Final Project Submission

Group 3.1

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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.

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 [ ]:
```
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
```

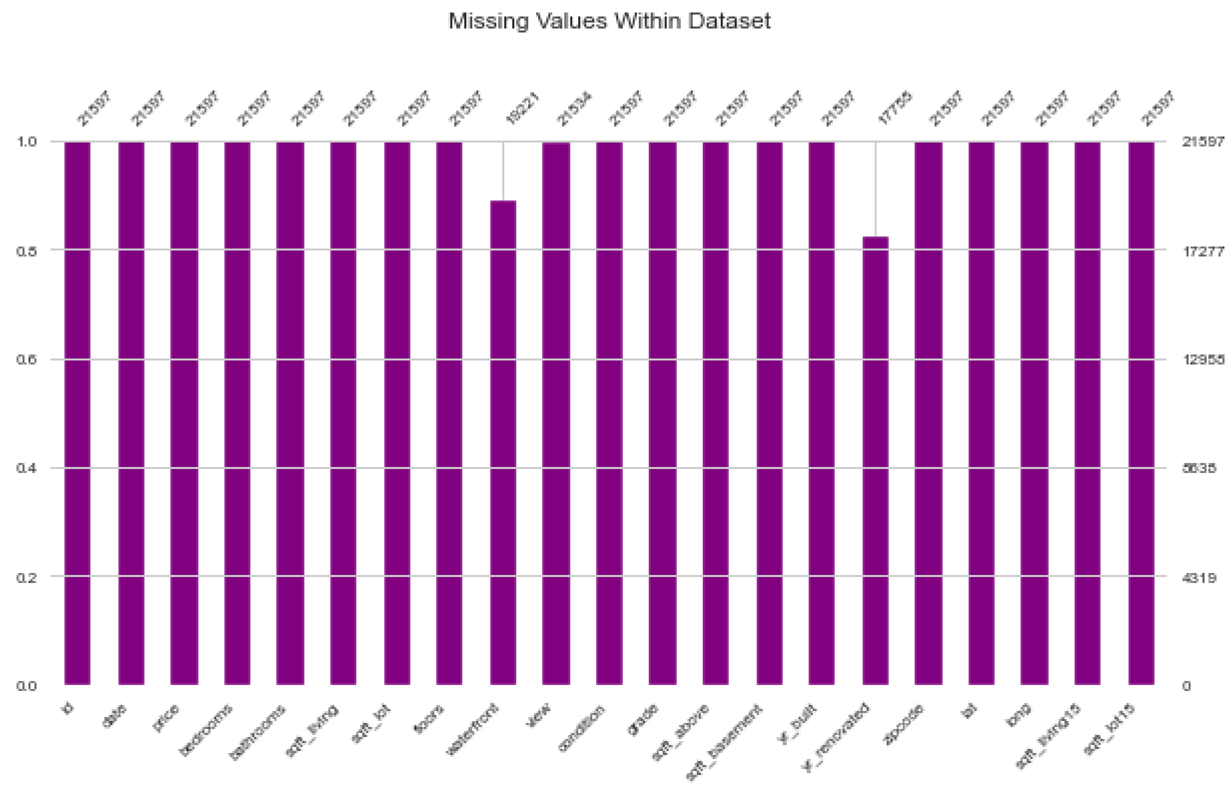
```
min    98001.000000     47.155900   -122.519000     399.000000     651.000000
25%    98033.000000     47.471100   -122.328000    1490.000000    5100.000000
50%    98065.000000     47.571800   -122.231000    1840.000000    7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000   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
```

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
```

The percentage value for the missing values dropped from our dataframe is 9.72%

Data Analysis

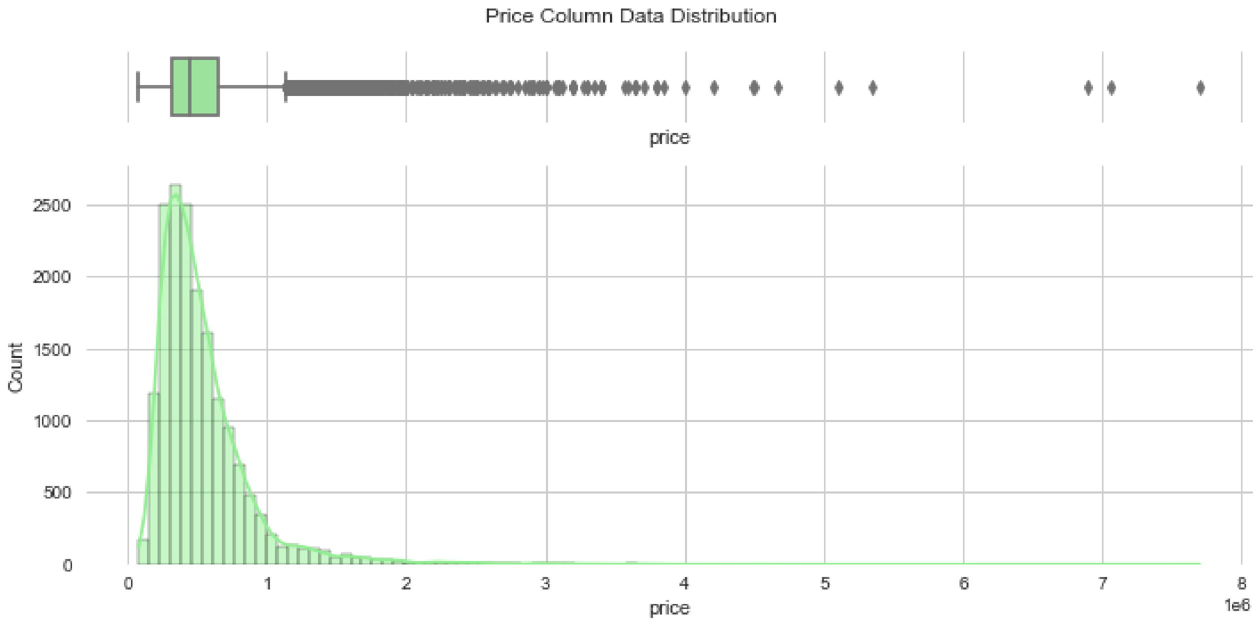
Objective 1. **Identifying features influencing the pricing.**

column distribution functions (numerical variables)

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();
```

