```
In [1]: import pandas as pd
         import numpy as np
         import warnings
         warnings.filterwarnings('ignore')
In [3]: # Importing the dataset
         housing = pd.read_excel('housing.xlsx')
         housing
Out[3]:
                longitude latitude housing_median_age total_rooms total_bedrooms population households median_income me
              0
                  -122.23
                            37.88
                                                 41
                                                            880
                                                                         129.0
                                                                                     322
                                                                                                126
                                                                                                             8.3252
              1
                  -122.22
                            37.86
                                                 21
                                                           7099
                                                                        1106.0
                                                                                    2401
                                                                                                1138
                                                                                                             8.3014
              2
                  -122.24
                            37.85
                                                 52
                                                           1467
                                                                         190.0
                                                                                     496
                                                                                                177
                                                                                                             7.2574
              3
                  -122.25
                            37.85
                                                 52
                                                           1274
                                                                         235.0
                                                                                     558
                                                                                                219
                                                                                                             5.6431
                  -122.25
                                                                                     565
              4
                            37.85
                                                 52
                                                           1627
                                                                         280.0
                                                                                                259
                                                                                                             3.8462
             ...
                                                  ...
                                                             ...
                                                                                      ...
                                                                                                  ...
          20635
                  -121.09
                            39.48
                                                 25
                                                           1665
                                                                         374.0
                                                                                     845
                                                                                                330
                                                                                                             1.5603
          20636
                  -121.21
                            39.49
                                                            697
                                                                         150.0
                                                                                     356
                                                                                                 114
                                                                                                             2.5568
                                                 18
                                                           2254
                                                                         485.0
          20637
                  -121.22
                            39.43
                                                 17
                                                                                    1007
                                                                                                433
                                                                                                             1.7000
          20638
                  -121.32
                            39.43
                                                 18
                                                           1860
                                                                         409.0
                                                                                     741
                                                                                                349
                                                                                                             1.8672
          20639
                  -121.24
                            39.37
                                                           2785
                                                                         616.0
                                                                                    1387
                                                                                                 530
                                                                                                             2.3886
                                                 16
         20640 rows × 10 columns
In [4]: housing.info()
         # housing.size
         # housing.shape
         # Exploratory Data Analysis
         # 20640 corresponds to the number of districts, 10 responds to the characteristics prevailing in \epsilon \epsilon
         # One categorical variable - ocean_proximity
         # median_house_value is the median sales of each district
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 20640 entries, 0 to 20639
         Data columns (total 10 columns):
          #
              Column
                                    Non-Null Count Dtype
          0
              longitude
                                    20640 non-null float64
          1
              latitude
                                    20640 non-null float64
              housing_median_age 20640 non-null int64
          2
          3
              total_rooms
                                    20640 non-null int64
          4
                                    20433 non-null float64
              total bedrooms
          5
                                    20640 non-null int64
              population
          6
                                    20640 non-null int64
              households
          7
              median income
                                    20640 non-null float64
          8
              median house value 20640 non-null int64
              ocean proximity
                                    20640 non-null object
         dtypes: float64(4), int64(5), object(1)
```

