# Weighted KNN

### Import dataset

```
In [18]: import sklearn
          from sklearn.datasets import fetch_california_housing
          # as_frame=True loads the data in a dataframe format, with other metadata besides i
          california_housing = fetch_california_housing(as_frame=True)
          # Select only the dataframe part and assign it to the df variable
          df = california_housing.frame
In [19]: import pandas as pd
          df.head()
Out[19]:
                      HouseAge
                                AveRooms AveBedrms Population
                                                                    AveOccup
                                                                               Latitude
                                                                                        Longitude
          0
              8.3252
                            41.0
                                   6.984127
                                               1.023810
                                                              322.0
                                                                      2.555556
                                                                                  37.88
                                                                                           -122.23
              8.3014
                                   6.238137
                                               0.971880
                                                             2401.0
                                                                      2.109842
                                                                                  37.86
                                                                                           -122.22
                            21.0
          2
              7.2574
                            52.0
                                   8.288136
                                                              496.0
                                                                      2.802260
                                                                                           -122.24
                                               1.073446
                                                                                  37.85
               5.6431
                            52.0
                                   5.817352
                                               1.073059
                                                              558.0
                                                                      2.547945
                                                                                           -122.25
                                                                                  37.85
              3.8462
                            52.0
                                   6.281853
                                               1.081081
                                                              565.0
                                                                      2.181467
                                                                                  37.85
                                                                                           -122.25
```

### **Preprocessing Data for KNN Regression**

```
In [20]: y = df['MedHouseVal']
           X = df.drop(['MedHouseVal'], axis = 1)
In [21]: # .T transposes the results, transforming rows into columns
           X.describe().T
Out[21]:
                         count
                                       mean
                                                       std
                                                                   min
                                                                               25%
                                                                                             50%
                                                                                                          75%
               MedInc 20640.0
                                    3.870671
                                                  1.899822
                                                               0.499900
                                                                           2.563400
                                                                                         3.534800
                                                                                                      4.743250
            HouseAge
                        20640.0
                                                               1.000000
                                                                           18.000000
                                                                                        29.000000
                                                                                                     37.000000
                                   28.639486
                                                 12.585558
            AveRooms
                        20640.0
                                    5.429000
                                                 2.474173
                                                               0.846154
                                                                           4.440716
                                                                                         5.229129
                                                                                                      6.05238
           AveBedrms
                        20640.0
                                    1.096675
                                                 0.473911
                                                               0.333333
                                                                            1.006079
                                                                                         1.048780
                                                                                                      1.099520
                        20640.0
                                                                         787.000000
                                                                                      1166.000000
           Population
                                 1425.476744
                                              1132.462122
                                                               3.000000
                                                                                                   1725.000000
            AveOccup
                        20640.0
                                    3.070655
                                                 10.386050
                                                               0.692308
                                                                            2.429741
                                                                                         2.818116
                                                                                                      3.28226
              Latitude
                        20640.0
                                                                                        34.260000
                                   35.631861
                                                 2.135952
                                                              32.540000
                                                                           33.930000
                                                                                                     37.710000
            Longitude
                        20640.0
                                 -119.569704
                                                            -124.350000
                                                                                      -118.490000
                                                                                                   -118.010000
                                                                         -121.800000
```

## **Splitting Data into Train and Test Sets**

```
In [22]: from sklearn.model_selection import train_test_split

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_st

In [23]: print(len(X)) # 20640
print(len(X_train)) # 15480
print(len(X_test)) # 5160

20640
15480
5160
```

