Final Project Submission

Group 3.1

- Evah Wangari
- Dorine Langat
- Grace Nyongesa
- Maureen Anduuru
- Stella Kitur
- Vivian Adhiambo

Business Overview

Introduction

Real estate is one of the most important sectors of any economy. Understanding the key drivers of housing prices can provide valuable insights for both buyers and sellers in the market. In this project, we analyze a data set of house sales in a northwestern county to identify the factors that influence housing prices in the area.

Business Understanding

The real estate agency helps homeowners buy and/or sell homes. One of the key services they provide is advice to homeowners about how home renovations can increase the estimated value of their homes. The agency is interested in developing a model that can predict the estimated value of a home after renovations, based on the type and cost of the renovations.

Metric of Success

We decided to opt for RMSE as our metric of success because it is measured in the same units as the response variable.

Business Problem

The real estate agency needs to provide accurate advice to homeowners about how home renovations can increase the estimated value of their homes, and by what amount. However, the agency currently lacks a reliable method for predicting the impact of specific home renovations on home value. As a result, the agency is unable to provide accurate advice to homeowners about the potential return on investment for different renovation projects.

The project objectives we aim to solve include:

1. To identify features influencing the pricing.

2. To analyse trends in house prices over time (time series analysis) and predict future prices.

3. To identify undervalued properties (outlier detection) and recommend better pricing strategies.

Data Understanding

The relevant dataset used in this project is the kc_house_data, found in the data folder of this repository.

The dataset contains information on sale prices for houses, property sizes, location, and the years of construction and renovation alongside other relavant information.

In [ ]:
```
# Loading the libraries

# data
import numpy as np
import pandas as pd

# visualization
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import folium
import warnings

# modeling
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# statistics
import scipy.stats as stats
from sklearn.metrics import mean_absolute_error

# styling
plt.style.use('seaborn')
```

```
sns.set_style('whitegrid')

warnings.filterwarnings('ignore')
```

In [ ]:
```
house_df = pd.read_csv("kc_house_data.csv")
house_df.head()
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	v
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NC
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NC
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NC
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NC
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NC

5 rows × 21 columns

In [ ]:
```
house_df.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
```

In [ ]:
```
house_df.describe()
```

Out[ ]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.00000

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.49409
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.53968
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.00000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.00000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.50000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.00000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.50000

In [ ]:
```
data = house_df.copy()
```

This function returns a comprehensive description for our data.

In [ ]:
```
def explore_data(df):
    '''
    Print some basic statistics and information about the DataFrame
    '''
    print("Number of rows:", df.shape[0])
    print("Number of columns:", df.shape[1])
    print("Data types:\n", df.dtypes)
    print("info:\n", df.info())
    print("columns:", df.columns)
    print("Head:\n", df.head())
    print("Tail:\n", df.tail())
    print("statistical summary:\n", df.describe())
    print("Missing values:\n", df.isnull().sum())
    print("duplicated values:\n", df.duplicated)
    #the correlation of other features with the price
    print("correlation with the price:\n", df.corr()['price'])
    print("condition column:\n", df['condition'].value_counts())
    print("grade column:\n", df['grade'].value_counts())
    print("view column:\n", df['view'].value_counts())
```

In [ ]:
```
explore_data(data)
```

```
Number of rows: 21597
Number of columns: 21
Data types:
 id                int64
date             object
price           float64
bedrooms          int64
bathrooms       float64
sqft_living       int64
sqft_lot          int64
floors          float64
waterfront       object
view             object
condition        object
grade            object
sqft_above        int64
sqft_basement    object
yr_built          int64
yr_renovated    float64
```

```
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
<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
info:
 None
columns: Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
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]
Tail:
                id        date     price  bedrooms  bathrooms  sqft_living  \
21592   263000018   5/21/2014  360000.0         3       2.50         1530
21593  6600060120   2/23/2015  400000.0         4       2.50         2310
21594  1523300141   6/23/2014  402101.0         2       0.75         1020
21595   291310100   1/16/2015  400000.0         3       2.50         1600
21596  1523300157  10/15/2014  325000.0         2       0.75         1020

       sqft_lot  floors waterfront  view  ...      grade sqft_above  \
21592      1131     3.0         NO  NONE  ...     8 Good       1530
21593      5813     2.0         NO  NONE  ...     8 Good       2310
21594      1350     2.0         NO  NONE  ...  7 Average       1020
21595      2388     2.0        NaN  NONE  ...     8 Good       1600
21596      1076     2.0         NO  NONE  ...  7 Average       1020

       sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
21592            0.0     2009           0.0    98103  47.6993 -122.346
21593            0.0     2014           0.0    98146  47.5107 -122.362
21594            0.0     2009           0.0    98144  47.5944 -122.299
21595            0.0     2004           0.0    98027  47.5345 -122.069
21596            0.0     2008           0.0    98144  47.5941 -122.299

       sqft_living15  sqft_lot15
21592           1530        1509
21593           1830        7200
21594           1020        2007
21595           1410        1287
21596           1020        1357

[5 rows x 21 columns]
statistical summary:
                  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
Missing values:
 id                  0
date              0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront     2376
view             63
condition         0
grade             0
sqft_above        0
sqft_basement     0
yr_built          0
yr_renovated   3842
zipcode           0
lat               0
long              0
sqft_living15     0
sqft_lot15        0
dtype: int64
duplicated values:
 <bound method DataFrame.duplicated of                 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
...           ...         ...       ...       ...        ...          ...
21592   263000018   5/21/2014  360000.0         3       2.50         1530
21593  6600060120   2/23/2015  400000.0         4       2.50         2310
21594  1523300141   6/23/2014  402101.0         2       0.75         1020
21595   291310100   1/16/2015  400000.0         3       2.50         1600
21596  1523300157  10/15/2014  325000.0         2       0.75         1020

       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
...         ...     ...        ...   ...  ...            ...        ...
21592      1131     3.0         NO  NONE  ...         8 Good       1530
21593      5813     2.0         NO  NONE  ...         8 Good       2310
21594      1350     2.0         NO  NONE  ...      7 Average       1020
21595      2388     2.0        NaN  NONE  ...         8 Good       1600
21596      1076     2.0         NO  NONE  ...      7 Average       1020

       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
...              ...      ...           ...      ...      ...      ...
21592            0.0     2009           0.0    98103  47.6993 -122.346
21593            0.0     2014           0.0    98146  47.5107 -122.362
21594            0.0     2009           0.0    98144  47.5944 -122.299
21595            0.0     2004           0.0    98027  47.5345 -122.069
21596            0.0     2008           0.0    98144  47.5941 -122.299
```

```
       sqft_living15  sqft_lot15
0               1340        5650
1               1690        7639
2               2720        8062
3               1360        5000
4               1800        7503
...              ...         ...
21592           1530        1509
21593           1830        7200
21594           1020        2007
21595           1410        1287
21596           1020        1357

[21597 rows x 21 columns]>
correlation with the price:
 id               -0.016772
price             1.000000
bedrooms          0.308787
bathrooms         0.525906
sqft_living       0.701917
sqft_lot          0.089876
floors            0.256804
sqft_above        0.605368
yr_built          0.053953
yr_renovated      0.129599
zipcode          -0.053402
lat               0.306692
long              0.022036
sqft_living15     0.585241
sqft_lot15        0.082845
Name: price, dtype: float64
condition column:
 Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64
grade column:
 7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
view column:
 NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

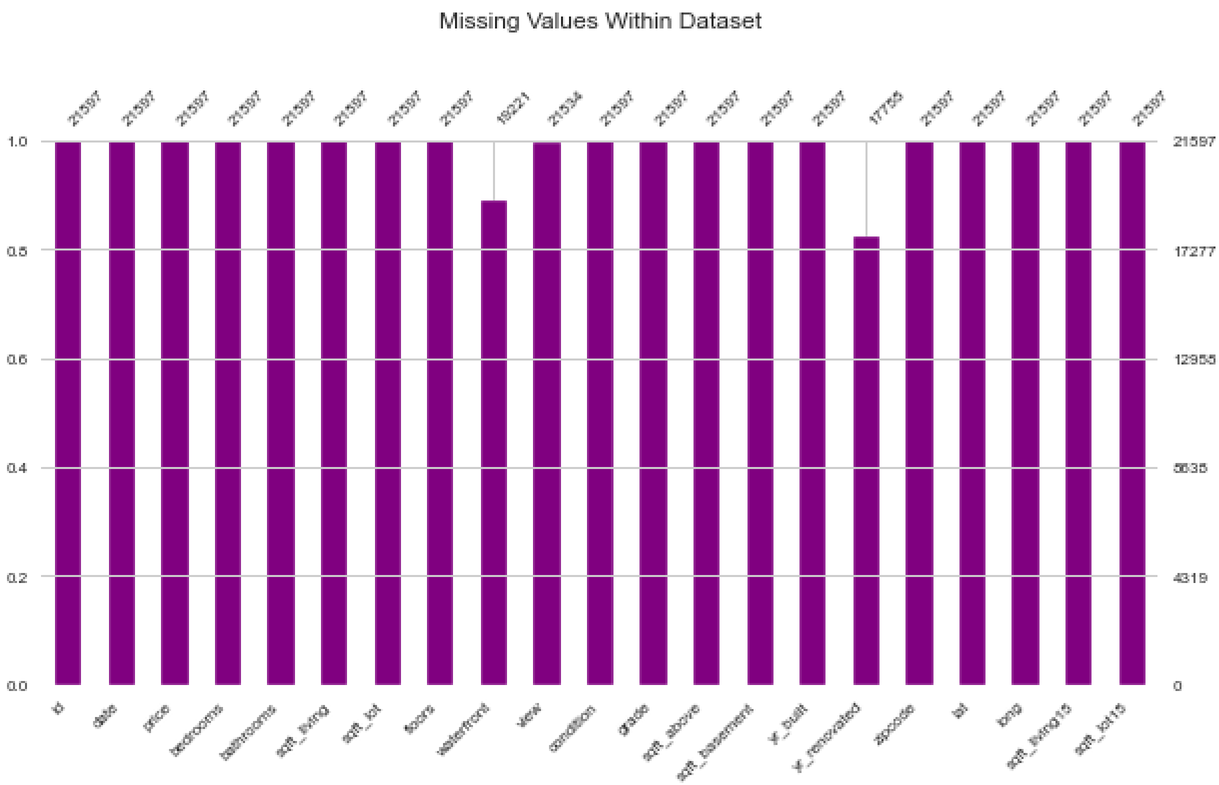
Column Names and Descriptions for the DataSet

