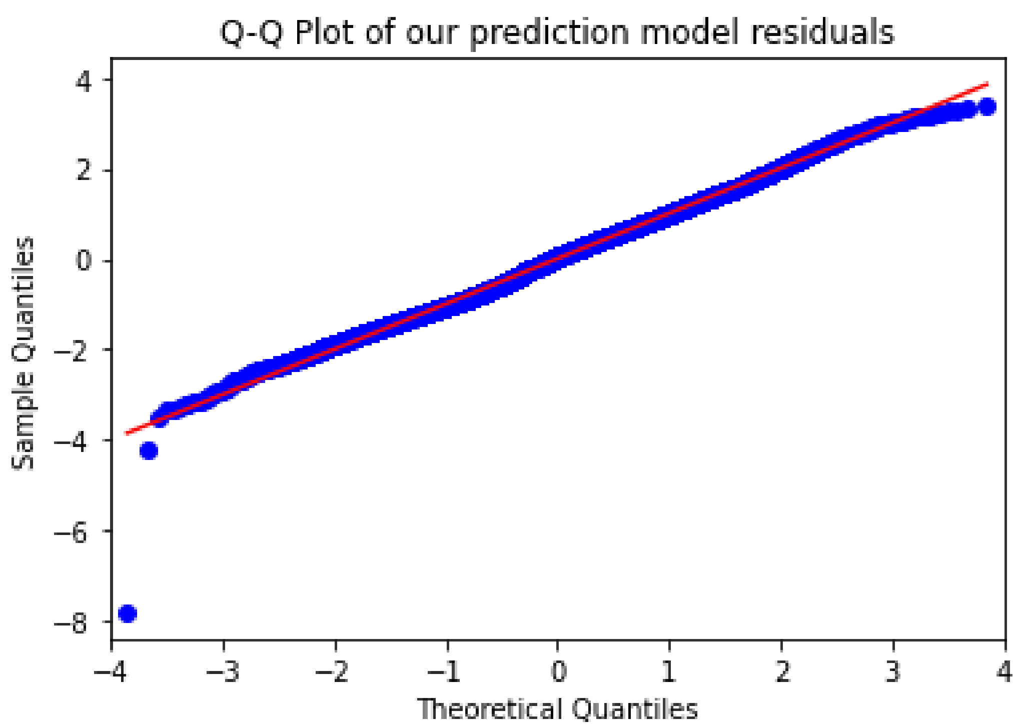
Prediction of our model

```
X_test = sm.add_constant(X_test)
y_pred = results.predict(X_test)

calculate_regression_metrics(y_test, y_pred)
```

```
{'MAE': 536828.527684868,
 'MSE': 352139274884.2067,
 'R-squared': -1250053982156.927}
```

Visualizing the transformed target residuals

```
# Generate a Q-Q plot
sm.qqplot(log_results.resid, line='s', fit=True, dist=stats.norm,
loc=0, scale=1)
plt.title('Q-Q Plot of our prediction model residuals')
plt.show()
```



The residuals of the log transformed target now follow a straight line compared to our first model. This is a good indication since it now meets the assumption of normal distribution.

Evaluation between the two baseline models

The first baseline model is much better than the second baseline model since it explains almost 50% in variance of the target variable compared to the second one which explains almost 48%. The second model prediction is also very poor since it has a negative R-squared value which indicates that the regression model's fit to the data is worse the model is not explaining any of the variance in the dependent variable, and it might be a poor fit for the data.

2nd Model

In this model we are going to improve our first baseline model which we did't transform by adding more features and see if our model is going to improve.

