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	sqft_lot
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080
...	...	...	...	...	...	...	...
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076

21597 rows × 21 columns

```
#The first five columns of the dataset
df.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	flo
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	

5 rows × 21 columns

```
#The last five columns of the dataset
df.tail()
```

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot

```
#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')
```

5 rows × 21 columns

```
#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
```

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

```
(21597, 21)
```

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

	id	price	bedrooms	bathrooms	sqft_living	sqf
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.15970
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.50994
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.14126
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.20000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.04000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.61800
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.06850
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.65135

```
# 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	sqft_lot	floors
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0

5 rows × 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

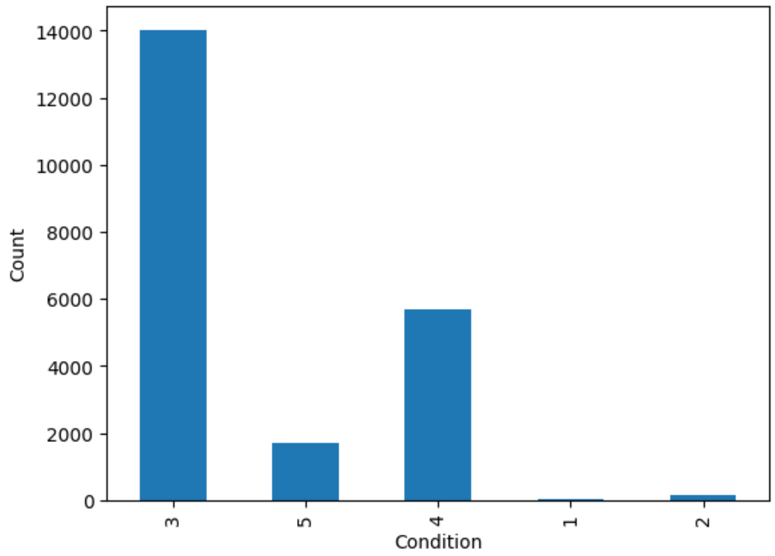
```
df['condition'].value_counts(sort=False)
```

```
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()
```

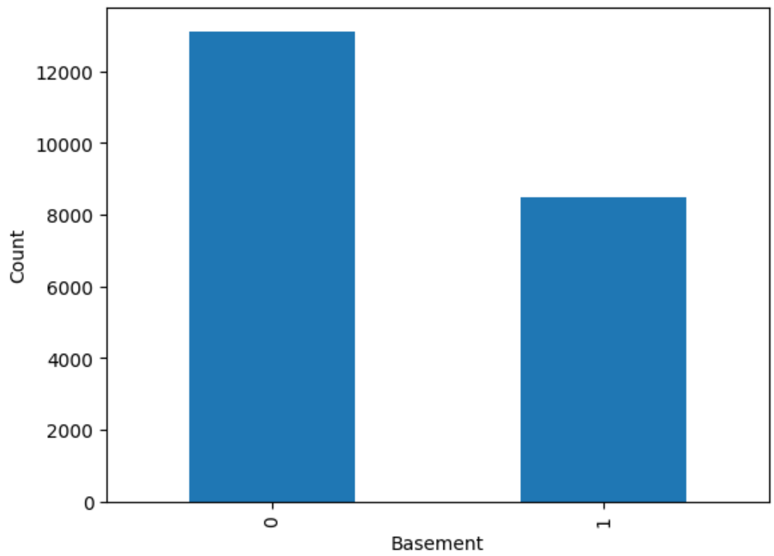
```
count    21597.000000
mean       291.725008
std        442.667800
min          0.000000
25%          0.000000
50%          0.000000
75%        560.000000
max       4820.000000
Name: sqft_basement, dtype: float64
```

```
#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	sqft_lot	flo
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	
...	...	...	...	...	...	...	...	
21592	263000018	2014-05-21	360000.0	3	2.50	1530	1131	
21593	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	
21594	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	
21595	291310100	2015-01-16	400000.0	3	2.50	1600	2388	
21596	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	

21597 rows × 22 columns

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

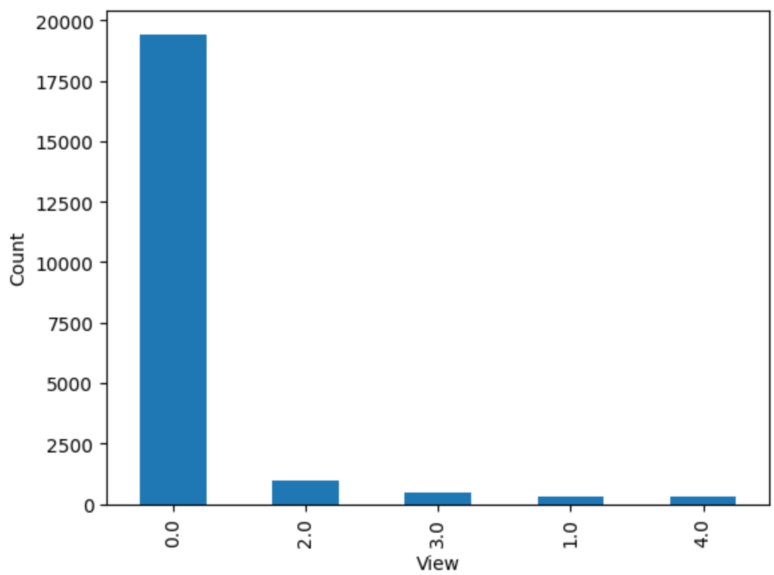


View