- `id` - Unique identifier for a house
- `date` - Date house was sold

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

In [ ]:

```
# Visualise the missing values in the dataset
msno.bar(data, color='purple', figsize=(10, 5), fontsize=8)
plt.title("""

Missing Values Within Dataset

""");
```



In [ ]:
```
# percentage of missing data
house_df.isnull().sum()/len(house_df)*100
```

Out[ ]:
```
id                0.000000
date              0.000000
price             0.000000
bedrooms          0.000000
bathrooms         0.000000
sqft_living       0.000000
sqft_lot          0.000000
floors            0.000000
waterfront       11.001528
view              0.291707
condition         0.000000
grade             0.000000
sqft_above        0.000000
sqft_basement     0.000000
yr_built          0.000000
yr_renovated     17.789508
zipcode           0.000000
lat               0.000000
long              0.000000
sqft_living15     0.000000
sqft_lot15        0.000000
dtype: float64
```

In [ ]:
```
house_df.dropna(inplace=True)
```

We have dropped all the missing values in our data because 11% and 17% are big

Data Cleaning and Preparation

In [ ]:
```
def clean_data(df):
    '''
    Clean data by removing missing values and duplicates
    '''
    # Remove duplicates
    df.drop_duplicates(inplace=True)

    # Replace "?" and " " values with NaN
    df['sqft_basement'] = df['sqft_basement'].replace('?', np.nan).replace('', np.nan)

    # Convert the column to float data type
    df['sqft_basement'] = df['sqft_basement'].astype(float)

    # Convert the 'date' column to a datetime data type
    df['date'] = pd.to_datetime(df['date'])

    #Converting the 'waterfront' column to a binary variable where 1 represents 'YES' a
    df['waterfront'] = df['waterfront'].apply(lambda x: 1 if x == 'YES' else 0)

    # Remove missing values
    df.dropna(inplace=True)

    return df
```

In [ ]:
```
clean_data(data)
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	v
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	N
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	N
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	N
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	N
5	7237550310	2014-05-12	1230000.0	4	4.50	5420	101930	1.0	0	N
...	...	...	...	...	...	...	...	...	...	
21592	263000018	2014-05-21	360000.0	3	2.50	1530	1131	3.0	0	N
21593	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	2.0	0	N
21594	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	2.0	0	N
21595	291310100	2015-01-16	400000.0	3	2.50	1600	2388	2.0	0	N
21596	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	2.0	0	N

17340 rows × 21 columns

In [ ]:
```
#confirming if our data is clean
explore_data(data)
```

```
Number of rows: 17340
Number of columns: 21
Data types:
 id                         int64
date             datetime64[ns]
price                   float64
bedrooms                  int64
bathrooms               float64
sqft_living               int64
sqft_lot                  int64
floors                  float64
waterfront                int64
view                     object
condition                object
grade                    object
sqft_above                int64
sqft_basement           float64
yr_built                  int64
yr_renovated            float64
zipcode                   int64
lat                     float64
long                    float64
sqft_living15             int64
sqft_lot15                int64
dtype: object
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17340 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             17340 non-null  int64
 1   date           17340 non-null  datetime64[ns]
 2   price          17340 non-null  float64
 3   bedrooms       17340 non-null  int64
 4   bathrooms      17340 non-null  float64
 5   sqft_living    17340 non-null  int64
 6   sqft_lot       17340 non-null  int64
 7   floors         17340 non-null  float64
 8   waterfront     17340 non-null  int64
 9   view           17340 non-null  object
 10  condition      17340 non-null  object
 11  grade          17340 non-null  object
 12  sqft_above     17340 non-null  int64
 13  sqft_basement  17340 non-null  float64
 14  yr_built       17340 non-null  int64
 15  yr_renovated   17340 non-null  float64
 16  zipcode        17340 non-null  int64
 17  lat            17340 non-null  float64
 18  long           17340 non-null  float64
 19  sqft_living15  17340 non-null  int64
 20  sqft_lot15     17340 non-null  int64
dtypes: datetime64[ns](1), float64(7), int64(10), object(3)
memory usage: 2.9+ MB
info:
 None
columns: Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

```
Head:
           id       date      price  bedrooms  bathrooms  sqft_living  \
0  7129300520 2014-10-13   221900.0         3       1.00         1180
1  6414100192 2014-12-09   538000.0         3       2.25         2570
3  2487200875 2014-12-09   604000.0         4       3.00         1960
4  1954400510 2015-02-18   510000.0         3       2.00         1680
5  7237550310 2014-05-12  1230000.0         4       4.50         5420

   sqft_lot  floors  waterfront  view  ...         grade sqft_above  \
0      5650     1.0           0  NONE  ...     7 Average       1180
1      7242     2.0           0  NONE  ...     7 Average       2170
3      5000     1.0           0  NONE  ...     7 Average       1050
4      8080     1.0           0  NONE  ...        8 Good       1680
5    101930     1.0           0  NONE  ...  11 Excellent       3890

   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
3          910.0      1965           0.0    98136  47.5208 -122.393
4            0.0      1987           0.0    98074  47.6168 -122.045
5         1530.0      2001           0.0    98053  47.6561 -122.005

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
3           1360        5000
4           1800        7503
5           4760      101930

[5 rows x 21 columns]
Tail:
               id       date     price  bedrooms  bathrooms  sqft_living  \
21592   263000018 2014-05-21  360000.0         3       2.50         1530
21593  6600060120 2015-02-23  400000.0         4       2.50         2310
21594  1523300141 2014-06-23  402101.0         2       0.75         1020
21595   291310100 2015-01-16  400000.0         3       2.50         1600
21596  1523300157 2014-10-15  325000.0         2       0.75         1020

       sqft_lot  floors  waterfront  view  ...      grade sqft_above  \
21592      1131     3.0           0  NONE  ...     8 Good       1530
21593      5813     2.0           0  NONE  ...     8 Good       2310
21594      1350     2.0           0  NONE  ...  7 Average       1020
21595      2388     2.0           0  NONE  ...     8 Good       1600
21596      1076     2.0           0  NONE  ...  7 Average       1020

       sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
21592            0.0      2009           0.0    98103  47.6993 -122.346
21593            0.0      2014           0.0    98146  47.5107 -122.362
21594            0.0      2009           0.0    98144  47.5944 -122.299
21595            0.0      2004           0.0    98027  47.5345 -122.069
21596            0.0      2008           0.0    98144  47.5941 -122.299

       sqft_living15  sqft_lot15
21592           1530        1509
21593           1830        7200
21594           1020        2007
21595           1410        1287
21596           1020        1357

[5 rows x 21 columns]
statistical summary:
                 id         price      bedrooms     bathrooms   sqft_living  \
count  1.734000e+04  1.734000e+04  17340.000000  17340.000000  17340.000000
mean   4.587395e+09  5.406210e+05      3.377682      2.121165   2084.768743
std    2.876085e+09  3.684592e+05      0.931706      0.767210    917.698694
```

```
min    1.000102e+06  8.000000e+04      1.000000      0.500000    370.000000
25%    2.126049e+09  3.215000e+05      3.000000      1.750000   1430.000000
50%    3.905030e+09  4.500000e+05      3.000000      2.250000   1920.000000
75%    7.326525e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.895000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors    waterfront    sqft_above  sqft_basement  \
count  1.734000e+04  17340.000000  17340.000000  17340.000000   17340.000000
mean   1.527911e+04      1.495386      0.006690   1792.411995     292.356747
std    4.225003e+04      0.538132      0.081519    827.514319     443.248527
min    5.200000e+02      1.000000      0.000000    370.000000       0.000000
25%    5.040000e+03      1.000000      0.000000   1200.000000       0.000000
50%    7.620000e+03      1.500000      0.000000   1562.000000       0.000000
75%    1.068250e+04      2.000000      0.000000   2220.000000     560.000000
max    1.651359e+06      3.500000      1.000000   9410.000000    4820.000000

           yr_built  yr_renovated       zipcode           lat          long  \
count  17340.000000  17340.000000  17340.000000  17340.000000  17340.000000
mean    1971.130681     83.111419  98077.688812     47.559528   -122.213367
std       29.312138    398.756281     53.529862      0.138592      0.140718
min     1900.000000      0.000000  98001.000000     47.155900   -122.519000
25%     1952.000000      0.000000  98033.000000     47.469575   -122.328000
50%     1975.000000      0.000000  98065.000000     47.571400   -122.229000
75%     1997.000000      0.000000  98117.000000     47.677500   -122.124000
max     2015.000000   2015.000000  98199.000000     47.777600   -121.315000

       sqft_living15    sqft_lot15
count   17340.000000   17340.00000
mean     1990.397693   12822.93466
std       685.542943   27532.07264
min       399.000000     659.00000
25%      1490.000000    5100.00000
50%      1840.000000    7623.00000
75%      2370.000000   10092.25000
max      6210.000000  871200.00000
Missing values:
 id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
duplicated values:
 <bound method DataFrame.duplicated of                id       date      price  bedrooms
bathrooms  sqft_living  \
0      7129300520 2014-10-13   221900.0         3       1.00         1180
1      6414100192 2014-12-09   538000.0         3       2.25         2570
3      2487200875 2014-12-09   604000.0         4       3.00         1960
4      1954400510 2015-02-18   510000.0         3       2.00         1680
```

```
5      7237550310 2014-05-12  1230000.0         4       4.50         5420
...           ...        ...        ...       ...        ...          ...
21592   263000018 2014-05-21   360000.0         3       2.50         1530
21593  6600060120 2015-02-23   400000.0         4       2.50         2310
21594  1523300141 2014-06-23   402101.0         2       0.75         1020
21595   291310100 2015-01-16   400000.0         3       2.50         1600
21596  1523300157 2014-10-15   325000.0         2       0.75         1020

       sqft_lot  floors  waterfront  view  ...         grade sqft_above  \
0          5650     1.0           0  NONE  ...     7 Average       1180
1          7242     2.0           0  NONE  ...     7 Average       2170
3          5000     1.0           0  NONE  ...     7 Average       1050
4          8080     1.0           0  NONE  ...        8 Good       1680
5        101930     1.0           0  NONE  ...   11 Excellent      3890
...         ...     ...         ...   ...  ...           ...        ...
21592      1131     3.0           0  NONE  ...        8 Good       1530
21593      5813     2.0           0  NONE  ...        8 Good       2310
21594      1350     2.0           0  NONE  ...     7 Average       1020
21595      2388     2.0           0  NONE  ...        8 Good       1600
21596      1076     2.0           0  NONE  ...     7 Average       1020

       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
3              910.0      1965           0.0    98136  47.5208 -122.393
4                0.0      1987           0.0    98074  47.6168 -122.045
5             1530.0      2001           0.0    98053  47.6561 -122.005
...              ...       ...           ...      ...      ...      ...
21592            0.0      2009           0.0    98103  47.6993 -122.346
21593            0.0      2014           0.0    98146  47.5107 -122.362
21594            0.0      2009           0.0    98144  47.5944 -122.299
21595            0.0      2004           0.0    98027  47.5345 -122.069
21596            0.0      2008           0.0    98144  47.5941 -122.299

       sqft_living15  sqft_lot15
0               1340        5650
1               1690        7639
3               1360        5000
4               1800        7503
5               4760      101930
...              ...         ...
21592           1530        1509
21593           1830        7200
21594           1020        2007
21595           1410        1287
21596           1020        1357

[17340 rows x 21 columns]>
correlation with the price:
 id              -0.017224
price            1.000000
bedrooms         0.306837
bathrooms        0.524719
sqft_living      0.703520
sqft_lot         0.086720
floors           0.256500
waterfront       0.263387
sqft_above       0.608209
sqft_basement    0.321079
yr_built         0.051421
yr_renovated     0.128517
zipcode         -0.052491
lat              0.307635
long             0.021837
sqft_living15    0.586046
```

```
sqft_lot15       0.082925
Name: price, dtype: float64
condition column:
 Average      11262
Good          4530
Very Good     1386
Fair           140
Poor            22
Name: condition, dtype: int64
grade column:
 7 Average        7193
8 Good           4869
9 Better         2117
6 Low Average    1642
10 Very Good      914
11 Excellent      320
5 Fair            184
12 Luxury          71
4 Low              18
13 Mansion         11
3 Poor              1
Name: grade, dtype: int64
view column:
 NONE         15649
AVERAGE        770
GOOD           393
FAIR           274
EXCELLENT      254
Name: view, dtype: int64
```