Selecting y and X variables for our model

```
#defining variables tu be used in our second model
drop = data.drop(['id', 'price',
'date','sqft_lot','floors','sqft_basement',  'yr_renovated',
'zipcode',
'lat', 'long', 'sqft_living15', 'sqft_lot15', "sqft_above"], axis= 1)
X_sec = drop
y_sec= data["price"]
X_sec
```

	bedrooms	bathrooms	sqft_living	sqft_above	yr_built	Grade_1 \
0	3	1.00	1180	1180	1955	7
1	3	2.25	2570	2170	1951	7
2	2	1.00	770	770	1933	6
3	4	3.00	1960	1050	1965	7
4	3	2.00	1680	1680	1987	8
...	...	...	...	...	...	...
21592	3	2.50	1530	1530	2009	8
21593	4	2.50	2310	2310	2014	8
21594	2	0.75	1020	1020	2009	7
21595	3	2.50	1600	1600	2004	8
21596	2	0.75	1020	1020	2008	7

	view_1	waterfront_1	condition1
0	0	1	2

```
1            0             1           2
2            0             1           2
3            0             1           4
4            0             1           2
...        ...           ...         ...
21592        0             1           2
21593        0             1           2
21594        0             1           2
21595        0             1           2
21596        0             1           2

[21143 rows x 9 columns]
```

In this model we have standardized the X variables (features) to have a mean of 0 and a standard deviation of 1 is known as standardization or z-score normalization.Scaling the features to have a standard deviation of 1 ensures that the features have the same variance, which can be important for modelling algorithms.Standardizing the features can help make the data closer to a normal distribution, which can improve the model's performance for such models.

```
ss = StandardScaler()

X1_scaled = ss.fit_transform(X_sec)
```

splitting data into train and test

```
split(X1_scaled, y_sec)
```

Building multiple linear model

```
model = sm.OLS(y_train, sm.add_constant(X_train))
results = model.fit()
results.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.650
Model:                            OLS   Adj. R-squared:
0.649
Method:                 Least Squares   F-statistic:
3481.
Date:                Thu, 26 Oct 2023   Prob (F-statistic):
0.00
Time:                        01:45:16   Log-Likelihood:            -
2.3188e+05
```

```
No. Observations:                   16914   AIC:
4.638e+05
Df Residuals:                       16904   BIC:
4.639e+05
Df Model:                               9

Covariance Type:            nonrobust

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const       5.393e+05   1673.474    322.268      0.000    5.36e+05
5.43e+05
x1         -3.469e+04   2111.891    -16.428      0.000   -3.88e+04   -
3.06e+04
x2          4.268e+04   2889.968     14.767      0.000     3.7e+04
4.83e+04
x3          1.476e+05   4505.256     32.765      0.000    1.39e+05
1.56e+05
x4          4653.5416   3826.021      1.216      0.224   -2845.858
1.22e+04
x5         -1.049e+05   2221.989    -47.216      0.000   -1.09e+05   -
1.01e+05
x6          1.491e+05   2882.270     51.727      0.000    1.43e+05
1.55e+05
x7          3.188e+04   1950.901     16.339      0.000    2.81e+04
3.57e+04
x8         -5.399e+04   1872.819    -28.826      0.000   -5.77e+04   -
5.03e+04
x9           1.13e+04   1812.824      6.231      0.000    7742.283
1.48e+04
==============================================================================
========
Omnibus:                        12604.697   Durbin-Watson:
2.006
Prob(Omnibus):                      0.000   Jarque-Bera (JB):
826533.213
Skew:                               2.997   Prob(JB):
0.00
Kurtosis:                          36.718   Cond. No.
6.64
==============================================================================
========

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

```
correctly specified.
"""
```

Our model is good overall with an R-squared value of 65% meaning it explains 65 % ov variance in our target variable. The p-values of our independent variables are below 0.05 meaning our model is statistically significant overall.

```
X_test = sm.add_constant(X_test)
y_pred = results.predict(X_test)

calculate_regression_metrics(y_test, y_pred)

{'MAE': 141592.73032447265,
 'MSE': 46826238256.493065,
 'R-squared': 0.6583531730583653}
```

Comparing the train and test model of our multiple linear model

The R-squared of our train model is 65% and that of our test model is also 65%. This is can be an indication that our model is performing consistently between the training and test datasets. This can be a positive sign, suggesting that our model has not overfit the training data. This is a good model because the test model has not predicted more than what the train model predicted

metrics

3. Polynomial Transformation of features

We will use polynomial transformation to see if our model will improve or not.

