## Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: 02/06/23
- Instructor name: Everlyn
- Blog post URL:

```
#Importing the required libraries
import numpy as np #linear algebra
import pandas as pd #datapreprocessing, CSV file I/O
import seaborn as sns #for plotting graphs
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline

#Reading the csv file
df = pd.read_csv('/content/kc_house_data.csv')
df
```

```
               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   0.0  ...      7        1180
1          7242     2.0         0.0   0.0  ...      7        2170
```

```
2         10000     1.0          0.0   0.0  ...      6         770
3          5000     1.0          0.0   0.0  ...      7        1050
4          8080     1.0          0.0   0.0  ...      8        1680
...         ...     ...          ...   ...  ...    ...         ...
21592      1131     3.0          0.0   0.0  ...      8        1530
21593      5813     2.0          0.0   0.0  ...      8        2310
21594      1350     2.0          0.0   0.0  ...      7        1020
21595      2388     2.0          NaN   0.0  ...      8        1600
21596      1076     2.0          0.0   0.0  ...      7        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]
```

```
#The first five columns of the dataset
df.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
sqft_basement  \
0      5650     1.0         NaN   0.0  ...      7        1180
0.0
1      7242     2.0         0.0   0.0  ...      7        2170
400.0
2     10000     1.0         0.0   0.0  ...      6         770
0.0
3      5000     1.0         0.0   0.0  ...      7        1050
910.0
4      8080     1.0         0.0   0.0  ...      8        1680
0.0

  yr_built  yr_renovated  zipcode      lat     long  sqft_living15
sqft_lot15
0     1955           0.0    98178  47.5112 -122.257           1340
5650
1     1951        1991.0    98125  47.7210 -122.319           1690
7639
2     1933           NaN    98028  47.7379 -122.233           2720
8062
3     1965           0.0    98136  47.5208 -122.393           1360
5000
4     1987           0.0    98074  47.6168 -122.045           1800
7503

[5 rows x 21 columns]
```

```
#The last five columns of the dataset
df.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         0.0   0.0  ...      8        1530
21593      5813     2.0         0.0   0.0  ...      8        2310
21594      1350     2.0         0.0   0.0  ...      7        1020
21595      2388     2.0         NaN   0.0  ...      8        1600
21596      1076     2.0         0.0   0.0  ...      7        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]
```

```
#A summary of the dataset's columns
df.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')
```

```python
#A summary of the dataset's general information
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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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(8), int64(11), object(2)
memory usage: 3.5+ MB
```

```python
#Assessing the shape of the dataset, i.e rows and columns
df.shape
```

```
(21597, 21)
```

```python
# A statistical summary of the dataset
df.describe()
```

```
                 id         price      bedrooms     bathrooms  
sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000  
21597.000000   
mean   4.580474e+09  5.402966e+05      3.373200      2.115826   
2080.321850   
std    2.876736e+09  3.673681e+05      0.926299      0.768984   
918.106125   
min    1.000102e+06  7.800000e+04      1.000000      0.500000   
370.000000   
25%    2.123049e+09  3.220000e+05      3.000000      1.750000   
```

```
1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000
1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000
2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000
13540.000000

           sqft_lot        floors    waterfront          view
condition  \
count  2.159700e+04  21597.000000  19221.000000  21534.000000
21597.000000
mean   1.509941e+04      1.494096      0.007596      0.233863
3.409825
std    4.141264e+04      0.539683      0.086825      0.765686
0.650546
min    5.200000e+02      1.000000      0.000000      0.000000
1.000000
25%    5.040000e+03      1.000000      0.000000      0.000000
3.000000
50%    7.618000e+03      1.500000      0.000000      0.000000
3.000000
75%    1.068500e+04      2.000000      0.000000      0.000000
4.000000
max    1.651359e+06      3.500000      1.000000      4.000000
5.000000

              grade    sqft_above      yr_built  yr_renovated
zipcode  \
count  21597.000000  21597.000000  21597.000000  17755.000000
21597.000000
mean       7.657915   1788.596842   1970.999676     83.636778
98077.951845
std        1.173200    827.759761     29.375234    399.946414
53.513072
min        3.000000    370.000000   1900.000000      0.000000
98001.000000
25%        7.000000   1190.000000   1951.000000      0.000000
98033.000000
50%        7.000000   1560.000000   1975.000000      0.000000
98065.000000
75%        8.000000   2210.000000   1997.000000      0.000000
98118.000000
max       13.000000   9410.000000   2015.000000   2015.000000
98199.000000

                lat          long  sqft_living15    sqft_lot15
count  21597.000000  21597.000000   21597.000000   21597.000000
mean      47.560093   -122.213982    1986.620318   12758.283512
std        0.138552      0.140724     685.230472   27274.441950
```

```
min       47.155900   -122.519000     399.000000     651.000000
25%       47.471100   -122.328000    1490.000000    5100.000000
50%       47.571800   -122.231000    1840.000000    7620.000000
75%       47.678000   -122.125000    2360.000000   10083.000000
max       47.777600   -121.315000    6210.000000  871200.000000
```

```
# Checking the columns with null values and how many they are
df.isnull().sum()
```

```
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
```

```
# Converting dates into datetime objects
df['date'] = pd.to_datetime(df['date'])
```

```
# Checking for the change in the new dataset
df.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   

2  5631500400 2015-02-25  180000.0         2       1.00          770   

3  2487200875 2014-12-09  604000.0         4       3.00         1960   

4  1954400510 2015-02-18  510000.0         3       2.00         1680   
```

```
   sqft_lot  floors  waterfront  view  ...  grade  sqft_above
sqft_basement  \
0      5650     1.0         NaN   0.0  ...      7        1180
0.0
1      7242     2.0         0.0   0.0  ...      7        2170
400.0
2     10000     1.0         0.0   0.0  ...      6         770
0.0
3      5000     1.0         0.0   0.0  ...      7        1050
910.0
4      8080     1.0         0.0   0.0  ...      8        1680
0.0

  yr_built  yr_renovated  zipcode      lat     long  sqft_living15
sqft_lot15
0     1955           0.0    98178  47.5112 -122.257           1340
5650
1     1951        1991.0    98125  47.7210 -122.319           1690
7639
2     1933           NaN    98028  47.7379 -122.233           2720
8062
3     1965           0.0    98136  47.5208 -122.393           1360
5000
4     1987           0.0    98074  47.6168 -122.045           1800
7503

[5 rows x 21 columns]
```

## Exploring the Features of the Dataset

This section explores the following features for the houses:

- Condition
- Basement
- View
- Waterfront
- zipcode
- Bedrooms
- Bathrooms

## Condition

```
df['condition'].value_counts(sort=False)
```

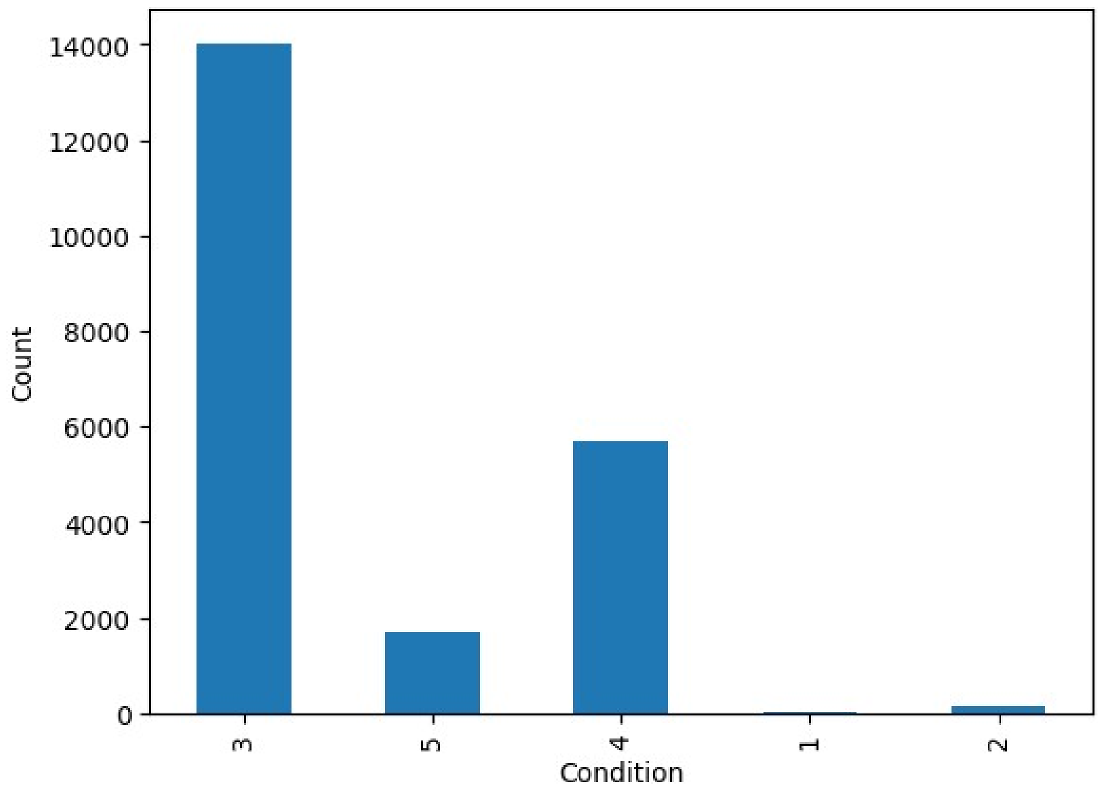
```
3    14020
5     1701
```

```
4     5677
1       29
2      170
Name: condition, dtype: int64
```

```
df['condition'].nunique()
```

```
5
```

```
df['condition'].value_counts(sort=False).plot.bar()
plt.xlabel('Condition')
plt.ylabel('Count')

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




## Basement