```
#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()
```

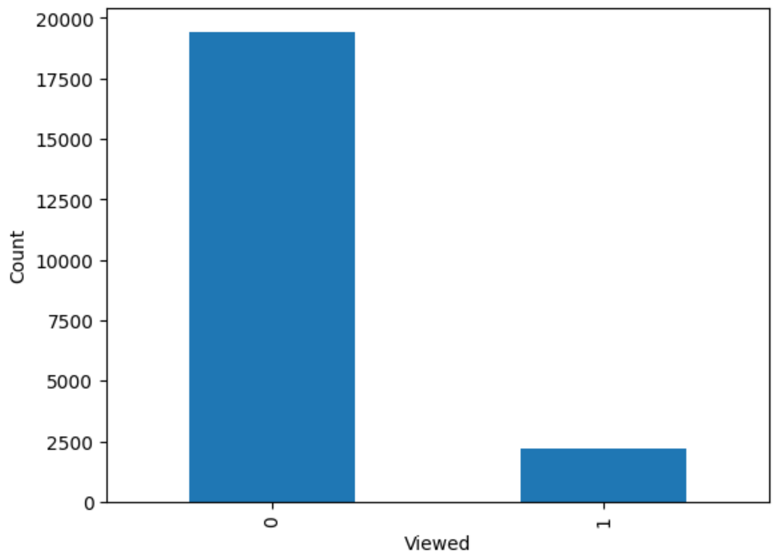



```
#Create a new variable called viewed and make it binary. 1 if the house has been viewed and 0 otherwise.
df['viewed'] = [0 if x == 0  else 1 for x in df['view']]
df['viewed'].value_counts()
```