Data Analysis

Converting the data types for `sqft_basement` and `date` columns to float and datetime respectively.

In [ ]:
```
# Replace "?" and " " values with NaN
house_df['sqft_basement'] = house_df['sqft_basement'].replace('?', np.nan).replace('',

# Convert the column to float data type
house_df['sqft_basement'] = house_df['sqft_basement'].astype(float)

# Convert the 'date' column to a datetime data type
house_df['date'] = pd.to_datetime(house_df['date'])
```

In [ ]:
```
house_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15762 entries, 1 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             15762 non-null  int64
 1   date           15762 non-null  datetime64[ns]
 2   price          15762 non-null  float64
 3   bedrooms       15762 non-null  int64
 4   bathrooms      15762 non-null  float64
 5   sqft_living    15762 non-null  int64
 6   sqft_lot       15762 non-null  int64
 7   floors         15762 non-null  float64
 8   waterfront     15762 non-null  object
 9   view           15762 non-null  object
 10  condition      15762 non-null  object
```

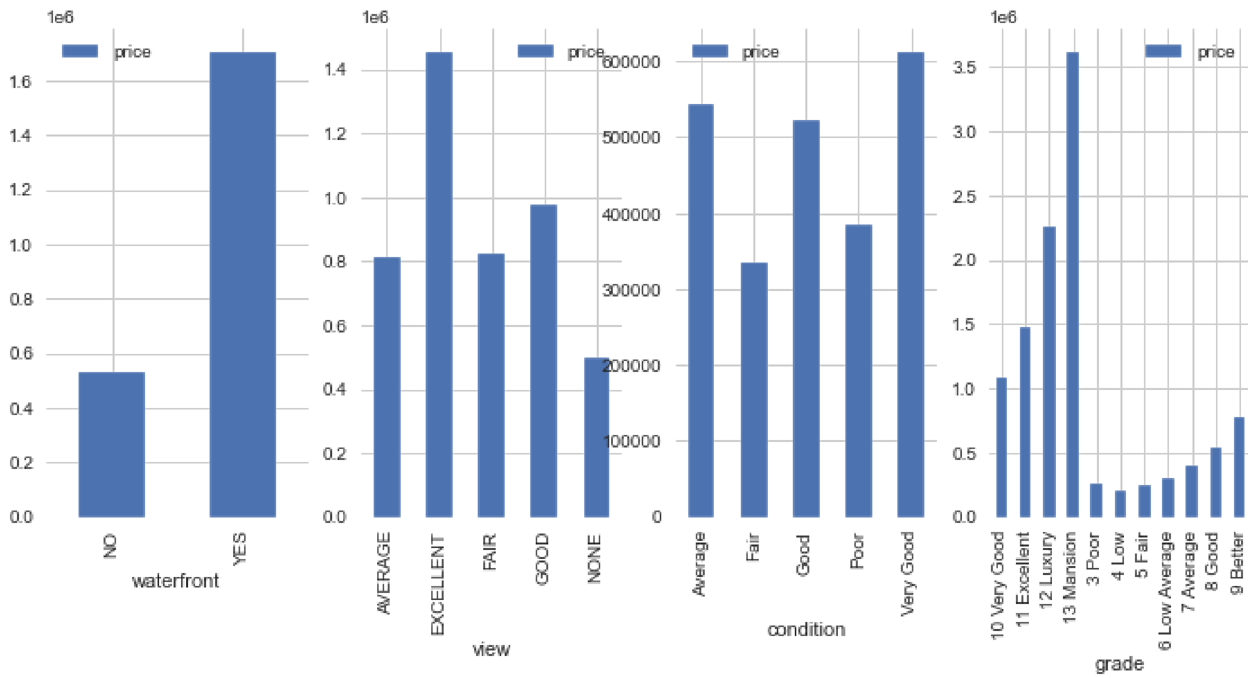
```
 11  grade          15762 non-null  object
 12  sqft_above     15762 non-null  int64
 13  sqft_basement  15429 non-null  float64
 14  yr_built       15762 non-null  int64
 15  yr_renovated   15762 non-null  float64
 16  zipcode        15762 non-null  int64
 17  lat            15762 non-null  float64
 18  long           15762 non-null  float64
 19  sqft_living15  15762 non-null  int64
 20  sqft_lot15     15762 non-null  int64
dtypes: datetime64[ns](1), float64(7), int64(9), object(4)
memory usage: 2.6+ MB
```