1.price distribution

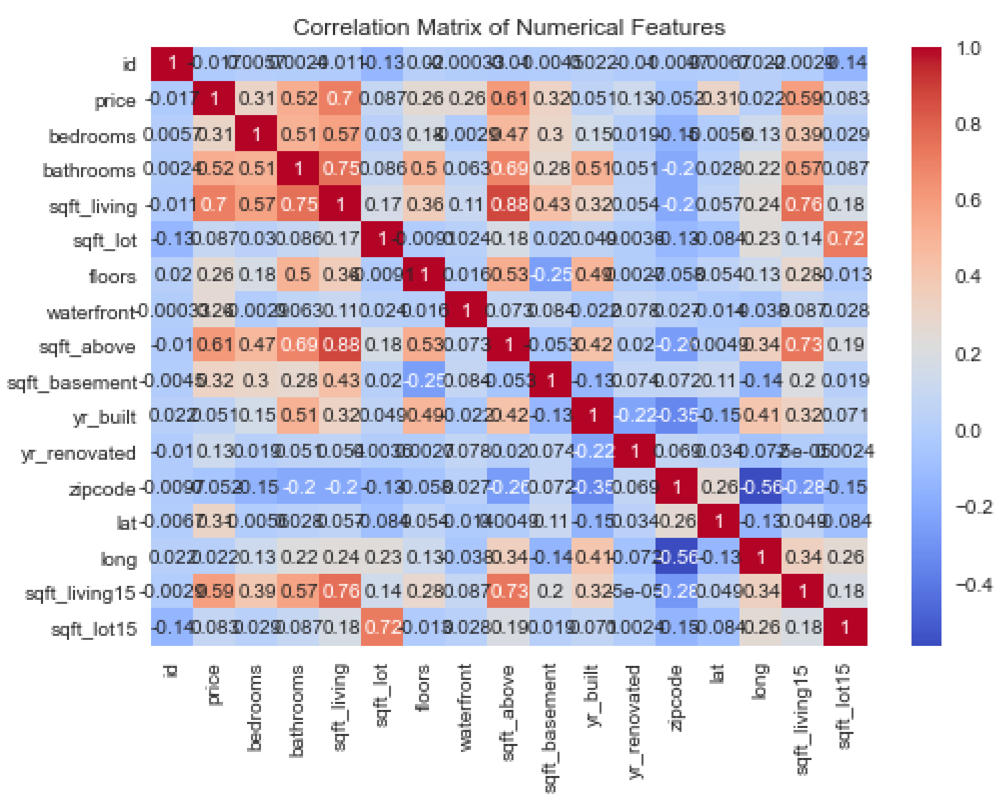
In [ ]:
```
# Visualise the data distribution
plot_distribution(data, 'price', 'Price Column Data Distribution', 100)
```



2.Plotting a correlation matrix of numerical features using Seaborn heatmap

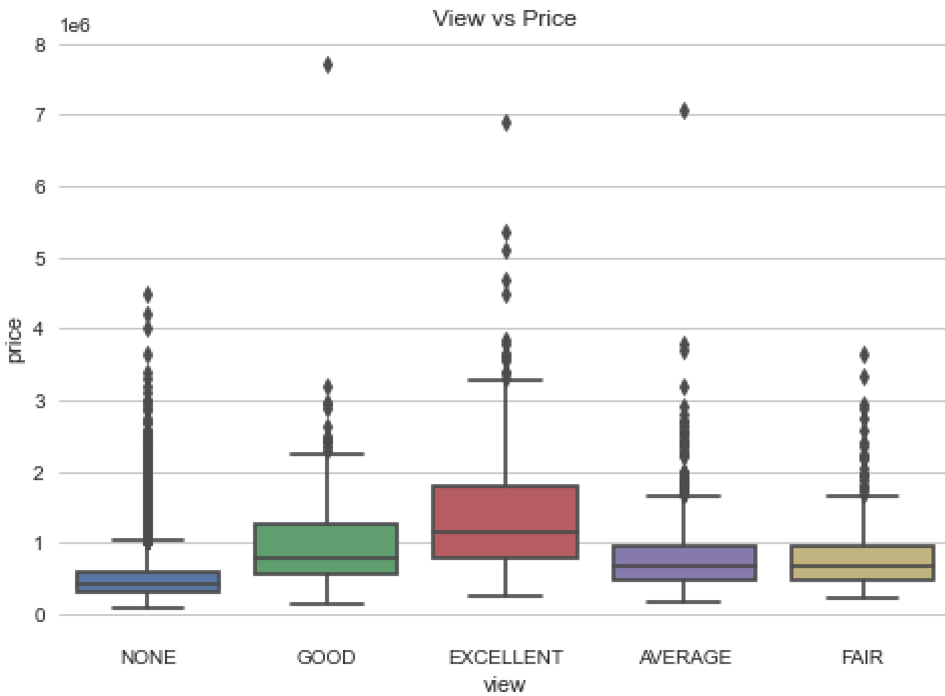
A correlation matrix can be used to identify variables that are strongly correlated with each other, and may therefore be important predictors of a target variable. This can help in feature selection for predictive modeling tasks.