```
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()
```

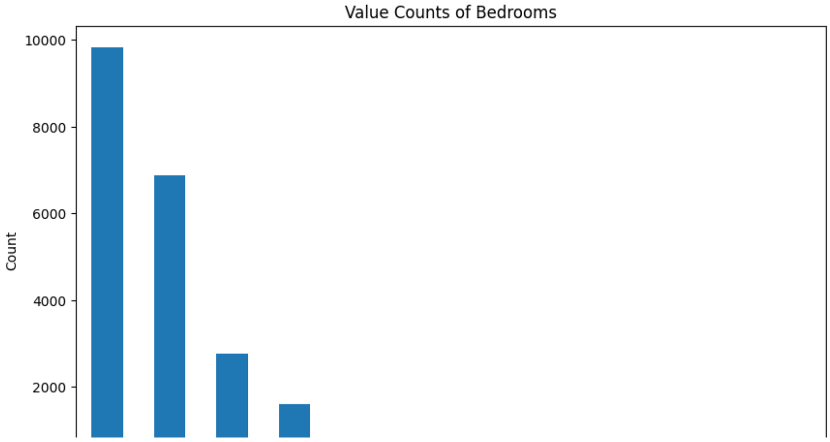
	id	price	bedrooms	bathrooms	sqft_living	sqf
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.15970
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.50994
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.14126
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.20000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.04000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.61800
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.06850
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.65135

8 rows × 22 columns

Bedrooms

```
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())

# 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
```

```
#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
```

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