Univariate Analysis

Visualizing categorical variables in our data

In [ ]:

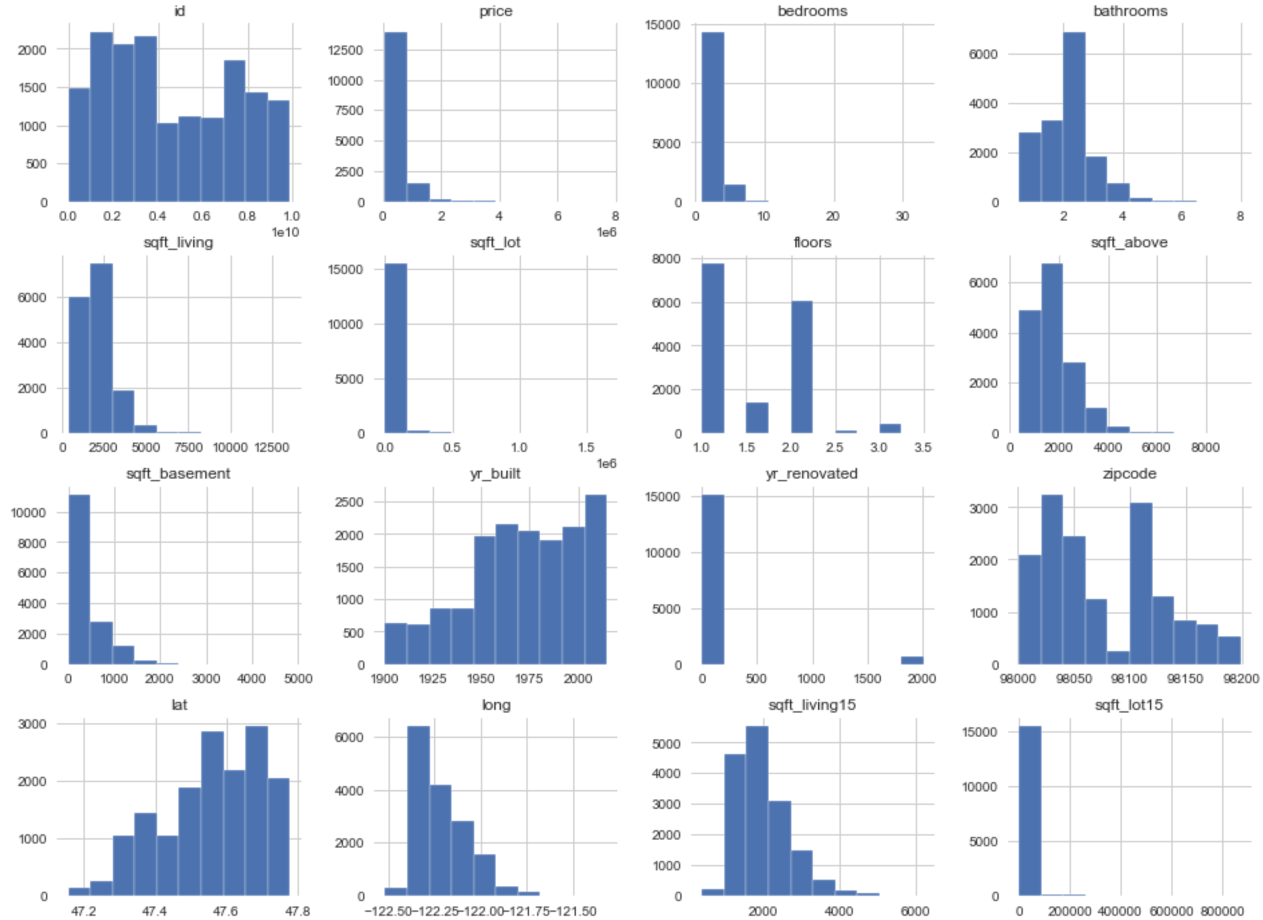
```python
categorical_features = house_df.select_dtypes("object").columns
fig, axes = plt.subplots(ncols=len(categorical_features), figsize=(12,5))

for index, feature in enumerate(categorical_features):
    house_df.groupby(feature).mean().plot.bar(
        y="price", ax=axes[index])
```



Visualizing our numerical variables

In [ ]:

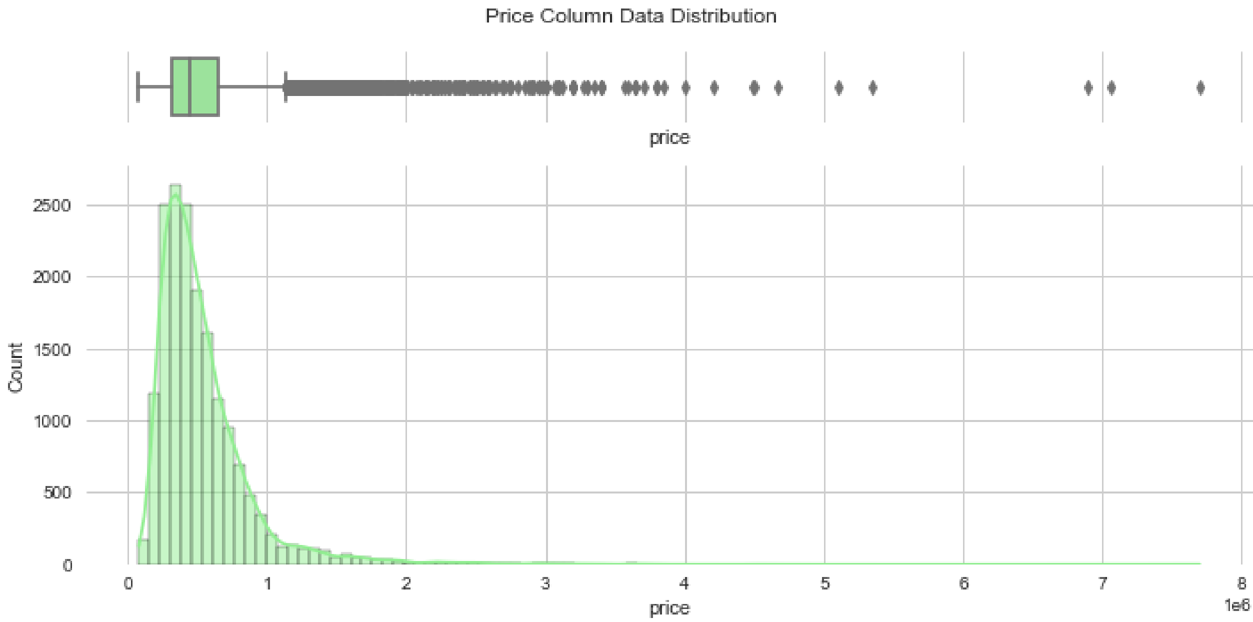
```python
house_df.hist(figsize=(16,12));
```



Visualizing the price column alone

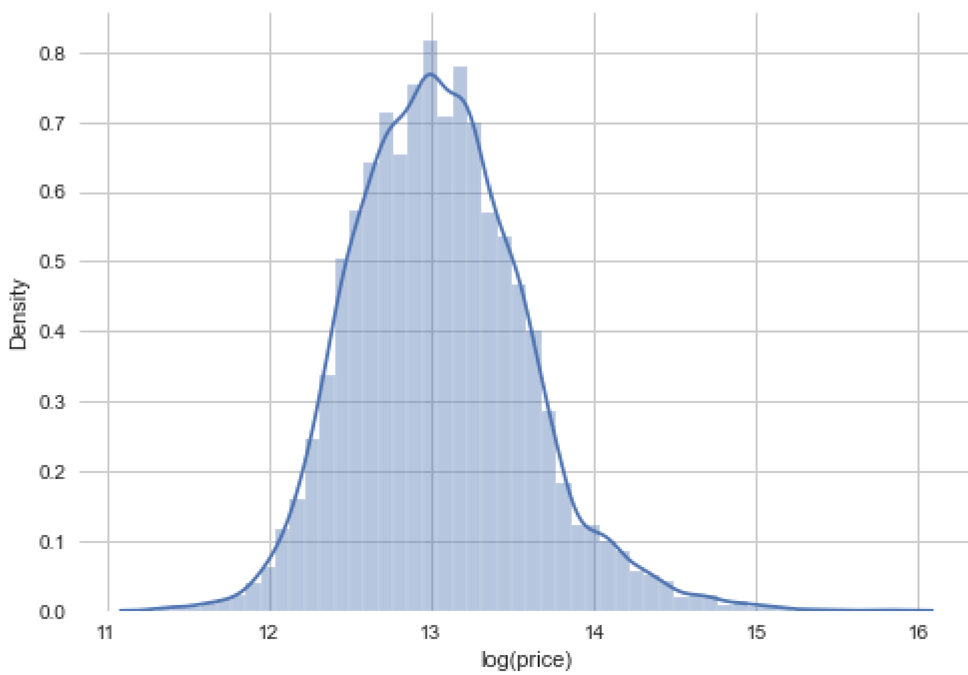
In [ ]:
```
# Function to plot the histogram, kde and boxplot of the data
def plot_distribution(df, col, title, bins_=10):
    ''' Plots the distribution of a column in a dataframe as a histogram, kde and boxpl
    # creating a figure composed of two matplotlib.Axes objects (ax_box and ax_hist)
    f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (

    # assign a graph to each ax
    sns.boxplot(df[col], ax=ax_box, color='lightgreen')
    sns.histplot(data=df, x=col, ax=ax_hist, kde=True, color='lightgreen', bins=bins_,
    plt.suptitle(title)
    plt.tight_layout();
```

In [ ]:
```
# Visualise the data distribution
plot_distribution(data, 'price', 'Price Column Data Distribution', 100)
```



Since we will be using `price` as our target variable, it is best if we log transformed this feature in order to normalize it.