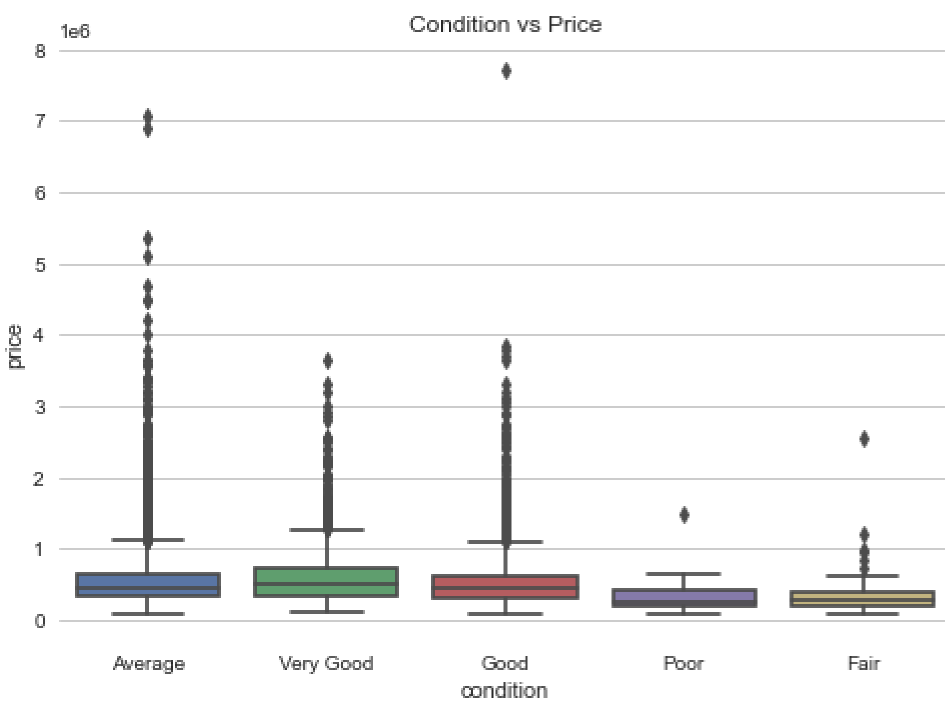
In [ ]:
```
# Plot correlation matrix of numerical features
corr = data.corr()
sns.heatmap(corr, cmap='coolwarm', annot=True)
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```

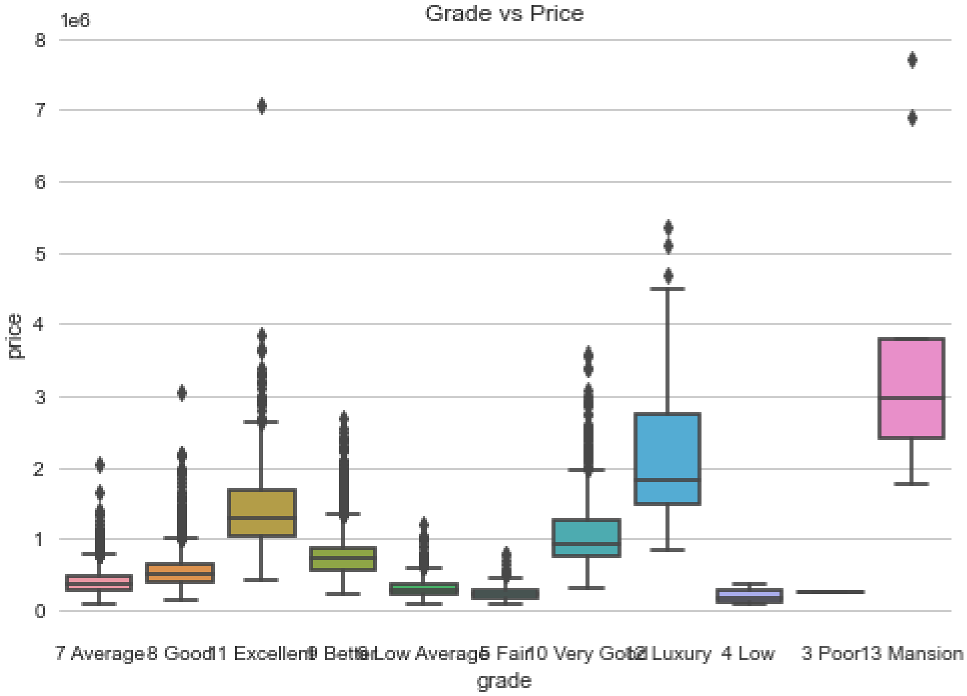


3. Plot boxplots of each categorical feature vs price using Seaborn boxplot

In [ ]:
```
# Plot boxplots of categorical features vs price
cat_features = [ 'view', 'condition', 'grade']
for feature in cat_features:
    sns.boxplot(x=feature, y='price', data=data)
    plt.title(f'{feature.capitalize()} vs Price')
    plt.show()
```







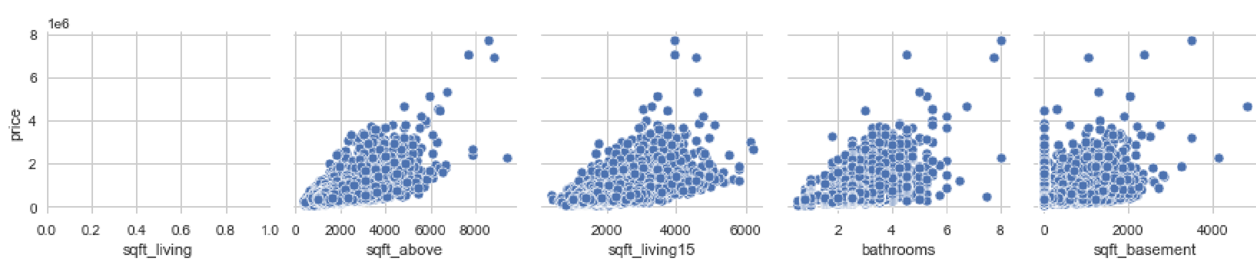
4. Features that has the highest correlation with the price and visualizing them

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'])
```