```
#calculating the square footage of the basement by subtracting the
square footage above ground from the total living square footage.
df['sqft_basement'] = df['sqft_living'] - df['sqft_above']

df['sqft_basement'].describe()
```

```
count    21597.000000
mean       291.725008
```

```
std        442.667800
min          0.000000
25%          0.000000
50%          0.000000
75%        560.000000
max       4820.000000
Name: sqft_basement, dtype: float64
```

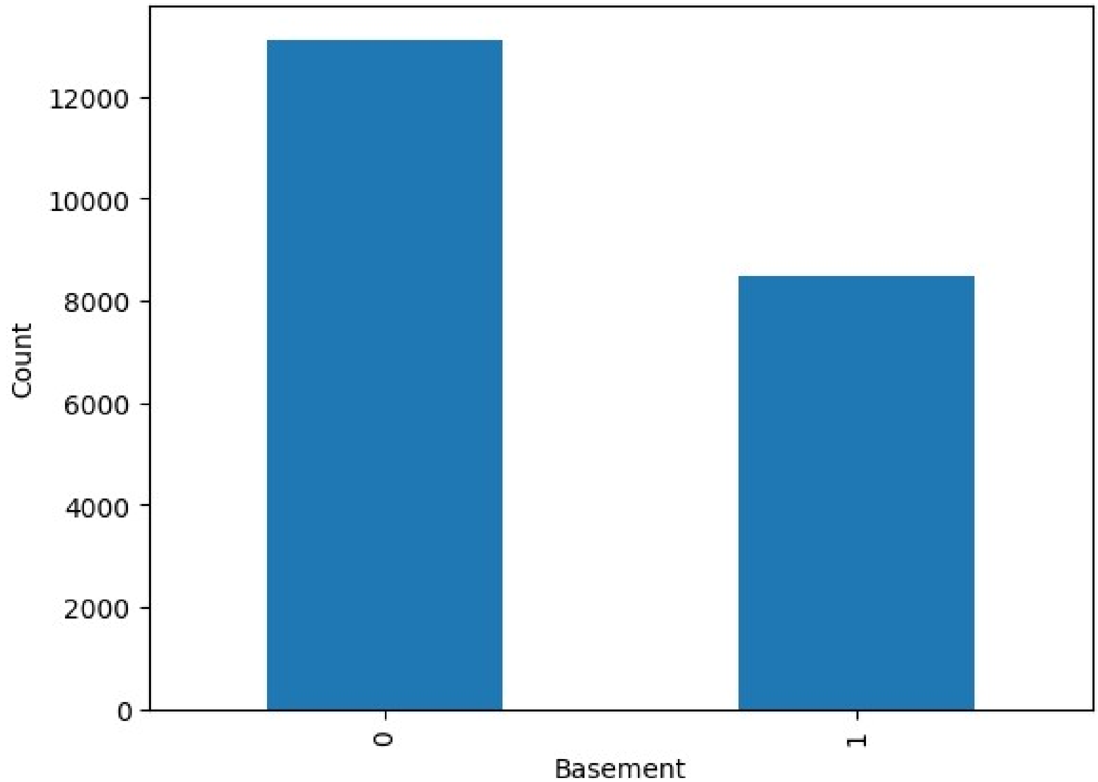
```
#Create a new variable to make the basement binary. 0 if there's no
basement and 1 otherwise
df['basement'] = [0 if x <= 0  else 1 for x in df['sqft_basement']]
df
```

```
               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
2      5631500400 2015-02-25  180000.0         2       1.00
770
3      2487200875 2014-12-09  604000.0         4       3.00
1960
4      1954400510 2015-02-18  510000.0         3       2.00
1680
...           ...        ...       ...       ...        ...          .
..
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  ...  sqft_above
sqft_basement  \
0          5650     1.0         NaN   0.0  ...        1180
0
1          7242     2.0         0.0   0.0  ...        2170
400
2         10000     1.0         0.0   0.0  ...         770
0
3          5000     1.0         0.0   0.0  ...        1050
910
4          8080     1.0         0.0   0.0  ...        1680
0
```

```
...          ...     ...          ...   ...  ...         ...
...
21592      1131     3.0          0.0   0.0  ...        1530
0
21593      5813     2.0          0.0   0.0  ...        2310
0
21594      1350     2.0          0.0   0.0  ...        1020
0
21595      2388     2.0          NaN   0.0  ...        1600
0
21596      1076     2.0          0.0   0.0  ...        1020
0

       yr_built  yr_renovated  zipcode      lat     long
sqft_living15  \
0          1955           0.0    98178  47.5112 -122.257
1340
1          1951        1991.0    98125  47.7210 -122.319
1690
2          1933           NaN    98028  47.7379 -122.233
2720
3          1965           0.0    98136  47.5208 -122.393
1360
4          1987           0.0    98074  47.6168 -122.045
1800
...         ...           ...      ...      ...      ...            ..
.
21592      2009           0.0    98103  47.6993 -122.346
1530
21593      2014           0.0    98146  47.5107 -122.362
1830
21594      2009           0.0    98144  47.5944 -122.299
1020
21595      2004           0.0    98027  47.5345 -122.069
1410
21596      2008           0.0    98144  47.5941 -122.299
1020

       sqft_lot15  basement
0            5650         0
1            7639         1
2            8062         0
3            5000         1
4            7503         0
...           ...       ...
21592        1509         0
21593        7200         0
21594        2007         0
21595        1287         0
21596        1357         0
```

```
[21597 rows x 22 columns]
```

```
df['basement'].value_counts().plot.bar()
plt.xlabel('Basement')
plt.ylabel('Count')
plt.show()
```

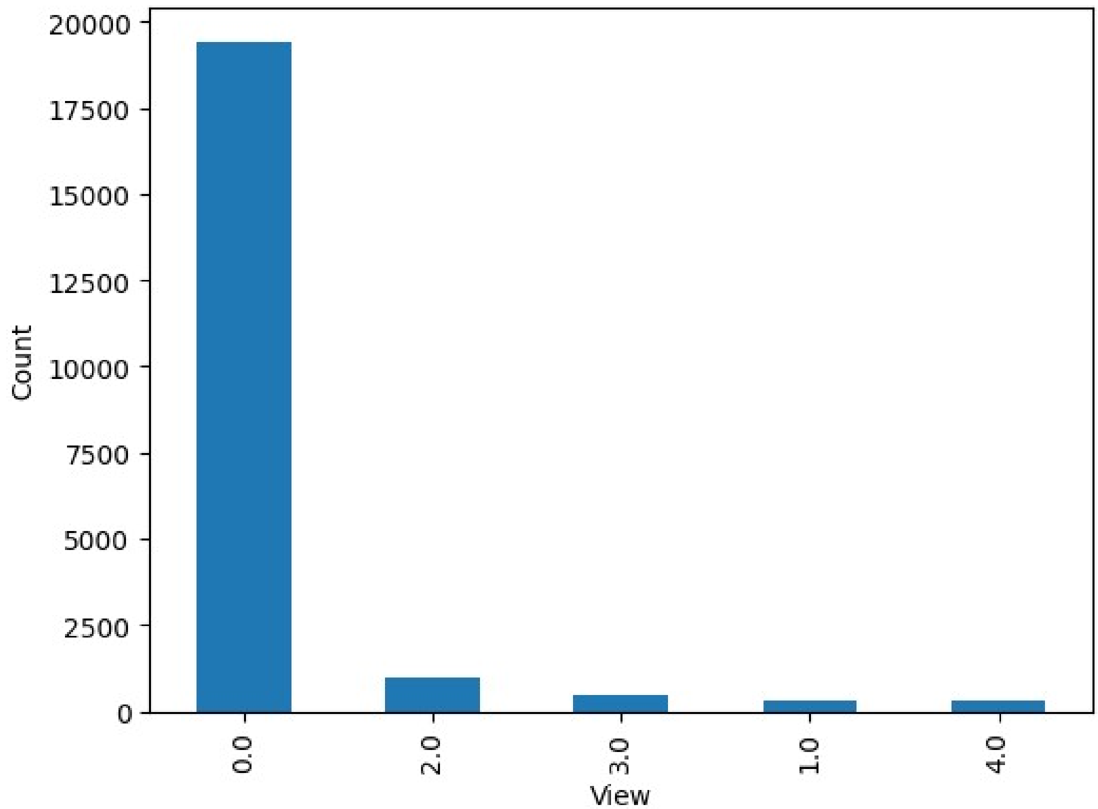



## View

```
#Finding the unique values in the view column, i.e the houses with a
view ranging from 0 to 5
df['view'].unique()
```