In [ ]:
```
# calculating the log of price
house_df["log(price)"] = np.log(house_df["price"])
#Visualize the price using the logprice column after log transformation
sns.distplot(house_df['log(price)'], kde=True);
```

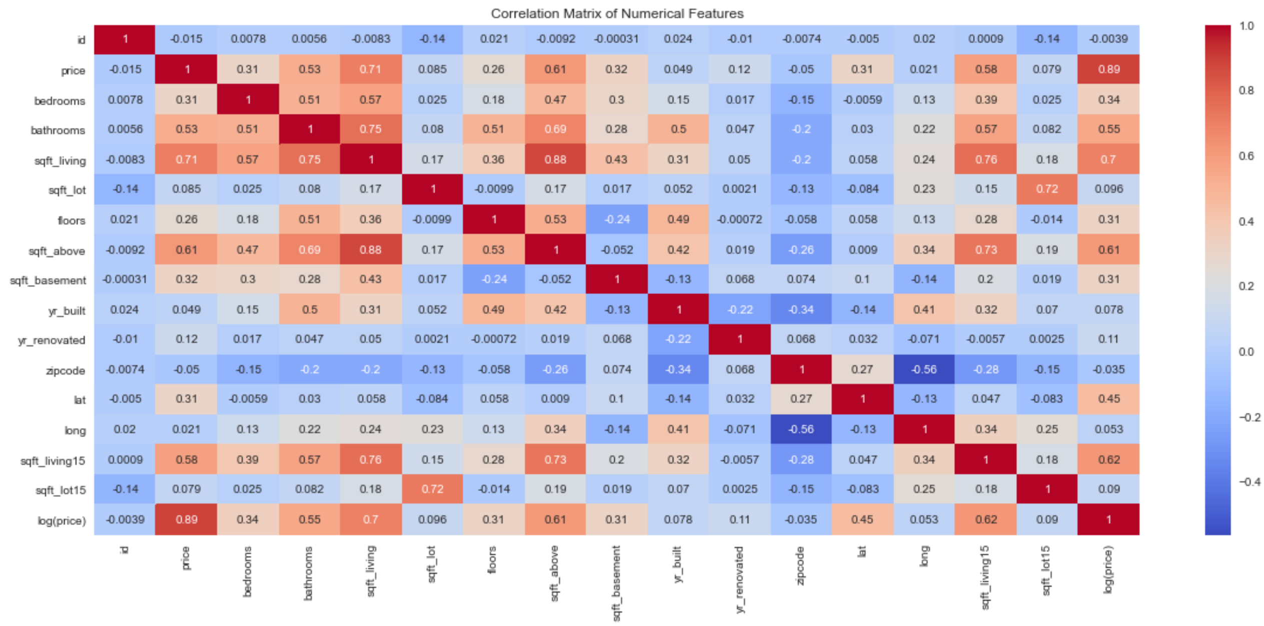


Bivariate Analysis

Heatmap to show the correlation between different features in our data, in order to identify variables that are strongly correlated with each other, and may therefore be important predictors of a target variable. This can help in feature selection for predictive modeling tasks.

In [ ]:
```
# Plot correlation matrix of numerical features
fig, ax = plt.subplots(figsize=(20,8))
```

```
corr = house_df.corr()
sns.heatmap(corr, cmap='coolwarm', annot=True, ax=ax)
plt.title('Correlation Matrix of Numerical Features')
plt.show()

# Display plot
plt.show()
```



Objective 1. **Identifying features influencing the pricing.**

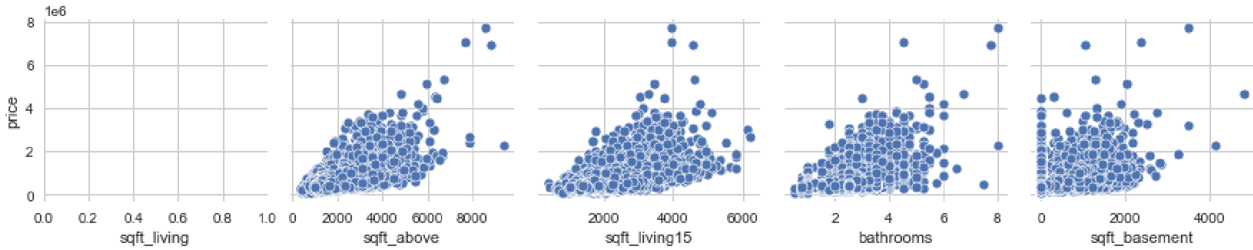
Top 5 features with the highest correlation with price

In [ ]:
```
# Identify top 5 features that have the highest correlation with price
corr_matrix = data.corr()
top_5_features = corr_matrix['price'].abs().sort_values(ascending=False)[1:6]
print("Top 5 features that have the highest correlation with price:\n", top_5_features)
```

```
Top 5 features that have the highest correlation with price:
 sqft_living      0.703520
sqft_above       0.608209
sqft_living15    0.586046
bathrooms        0.524719
sqft_basement    0.321079
Name: price, dtype: float64
```

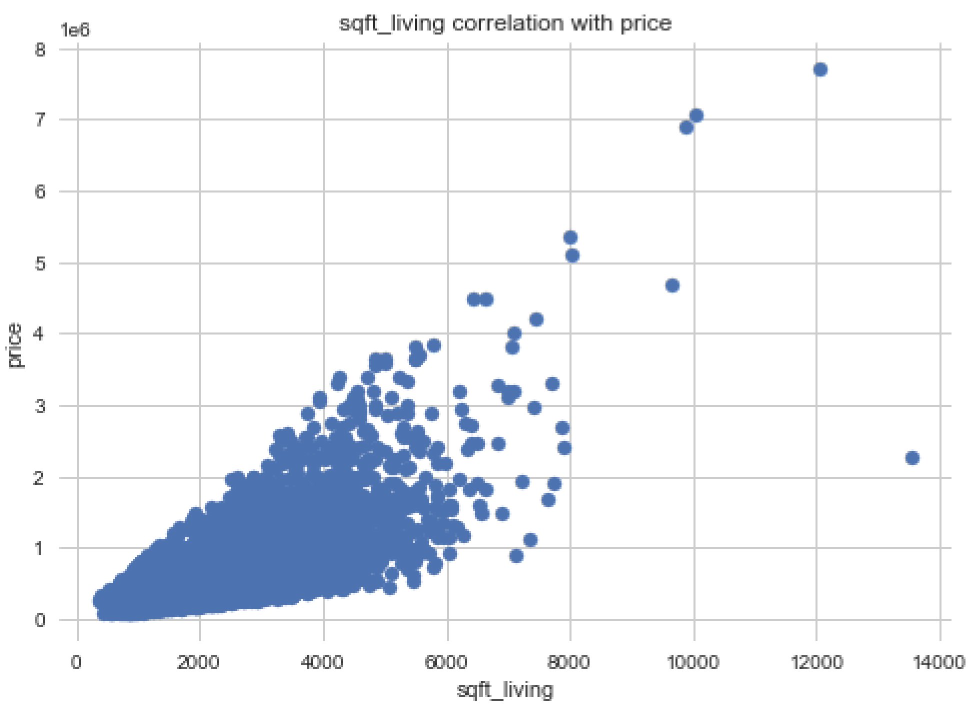
In [ ]:
```
# Visualize the relationship between the top 5 features and price
sns.pairplot(data, x_vars=top_5_features.index, y_vars=['price'])
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x20bc196b850>



In [ ]:
```python
def plot_scatter(x, y, x_label, y_label, title):
    """
    Plots a scatter plot of x and y values with labeled axes and title.