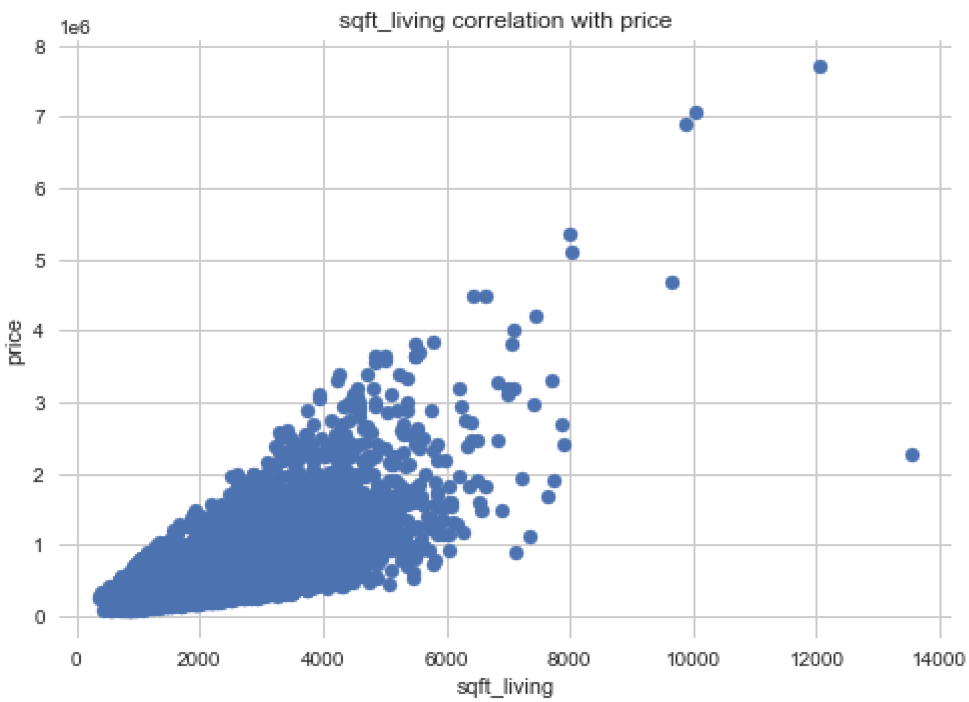
Out[ ]: <seaborn.axisgrid.PairGrid at 0x1c67364d6a0>



In [ ]:
```
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 [ ]:
```
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 [ ]:
```
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:                        04:03:57   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:                        04:03:58   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

The model is off by about 174670

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

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
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	NaN	NONE
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO	NONE
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	NO	NONE
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO	NONE

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	NO	NONE

5 rows × 23 columns

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

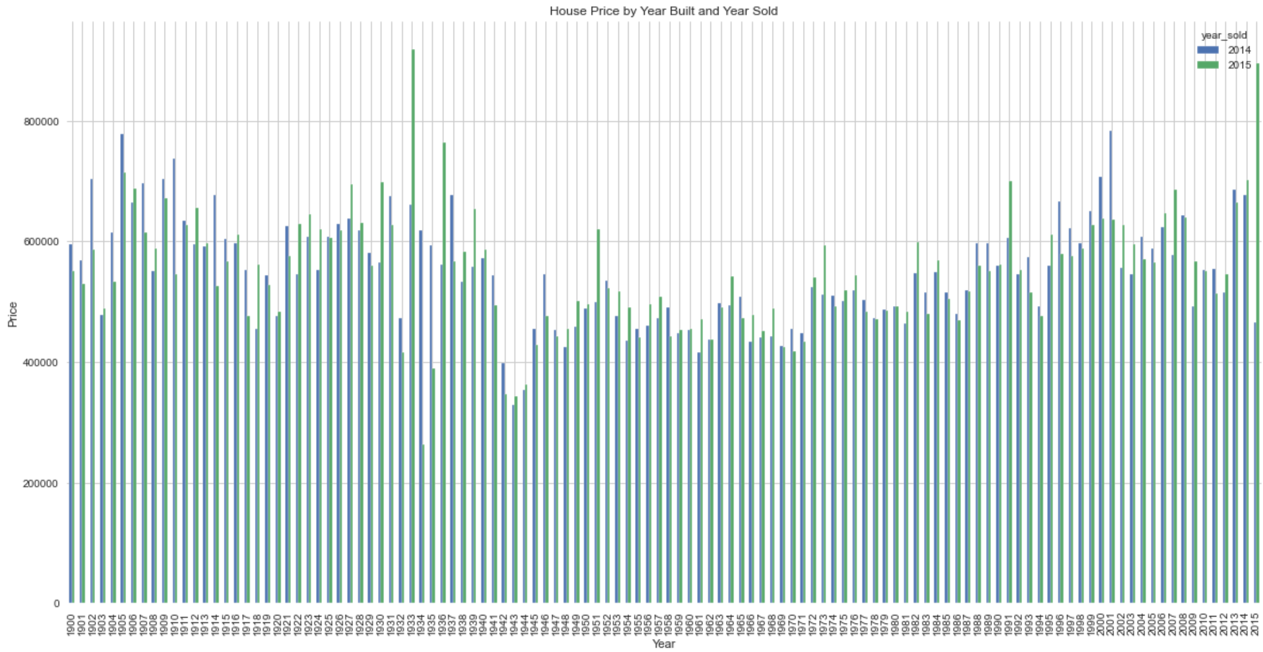
Out[ ]: 6.573968606750937

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 [ ]:
```
# pivot table with the sale price for the houses for each year built and year sold comb
yearly_price = data_2.pivot_table(index='yr_built', columns='year_sold', values='price'

# plot bar chart with two bars for each year, one for year built and one for year sold
fig, ax = plt.subplots(figsize=(20,10))
yearly_price.plot(kind='bar', ax=ax)
ax.set_xlabel('Year')
ax.set_ylabel('Price')
```

```
ax.set_title('House Price by Year Built and Year Sold')
plt.xticks(rotation=90)

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 [ ]:
```
data_2['yr_renovated'] = data_2['yr_renovated'].astype('Int64').fillna(0)
data_2['yr_renovated']
```

Out[ ]:
```
0           0
1        1991
2           0
3           0
4           0
         ...
21592       0
21593       0
21594       0
21595       0
21596       0
Name: yr_renovated, Length: 21597, 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    20853
1      744
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
```