```
# Polynomial transforming
y_pol= data["price"]
X_pol = X_sec
X_pol

       bedrooms  bathrooms  sqft_living  sqft_above  yr_built  Grade_1  \
0             3       1.00         1180        1180      1955        7

1             3       2.25         2570        2170      1951        7

2             2       1.00          770         770      1933        6

3             4       3.00         1960        1050      1965        7

4             3       2.00         1680        1680      1987        8

...         ...        ...          ...         ...       ...      ...

21592         3       2.50         1530        1530      2009        8
```

```
21593          4        2.50          2310         2310        2014          8

21594          2        0.75          1020         1020        2009          7

21595          3        2.50          1600         1600        2004          8

21596          2        0.75          1020         1020        2008          7


       view_1  waterfront_1  condition1
0           0             1           2
1           0             1           2
2           0             1           2
3           0             1           4
4           0             1           2
...       ...           ...         ...
21592       0             1           2
21593       0             1           2
21594       0             1           2
21595       0             1           2
21596       0             1           2

[21143 rows x 9 columns]
```

He we also standardized our data to have a mean of 0 and standard deviation of 1

```
ss = StandardScaler()

X1_scaled = ss.fit_transform(X_pol)
```

splitting the data

```
split(X1_scaled, y_sec)
```

Building the polynomial model

```
def build_polynomial_linear_model(X, y, degree=2):
    # Create polynomial features
    poly = PolynomialFeatures(degree=degree, include_bias=False)
    X_poly = poly.fit_transform(X)

    # Add a constant term (intercept)
    X_poly = (X_poly)

    # Build and fit a linear regression model using statsmodels
    model = sm.OLS(y, X_poly).fit()

    return model
```

```
# Build the polynomial linear model
model = build_polynomial_linear_model(X_train, y_train, degree=2)

# Print the summary of the model
model.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results                            

==============================================================================
========
Dep. Variable:                  price   R-squared:                       
0.719
Model:                            OLS   Adj. R-squared:                  
0.719
Method:                 Least Squares   F-statistic:                     
815.8
Date:                Thu, 26 Oct 2023   Prob (F-statistic):              
0.00
Time:                        01:46:05   Log-Likelihood:            -
2.3000e+05
No. Observations:               16914   AIC:                         
4.601e+05
Df Residuals:                   16860   BIC:                         
4.605e+05
Df Model:                          53                                         

Covariance Type:            nonrobust                                         

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
--------
x1         -1.334e+04   2241.953     -5.952      0.000   -1.77e+04   -
8949.858
x2          2.851e+04   2972.717      9.591      0.000    2.27e+04    
3.43e+04
x3          1.458e+05   5967.287     24.434      0.000    1.34e+05    
1.57e+05
x4         -3.598e+04   4920.108     -7.312      0.000   -4.56e+04   -
2.63e+04
x5         -7.013e+04   2713.742    -25.844      0.000   -7.55e+04   -
```