    Args:
        x (list): A list of x values.
        y (list): A list of y values.
        x_label (str): The label for the x axis.
        y_label (str): The label for the y axis.
        title (str): The title for the plot.
    """
    plt.scatter(x, y)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title)
    plt.show()
```

In [ ]:
```python
plot_scatter(data['sqft_living'], data['price'],'sqft_living', 'price','sqft_living cor
```



The above scatter plots shows a high correlation with the price.

Modelling

In [ ]:
```python
y = data['price']
X_baseline = data[['sqft_living']]
baseline_model = sm.OLS(y, sm.add_constant(X_baseline))
```

```
baseline_results = baseline_model.fit()
print(baseline_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.495
Model:                            OLS   Adj. R-squared:                  0.495
Method:                 Least Squares   F-statistic:                 1.699e+04
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        23:16:41   Log-Likelihood:            -2.4093e+05
No. Observations:               17340   AIC:                         4.819e+05
Df Residuals:                   17338   BIC:                         4.819e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -4.825e+04   4936.020     -9.776      0.000   -5.79e+04   -3.86e+04
sqft_living   282.4658      2.167    130.348      0.000     278.218     286.713
==============================================================================
Omnibus:                    12129.027   Durbin-Watson:                   1.971
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           482954.874
Skew:                           2.877   Prob(JB):                         0.00
Kurtosis:                      28.206   Cond. No.                     5.65e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 5.65e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

- The model is statistically significant overall, with an F-statistic p-value well below 0.05
- The model explains about 49.9% of the variance in price
- The model coefficients (const and sqft_living) are both statistically significant, with t-statistic p-values well below 0.05
- The coefficient for sqft_living is 286.5963, which means that for every additional square foot of living space, the price of the property increases by $286.60.
- The intercept (const) of the model is -56200, which means that when the size of the living space is zero, the estimated price is -$56,200. However, this value does not have a practical interpretation since it is not possible for a house to have zero square feet of living space.
- The Jarque-Bera test for normality shows that the errors are not normally distributed since the p-value is less than 0.05. This suggests that there may be some non-linearity or heteroscedasticity in the relationship between the independent variable and dependent variable.

Overall, we can conclude that sqft_living is a significant predictor of price, but there may be other factors that also affect the price of a property. Additionally, the model may not be the best fit for the data due to the issues with normality and multicollinearity.

Multiple linear regression

In [ ]:
```
#Convert the 'condition' and 'grade' columns to ordinal variables
conditions = {'Poor': 1, 'Average': 2, 'Fair': 3, 'Good': 4, 'Very Good': 5, 'Excellent
data['condition'] = data['condition'].map(conditions)
```

```
grades = {'3 Poor': 1,'4 Low': 2,'5 Fair' : 3, '6 Low Average': 4, '7 Average': 5, '8 G
data['grade'] = data['grade'].map(grades)
```

In [ ]:

```
# set the predictor variables
X = data[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', "

# add a constant to the predictor variables
X = sm.add_constant(X)

# set the response variable
y = data['price']

# create the model
model = sm.OLS(y, X)
model_results = model.fit()

# print the model summary
print(model_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.634
Model:                            OLS   Adj. R-squared:                  0.634
Method:                 Least Squares   F-statistic:                     3002.
Date:                Thu, 20 Apr 2023   Prob (F-statistic):               0.00
Time:                        23:16:41   Log-Likelihood:            -2.3814e+05
No. Observations:               17340   AIC:                         4.763e+05
Df Residuals:                   17329   BIC:                         4.764e+05
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const         6.914e+06   1.57e+05     44.032      0.000    6.61e+06    7.22e+06
bedrooms     -4.684e+04   2303.899    -20.333      0.000   -5.14e+04   -4.23e+04
bathrooms     5.248e+04   3955.418     13.267      0.000    4.47e+04    6.02e+04
sqft_living    199.0908      3.660     54.396      0.000     191.917     206.265
sqft_lot        -0.2479      0.041     -6.049      0.000      -0.328      -0.168
floors        2.225e+04   3965.298      5.612      0.000    1.45e+04       3e+04
waterfront    7.663e+05    2.1e+04     36.428      0.000    7.25e+05    8.08e+05
grade         1.182e+05   2539.234     46.540      0.000    1.13e+05    1.23e+05
condition     1.005e+04   1752.247      5.735      0.000    6614.368    1.35e+04
yr_renovated    12.8354      4.540      2.827      0.005       3.937      21.733
yr_built     -3790.5046     81.120    -46.727      0.000   -3949.508   -3631.501
==============================================================================
Omnibus:                    12996.616   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           868405.626
Skew:                           3.018   Prob(JB):                         0.00
Kurtosis:                      37.139   Cond. No.                     4.17e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 4.17e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

According to the output, our multiple linear regression model has an R-squared value of 0.638, indicating that approximately 63.4% of the variance in home prices can be explained by the predictor variables included in the model.

The coefficients of the predictor variables indicate the impact of each variable on the home price.

1. Waterfront property: Homes located on the waterfront have an average increase of $761,500 in value compared to homes that are not on the waterfront.
2. Square footage of living area: An increase in one square foot of living area leads to an increase of $196.33 in home price.
3. Grade: Higher-grade properties have an average increase of $120,400 in value compared to lower-grade properties.
4. Number of bathrooms: Each additional bathroom adds an average of $51,180 to the home price
5. Bedrooms: Each additional bedroom adds an average of $48,080 to the home price

The p-values of the coefficients indicate the statistical significance of the impact of each variable on the home price. All the predictor variables in our model have a p-value of 0.000, indicating that they are statistically significant in predicting the home price.

Metric for Evaluation

In [ ]:
```
# Calculate the mean absolute error of the baseline model
baseline_mae = mean_absolute_error(y, baseline_results.predict(sm.add_constant(X_baseli
baseline_mae
```

Out[ ]: 173788.4850613264

In [ ]:
```
#calculating the RMSE for the baseline model
rmse = np.sqrt(baseline_mae)
rmse
```

Out[ ]: 416.87946106917576

In [ ]:
```
# calculating the MAE
multiple_linear_mae = mean_absolute_error(y, model_results.predict(sm.add_constant(X)))
multiple_linear_mae
```

Out[ ]: 144189.40880555194

In [ ]:
```
#Calculating the RMSE
rmse = np.sqrt(multiple_linear_mae)
rmse
```

Out[ ]: 379.7228052218512

Our multiple linear regression model is a better model since the RMSE value is lower than that of the baseline model

Objective 2 : **To analyse trends in house prices over time (time series analysis) and predict future prices.**

In [ ]:
```
data_2 = house_df.copy()
```

In [ ]:
```
#seperating date into month and year
data_2['date'] = pd.to_datetime(data_2['date'])
```

```
# extracting month and year
data_2['month_sold'] = data_2['date'].dt.month
data_2['year_sold'] = data_2['date'].dt.year

data_2.head()
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO	NONE
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO	NONE
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	NO	NONE
5	7237550310	2014-05-12	1230000.0	4	4.50	5420	101930	1.0	NO	NONE
6	1321400060	2014-06-27	257500.0	3	2.25	1715	6819	2.0	NO	NONE

5 rows × 24 columns

In [ ]:

```
# Retrieve the mean
data_monthly = data_2['month_sold'].mean()
data_monthly
```

Out[ ]: 6.5760690267732524

Based on the output given, the average month the houses were sold was in June

In [ ]:

```
# assuming 'date' column is already converted to datetime format

# group data by date and calculate mean price
monthly_avg_price = data_2.groupby(pd.Grouper(key='date', freq='M'))['price'].mean()

# plot time series
plt.plot(monthly_avg_price.index, monthly_avg_price.values)
plt.xlabel('Date')
plt.ylabel('Average price')
plt.title('Price over time')
plt.show()
```

In [ ]:
```
# Convert 'yr_renovated' to datetime format and extract year
data_2['yr_renovated'] = pd.to_datetime(data_2['yr_renovated'], format='%Y', errors='co
```

In [ ]:
```
# filling NaN values with 0 and converted it to integer data type.
data_2['yr_renovated'] = data_2['yr_renovated'].astype('Int64').fillna(0)
data_2['yr_renovated']
```

Out[ ]:
```
1        1991
3           0
4           0
5           0
6           0
         ...
21591       0
21592       0
21593       0
21594       0
21596       0
Name: yr_renovated, Length: 15762, dtype: Int64
```

In [ ]:
```
# One hot encoding for the column 'yr_renovated'

data_2['renovated'] = (data_2['yr_renovated'] > 0).astype(int)

data_2['renovated'].value_counts()
```

Out[ ]:
```
0    15111
1      651
Name: renovated, dtype: int64
```

We notice that there are 651 houses that have been renovated and 15,111 houses that have not been renovated.

In [ ]:
```
#creating a new column - age of the house- which will be given by the latest year minus
#latest year
yr_built_max = data_2['yr_built'].max()
print(yr_built_max)
```

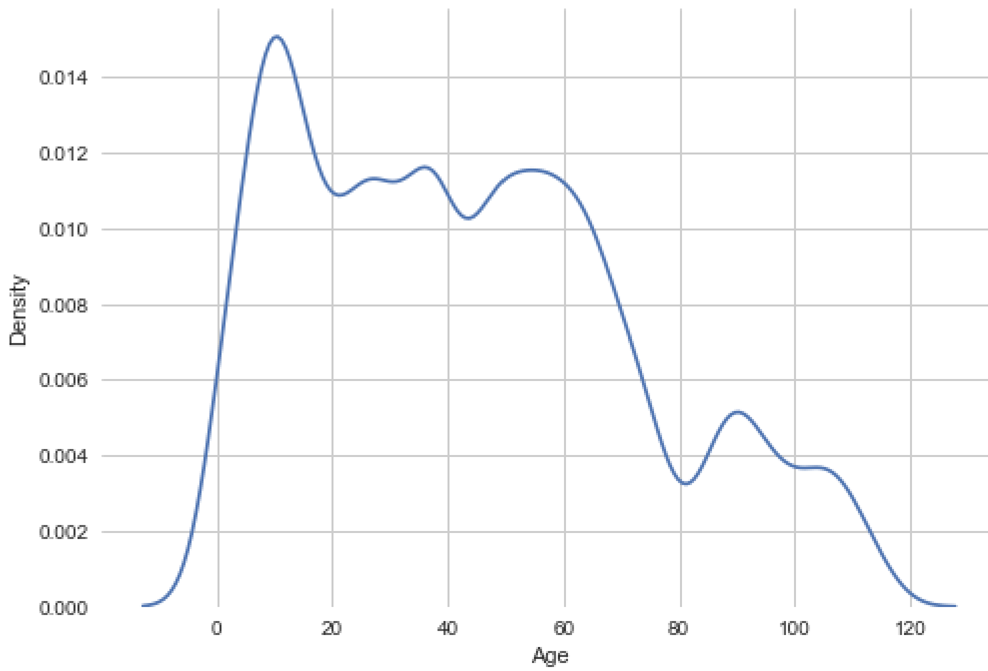
```
#age column
data_2['Age'] = yr_built_max - data_2['yr_built']
data_2.columns
```

```
2015
```

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

Below is a density plot for Age column

In [ ]:
```
# Explore the Age column created

sns.kdeplot(data_2['Age']);
```



The following correlation matrix shows some of the features as well as including the newly created column, age.