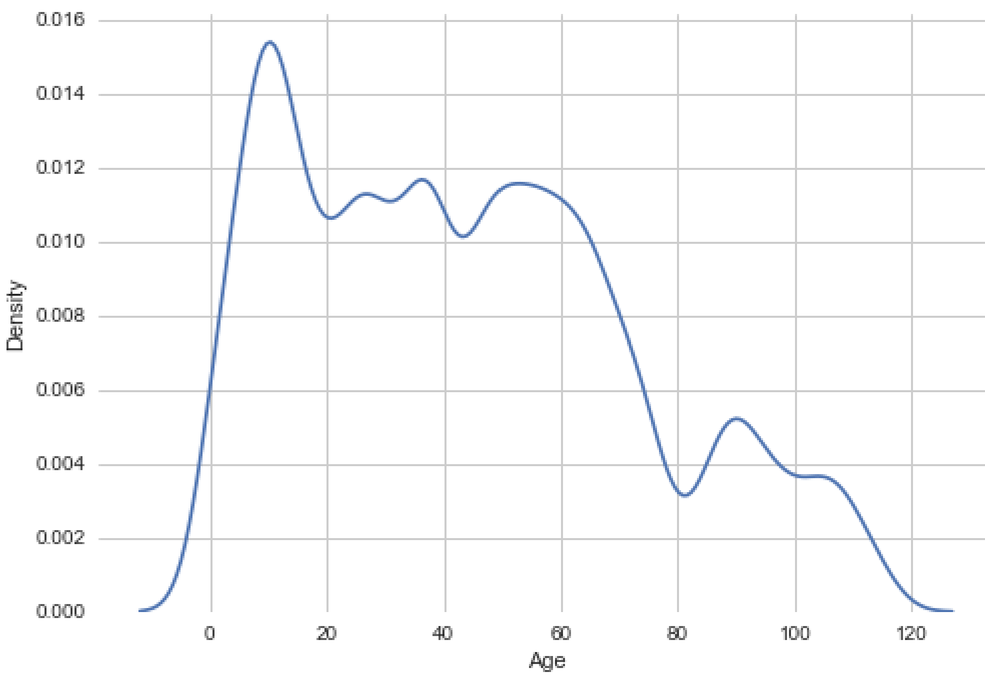
```
yr_built_max = data_2['yr_built'].max()
print(yr_built_max)
#age column
data_2['Age'] = yr_built_max - data_2['yr_built']
data_2.columns
```

```
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', 'month_sold', 'year_sold',
       'renovated', 'Age'],
      dtype='object')
```

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

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

Out[ ]:
```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



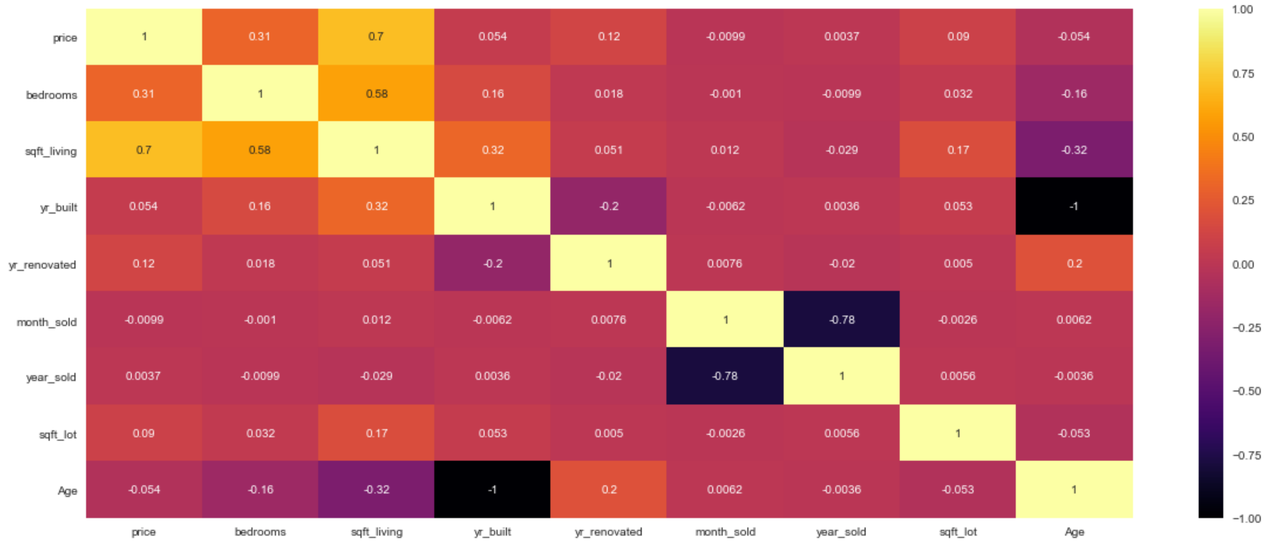
In [ ]:
```
data_2[['price','bedrooms','sqft_living','condition','grade', 'yr_built','yr_renovated'
```

Out[ ]:

	price	bedrooms	sqft_living	yr_built	yr_renovated	month_sold	year_sold	sqft_lc
price	1.000000	0.308787	0.701917	0.053953	0.117855	-0.009928	0.003727	0.08987
bedrooms	0.308787	1.000000	0.578212	0.155670	0.017900	-0.001046	-0.009949	0.03247
sqft_living	0.701917	0.578212	1.000000	0.318152	0.051060	0.012112	-0.029014	0.17345
yr_built	0.053953	0.155670	0.318152	1.000000	-0.202555	-0.006235	0.003574	0.05294
yr_renovated	0.117855	0.017900	0.051060	-0.202555	1.000000	0.007649	-0.019713	0.00497
month_sold	-0.009928	-0.001046	0.012112	-0.006235	0.007649	1.000000	-0.782325	-0.00259
year_sold	0.003727	-0.009949	-0.029014	0.003574	-0.019713	-0.782325	1.000000	0.00562
sqft_lot	0.089876	0.032471	0.173453	0.052946	0.004979	-0.002591	0.005628	1.00000

	price	bedrooms	sqft_living	yr_built	yr_renovated	month_sold	year_sold	sqft_lo
Age	-0.053953	-0.155670	-0.318152	-1.000000	0.202555	0.006235	-0.003574	-0.05294

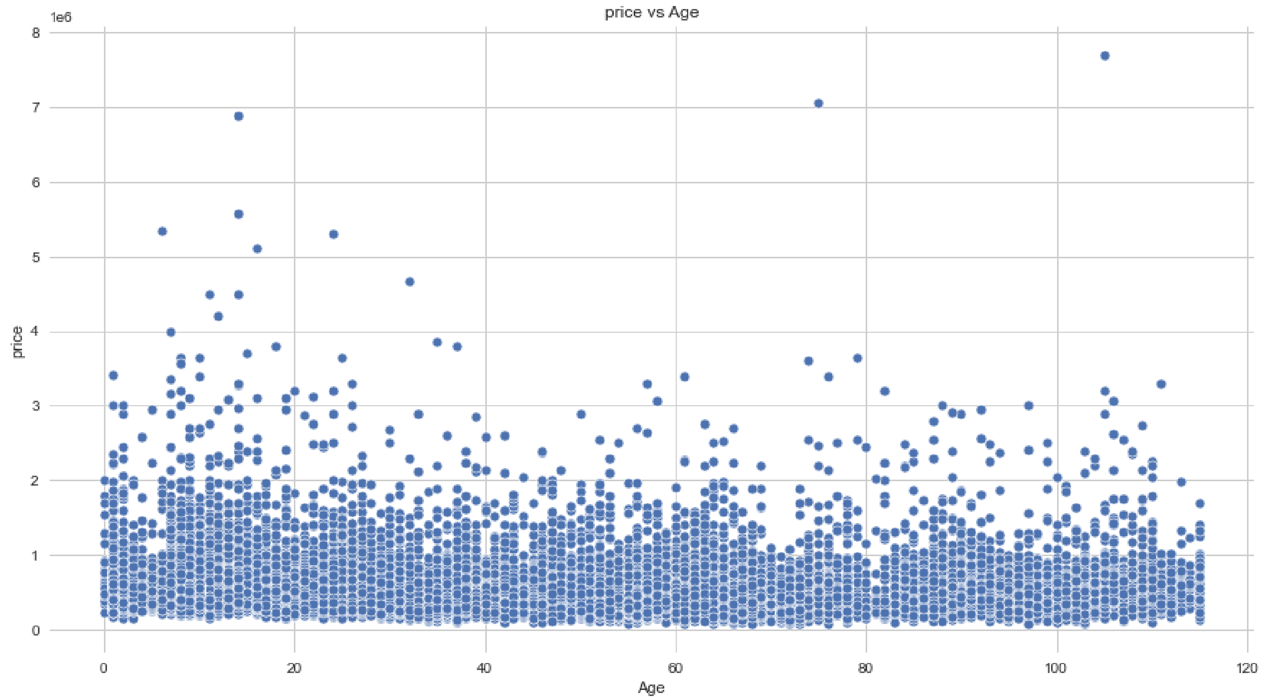
In [ ]:
```
#Looking at a correlation heatmap between different variables, including the age column
plt.figure(figsize=(20, 8))
corr_matrix1 =data_2[['price','bedrooms','sqft_living','condition','grade', 'yr_built',
sns.heatmap(corr_matrix1, cmap='inferno',annot=True)
plt.show()
```



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

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')
```

