```
In [39]: # KNN
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.preprocessing import StandardScaler
In [40]: # read the data
         raw_data = pd.read_csv('winequality-red.csv', sep=';')
In [41]: # remove outliers
         for col in raw data.columns:
                 if col != 'quality':
                        iqr = raw_data[col].quantile(0.75) - raw_data[col].quantile(
                        upper_bound = raw_data[col].quantile(0.75) + 2.5 * iqr
                        lower bound = raw data[col].quantile(0.25) - 2.5 * iqr
                        raw_data = raw_data[(raw_data[col] < upper_bound) & (raw_dat</pre>
         # save the cleaned data
         raw_data.to_csv('cleaned_data.csv', index=False)
In [42]: # raw_data.info()
         # remove repeated data
         raw_data = raw_data.drop_duplicates()
         raw_data.info()
         <class 'pandas.core.frame.DataFrame'>
         Int64Index: 1182 entries, 0 to 1598
         Data columns (total 12 columns):
          #
             Column
                                  Non-Null Count Dtype
         ____
          0
             fixed acidity
                                 1182 non-null float64
             volatile acidity
                                 1182 non-null float64
          1
                                  1182 non-null float64
          2 citric acid
                             1182 non-null float64
          3 residual sugar
                                  1182 non-null float64
          4
            chlorides
          5
            free sulfur dioxide 1182 non-null float64
             total sulfur dioxide 1182 non-null float64
          6
          7
                                  1182 non-null float64
             density
                                  1182 non-null float64
          8
             рΗ
          9
             sulphates
                                  1182 non-null float64
          10 alcohol
                                  1182 non-null float64
          11 quality
                                   1182 non-null int64
         dtypes: float64(11), int64(1)
         memory usage: 120.0 KB
In [43]: raw_data.describe()
```

```
Out[43]:
                                                                               free sulfur
                                 volatile
                                                         residual
                                                                                           tota
                 fixed acidity
                                           citric acid
                                                                    chlorides
                                  acidity
                                                           sugar
                                                                                  dioxide
          count 1182.000000 1182.000000 1182.000000 1182.000000 1182.000000 1182.000000 1182.000000
           mean
                    8.268613
                                0.525816
                                            0.260398
                                                         2.255118
                                                                    0.078864
                                                                                15.692893
                                                                                            45
            std
                    1.674834
                                0.176989
                                            0.189768
                                                        0.545431
                                                                     0.015813
                                                                                 9.689748
                                                                                            30
            min
                    4.700000
                                0.120000
                                            0.000000
                                                        0.900000
                                                                    0.038000
                                                                                 1.000000
                                                                                             6.
           25%
                    7.100000
                                0.390000
                                            0.090000
                                                        1.900000
                                                                    0.069000
                                                                                8.000000
                                                                                            22.
           50%
                    7.900000
                                0.520000
                                            0.245000
                                                        2.200000
                                                                    0.078000
                                                                                14.000000
                                                                                            37.
                   9.200000
                                0.640000
           75%
                                            0.410000
                                                        2.500000
                                                                    0.088000
                                                                                21.000000
                                                                                            60.
                   14.300000
                                1.240000
                                            0.760000
                                                        4.300000
                                                                     0.136000
                                                                                53.000000
                                                                                           152.