```
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
```

```
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

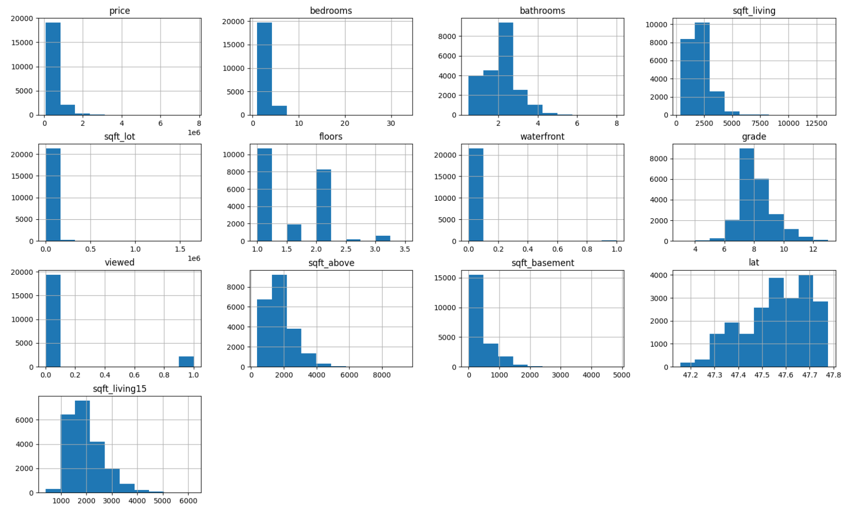
```
#Viewing the distributions of all variables
df.hist(figsize=(20,12))
plt.show()
```

```
#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',
```

```
new_df.head()
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	grade
0	221900.0	3	1.00	1180	5650	1.0	0.0	7
1	538000.0	3	2.25	2570	7242	2.0	0.0	7
2	180000.0	2	1.00	770	10000	1.0	0.0	6
3	604000.0	4	3.00	1960	5000	1.0	0.0	7
4	510000.0	3	2.00	1680	8080	1.0	0.0	8

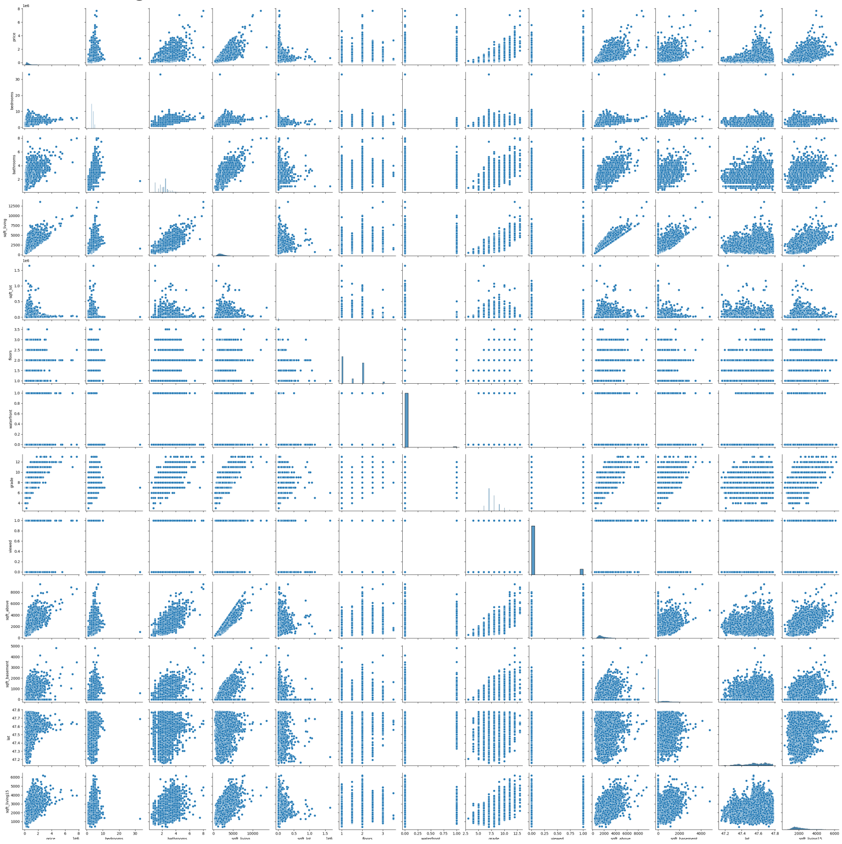
```
#Plotting the new dataframe
new_df.hist(figsize=(20,12))
plt.show()
plt.savefig('/content/download (2).png', dpi = 150)
```



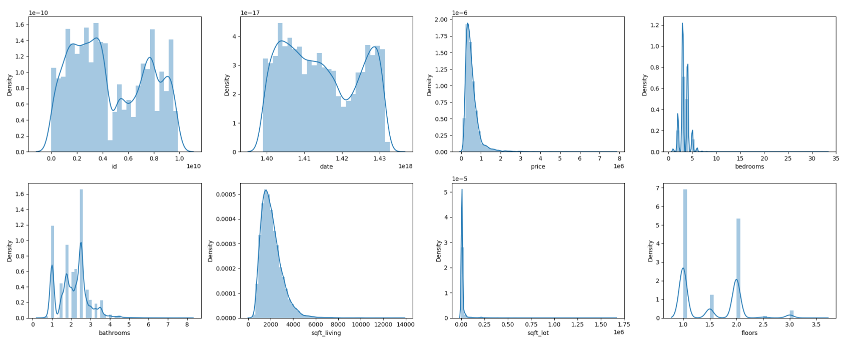
<Figure size 640x480 with 0 Axes>

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

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



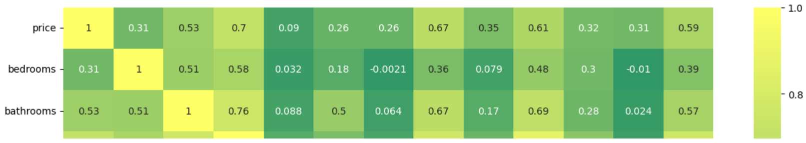
```
import warnings
warnings.filterwarnings('ignore')
#Viewing the univariate distribution for each feature in the testing dataframe

#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	wat
price	1.000000	0.308787	0.525906	0.701917	0.089876	0.256804	C
bedrooms	0.308787	1.000000	0.514508	0.578212	0.032471	0.177944	-C
bathrooms	0.525906	0.514508	1.000000	0.755758	0.088373	0.502582	C
sqft_living	0.701917	0.578212	0.755758	1.000000	0.173453	0.353953	C
sqft_lot	0.089876	0.032471	0.088373	0.173453	1.000000	-0.004814	C
floors	0.256804	0.177944	0.502582	0.353953	-0.004814	1.000000	C
waterfront	0.264306	-0.002127	0.063629	0.104637	0.021459	0.020797	1
grade	0.667951	0.356563	0.665838	0.762779	0.114731	0.458794	C
viewed	0.353770	0.078782	0.174090	0.266760	0.068035	0.015920	C
sqft_above	0.605368	0.479386	0.686668	0.876448	0.184139	0.523989	C
sqft_basement	0.323799	0.302808	0.283440	0.435130	0.015418	-0.245715	C
lat	0.306692	-0.009951	0.024280	0.052155	-0.085514	0.049239	-C
sqft_living15	0.585241	0.393406	0.569884	0.756402	0.144763	0.280102	C