Out[ ]:
```
Text(0.5, 1.0, 'price vs Age')
```



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()

model.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.003
Model:	OLS	**Adj. R-squared:**	0.003
Method:	Least Squares	**F-statistic:**	63.05
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	2.12e-15
Time:	04:04:16	**Log-Likelihood:**	-3.0736e+05
No. Observations:	21597	**AIC:**	6.147e+05
Df Residuals:	21595	**BIC:**	6.147e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	5.7e+05	4495.766	126.783	0.000	5.61e+05	5.79e+05
Age	-674.7431	84.979	-7.940	0.000	-841.308	-508.178

Omnibus:	19135.901	**Durbin-Watson:**	1.972

Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1142512.023
Skew:	4.031	**Prob(JB):**	0.00
Kurtosis:	37.708	**Cond. No.**	95.3

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

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 -626.0922 indicates that, a one year increase would be associated with a $626.09 decrease in the sale price, on average.
- The R-Squared and Adjusted R-Squared of 0.002, would suggest that only a small proportion of the variation in price can be explained by the age of the property.
- F-statistic of 38.47 & the associated p-value of 5.70e-10, indicates overall the model is statistically significant. In addition, the p-value for the coefficient of age is 0.000, which would also confirm that the variable is also statistically significant.
- 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))
mae


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

rmse = np.sqrt(mse)
rmse
```

Out[ ]:
```
366824.560246138
```

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 = ols(formula = formula, data = data_2[features]).fit()
model.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.542
Model:	OLS	**Adj. R-squared:**	0.542
Method:	Least Squares	**F-statistic:**	3645.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	04:04:16	**Log-Likelihood:**	-2.9897e+05
No. Observations:	21597	**AIC:**	5.979e+05
Df Residuals:	21589	**BIC:**	5.980e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-6.426e+04	7469.137	-8.604	0.000	-7.89e+04	-4.96e+04
condition[T.Fair]	-6.98e+04	1.93e+04	-3.615	0.000	-1.08e+05	-3.2e+04
condition[T.Good]	-4200.7601	4138.421	-1.015	0.310	-1.23e+04	3910.851
condition[T.Poor]	-6.039e+04	4.64e+04	-1.303	0.193	-1.51e+05	3.05e+04
condition[T.Very Good]	4.104e+04	6738.584	6.090	0.000	2.78e+04	5.42e+04
sqft_living	340.3250	2.359	144.294	0.000	335.702	344.948
bedrooms	-6.174e+04	2246.271	-27.484	0.000	-6.61e+04	-5.73e+04
Age	2348.3762	66.234	35.456	0.000	2218.552	2478.201

Omnibus:	13970.999	**Durbin-Watson:**	1.976
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	474274.361
Skew:	2.608	**Prob(JB):**	0.00
Kurtosis:	25.357	**Cond. No.**	6.23e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.23e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

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 54.9% 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 $40,210 morethantheaverageprice, incomparisontoahousethatisinfairconditionthatsells$ 70,200 less!

- The coefficient for **sqft_living** of 346.6924 goes to imply that, on average, the price of a house increases by $346.69 foreachadditionalsquarefootoflivingspace. Thecoefficientforbedroomsof - 6.27$ 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 2744 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()
```

In order to identify a promising categorical predictor, we need to create bar graphs for each of these categorical features.

Identifying outliers in our dataset.