memory usage: 1.6+ MB

```
In [5]: # Looking at the basic statistics
         housing.describe()
         housing.describe().T
Out[5]:
                               count
                                                             std
                                                                       min
                                                                                   25%
                                                                                               50%
                                                                                                            75%
                                             mean
                                        -119.569704
                                                        2.003532
                                                                   -124.3500
                                                                               -121.8000
                                                                                                       -118.01000
                    longitude 20640.0
                                                                                           -118.4900
                                                                                                                    -114.
                      latitude 20640.0
                                          35.631861
                                                        2.135952
                                                                    32.5400
                                                                                33.9300
                                                                                            34.2600
                                                                                                        37.71000
                                                                                                                     41.
                                          28.639486
                                                       12.585558
                                                                                18.0000
                                                                                            29.0000
                                                                                                        37.00000
          housing_median_age 20640.0
                                                                     1.0000
                                                                                                                     52.
                  total_rooms 20640.0
                                        2635.763081
                                                                              1447.7500
                                                                                          2127.0000
                                                     2181.615252
                                                                     2.0000
                                                                                                      3148.00000
                                                                                                                  39320.
               total_bedrooms 20433.0
                                         537.870553
                                                      421.385070
                                                                     1.0000
                                                                               296.0000
                                                                                           435.0000
                                                                                                       647.00000
                                                                                                                   6445.
                   population 20640.0
                                        1425.476744
                                                      1132.462122
                                                                     3.0000
                                                                               787.0000
                                                                                          1166.0000
                                                                                                      1725.00000
                                                                                                                  35682.
                  households 20640.0
                                                      382.329753
                                                                     1.0000
                                                                               280.0000
                                                                                           409.0000
                                                                                                       605.00000
                                        499.539680
                                                                                                                   6082.
                                           3.870671
                                                        1.899822
                                                                     0.4999
                                                                                 2.5634
                                                                                             3.5348
                                                                                                         4.74325
               median_income 20640.0
                                                                                                                     15.
          median_house_value 20640.0 206855.816909 115395.615874 14999.0000 119600.0000 179700.0000 264725.00000 500001.
In [6]: # Checking for null values
         # total bedrooms has 207 NaN values
         housing.isnull()
         housing.isnull().sum()
Out[6]: longitude
                                    0
         latitude
                                    0
         housing_median_age
                                    0
         total rooms
                                    0
         total_bedrooms
                                  207
         population
                                    0
         households
                                    0
         median_income
                                    0
         median_house_value
                                    0
         ocean_proximity
                                    0
         dtype: int64
In [7]: # Dropping null values
         housing.dropna(inplace = True)
In [8]: housing.isnull().sum()
Out[8]: longitude
                                  0
         latitude
                                  0
         housing_median_age
                                  0
         total_rooms
                                  0
         total bedrooms
                                  0
         population
                                  0
                                  0
         households
         median_income
                                  0
         median_house_value
                                  0
         ocean_proximity
                                  0
         dtype: int64
In [9]: housing.columns
Out[9]: Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
                  'total_bedrooms', 'population', 'households', 'median_income',
                 'median_house_value', 'ocean_proximity'],
                dtype='object')
```

```
In [10]: # Encode categorical data - Convert categorical to numerical data
         # The feature column ocean_proximity is in categorical format
         # The are multiple ways to convert categorical data - label encoding, binary encone, dummies, etc
        # Pandas supports many more methods for the same
         # Label encoding involves converting each value from the column into a number
         # Ocean_proximity -'Near Bay' | '<1H Ocean' | 'Inland' | 'Near Ocean' | 'Island'
         # Assigning a specific number
         # <1H Ocean = 0, Inland = 1, Island = 2, Near Bay = 3, Near Ocean = 4
         from sklearn.preprocessing import LabelEncoder
         LabelEncoder = LabelEncoder()
In [11]: # Converting the column from object to category
         housing['ocean_proximity'] = housing['ocean_proximity'].astype('category')
        housing.dtypes
Out[11]: longitude
                               float64
        latitude
                               float64
        housing_median_age
                               int64
                                int64
        total_rooms
         total_bedrooms
                            float64
         population
                               int64
         households
                                int64
        median_income
                             float64
         median_house_value
                               int64
         ocean_proximity
                              category
        dtype: object
```

In [12]: # Assigning the encoded variable to a new column using the cat.codes accesor
housing['ocean_proximity_value'] = housing['ocean_proximity'].cat.codes
housing.head()

Out[12]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	mediar
0	-122.23	37.88	41	880	129.0	322	126	8.3252	
1	-122.22	37.86	21	7099	1106.0	2401	1138	8.3014	
2	-122.24	37.85	52	1467	190.0	496	177	7.2574	
3	-122.25	37.85	52	1274	235.0	558	219	5.6431	
4	-122.25	37.85	52	1627	280.0	565	259	3.8462	

```
In [13]: # Since we are using regression analysis, it is better to standardize the data
          # Standardization involves shifting the distribution of each data point to a mean of 0 and an SD _{
m O}
         from sklearn.preprocessing import StandardScaler
          sc_x = StandardScaler()
          x = pd.DataFrame(sc_x.fit_transform(housing.drop(["ocean_proximity", "median_house_value"], axis
                  columns=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
                  'total_bedrooms', 'population', 'households', 'median_income', 'ocean_proximity_value'])
          x.head()
          # x.shape
Out[13]:
             longitude
                       latitude housing_median_age total_rooms total_bedrooms
                                                                           population households median_income ocear
          0 -1.327314 1.051717
                                                                                       -0.976833
                                         0.982163
                                                    -0.803813
                                                                  -0.970325
                                                                            -0.973320
                                                                                                      2.345163
           1 -1.322323 1.042355
                                                    2.042130
                                                                                       1.670373
                                        -0.606210
                                                                  1.348276
                                                                            0.861339
                                                                                                      2.332632
          2 -1.332305 1.037674
                                         1.855769
                                                    -0.535189
                                                                  -0.825561
                                                                            -0.819769
                                                                                       -0.843427
                                                                                                      1.782939
           3 -1.337296 1.037674
                                         1.855769
                                                    -0.623510
                                                                  -0.718768
                                                                            -0.765056
                                                                                       -0.733562
                                                                                                      0.932970
            -1.337296 1.037674
                                         1.855769
                                                    -0.461970
                                                                  -0.611974
                                                                            -0.758879
                                                                                       -0.628930
                                                                                                     -0.013143
In [14]: # Standardizing the target variable - median_house_value
          y = pd.DataFrame(sc_x.fit_transform(housing.drop(['ocean_proximity','longitude', 'latitude', 'hous
                 'total_bedrooms', 'population', 'households', 'median_income', 'ocean_proximity_value' ], a
                            columns=['median_house_value'])
          y.head()
          # y.shape
Out[14]:
             median_house_value
          0
                       2.128819
                       1.313626
           1
          2
                       1.258183
                       1.164622
          3
                       1.172418
In [15]: # splitting the data
          from sklearn.model_selection import train_test_split
          x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = .20, random_state = 1,)
In [16]: # Linear Regression
          from sklearn.linear_model import LinearRegression
          model1 = LinearRegression()
          model1.fit(x_train, y_train)
Out[16]:
          ▼ LinearRegression
          LinearRegression()
In [17]: # Printing the coefficients and intercept
          print(model1.intercept )
         print(model1.coef_)
          [0.00280687]
          [[-0.74612343 -0.79186502 0.12810082 -0.15758988 0.41665016 -0.36991155
             0.15622207 0.66336783 0.00130051]]
```