In [ ]:
```
data_2[['price','bedrooms','sqft_living','condition','grade', 'yr_built','yr_renovated'
```

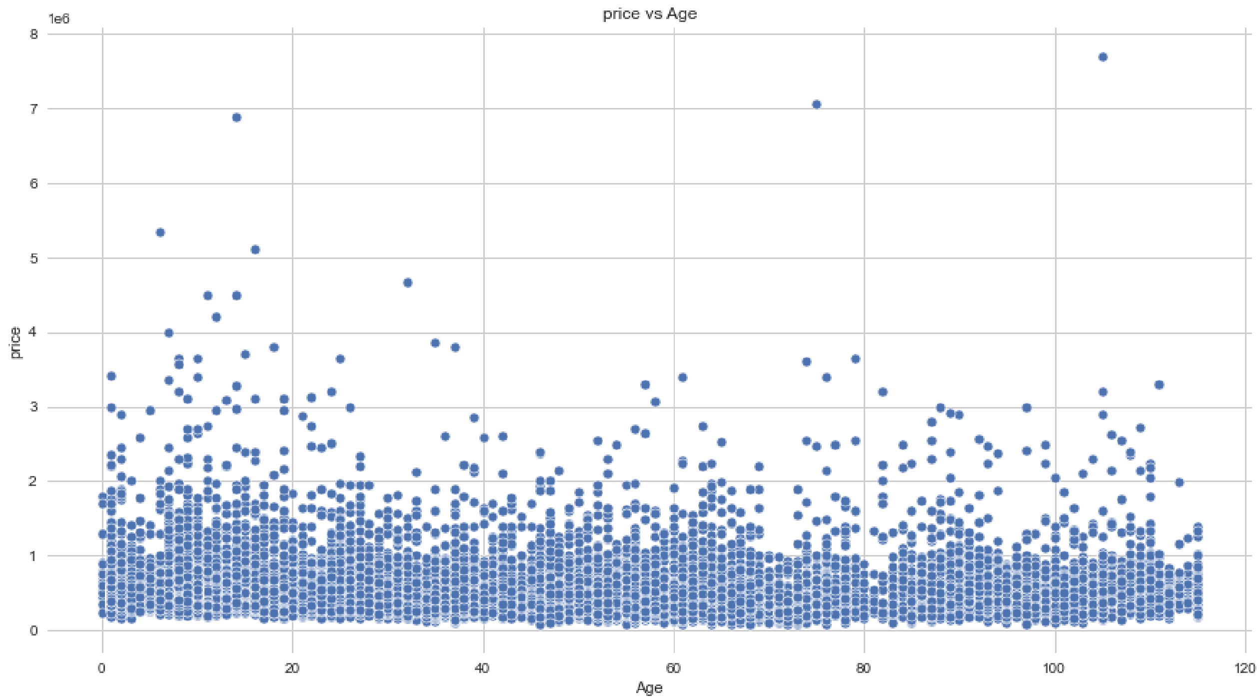
Out[ ]:

	price	bedrooms	sqft_living	yr_built	yr_renovated	month_sold	year_sold	sqft_lo
price	1.000000	0.305489	0.706189	0.049345	0.122731	-0.008244	0.003856	0.08450
bedrooms	0.305489	1.000000	0.573575	0.153229	0.017430	-0.005990	-0.003506	0.02546
sqft_living	0.706189	0.573575	1.000000	0.314220	0.050232	0.011668	-0.026198	0.16533
yr_built	0.049345	0.153229	0.314220	1.000000	-0.223541	-0.005769	0.003920	0.05157
yr_renovated	0.122731	0.017430	0.050232	-0.223541	1.000000	0.010854	-0.022068	0.00214
month_sold	-0.008244	-0.005990	0.011668	-0.005769	0.010854	1.000000	-0.781186	-0.00313
year_sold	0.003856	-0.003506	-0.026198	0.003920	-0.022068	-0.781186	1.000000	0.00612
sqft_lot	0.084504	0.025460	0.165336	0.051578	0.002147	-0.003134	0.006120	1.00000

	price	bedrooms	sqft_living	yr_built	yr_renovated	month_sold	year_sold	sqft_lc
Age	-0.049345	-0.153229	-0.314220	-1.000000	0.223541	0.005769	-0.003920	-0.05157

Visualizing the relationship of the age of the property against price

In [ ]:
```
# Visualization on Age v Price on a scatter plot

plt.figure(figsize=(15, 8))
sns.scatterplot(data=data_2, x='Age',  y='price')
plt.title('price vs Age');
```



A linear regression model for Age and price

In [ ]:
```
X = data_2[['Age']]
y = data_2['price']

# Add constant to X
X = sm.add_constant(X)

# Create and fit OLS model
model = sm.OLS(y, X).fit()

print(model.params)
print()
print(model.pvalues)
```

```
const    568795.600304
Age        -626.092195
dtype: float64

const    0.000000e+00
Age      5.703425e-10
dtype: float64
```

Interpretation

Based on this simple regression model, we can note that there is a statistically negative significant relationship between the age of the property and the price at which it was sold.

- The coefficient of -674.743074 indicates that, a one year increase would be associated with a $674.74 decrease in the sale price, on average.

- Overall, the results suggest that the age of a property may be a significant predictor of its price, however there are other variables that would need further exploration in order to understand better the determinants of house prices.

In [ ]:
```
# Predicts the values using the model
y_pred = model.predict(X)

# Calculate the mean absolute error
mae = np.mean(np.abs(y - y_pred))
print('MAE:', mae)

mse = np.mean((y - y_pred)** 2)

rmse = np.sqrt(mse)
print('RMSE', rmse)
```

```
MAE: 234721.94876067538
RMSE 371760.5937215026
```

Although, we have a higher RMSE compared to the MAE in this model, we will still remain with it as the metric of evaluation as based on the conclusion, it may be attributed to other factors.

Multiple Linear Regression

We created a multiple linear regression model that includes price as the dependent variable and different features such as :

- bedrooms
- sqft_living
- condition
- year_sold and month_sold &
- age

as the independent variables in this model.

In [ ]:
```
from statsmodels.formula.api import ols

features = ['bedrooms','sqft_living','condition', 'yr_built', 'Age', 'year_sold', 'mont

formula = 'price ~ sqft_living + bedrooms + Age + condition'
model_2 = ols(formula = formula, data = data_2[features]).fit()

print('R_squared:', model_2.rsquared)
print()
print('F_Statistic:', model_2.fvalue)
print()
print(model_2.params)
print()
print(model_2.pvalues)
```

```
R_squared: 0.5493984181963636

F_Statistic: 2744.021399005872

Intercept                  -76684.708715
condition[T.Fair]          -70198.774025
condition[T.Good]           -6597.693663
condition[T.Poor]          -39795.351992
condition[T.Very Good]      40213.720215
sqft_living                   346.692388
bedrooms                   -62773.970748
Age                          2428.664229
dtype: float64

Intercept                  1.777015e-18
condition[T.Fair]          1.504801e-03
condition[T.Good]          1.759438e-01
condition[T.Poor]          4.890063e-01
condition[T.Very Good]     3.647666e-07
sqft_living                0.000000e+00
bedrooms                  4.781444e-126
Age                       3.190623e-206
dtype: float64
```

Interpretation

This multiple linear regression model purpose was to predict house prices based on several independent variables.

- The **R-Squared value** 0.549 suggests that the model can explain for 54.17% of the variance in house prices, this may be interpreted as a moderate fit.

- Under the **intercept** coefficient of -7.668e+04 means that, on average, the coefficients of the different conditions show that, a house that is in very good condition can be sold for $40,210 more than the average price, in comparison to a house that is in fair condition that sells$ 70,200 less!

- The coefficient for **sqft_living** of 346.6924 goes to imply that, on average, the price of a house increases by $346.69 for each additional square foot of living space. The coefficient for bedrooms of -6.27$ 62,770.