In [ ]:
```
clean_data(data_3)
```

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

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	\
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 [ ]:

```
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")
```

```
325 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	0	EXCE
153	7855801670	2015-04-01	2250000.0	4	3.25	5180	19850	2.0	0	
246	2025069065	2014-09-29	2400000.0	4	2.50	3650	8354	1.0	1	EXCE
282	7424700045	2015-05-13	2050000.0	5	3.00	3830	8480	2.0	0	
300	3225069065	2014-06-24	3080000.0	4	5.00	4550	18641	1.0	1	EXCE

5 rows × 21 columns

In [ ]:

```
data_outliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 325 entries, 21 to 21560
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             325 non-null    object
 1   date           325 non-null    datetime64[ns]
 2   price          325 non-null    float64
 3   bedrooms       325 non-null    object
 4   bathrooms      325 non-null    float64
 5   sqft_living    325 non-null    object
 6   sqft_lot       325 non-null    object
 7   floors         325 non-null    float64
 8   waterfront     325 non-null    object
 9   view           325 non-null    object
 10  condition      325 non-null    object
 11  grade          325 non-null    object
 12  sqft_above     325 non-null    object
 13  sqft_basement  325 non-null    float64
 14  yr_built       325 non-null    object
 15  yr_renovated   325 non-null    float64
 16  zipcode        325 non-null    object
 17  lat            325 non-null    float64
 18  long           325 non-null    float64
 19  sqft_living15  325 non-null    object
 20  sqft_lot15     325 non-null    object
dtypes: datetime64[ns](1), float64(7), object(13)
memory usage: 55.9+ 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: 325 entries, 21 to 21560
Data columns (total 21 columns):
```

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             325 non-null    object
 1   date           325 non-null    datetime64[ns]
 2   price          325 non-null    float64
 3   bedrooms       325 non-null    float64
 4   bathrooms      325 non-null    float64
 5   sqft_living    325 non-null    float64
 6   sqft_lot       325 non-null    float64
 7   floors         325 non-null    float64
 8   waterfront     325 non-null    object
 9   view           325 non-null    object
 10  condition      325 non-null    object
 11  grade          325 non-null    object
 12  sqft_above     325 non-null    float64
 13  sqft_basement  325 non-null    float64
 14  yr_built       325 non-null    object
 15  yr_renovated   325 non-null    float64
 16  zipcode        325 non-null    object
 17  lat            325 non-null    float64
 18  long           325 non-null    float64
 19  sqft_living15  325 non-null    float64
 20  sqft_lot15     325 non-null    float64
dtypes: datetime64[ns](1), float64(13), object(7)
memory usage: 55.9+ KB
```

Creating our baseline 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()
print(baseline_results_outliers.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.363
Model:                            OLS   Adj. R-squared:                  0.361
Method:                 Least Squares   F-statistic:                     184.1
Date:                Thu, 20 Apr 2023   Prob (F-statistic):           1.70e-33
Time:                        04:04:25   Log-Likelihood:                -4799.4
No. Observations:                 325   AIC:                             9603.
Df Residuals:                     323   BIC:                             9610.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        7.178e+05   1.21e+05      5.946      0.000     4.8e+05    9.55e+05
sqft_living   341.3422     25.158     13.568      0.000     291.847     390.837
==============================================================================
Omnibus:                       68.836   Durbin-Watson:                   1.968
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              335.990
Skew:                           0.773   Prob(JB):                     1.10e-73
Kurtosis:                       7.735   Cond. No.                     1.66e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 1.66e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