### **Feature Scaling for KNN Regression**

```
In [24]: from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()
          # Fit only on X_train
          scaler.fit(X_train)
          # Scale both X train and X test
          X_train = scaler.transform(X_train)
          X_test = scaler.transform(X_test)
In [25]: col_names=['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup']
          scaled_df = pd.DataFrame(X_train, columns=col_names)
          scaled_df.describe().T
Out[25]:
                        count
                                                                   25%
                                                                             50%
                                                                                       75%
                                    mean
                                                std
                                                         min
                                                                                                  max
                                2.172968e-
              MedInc 15480.0
                                           1.000032 -1.774632 -0.688854
                                                                         -0.175663
                                                                                   0.464450
                                                                                               5.842113
                                       16
                               -1.254954e-
           HouseAge
                      15480.0
                                           1.000032 -2.188261
                                                              -0.840224
                                                                          0.032036
                                                                                   0.666407
                                                                                               1.855852
                                       16
                               -1.148163e-
           AveRooms
                      15480.0
                                           1.000032 -1.877586
                                                              -0.407008
                                                                         -0.083940
                                                                                   0.257082
                                                                                              56.357392
                                1.239408e-
           AveBedrms
                     15480.0
                                           1.000032
                                                   -1.740123
                                                              -0.205765
                                                                         -0.108332
                                                                                              55.925392
                               -7.874838e-
           Population
                      15480.0
                                           1.000032
                                                   -1.246395
                                                              -0.558886
                                                                         -0.227928
                                                                                   0.262056
                                                                                              29.971725
                                       17
                                2.672550e-
                     15480.0
            AveOccup
                                           1.000032 -0.201946
                                                              -0.056581
                                                                         -0.024172 0.014501
                                                                                             103.737365
                                       17
                                8.022581e-
             Latitude 15480.0
                                           1.000032
                                                   -1.451215 -0.799820
                                                                         -0.645172 0.971601
                                                                                               2.953905
                                       16
                                2.169625e-
            Longitude 15480.0
                                           1.000032 -2.380303 -1.106817
                                                                          0.536231 0.785934
                                                                                               2.633738
```

# **Training and Predicting KNN Regression**

```
In [26]: from sklearn.neighbors import KNeighborsRegressor
    regressor = KNeighborsRegressor(n_neighbors=5, weights="distance")
    regressor.fit(X_train, y_train)
```

```
Out[26]: KNeighborsRegressor(weights='distance')
In [27]: y_pred = regressor.predict(X_test)
```

## **Evaluating the Algorithm for KNN Regression**

```
In [28]: from sklearn.metrics import mean_absolute_error, mean_squared_error
         mae = mean_absolute_error(y_test, y_pred)
         mse = mean_squared_error(y_test, y_pred)
         rmse = mean_squared_error(y_test, y_pred, squared=False)
         print(f'mae: {mae}')
         print(f'mse: {mse}')
         print(f'rmse: {rmse}')
         mae: 0.44330658993325084
         mse: 0.4284245302766481
         rmse: 0.6545414656663457
In [29]: regressor.score(X_test, y_test)
Out[29]: 0.6762253110912666
In [30]: y.describe()
Out[30]: count
                  20640.000000
                      2.068558
         mean
         std
                      1.153956
         min
                      0.149990
         25%
                      1.196000
         50%
                      1.797000
         75%
                      2.647250
         max
                      5.000010
         Name: MedHouseVal, dtype: float64
```

# Finding the Best K for KNN Regression

```
In [31]: error = []
         # Calculating MAE error for K values between 1 and 39
         for i in range(1, 40):
             knn = KNeighborsRegressor(n_neighbors=i, weights="distance")
             knn.fit(X_train, y_train)
             pred_i = knn.predict(X_test)
             mae = mean_absolute_error(y_test, pred_i)
             error.append(mae)
In [32]: import matplotlib.pyplot as plt
         plt.figure(figsize=(12, 6))
         plt.plot(range(1, 40), error, color='red',
                  linestyle='dashed', marker='o',
                  markerfacecolor='blue', markersize=10)
         plt.title('K Value MAE')
         plt.xlabel('K Value')
         plt.ylabel('Mean Absolute Error')
```

Out[32]: Text(0, 0.5, 'Mean Absolute Error')

```
0.52 - K Value MAE

0.50 - 0.44 - 0.44 - 0.44 - 0.44 - 0.50 - 10 15 20 25 30 35 40 K Value
```

### KNN with 12 neighbours

```
In [34]: knn_reg12 = KNeighborsRegressor(n_neighbors=12, weights="distance")
knn_reg12.fit(X_train, y_train)
y_pred12 = knn_reg12.predict(X_test)
r2 = knn_reg12.score(X_test, y_test)

mae12 = mean_absolute_error(y_test, y_pred12)
mse12 = mean_squared_error(y_test, y_pred12)
rmse12 = mean_squared_error(y_test, y_pred12, squared=False)
print(f'r2: {r2}, \nmae: {mae12} \nmse: {mse12} \nrmse: {rmse12}')

r2: 0.6925746041555878,
mae: 0.43265872078512396
mse: 0.40679084969140783
rmse: 0.6378015754852036
```