```
6.48e+04
x6           1.373e+05   2775.927     49.475      0.000    1.32e+05
1.43e+05
x7           1.559e+04   5007.623      3.114      0.002    5778.958
2.54e+04
x8           5.948e+06   4.21e+04    141.228      0.000    5.87e+06
6.03e+06
x9           1.931e+04   2446.360      7.894      0.000    1.45e+04
2.41e+04
x10           638.3932    252.167      2.532      0.011     144.119
1132.668
x11          3431.9165   2932.150      1.170      0.242   -2315.405
9179.238
x12         -8264.1989   4494.629     -1.839      0.066   -1.71e+04
545.744
x13          6834.6904   4042.086      1.691      0.091   -1088.221
1.48e+04
x14         -3094.1989   2344.446     -1.320      0.187   -7689.558
1501.161
x15         -3005.7492   3100.612     -0.969      0.332   -9083.274
3071.775
x16           702.2192   2066.712      0.340      0.734   -3348.753
4753.192
x17         -2103.9682   1962.403     -1.072      0.284   -5950.483
1742.547
x18            -9.0281   2066.704     -0.004      0.997   -4059.984
4041.928
x19         -6142.8575   2645.867     -2.322      0.020   -1.13e+04
-956.682
x20          7820.0516   5934.096      1.318      0.188   -3811.398
1.95e+04
x21          3564.2530   5237.666      0.681      0.496   -6702.122
1.38e+04
x22          1.037e+04   3258.857      3.181      0.001    3979.567
1.68e+04
x23          1.484e+04   4213.910      3.521      0.000    6579.119
2.31e+04
x24          -591.2297   2533.067     -0.233      0.815   -5556.306
4373.847
x25         -9710.6946   2166.193     -4.483      0.000     -1.4e+04    -
5464.729
x26           -90.7363   2778.952     -0.033      0.974   -5537.773
5356.300
x27         -6.847e+04   6956.386     -9.843      0.000   -8.21e+04    -
5.48e+04
x28          1.324e+05   1.29e+04     10.263      0.000    1.07e+05
1.58e+05
x29         -3.224e+04   5390.309     -5.980      0.000   -4.28e+04    -
2.17e+04
```

x30	6.559e+04	6218.224	10.548	0.000	5.34e+04	7.78e+04
x31	-9808.4678	3381.602	-2.901	0.004	-1.64e+04	-3180.173
x32	-1.649e+04	2407.166	-6.848	0.000	-2.12e+04	-1.18e+04
x33	1.2e+04	4252.296	2.821	0.005	3660.688	2.03e+04
x34	-6.102e+04	7239.149	-8.430	0.000	-7.52e+04	-4.68e+04
x35	988.7095	5056.387	0.196	0.845	-8922.338	1.09e+04
x36	-3.029e+04	5403.455	-5.606	0.000	-4.09e+04	-1.97e+04
x37	-1.112e+04	3094.758	-3.592	0.000	-1.72e+04	-5051.385
x38	-9445.1735	2477.159	-3.813	0.000	-1.43e+04	-4589.683
x39	-1072.1197	3816.331	-0.281	0.779	-8552.529	6408.289
x40	2.318e+04	1993.588	11.628	0.000	1.93e+04	2.71e+04
x41	-2.043e+04	3294.082	-6.202	0.000	-2.69e+04	-1.4e+04
x42	3191.8380	2163.355	1.475	0.140	-1048.563	7432.239
x43	-7074.8195	2437.320	-2.903	0.004	-1.19e+04	-2297.417
x44	-4555.7862	2118.670	-2.150	0.032	-8708.602	-402.971
x45	5550.3683	2700.825	2.055	0.040	256.469	1.08e+04
x46	1.62e+04	2608.060	6.212	0.000	1.11e+04	2.13e+04
x47	1.406e+04	2078.162	6.766	0.000	9986.589	1.81e+04
x48	7713.3382	2966.867	2.600	0.009	1897.967	1.35e+04
x49	4060.2728	1511.952	2.685	0.007	1096.688	7023.857
x50	4985.3976	1866.230	2.671	0.008	1327.391	8643.404
x51	4054.5667	1757.513	2.307	0.021	609.657	7499.476
x52	4.965e+05	3524.436	140.886	0.000	4.9e+05	5.03e+05
x53	859.3544	1587.879	0.541	0.588	-2253.055	3971.764
x54	-889.9978	1311.948	-0.678	0.498	-3461.554	

```
1681.559
==============================================================================
========
Omnibus:                     7713.330   Durbin-Watson:
1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
171655.002
Skew:                           1.678   Prob(JB):
0.00
Kurtosis:                      18.242   Cond. No.
369.
==============================================================================
========