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

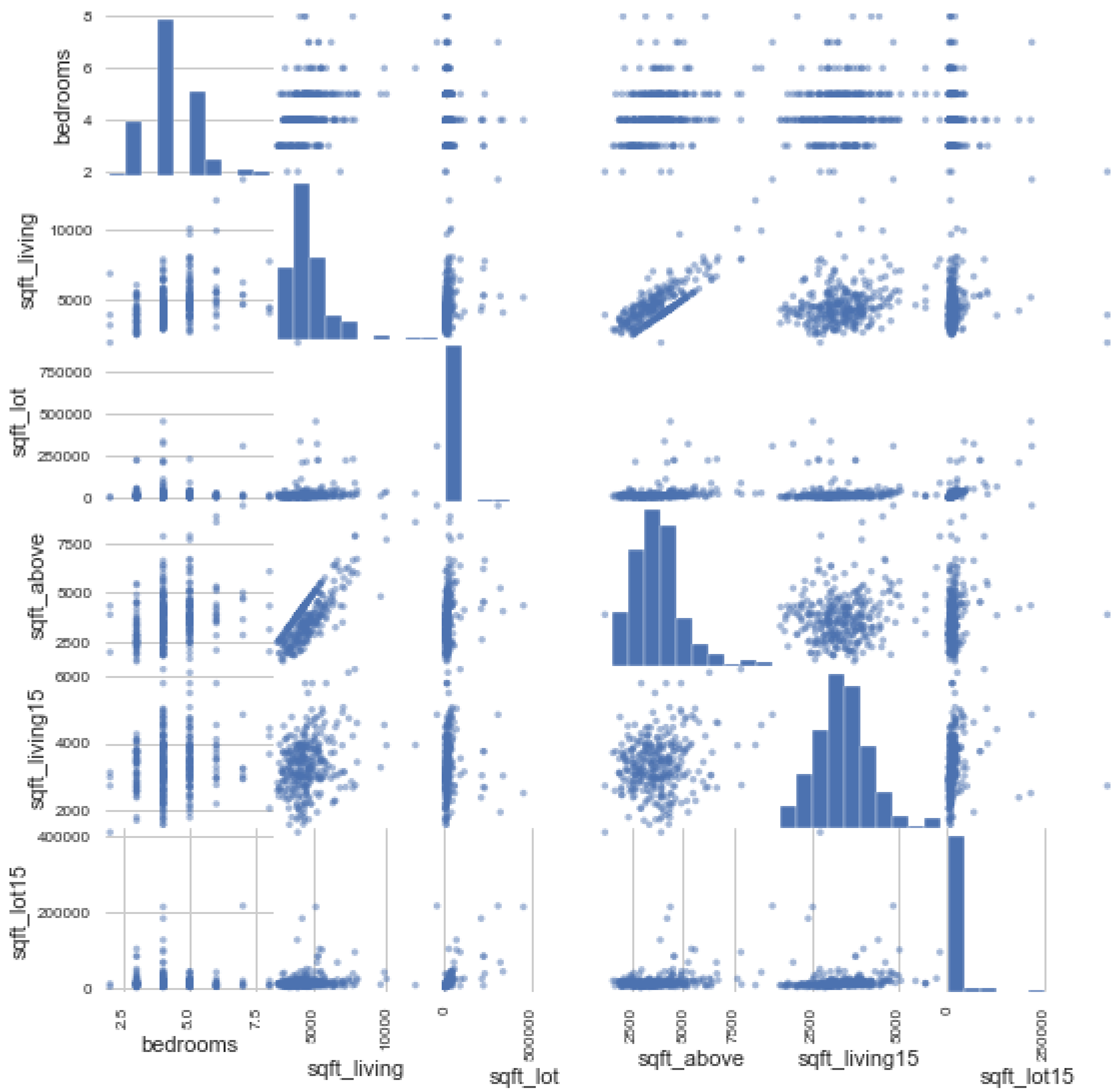
Out[ ]: 450035.3925535948

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

Out[ ]: 670.8467727831705

Creating a multiple linear regression model using additional variables

In [ ]:
```
pd.plotting.scatter_matrix(data_outliers[cols_to_convert],figsize  = [9, 9]);
plt.show()
```



The above visualization, shows scatterplots for relationships between two predictors, and histograms for a single feature on the diagonal

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

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.393
Model:                            OLS   Adj. R-squared:                  0.381
Method:                 Least Squares   F-statistic:                     34.26
Date:                Thu, 20 Apr 2023   Prob (F-statistic):           7.53e-32
Time:                        04:04:31   Log-Likelihood:                -4791.7
No. Observations:                 325   AIC:                             9597.
Df Residuals:                     318   BIC:                             9624.
Df Model:                           6
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const          8.412e+05   2.08e+05      4.043      0.000    4.32e+05    1.25e+06
bedrooms      -8.721e+04   3.88e+04     -2.249      0.025   -1.63e+05   -1.09e+04
sqft_living     371.8604     45.349      8.200      0.000     282.638     461.083
sqft_lot         -1.3714      1.013     -1.354      0.177      -3.364       0.621
sqft_above        0.9192     49.329      0.019      0.985     -96.134      97.972
sqft_living15    48.3490     47.378      1.020      0.308     -44.866     141.564
sqft_lot15       -0.8813      2.203     -0.400      0.689      -5.215       3.452
==============================================================================
Omnibus:                       66.284   Durbin-Watson:                   1.891
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              248.828
Skew:                           0.827   Prob(JB):                     9.28e-55
Kurtosis:                       6.954   Cond. No.                     5.01e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 5.01e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [ ]:

```
model_outliers_mae = mean_absolute_error(y, model_outliers_results.predict(sm.add_const
model_outliers_mae
```

Out[ ]: 439487.80576288764

In [ ]:

```
rmse = np.sqrt(model_outliers_mae)
rmse
```

Out[ ]: 662.9387647157826

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

In [ ]:
```
#function that takes in the column name and data, and returns different plots for our r

def plot_regression(column_name, data):
    X = data[column_name]
    y = data['price']
    X = sm.add_constant(X)
    model = sm.OLS(y, X).fit()
    fig = plt.figure(figsize=(15,8))
    sm.graphics.plot_regress_exog(model_outliers, column_name, fig=fig)
    plt.show()
```

In [ ]:
```
data_outliers[cols_to_convert].corr()
```

Out[ ]:

	bedrooms	sqft_living	sqft_lot	sqft_above	sqft_living15	sqft_lot15
bedrooms	1.000000	0.387054	-0.107488	0.310058	0.112113	-0.097571
sqft_living	0.387054	1.000000	0.166530	0.815015	0.283288	0.184541
sqft_lot	-0.107488	0.166530	1.000000	0.210880	-0.023520	0.859677
sqft_above	0.310058	0.815015	0.210880	1.000000	0.188626	0.238080
sqft_living15	0.112113	0.283288	-0.023520	0.188626	1.000000	0.129114
sqft_lot15	-0.097571	0.184541	0.859677	0.238080	0.129114	1.000000

In [ ]:
```
abs(data_outliers[cols_to_convert].corr()) > 0.75
```

Out[ ]:

	bedrooms	sqft_living	sqft_lot	sqft_above	sqft_living15	sqft_lot15
bedrooms	True	False	False	False	False	False
sqft_living	False	True	False	True	False	False
sqft_lot	False	False	True	False	False	True
sqft_above	False	True	False	True	False	False
sqft_living15	False	False	False	False	True	False
sqft_lot15	False	False	True	False	False	True

In [ ]:
```
#checking and dropping highly correlated features
corr_price_df = pd.DataFrame(data_outliers.corr()['price'])
corr_price_df.columns = ['Correlations']
```

```
corr_price_df = corr_price_df[(corr_price_df['Correlations'].abs() >= 0.3) & (corr_pric

multi_df = pd.DataFrame()
for col in data_outliers.corr().columns:
    if any((data_outliers.corr()[col].abs() >= 0.75) & (data_outliers.corr()[col].index
        multi_df = multi_df.append(data_outliers.corr()[col].abs()[data_outliers.corr()
print('Correlations with Price')
display(corr_price_df)
```

```
Correlations with Price
```

	Correlations
bathrooms	0.458543
sqft_living	0.602516
sqft_above	0.477815
sqft_basement	0.311576

To reduce multicollinearity in our model, we drop the highly correlated variables because they make it difficult to interpret the effects of individual predictors on the outcome variable.

We create a function that gives suggestions based on budget price.

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

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
data_outliers['house_age'].value_counts()
```

Out[ ]:
```
9       15
1       14
14      10
```

```
2      10
11     10
       ..
40      1
86      1
36      1
81      1
115     1
Name: house_age, Length: 98, dtype: int64
```

In [ ]:

```
# 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[ ]:

```
117
```

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.

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 need to do further exploration into other variables 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.

3. The agency should consider investing in properties with waterfronts as this could increase their profitability.

Next Steps

1. Additional cleaning and feature engineering can be performed to improve the data's quality because the dataset contains some missing values and inconsistencies. Missing data, for example, might be imputed using proper procedures, and new features can be generated from existing ones to provide more insights into the housing market.

2. Conduct further exploration to visualize the location of the properties on a map. This will help us compare the affordability of properties per region. It will also help in determining the best regions to invest in.

3. Retrieve more recent data that would allow us to make better models in order to predict prices based on the current market trends.