```
array([ 0., nan,  3.,  4.,  2.,  1.])
```

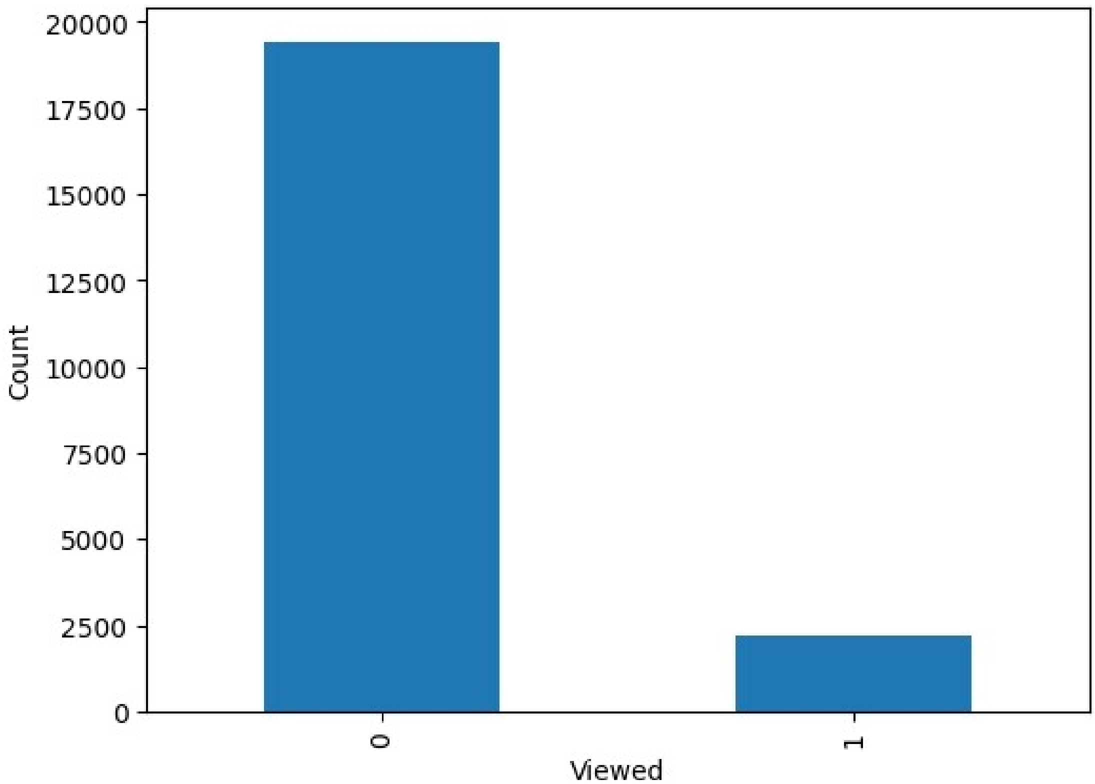
```
df['view'].value_counts().plot.bar()
plt.xlabel('View')
plt.ylabel('Count')
plt.show()
```




```
#Create a new variable called viewed and make it binary. 1 if the
house has been viewed and 0 otherwise.
df['viewed'] = [0 if x == 0  else 1 for x in df['view']]
df['viewed'].value_counts()
```

```
0    19422
1     2175
Name: viewed, dtype: int64
```

```
#Plotting the viewed houses against the ones that haven't been viewed
yet
df['viewed'].value_counts().plot.bar()
plt.xlabel('Viewed')
plt.ylabel('Count')
plt.show()
```




## Waterfront

```
#Revisiting the null values in the waterfront column
df['waterfront'].isnull().sum()
```

```
2376
```

```
#Checking the number of unique values in the waterfront column
df['waterfront'].value_counts()
```

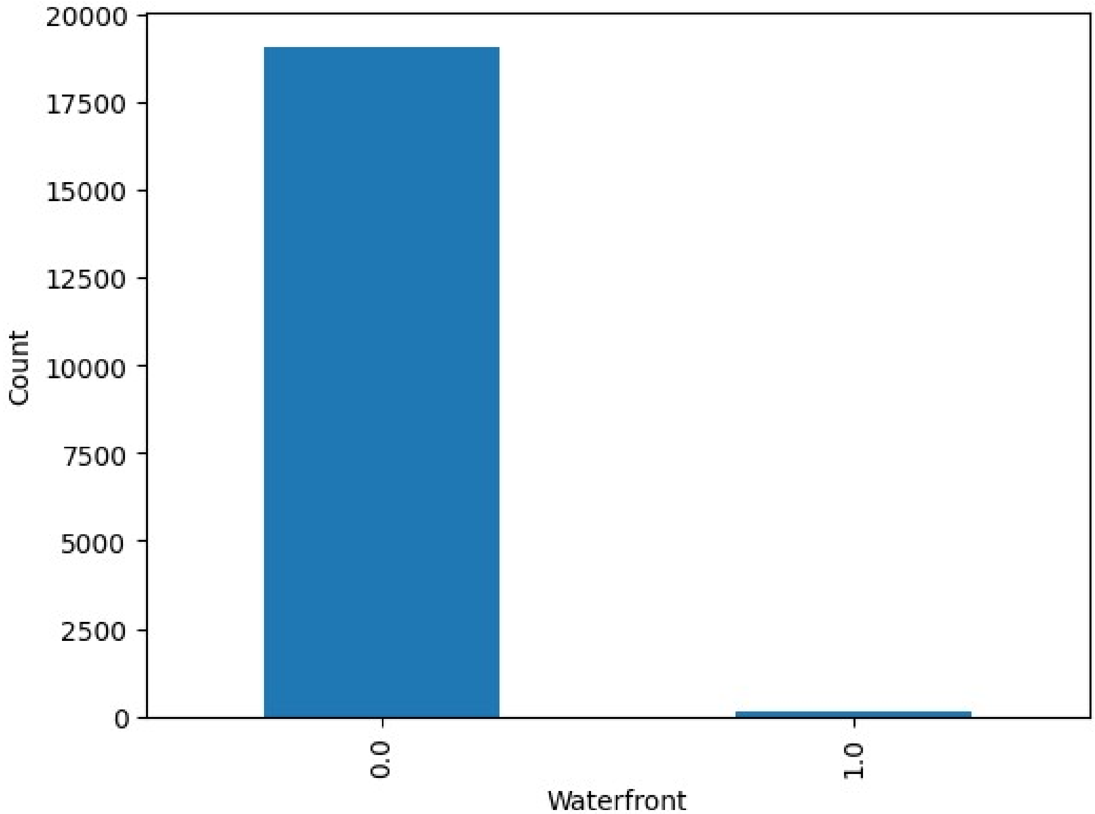
```
0.0    19075
1.0      146
Name: waterfront, dtype: int64
```

```
#Replacing null values with 0s
df['waterfront'].fillna(0).head()
```

```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: waterfront, dtype: float64
```

```
#Plotting the number of houses with a waterfront (146)against the ones
without(19075)
```

```
df['waterfront'].value_counts().plot.bar()
plt.xlabel('Waterfront')
plt.ylabel('Count')
plt.show()
```




## Zip Code

```
df['zipcode'].unique()
```

```
array([98178, 98125, 98028, 98136, 98074, 98053, 98003, 98198, 98146,
       98038, 98007, 98115, 98107, 98126, 98019, 98103, 98002, 98133,
       98040, 98092, 98030, 98119, 98112, 98052, 98027, 98117, 98058,
       98001, 98056, 98166, 98023, 98070, 98148, 98105, 98042, 98008,
       98059, 98122, 98144, 98004, 98005, 98034, 98075, 98116, 98010,
       98118, 98199, 98032, 98045, 98102, 98077, 98108, 98168, 98177,
       98065, 98029, 98006, 98109, 98022, 98033, 98155, 98024, 98011,
       98031, 98106, 98072, 98188, 98014, 98055, 98039])
```

```
#Summary statistics for the modified dataframe
df.describe()
```

```
                 id         price      bedrooms     bathrooms
sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000
21597.000000
```

```
mean   4.580474e+09  5.402966e+05      3.373200      2.115826
2080.321850
std    2.876736e+09  3.673681e+05      0.926299      0.768984
918.106125
min    1.000102e+06  7.800000e+04      1.000000      0.500000
370.000000
25%    2.123049e+09  3.220000e+05      3.000000      1.750000
1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000
1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000
2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000
13540.000000

           sqft_lot        floors    waterfront          view
condition  \
count  2.159700e+04  21597.000000  19221.000000  21534.000000
21597.000000
mean   1.509941e+04      1.494096      0.007596      0.233863
3.409825
std    4.141264e+04      0.539683      0.086825      0.765686
0.650546
min    5.200000e+02      1.000000      0.000000      0.000000
1.000000
25%    5.040000e+03      1.000000      0.000000      0.000000
3.000000
50%    7.618000e+03      1.500000      0.000000      0.000000
3.000000
75%    1.068500e+04      2.000000      0.000000      0.000000
4.000000
max    1.651359e+06      3.500000      1.000000      4.000000
5.000000

       ...  sqft_basement      yr_built  yr_renovated       zipcode  \
count  ...   21597.000000  21597.000000  17755.000000  21597.000000
mean   ...     291.725008   1970.999676     83.636778  98077.951845
std    ...     442.667800     29.375234    399.946414     53.513072
min    ...       0.000000   1900.000000      0.000000  98001.000000
25%    ...       0.000000   1951.000000      0.000000  98033.000000
50%    ...       0.000000   1975.000000      0.000000  98065.000000
75%    ...     560.000000   1997.000000      0.000000  98118.000000
max    ...    4820.000000   2015.000000   2015.000000  98199.000000