# Classification using K-Nearest Neighbors with Scikit-Learn

# **Preprocessing Data for Classification**

```
In [35]: # Creating 4 categories and assigning them to a MedHouseValCat column
    df["MedHouseValCat"] = pd.qcut(df["MedHouseVal"], 4, retbins=False, labels=[1, 2, 3]
In [36]: y = df['MedHouseValCat']
    X = df.drop(['MedHouseVal', 'MedHouseValCat'], axis = 1)
```

### **Splitting Data into Train and Test Sets**

```
In [37]: from sklearn.model_selection import train_test_split

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_st
```

### **Feature Scaling for Classification**

```
In [38]: from sklearn.preprocessing import StandardScaler

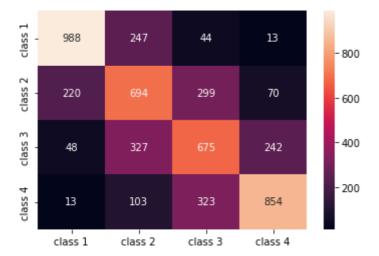
scaler = StandardScaler()
scaler.fit(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

### **Training and Predicting for Classification**

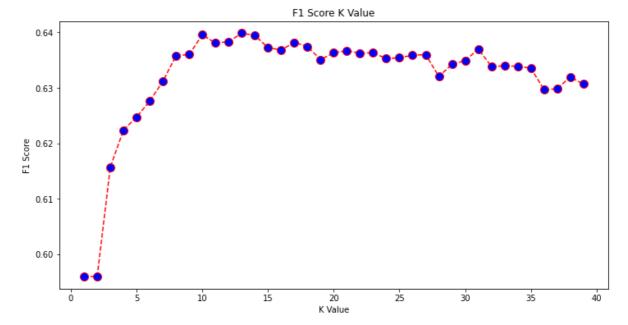
# **Evaluating KNN for Classification**

		precision	recall	f1-score	support
	1	0.78	0.76	0.77	1292
	2	0.51	0.54	0.52	1283
	3	0.50	0.52	0.51	1292
	4	0.72	0.66	0.69	1293
accurac	у			0.62	5160
macro av	′g	0.63	0.62	0.62	5160
weighted av	′g	0.63	0.62	0.62	5160



## Finding the Best K for KNN Classification

```
In [43]: from sklearn.metrics import f1_score
         f1s = []
         # Calculating f1 score for K values between 1 and 40
         for i in range(1, 40):
             knn = KNeighborsClassifier(n_neighbors=i, weights="distance")
             knn.fit(X_train, y_train)
             pred_i = knn.predict(X_test)
             # using average='weighted' to calculate a weighted average for the 4 classes
             f1s.append(f1_score(y_test, pred_i, average='weighted'))
In [44]: plt.figure(figsize=(12, 6))
         plt.plot(range(1, 40), f1s, color='red', linestyle='dashed', marker='o',
                  markerfacecolor='blue', markersize=10)
         plt.title('F1 Score K Value')
         plt.xlabel('K Value')
         plt.ylabel('F1 Score')
Out[44]: Text(0, 0.5, 'F1 Score')
```



# From the output, we can see that the f1-score is the highest when the value of the K is 10.

```
In [48]: classifier15 = KNeighborsClassifier(n_neighbors=10, weights="distance")
         classifier15.fit(X_train, y_train)
         y_pred15 = classifier15.predict(X_test)
         print(classification_report(y_test, y_pred15))
                        precision
                                     recall f1-score
                                                        support
                    1
                             0.79
                                       0.77
                                                 0.78
                                                           1292
                     2
                             0.53
                                       0.56
                                                 0.54
                                                           1283
                     3
                             0.51
                                       0.55
                                                 0.53
                                                           1292
                    4
                             0.74
                                       0.67
                                                 0.70
                                                           1293
                                                 0.64
                                                           5160
             accuracy
            macro avg
                             0.64
                                       0.64
                                                 0.64
                                                           5160
         weighted avg
                             0.64
                                       0.64
                                                 0.64
                                                           5160
In [49]: acc = classifier.score(X_test, y_pred15)
         print(acc)
         0.8560077519379845
In [47]: cm = pd.DataFrame(confusion_matrix(y_test, y_pred15),
```

columns=classes\_names, index = classes\_names)

```
localhost:8888/nbconvert/html/LAB 5/Weighted KNN.ipynb?download=false
```

sns.heatmap(cm, annot=True, fmt='d');