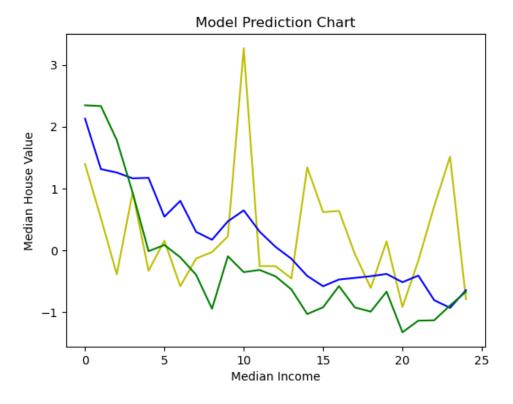
```
In [18]: # Predicting on the test data
         y_p = model1.predict(x_test)
         print(y_p)
         print(y_test)
         [[ 1.47657526]
          [ 0.5809054 ]
          [-0.51896355]
          [-0.62287874]
          [ 1.92401337]
          [ 0.58810714]]
                median house value
         6643
                          1.334417
         4084
                          0.733202
                         -0.654618
         15284
                         2.539456
         20068
                         -0.762906
         11726
         6607
                         0.307846
         9765
                          0.096468
         9364
                          -1.187395
         16981
                          2.539456
         3933
                          0.115527
         [4087 rows x 1 columns]
In [19]: # Calculating the Root Mean Squared Error - RMSE
         # Test and train scores
         from sklearn import metrics
         print(np.sqrt(metrics.mean_squared_error(y_test, y_p)))
         print(np.sqrt(metrics.mean_squared_error(y_train, model1.predict(x_train))))
         0.5949339345602463
         0.6045058776630716
In [20]: # Univariate regression
         x1 = x[['median_income']]
         y1 = y[['median_house_value']]
In [21]: # Splitting the data
         x1_train, x1_test, y1_train, y1_test = train_test_split(x1, y1, test_size = .20, random_state = 1,
In [22]: # Linear Regression
         from sklearn.linear_model import LinearRegression
         model2 = LinearRegression()
         model2.fit(x1_train, y1_train)
Out[22]:
          ▼ LinearRegression
          LinearRegression()
In [23]: # Printing the coefficients and intercept
         print(model2.intercept_)
         print(model2.coef_)
         [0.00341938]
         [[0.68861017]]
```

```
In [24]: # Predicting on the test data
        y_p1 = model2.predict(x1_test)
         print(y_p1)
         print(y1_test)
         [[ 1.39584913]
          [ 0.52009629]
          [-0.38636627]
          [-0.85803426]
          [ 1.58873665]
          [ 0.46574697]]
                median house value
         6643
                        1.334417
         4084
                        0.733202
         15284
                       -0.654618
         20068
                        2.539456
                       -0.762906
         11726
         6607
                       0.307846
                        0.096468
         9765
         9364
                        -1.187395
         16981
                         2.539456
         3933
                         0.115527
         [4087 rows x 1 columns]
In [25]: # Calculating the Root Mean Squared Error - RMSE
         # Test and train scores
         from sklearn import metrics
         print(np.sqrt(metrics.mean_squared_error(y1_test, y_p1)))
         print(np.sqrt(metrics.mean_squared_error(y1_train, model2.predict(x1_train))))
         0.7103347089635074
         0.7290952831251405
```

```
In [26]: # Lets plot the fitted model2 with the revised dataset
    import matplotlib.pyplot as plt
    %matplotlib inline

plt.plot(y_p1[0:25], 'y')
    plt.plot(y1[0:25], 'b')
    plt.plot(x1[0:25], 'g')
    plt.xlabel('Median Income')
    plt.ylabel('Median House Value')
    plt.title('Model Prediction Chart')
```

Out[26]: Text(0.5, 1.0, 'Model Prediction Chart')



```
In [27]: # Thank You :)
In []:
```