                lat          long  sqft_living15    sqft_lot15
basement  \
count  21597.000000  21597.000000   21597.000000   21597.000000
21597.000000
mean      47.560093   -122.213982    1986.620318   12758.283512
0.392971
```

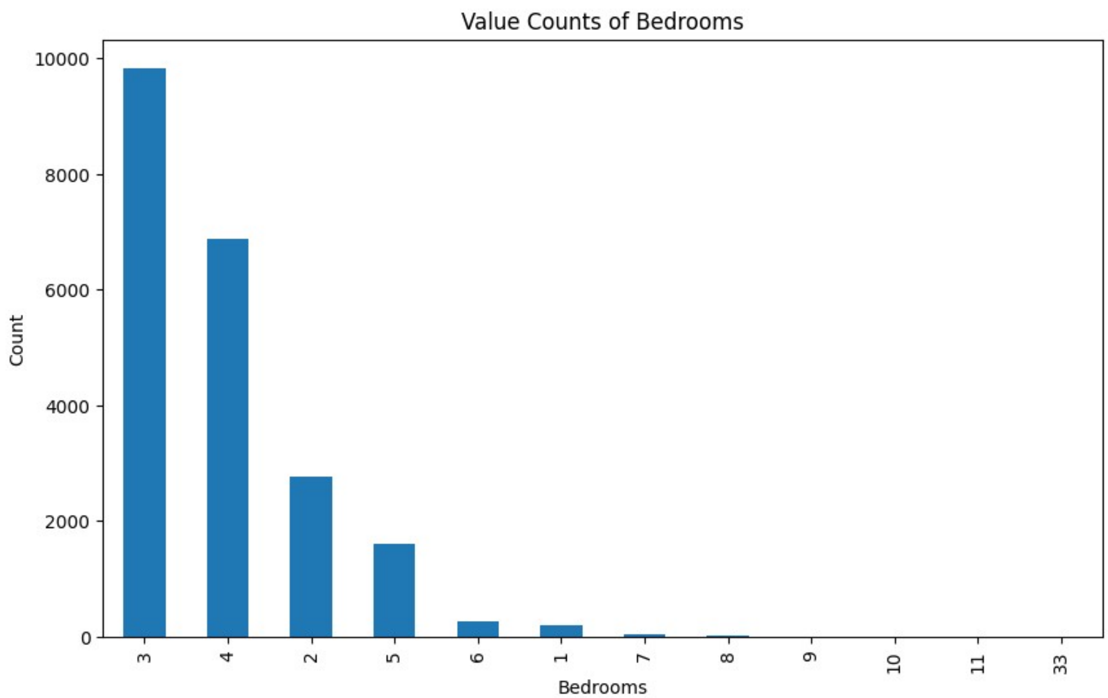
```
std        0.138552      0.140724     685.230472   27274.441950
0.488422
min       47.155900   -122.519000     399.000000     651.000000
0.000000
25%       47.471100   -122.328000    1490.000000    5100.000000
0.000000
50%       47.571800   -122.231000    1840.000000    7620.000000
0.000000
75%       47.678000   -122.125000    2360.000000   10083.000000
1.000000
max       47.777600   -121.315000    6210.000000  871200.000000
1.000000

             viewed
count  21597.000000
mean       0.100708
std        0.300949
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 22 columns]
```

## Bedrooms

```python
bedrooms_column = df['bedrooms']

# Print unique bedroom values
print("Unique bedroom Values:")
print(bedrooms_column.unique())

# Print value counts
print("\nValue Counts:")
print(bedrooms_column.value_counts())

# Plotting the value counts
plt.figure(figsize=(10, 6))
bedrooms_column.value_counts().plot(kind='bar')
plt.xlabel('Bedrooms')
plt.ylabel('Count')
plt.title('Value Counts of Bedrooms')
plt.show()
```

```
Unique bedroom Values:
[ 3  2  4  5  1  6  7  8  9 11 10 33]
```

```
Value Counts:
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

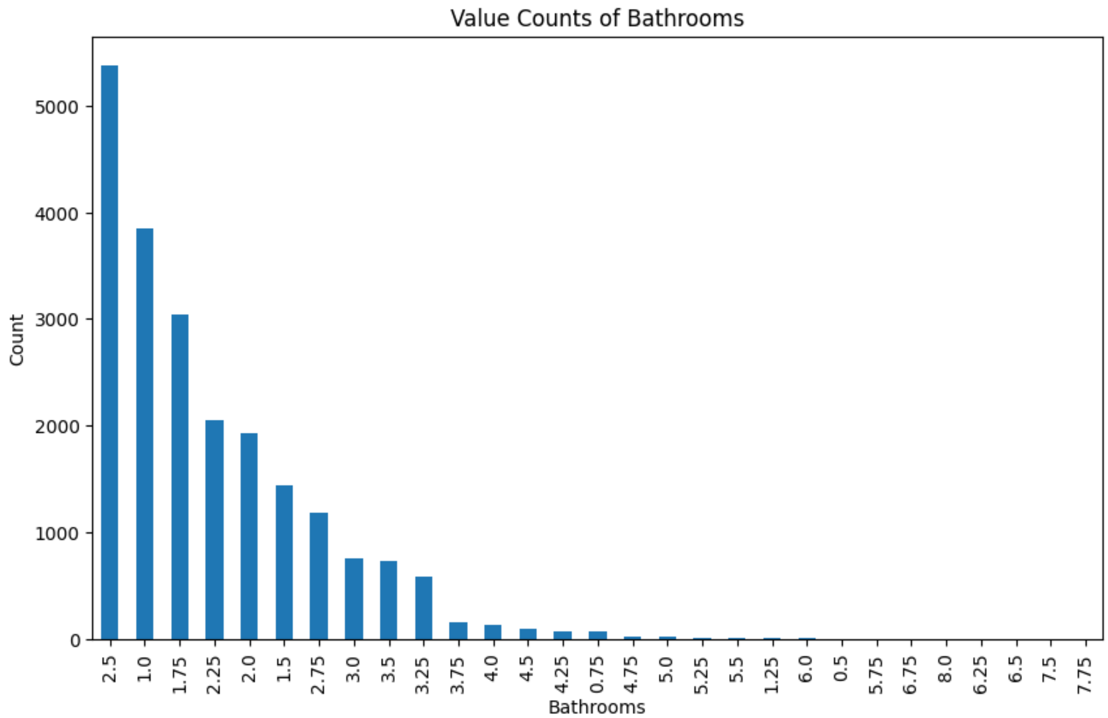



## Bathrooms

```
import matplotlib.pyplot as plt

bathrooms_column = df['bathrooms']

# Print unique bathroom values
print("Unique bathrooms Values:")
print(bathrooms_column.unique())

# Print value counts
print("\nValue Counts:")
print(bathrooms_column.value_counts())
```

```python
# Plotting the value counts
plt.figure(figsize=(10, 6))
bathrooms_column.value_counts().plot(kind='bar')
plt.xlabel('Bathrooms')
plt.ylabel('Count')
plt.title('Value Counts of Bathrooms')
plt.show()
```

```
Unique bathrooms Values:
[1.   2.25 3.   2.   4.5  1.5  2.5  1.75 2.75 3.25 4.   3.5  0.75 4.75
 5.   4.25 3.75 1.25 5.25 6.   0.5  5.5  6.75 5.75 8.   7.5  7.75 6.25
 6.5 ]

Value Counts:
2.50    5377
1.00    3851
1.75    3048
2.25    2047
2.00    1930
1.50    1445
2.75    1185
3.00     753
3.50     731
3.25     589
3.75     155
4.00     136
4.50     100
4.25      79
0.75      71
4.75      23
5.00      21
5.25      13
5.50      10
1.25       9
6.00       6
0.50       4
5.75       4
6.75       2
8.00       2
6.25       2
6.50       2
7.50       1
7.75       1
Name: bathrooms, dtype: int64
```




```
#checking for null values again
df.isnull().sum()
```

```
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
basement            0
viewed              0
dtype: int64
```

```python
df['waterfront'].fillna(0, inplace=True)
```

```python
df.isnull().sum()
```

```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront          0
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
basement            0
viewed              0
dtype: int64
```

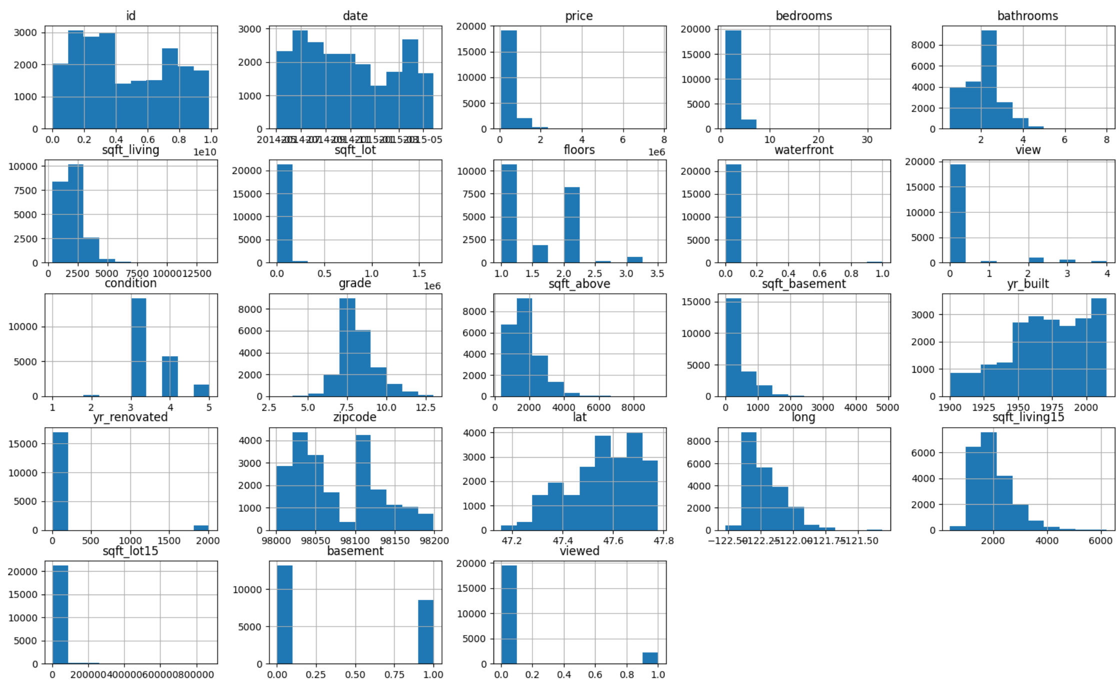
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     21597 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64
 11  grade          21597 non-null  int64
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  int64
 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
 21  basement       21597 non-null  int64
 22  viewed         21597 non-null  int64
dtypes: datetime64[ns](1), float64(8), int64(14)
memory usage: 3.8 MB
```

## Exploratory Data Analysis

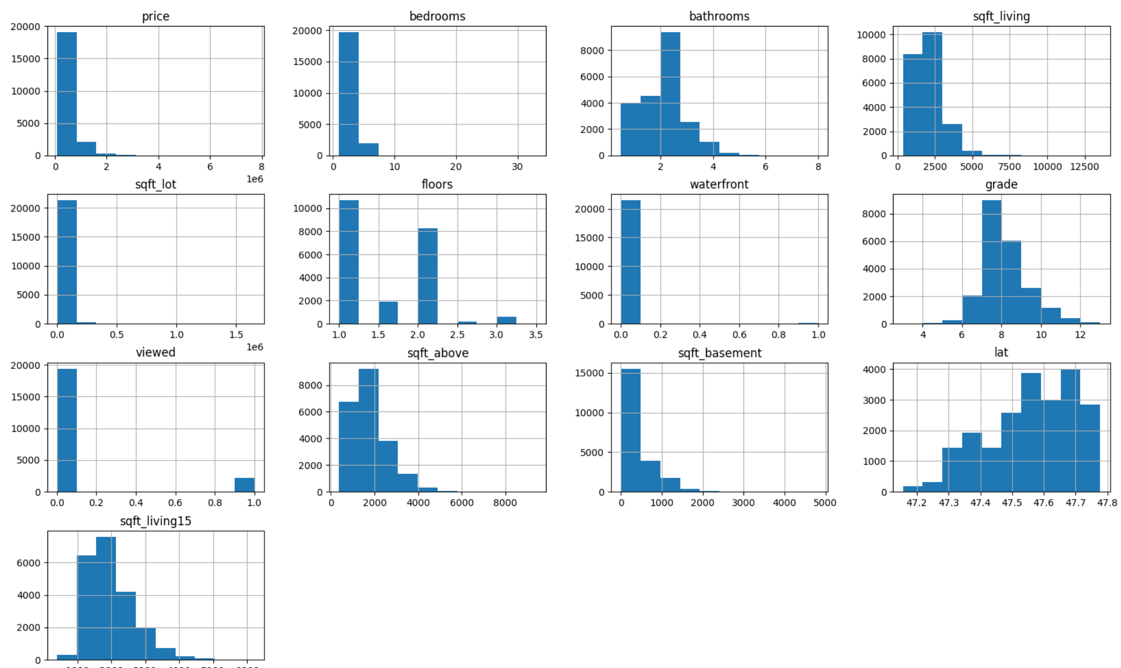
```
#Viewing the distributions of all variables
df.hist(figsize=(20,12))
plt.show()
```