- The coefficient for **age** suggests that, on average, the price of a house increases by $2,428.66 for each additional year of age.

- The model has a significant F-statistic of 3644.89 and a low p-value, indicating that the model is statistically significant.

Objective 3 : **To identify extreme prices (outlier detection) and recommend better pricing strategy.**

In this section, we analyse the outliers in price category. We identify the houses with extremely high and low prices, and try to find out the reason for it. We also suggest a better pricing strategy.

In [ ]:
```
data_3 = house_df.copy()
```

Identifying outliers in the price column of our dataset.

In [ ]:
```
count = 0
price_outliers = []

# Calculate the z-score for each data point
z_scores = (data_3['price'] - data_3['price'].mean()) / data_3['price'].std()

# Create a new empty DataFrame to store the outliers
data_outliers = pd.DataFrame(columns=data_3.columns)

for idx, row in data_3['price'].T.iteritems():
    if abs(z_scores[idx]) > 3:
        count += 1
        # Append the outlier row to the data_outliers DataFrame
        data_outliers = data_outliers.append(data_3.loc[idx])
        # Add the index of the outlier row to the price_outliers list (if needed)
        price_outliers.append(idx)

# Print the count of outliers found
print(f"{count} outliers found")
```

```
282 outliers found
```

The code above checks if there is any extreme prices for the houses. It then adds them to the new list of extreme prices and shows how many it found.

In [ ]:
```
data_outliers.head()
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
21	2524049179	2014-08-26	2000000.0	3	2.75	3050	44867	1.0	NO	EXCE
153	7855801670	2015-04-01	2250000.0	4	3.25	5180	19850	2.0	NO	
246	2025069065	2014-09-29	2400000.0	4	2.50	3650	8354	1.0	YES	EXCE
282	7424700045	2015-05-13	2050000.0	5	3.00	3830	8480	2.0	NO	
300	3225069065	2014-06-24	3080000.0	4	5.00	4550	18641	1.0	YES	EXCE

5 rows × 22 columns

In [ ]:
```
data_outliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 282 entries, 21 to 21560
Data columns (total 22 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              282 non-null    object
 1   date            282 non-null    datetime64[ns]
```

```
 2   price          282 non-null    float64
 3   bedrooms       282 non-null    object
 4   bathrooms      282 non-null    float64
 5   sqft_living    282 non-null    object
 6   sqft_lot       282 non-null    object
 7   floors         282 non-null    float64
 8   waterfront     282 non-null    object
 9   view           282 non-null    object
 10  condition      282 non-null    object
 11  grade          282 non-null    object
 12  sqft_above     282 non-null    object
 13  sqft_basement  279 non-null    float64
 14  yr_built       282 non-null    object
 15  yr_renovated   282 non-null    float64
 16  zipcode        282 non-null    object
 17  lat            282 non-null    float64
 18  long           282 non-null    float64
 19  sqft_living15  282 non-null    object
 20  sqft_lot15     282 non-null    object
 21  log(price)     282 non-null    float64
dtypes: datetime64[ns](1), float64(8), object(13)
memory usage: 50.7+ KB
```

In [ ]:

```
# Convert the column to float data type
cols_to_convert = ['bedrooms','sqft_living', 'sqft_lot', 'sqft_above', 'sqft_living15',

data_outliers[cols_to_convert] = data_outliers[cols_to_convert].astype(float)
```

In [ ]:

```
data_outliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 282 entries, 21 to 21560
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             282 non-null    object
 1   date           282 non-null    datetime64[ns]
 2   price          282 non-null    float64
 3   bedrooms       282 non-null    float64
 4   bathrooms      282 non-null    float64
 5   sqft_living    282 non-null    float64
 6   sqft_lot       282 non-null    float64
 7   floors         282 non-null    float64
 8   waterfront     282 non-null    object
 9   view           282 non-null    object
 10  condition      282 non-null    object
 11  grade          282 non-null    object
 12  sqft_above     282 non-null    float64
 13  sqft_basement  279 non-null    float64
 14  yr_built       282 non-null    object
 15  yr_renovated   282 non-null    float64
 16  zipcode        282 non-null    object
 17  lat            282 non-null    float64
 18  long           282 non-null    float64
 19  sqft_living15  282 non-null    float64
 20  sqft_lot15     282 non-null    float64
 21  log(price)     282 non-null    float64
dtypes: datetime64[ns](1), float64(14), object(7)
memory usage: 50.7+ KB
```

In [ ]:

```
# calculating the age of the houses in the price outliers
data_outliers['house_age'] = np.where(data_outliers['yr_built']==0, 0, 2015 - data_outl

# the number of houses older than 50 years in our outliers
```

```
house_age_gt_50 = list(data_outliers[data_outliers['house_age']>50]['house_age'])
len(house_age_gt_50)
```

Out[ ]: 103

Creating a linear regression model

In [ ]:
```
y = data_outliers['price']
X_baseline = data_outliers[['sqft_living']]
baseline_model_outliers = sm.OLS(y, sm.add_constant(X_baseline))
baseline_results_outliers = baseline_model_outliers.fit()
```

In [ ]:
```
baseline_model_outliers_mae = mean_absolute_error(y, baseline_results_outliers.predict(
baseline_model_outliers_mae
```

Out[ ]: 462016.1954674735

In [ ]:
```
rmse = np.sqrt(baseline_model_outliers_mae)
rmse
```

Out[ ]: 679.7177322002667

Creating a multiple linear regression model using additional variables

In [ ]:
```
# set the predictor variables
X = data_outliers[['bedrooms','sqft_living', 'sqft_lot', 'sqft_above', 'sqft_living15',

# add a constant to the predictor variables
X = sm.add_constant(X)

# set the response variable
y = data_outliers['price']

# create the model
model_outliers = sm.OLS(y, X)
model_outliers_results = model_outliers.fit()
```

In [ ]:
```
model_outliers_mae = mean_absolute_error(y, model_outliers_results.predict(sm.add_const
model_outliers_mae
```

Out[ ]: 457477.0422931807

In [ ]:
```
rmse = np.sqrt(model_outliers_mae)
rmse
```

Out[ ]: 676.3704918853133

Creating a function that predicts house prices using the multiple linear regression formula. The function takes in different variables that influence the price

In [ ]:
```
# function that predicts the house prices
def predict_house_price(bedrooms,sqft_living, sqft_lot, sqft_above, sqft_living15, sqft
    # set the coefficients and intercept values
    b0 = 8.412e+05
    b1 = -8.721e+04
    b2 = 371.8604
    b3 = -1.3714
```

```
    b4 = 0.9192
    b5 = 48.3490
    b6 = -0.8813
    # calculate the predicted house price
    house_price = b0 + (b1 * bedrooms) + (b2 * sqft_living) + (b3 * sqft_lot) + (b4 * s
    return house_price
```

let's use the `predict_house_function` to predict house price for a house with 4bedrooms, 1000sqft_living, 1100sqft_lot, 1200sqft_above, 1300sqft_living15, and 1400sqft_lot15

In [ ]:
```
predict_house_price(4,1000, 1100, 1200, 1300, 1400)
```

Out[ ]:
```
925434.78
```

We create a function that gives suggestions of the houses in our dataset, based on budget price range.

In [ ]:
```
def suggest_houses(price_range):

    # Filter by price range
    data_filtered = data[(data['price'] >= price_range[0]) & (data['price'] <= price_ra

    # Sort by price ascending
    data_sorted = data_filtered.sort_values(by='price')

    # Select top 5 suggestions
    data_suggestions = data_sorted.head(5)

    # Return the specifications of the suggested houses
    return data_suggestions[['bedrooms', 'sqft_living', 'floors', 'zipcode']]
```

In [ ]:
```
suggest_houses((78000, 100000))
```

Out[ ]:

	bedrooms	sqft_living	floors	zipcode
465	1	430	1.0	98014
16184	2	730	1.0	98168
8267	3	860	1.0	98146
2139	2	520	1.0	98168
18453	2	900	1.0	98168

Conclusion

1. Some of the features that influence the pricing of houses include:

- Square footage of living space in the home: an additional square footage increases the price by $199.09
- Waterfront: the presence of a waterfront has an associated increase in price of $70,000
- Condition of the house: houses in good conditions have an associated increase in price of $35,650 compared to houses with average condition.

2. - For every additional year in the age of a house, there is an associated decrease in price of $626.09
3. - Some of the overvalued properties were found to be older than 50 years of age
   - The square footage of interior housing living space for the nearest 15 neighbors influences the pricing of houses, in that, an additional square footage leads to an increse in price by $48.35

Recommendations

We recommend that:

1. There is a need to do further exploration into other features in order to better understand the determinants of house prices.

2. The agency should consider re-purposing the old houses and targeting business owners rather than homeowners, this may also be achieved by market research.

3. The agency should consider investing in properties that can increase their profitability, such as properties that have a waterfront.

Next Steps

1. New features can be generated from the existing data to provide more insights into the housing market. For example: In-depth information about regions

2. Visualise the properties on a map. This would enable our stakeholders to see the affordability of properties per region. Additionally, this would help to also determine the best regions to invest in.

3. Revise the models so that it reflects the current market trends so that this will allow for better accuracy in predicting the prices.