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

Interpreting the polynomial results

Our model is good overall with an R-squared value of 71% meaning it explains 71 % ov variance in our target variable. The p-values of our independent variables are below 0.05 meaning our model is statistically significant overall.

coefficients and p_values

```
model.params[:5]
```

```
x1    -1.334432e+04
x2     2.851020e+04
x3     1.458025e+05
x4    -3.597659e+04
x5    -7.013461e+04
x6     1.373397e+05
x7     1.559442e+04
x8     5.947704e+06
x9     1.931195e+04
x10    6.383932e+02
x11    3.431917e+03
x12   -8.264199e+03
x13    6.834690e+03
x14   -3.094199e+03
x15   -3.005749e+03
x16    7.022192e+02
x17   -2.103968e+03
x18   -9.028054e+00
x19   -6.142858e+03
x20    7.820052e+03
```

```
x21    3.564253e+03
x22    1.036727e+04
x23    1.483882e+04
x24   -5.912297e+02
x25   -9.710695e+03
x26   -9.073632e+01
x27   -6.847166e+04
x28    1.324299e+05
x29   -3.223643e+04
x30    6.558897e+04
x31   -9.808468e+03
x32   -1.648529e+04
x33    1.199563e+04
x34   -6.102379e+04
x35    9.887095e+02
x36   -3.029283e+04
x37   -1.111744e+04
x38   -9.445173e+03
x39   -1.072120e+03
x40    2.318242e+04
x41   -2.042966e+04
x42    3.191838e+03
x43   -7.074819e+03
x44   -4.555786e+03
x45    5.550368e+03
x46    1.620088e+04
x47    1.406000e+04
x48    7.713338e+03
x49    4.060273e+03
x50    4.985398e+03
x51    4.054567e+03
x52    4.965438e+05
x53    8.593544e+02
x54   -8.899978e+02
dtype: float64
```

```
model.pvalues[:5]
```

```
x1      2.699746e-09
x2      9.948197e-22
x3     1.335751e-129
x4      2.746822e-13
x5     1.813546e-144
x6      0.000000e+00
x7      1.847929e-03
x8      0.000000e+00
x9      3.101291e-15
x10     1.136250e-02
x11     2.418390e-01
x12     6.597936e-02
```

```
x13     9.087783e-02
x14     1.869198e-01
x15     3.323570e-01
x16     7.340295e-01
x17     2.836730e-01
x18     9.965146e-01
x19     2.026199e-02
x20     1.875829e-01
x21     4.961947e-01
x22     1.469021e-03
x23     4.304233e-04
x24     8.154500e-01
x25     7.414201e-06
x26     9.739531e-01
x27     8.466214e-23
x28     1.224674e-24
x29     2.270258e-09
x30     6.258948e-26
x31     3.730033e-03
x32     7.724659e-12
x33     4.793341e-03
x34     3.742282e-17
x35     8.449751e-01
x36     2.100622e-08
x37     3.286498e-04
x38     1.378315e-04
x39     7.787680e-01
x40     3.882083e-31
x41     5.707568e-10
x42     1.401206e-01
x43     3.704348e-03
x44     3.154532e-02
x45     3.988816e-02
x46     5.359265e-10
x47     1.371273e-11
x48     9.335244e-03
x49     7.250297e-03
x50     7.561412e-03
x51     2.106737e-02
x52     0.000000e+00
x53     5.883794e-01
x54     4.975410e-01
dtype: float64
```

Prediction metrics

```
X_test = sm.add_constant(X_test)
y_pred = results.predict(X_test)
```

```
calculate_regression_metrics(y_test, y_pred)
```

```
{'MAE': 141592.73032447265,
 'MSE': 46826238256.493065,
 'R-squared': 0.6583531730583653}
```

Comparing the polynomial train and test model

On looking on the metrics of the two models we can say that our training data did well in training the model. We can see that the training model has a R-squared value of 65 while our training model has a R-squared of 71%. This shows our test model predicts well since it did not exceed the training model value and it also means that we did not overfit our data.