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

def correlation_heatmap(dataframe):
    _, 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

```
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])

    # 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
```

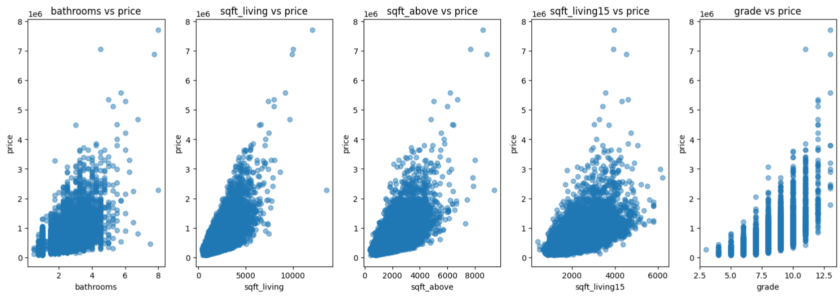
	Corr Value
price	1.000000
bathrooms	0.525906
sqft_living	0.701917
grade	0.667951
sqft_above	0.605368
sqft_living15	0.585241

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

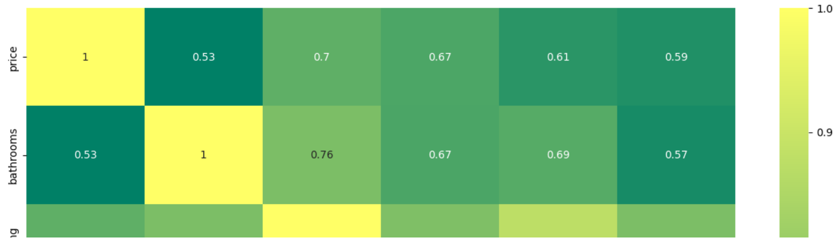
	price	bathrooms	sqft_living	grade	sqft_above	sqft_living15
0	221900.0	1.00	1180	7	1180	1340
1	538000.0	2.25	2570	7	2170	1690
2	180000.0	1.00	770	6	770	2720
3	604000.0	3.00	1960	7	1050	1360
4	510000.0	2.00	1680	8	1680	1800

```
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
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()
```




```
correlation_heatmap(corr_data)
```



Simple Linear Regression

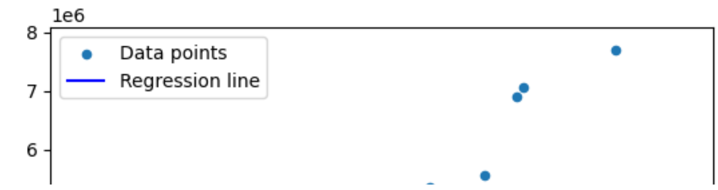
```
import statsmodels.api as sm

# 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))
```

price bathrooms sqft_living grade sqft_above sqft_living15

```
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 × 1 columns

```
#getting attributes to use in the model

df2 = df.copy(deep=True)
df2.drop(['waterfront','id','date','bedrooms','sqft_lot','floors','view',
          '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]
```