```
#Creating a new dataframe with all the relevant features
new_df =
df[['price','bedrooms','bathrooms','sqft_living','sqft_lot','floors','
waterfront','grade','viewed','sqft_above','sqft_basement','lat','sqft_
living15']]
new_df.head()

      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
waterfront  \
0  221900.0         3       1.00         1180      5650     1.0
0.0
1  538000.0         3       2.25         2570      7242     2.0
```

```
0.0
2  180000.0         2       1.00           770     10000     1.0
0.0
3  604000.0         4       3.00          1960      5000     1.0
0.0
4  510000.0         3       2.00          1680      8080     1.0
0.0

   grade  viewed  sqft_above  sqft_basement      lat  sqft_living15
0      7       0        1180              0  47.5112           1340
1      7       0        2170            400  47.7210           1690
2      6       0         770              0  47.7379           2720
3      7       0        1050            910  47.5208           1360
4      8       0        1680              0  47.6168           1800
```

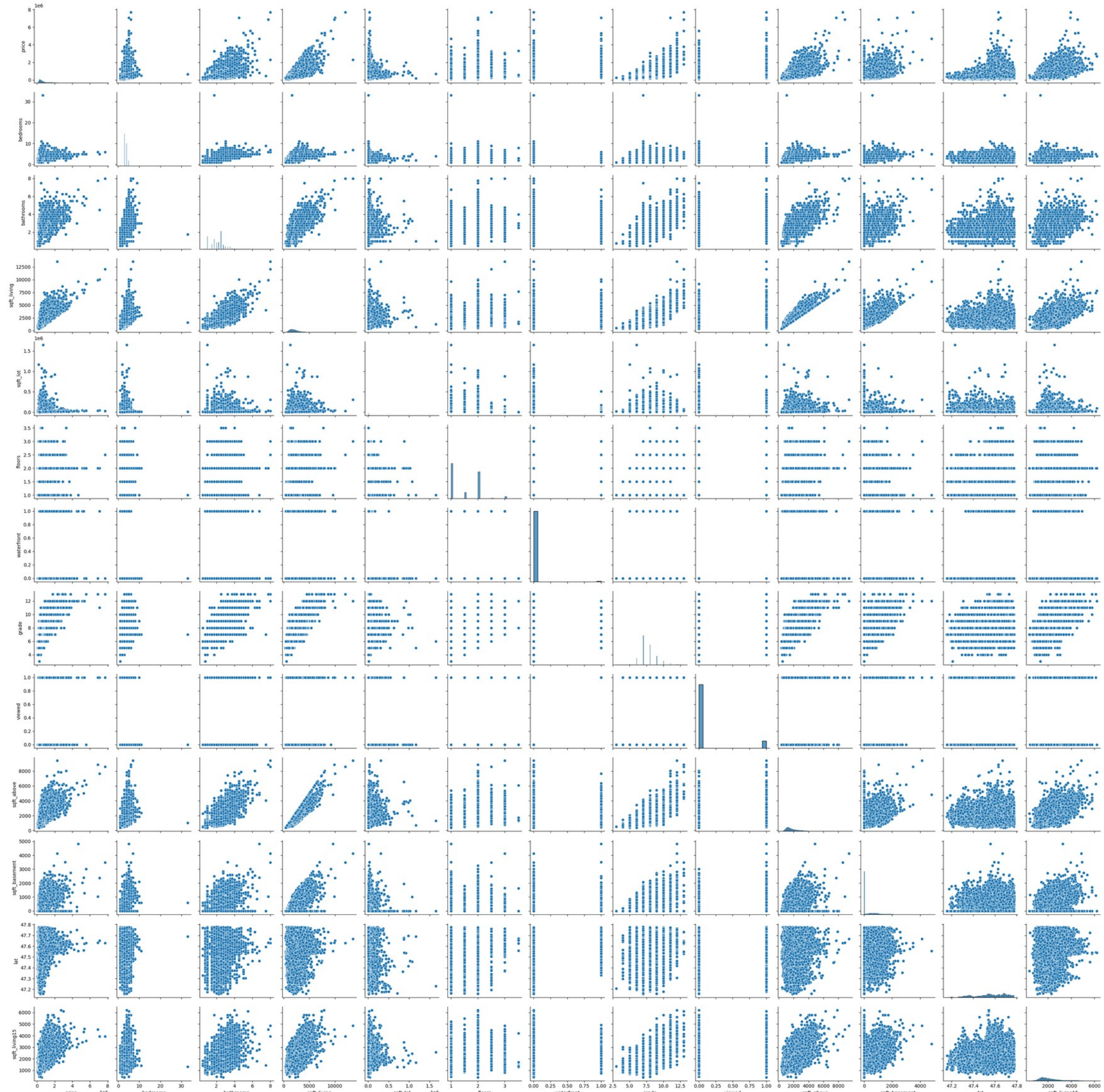
```
#Plotting the new dataframe
new_df.hist(figsize=(20,12))
plt.show()
plt.savefig('/content/download (2).png', dpi = 150)
```




```
<Figure size 640x480 with 0 Axes>
```

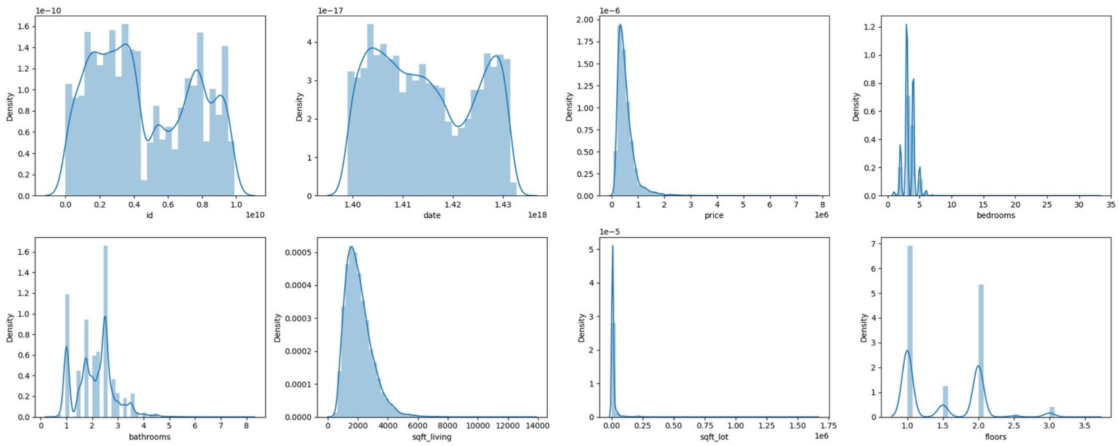
```
#Viewing each feature paired against each other to view correlations
and see trends
sns.pairplot(new_df)
```

```
<seaborn.axisgrid.PairGrid at 0x7f5d59051300>
```



```
import warnings
warnings.filterwarnings('ignore')
#Viewing the univariate distribution for each feature in the testing
dataframe

#Creating variables for the number of rows and columns
rows = 2
cols = 4

#Creating subplot
fig, ax = plt.subplots(nrows = rows, ncols = cols, figsize = (20,8))

#Iterating through each row and column of the testing dataframe
col = df.columns
index = 0
for i in range(rows):
```

```
    for j in range(cols):
        sns.distplot(df[col[index]], ax = ax[i][j])
        index += 1

plt.tight_layout()
```




```
#Checking correlation in the new dataframe
corr = new_df.corr
corr()
```

```
                  price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
price          1.000000  0.308787   0.525906     0.701917  0.089876
0.256804
bedrooms       0.308787  1.000000   0.514508     0.578212  0.032471
0.177944
bathrooms      0.525906  0.514508   1.000000     0.755758  0.088373
0.502582
sqft_living    0.701917  0.578212   0.755758     1.000000  0.173453
0.353953
sqft_lot       0.089876  0.032471   0.088373     0.173453  1.000000 -
0.004814
floors         0.256804  0.177944   0.502582     0.353953 -0.004814
1.000000
waterfront     0.264306 -0.002127   0.063629     0.104637  0.021459
0.020797
grade          0.667951  0.356563   0.665838     0.762779  0.114731
0.458794
viewed         0.353770  0.078782   0.174090     0.266760  0.068035
0.015920
sqft_above     0.605368  0.479386   0.686668     0.876448  0.184139
0.523989
sqft_basement  0.323799  0.302808   0.283440     0.435130  0.015418 -
0.245715
lat            0.306692 -0.009951   0.024280     0.052155 -0.085514
0.049239
sqft_living15  0.585241  0.393406   0.569884     0.756402  0.144763
```

```
0.280102

                waterfront     grade    viewed  sqft_above  
sqft_basement  \
price             0.264306  0.667951  0.353770    0.605368       
0.323799
bedrooms         -0.002127  0.356563  0.078782    0.479386       
0.302808
bathrooms         0.063629  0.665838  0.174090    0.686668       
0.283440
sqft_living       0.104637  0.762779  0.266760    0.876448       
0.435130
sqft_lot          0.021459  0.114731  0.068035    0.184139       
0.015418
floors            0.020797  0.458794  0.015920    0.523989      -
0.245715
waterfront        1.000000  0.082818  0.246530    0.071778       
0.082800
grade             0.082818  1.000000  0.233579    0.756073       
0.168220
viewed            0.246530  0.233579  1.000000    0.150093       
0.272605
sqft_above        0.071778  0.756073  0.150093    1.000000      -
0.052156
sqft_basement     0.082800  0.168220  0.272605   -0.052156       
1.000000
lat              -0.012157  0.113575  0.007311   -0.001199       
0.110414
sqft_living15     0.083823  0.713867  0.269870    0.731767       
0.200443

                    lat  sqft_living15  
price          0.306692       0.585241  
bedrooms      -0.009951       0.393406  
bathrooms      0.024280       0.569884  
sqft_living    0.052155       0.756402  
sqft_lot      -0.085514       0.144763  
floors         0.049239       0.280102  
waterfront    -0.012157       0.083823  
grade          0.113575       0.713867  
viewed         0.007311       0.269870  
sqft_above    -0.001199       0.731767  
sqft_basement  0.110414       0.200443  
lat            1.000000       0.048679  
sqft_living15  0.048679       1.000000  
```

```python
import seaborn as sns
import matplotlib.pyplot as plt

def correlation_heatmap(dataframe):
```

```python
    _, ax = plt.subplots(figsize=(15, 10))
    sns.heatmap(dataframe.corr(), annot=True, cmap='summer')

correlation_heatmap(new_df)
plt.savefig('/content/download (1).png', dpi=150)
```


The features that are most correlated with the price include:

- sqrft_living = 0.7
- Grade = 0.67
- Sqrft_above = 0.61
- Sqrft_living15 = 0.59
- Bathrooms = 0.53

```python
def get_correlation_features(corrdata, threshold):
    features = []
    values = []  # Define the 'values' list

    # Iterate over the correlation data
    for i, index in enumerate(corrdata.index):
        # Check if the absolute value of the correlation is above the
threshold
        if abs(corrdata[index]) > threshold:
            features.append(index)
            values.append(corrdata[index])
```

```python
    # Create a DataFrame with the correlated features and values
    df = pd.DataFrame(data=values, index=features, columns=['Corr
Value'])
    return df

#Setting the threshold
threshold = 0.5

#The correlated features for price greater than 50%
corr_value = get_correlation_features(corr()['price'], threshold)
corr_value
```

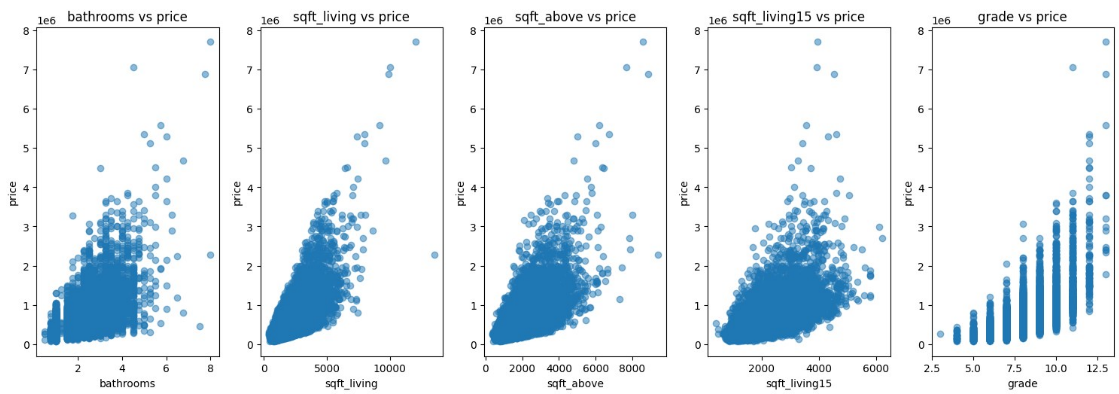
```
               Corr Value
price            1.000000
bathrooms        0.525906
sqft_living      0.701917
grade            0.667951
sqft_above       0.605368
sqft_living15    0.585241
```

```python
#Creating a dataframe from the indices of the corr value
corr_data = df[corr_value.index]
corr_data.head()
```

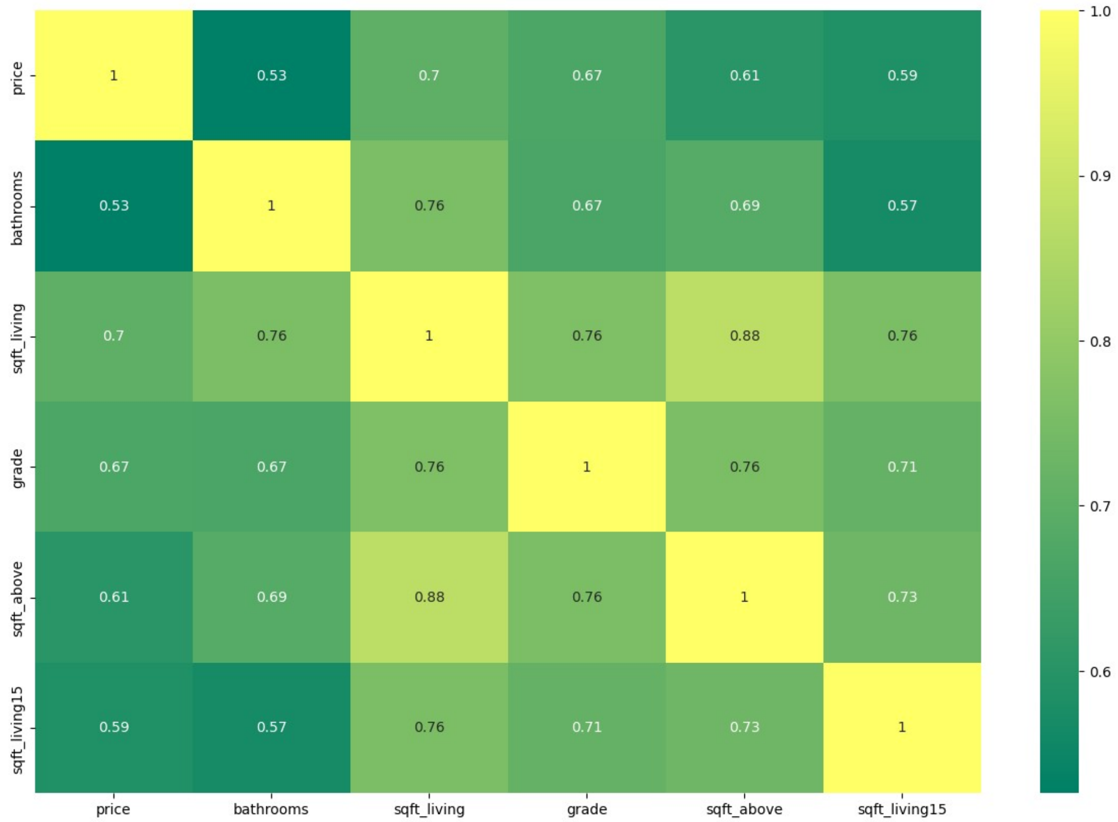
| | price | bathrooms | sqft_living | grade | sqft_above | sqft_living15 |
|---|---|---|---|---|---|---|
| 0 | 221900.0 | 1.00 | 1180 | 7 | 1180 | 1340 |
| 1 | 538000.0 | 2.25 | 2570 | 7 | 2170 | 1690 |
| 2 | 180000.0 | 1.00 | 770 | 6 | 770 | 2720 |
| 3 | 604000.0 | 3.00 | 1960 | 7 | 1050 | 1360 |
| 4 | 510000.0 | 2.00 | 1680 | 8 | 1680 | 1800 |

```python
import numpy as np
import matplotlib.pyplot as plt

# Select the desired features and the target variable
features = ['bathrooms', 'sqft_living', 'sqft_above', 'sqft_living15',
'grade']
target = 'price'

# Calculate the number of rows and columns for the subplot grid
n_rows = 2
n_cols = 5

# Create subplots
fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 10))

# Flatten the axes array
axes = axes.flatten()

# Plotting bivariate relationships
```

```python
for i, feature in enumerate(features):
    axes[i].scatter(df[feature], df[target], alpha=0.5)
    axes[i].set_xlabel(feature)
    axes[i].set_ylabel(target)
    axes[i].set_title(f'{feature} vs {target}')