```
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()
```

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		

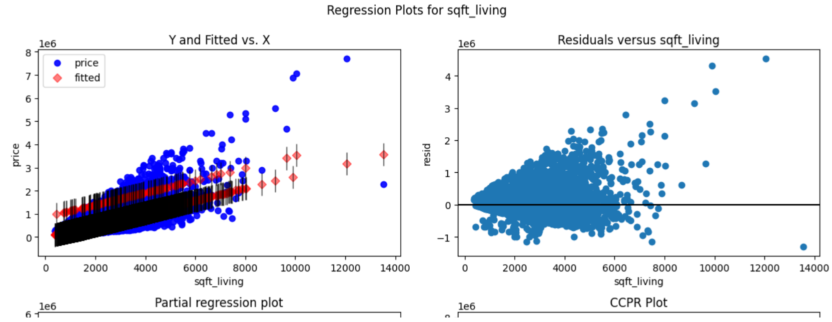
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
bathrooms	-1.325e+04	2874.067	-4.610	0.000	-1.89e+04	-7616.069
sqft_living	272.1194	2.851	95.442	0.000	266.531	277.708
waterfront	8.701e+05	2.1e+04	41.338	0.000	8.29e+05	9.11e+05

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] R^2 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)));
```

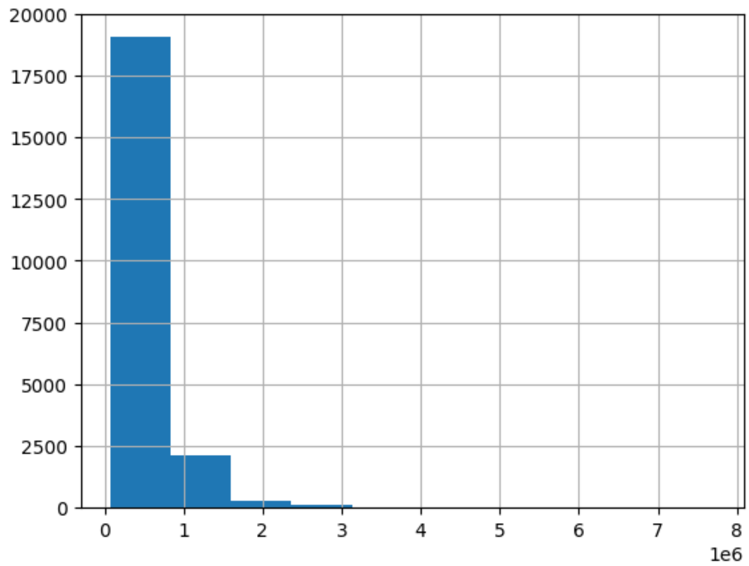
```
eval_env: 1
```



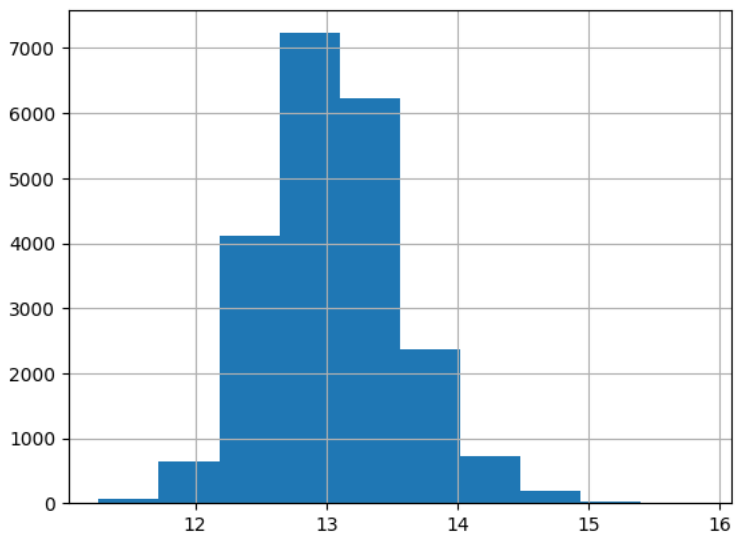
Double-click (or enter) to edit

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()
```

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] R^2 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.

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

Double-click (or enter) to edit