# Remove any unused subplots
if len(features) < n_rows * n_cols:
    for j in range(len(features), n_rows * n_cols):
        fig.delaxes(axes[j])

# Adjust the layout and spacing
plt.tight_layout()

# Display the plots
plt.show()
```




```python
correlation_heatmap(corr_data)
```




## Simple Linear Regression

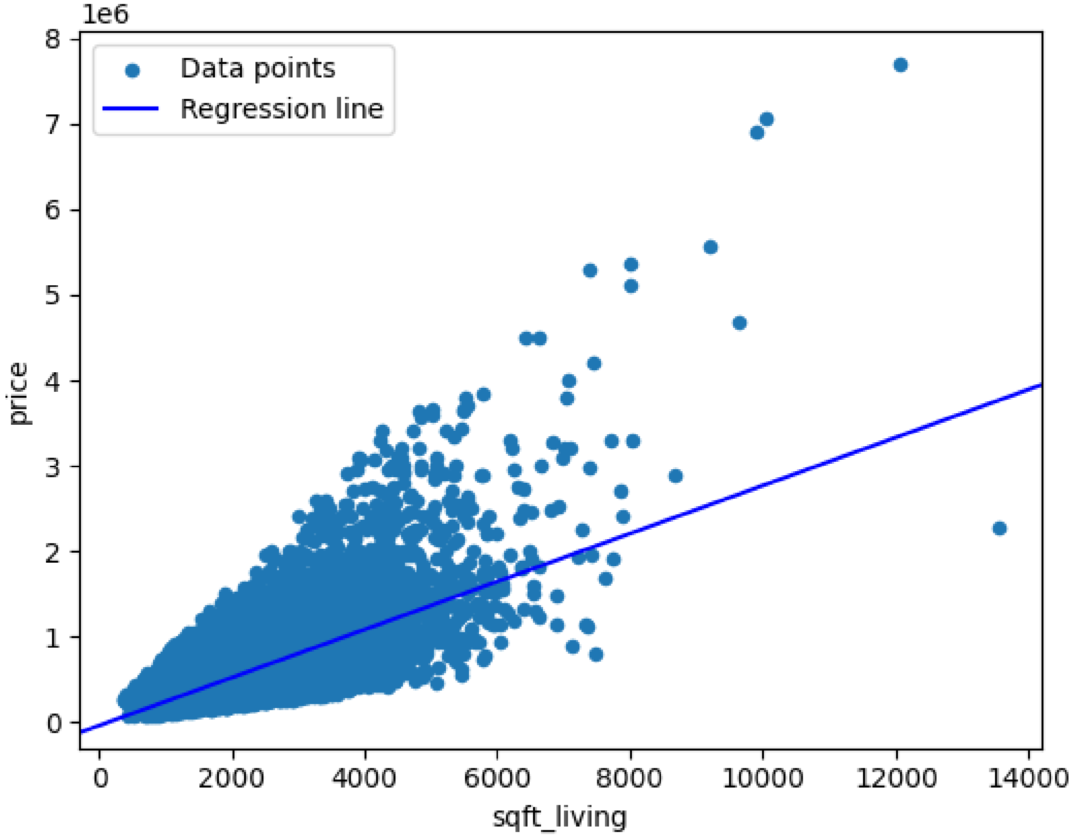
```
import statsmodels.api as sm

# defining our x and y parameters
x = df["sqft_living"]
y = df["price"]

x_predict = sm.OLS(y, sm.add_constant(x))
model = sm.OLS(endog=y,exog=sm.add_constant(x))

results =model.fit()
summary = results.summary()
print(summary)
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.493
Model:                            OLS   Adj. R-squared:
0.493
Method:                 Least Squares   F-statistic:
```

```
2.097e+04
Date:                  Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                          09:33:09   Log-Likelihood:            -
3.0006e+05
No. Observations:                 21597   AIC:
6.001e+05
Df Residuals:                     21595   BIC:
6.001e+05
Df Model:                             1

Covariance Type:              nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
const       -4.399e+04   4410.023     -9.975      0.000   -5.26e+04
-3.53e+04
sqft_living   280.8630      1.939    144.819      0.000     277.062
284.664
======================================================================
========
Omnibus:                      14801.942   Durbin-Watson:
1.982
Prob(Omnibus):                    0.000   Jarque-Bera (JB):
542662.604
Skew:                             2.820   Prob(JB):
0.00
Kurtosis:                        26.901   Cond. No.
5.63e+03
======================================================================
========

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

```
import matplotlib.pyplot as plt
import statsmodels.api as sm

fig, ax = plt.subplots()
df.plot.scatter(x="sqft_living", y="price", label="Data points",
ax=ax)
sm.graphics.abline_plot(model_results=results, label="Regression
```

```
line", ax=ax, color="blue")
ax.legend()
plt.show()
```




## Multiple Linear Regression

```
#importing libraries
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics
from random import gauss
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline

# Create dataframe for get dummies
# waterfront

df_dummy = df.copy(deep=True)

# The attributes to be used
```

```
dummy_df = df_dummy[['waterfront']]
df3 = pd.get_dummies(dummy_df, drop_first=True)
df3
```

```
       waterfront
0             0.0
1             0.0
2             0.0
3             0.0
4             0.0
...           ...
21592         0.0
21593         0.0
21594         0.0
21595         0.0
21596         0.0

[21597 rows x 1 columns]
```

```
#getting attributes to use in the model

df2 = df.copy(deep=True)
df2.drop(['waterfront','id','date','bedrooms','sqft_lot','floors','vie
w',
          'condition','sqft_basement','yr_built','yr_renovated',
          'zipcode','lat','long','sqft_lot15','viewed','basement',
'sqft_living15', 'sqft_above', 'grade'], axis=1, inplace=True)
df2.head()
```

```
      price  bathrooms  sqft_living
0  221900.0       1.00         1180
1  538000.0       2.25         2570
2  180000.0       1.00          770
3  604000.0       3.00         1960
4  510000.0       2.00         1680
```

```
df2['waterfront'] = df3
print(df2)
```

```
          price  bathrooms  sqft_living  waterfront
0      221900.0       1.00         1180         0.0
1      538000.0       2.25         2570         0.0
2      180000.0       1.00          770         0.0
3      604000.0       3.00         1960         0.0
4      510000.0       2.00         1680         0.0
...         ...        ...          ...         ...
21592  360000.0       2.50         1530         0.0
21593  400000.0       2.50         2310         0.0
21594  402101.0       0.75         1020         0.0
21595  400000.0       2.50         1600         0.0
21596  325000.0       0.75         1020         0.0
```

```
[21597 rows x 4 columns]
```

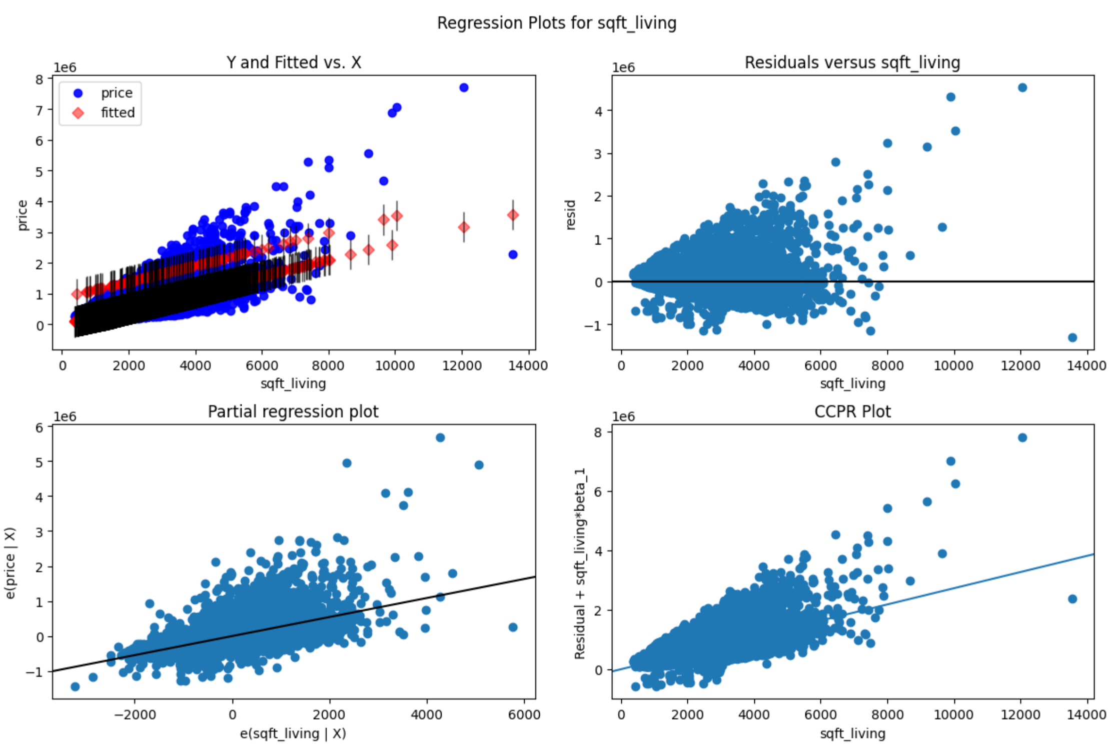
```python
X = df2.drop('price', axis=1)
y = df2['price']

#Creating multiple linear regression model

model = sm.OLS(endog=y, exog=X)
results = model.fit()
results.summary()
```

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

=======================================================================
=================
Dep. Variable:                  price   R-squared (uncentered):
0.851
Model:                            OLS   Adj. R-squared (uncentered):
0.851
Method:                 Least Squares   F-statistic:
4.111e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        09:33:10   Log-Likelihood:
-2.9927e+05
No. Observations:               21597   AIC:
5.985e+05
Df Residuals:                   21594   BIC:
5.986e+05
Df Model:                           3

Covariance Type:            nonrobust

=======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
-----------------------------------------------------------------------
---------
bathrooms   -1.325e+04   2874.067     -4.610      0.000   -1.89e+04
-7616.069
sqft_living   272.1194      2.851     95.442      0.000     266.531
277.708
waterfront   8.701e+05    2.1e+04     41.338      0.000    8.29e+05
9.11e+05
=======================================================================
========
```

```
Omnibus:                    14013.812   Durbin-Watson:
1.976
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
491344.628
Skew:                           2.609   Prob(JB):
0.00
Kurtosis:                      25.777   Cond. No.
2.79e+04
======================================================================
========

Notes:
[1] R² is computed without centering (uncentered) since the model does
not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[3] The condition number is large, 2.79e+04. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

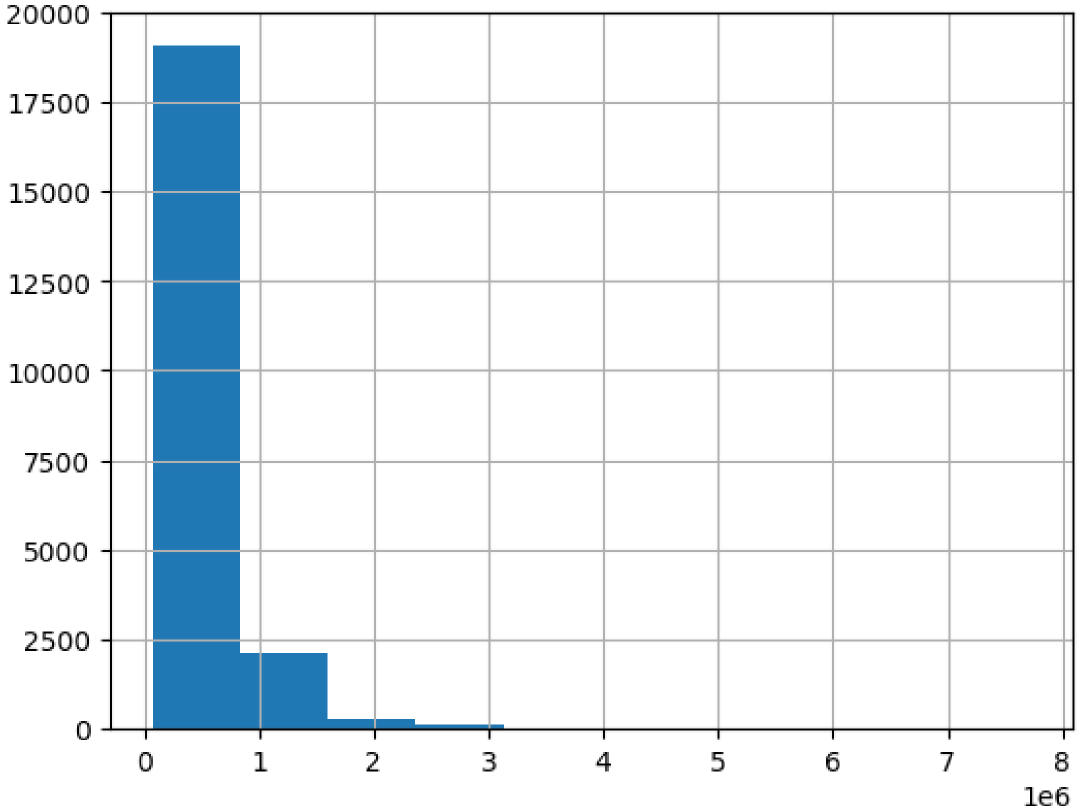
```
#checking residuals for sqft_living vairables
sm.graphics.plot_regress_exog(results, 'sqft_living',
fig=plt.figure(figsize=(12,8)));
```

```
eval_env: 1
```

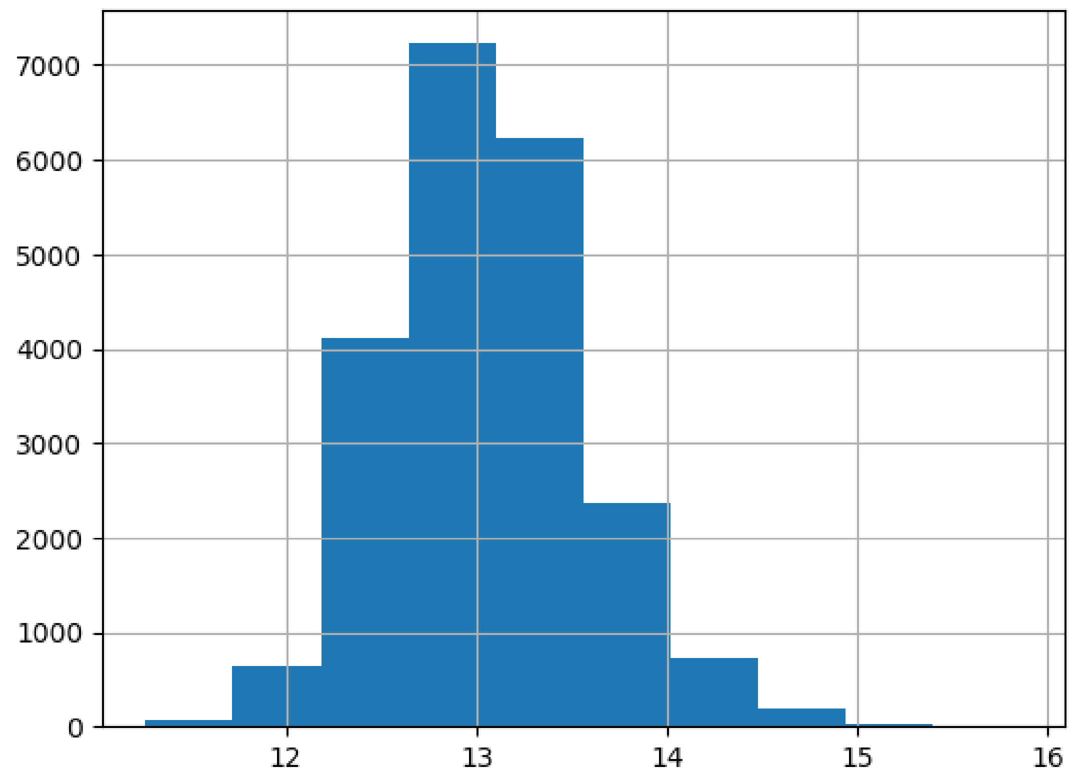


## Checking the distribution of the target

```
y.hist();
```




```
y_new= np.log(y)
y_new.hist();
```




```
#model with transformed target (log_scaled target)
model2 = sm.OLS(y_new, X)
results2 = model2.fit()
results2.summary()
```

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

======================================================================
=================
Dep. Variable:                  price   R-squared (uncentered):
0.899
Model:                            OLS   Adj. R-squared (uncentered):
0.899
Method:                 Least Squares   F-statistic:
6.378e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        09:33:13   Log-Likelihood:
-61424.
No. Observations:               21597   AIC:
1.229e+05
Df Residuals:                   21594   BIC:
1.229e+05
Df Model:                           3
```

```
Covariance Type:            nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
bathrooms       4.4689      0.047     94.303      0.000       4.376
4.562
sqft_living     0.0011    4.7e-05     22.447      0.000       0.001
0.001
waterfront     -1.3921      0.347     -4.011      0.000      -2.072
-0.712
======================================================================
========
Omnibus:                     2152.901   Durbin-Watson:
1.688
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
4674.847
Skew:                          -0.629   Prob(JB):
0.00
Kurtosis:                       4.901   Cond. No.
2.79e+04
======================================================================
========

Notes:
[1] R² is computed without centering (uncentered) since the model does
not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[3] The condition number is large, 2.79e+04. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

## Conclusions

Model 2 can be considered a better predictor compared to Model 1 based on the R-squared value. The R-squared value for Model 2 is 0.899, indicating that approximately 89.9% of the variance in the dependent variable (price) can be explained by the independent variables; bathrooms, sqrft_living and waterfront The best features that determine the price depending on the original dataframe include:

R-squared (uncentered): The R-squared value of 0.899 indicates that the model explains approximately 89.9% of the variance in the dependent variable (price). This suggests that the independent variables included in the model (bathrooms, sqft_living, waterfront) collectively have a strong association with the price.

Adjusted R-squared (uncentered): The adjusted R-squared value is also 0.899, which means that the inclusion of the three independent variables in the model is not significantly impacting the overall goodness of fit. The adjusted R-squared value is useful for comparing models with different numbers of predictors.

F-statistic: The F-statistic has a very large value of 6.378e+04, and the associated probability (Prob (F-statistic)) is 0.00. This indicates that the overall model is statistically significant, suggesting that at least one of the independent variables has a significant impact on the price.

Coefficients: The coefficients for the independent variables indicate the magnitude and direction of their relationship with the dependent variable (price).

Bathrooms: The coefficient for the "bathrooms" variable is 4.4689, indicating a positive relationship with the price. A one-unit increase in the number of bathrooms is associated with an increase in the price by approximately 4.4689 units.

Sqft_living: The coefficient for the "sqft_living" variable is 0.0011, indicating a positive relationship with the price. A one-unit increase in the square footage of living area is associated with an increase in the price by approximately 0.0011 units.

Waterfront: The coefficient for the "waterfront" variable is -1.3921, indicating a negative relationship with the price. A property with a waterfront location is associated with a decrease in the price by approximately 1.3921 units.

All three variables have p-values close to zero, indicating that they are highly statistically significant in relation to the price