            max
In [44]:
          # Standardization
          scaler = StandardScaler()
          raw_data.iloc[:, :-1] = scaler.fit_transform(raw_data.iloc[:, :-1])
In [45]:
          # train test split
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(raw_data.iloc[:, :-1], r
In [46]: # # gird search on K and distance function
          # from sklearn.model_selection import GridSearchCV
          \# k \text{ range} = list(range(1, 50))
          # weight_options = ['uniform', 'distance']
           # distance metric = ['euclidean', 'manhattan', 'minkowski', 'cosine']
           # param grid = dict(n neighbors=k range, weights=weight options, metric=dist
           # knn = KNeighborsClassifier()
           # grid = GridSearchCV(knn, param grid, cv=10, scoring='accuracy', return tra
          # grid.fit(X train, y train)
          # # print the best parameters
           # print(grid.best params )
           # print(grid.best score )
```

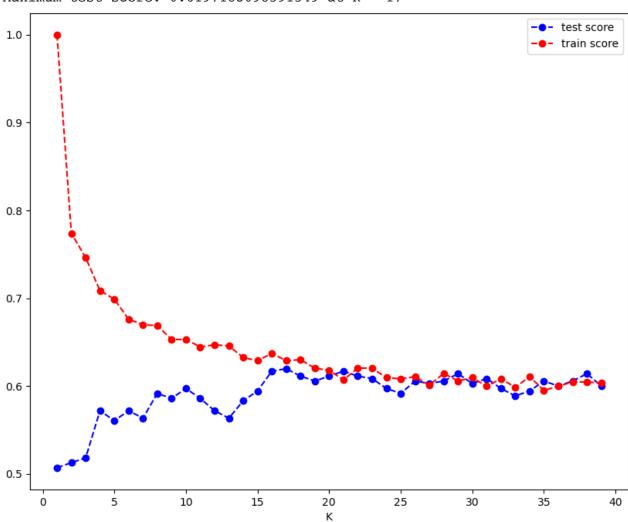
```
In [47]: train_score = []
          test score = []
          for i in range(1, 40):
                  knn = KNeighborsClassifier(n neighbors = i)
                  knn.fit(X_train, y_train)
                  pred_i = knn.predict(X_test)
                  test_score.append(knn.score(X_test, y_test))
                  train_score.append(knn.score(X_train, y_train))
          plt.figure(figsize =(10, 8))
          plt.plot(range(1, 40), test_score, color = 'blue', linestyle = 'dashed', marke
          plt.plot(range(1, 40), train score, color = 'red', linestyle = 'dashed', marke
          plt.xlabel('K')
          plt.legend(['test score', 'train score'], loc ='upper right')
          print("Maximum test score:", max(test_score), "at K =", test_score.index(max(test_score)))
          Maximum test score: 0.6197183098591549 at K = 17

    test score

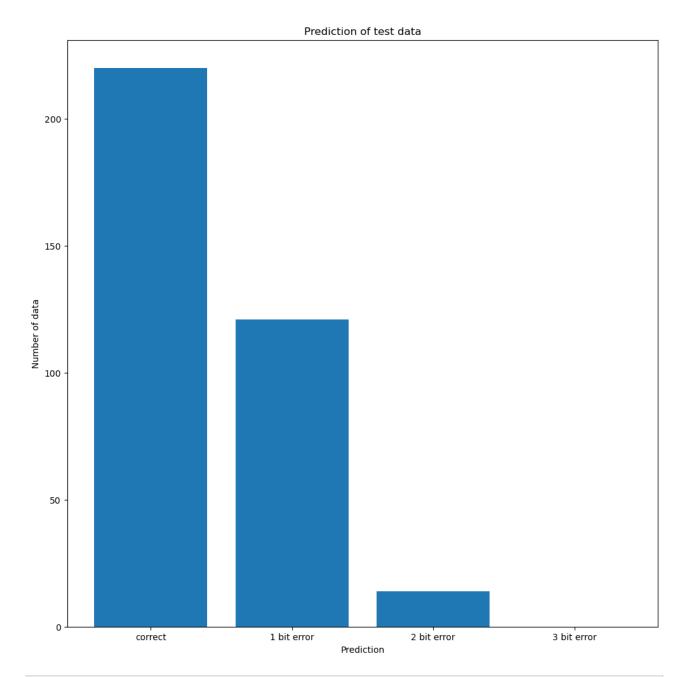
          1.0

    train score

          0.9
```



```
In [48]: \# k = 17
         classifier = KNeighborsClassifier(n neighbors = 17)
         classifier.fit(X_train,y_train)
Out[48]: 🔻
                   KNeighborsClassifier
         KNeighborsClassifier(n_neighbors=17)
In [49]: #Predicting the ouput from input data (x train) and (y train)
         y pred1 = classifier.predict(X train)
         y_pred2 = classifier.predict(X_test)
In [50]: from sklearn.metrics import accuracy_score, mean_squared_error
         print("train score", accuracy_score(y_train, y_pred1))
         print("test score",accuracy_score(y_test, y_pred2))
         print("MSE", mean_squared_error(y_test, y_pred2))
         y_test = np.array(y_test)
         train score 0.6287787182587666
         test score 0.6197183098591549
         MSE 0.49859154929577465
In [51]: # visualization
         correct = 0
         one_bit_error = 0
         two_bit_error = 0
         threemore bit error = 0
         print('Shap of y pred: ', y test.shape)
         for i in range(len(y_pred2)):
                 if y_pred2[i] == y_test[i]:
                          correct += 1
                 elif abs(y_pred2[i] - y_test[i]) == 1:
                          one bit_error += 1
                 elif abs(y pred2[i] - y test[i]) == 2:
                         two_bit_error += 1
                 else:
                          threemore_bit_error += 1
         plt.figure(figsize=(12, 12))
         plt.bar(['correct', '1 bit error', '2 bit error', '3 bit error'], [correct,
         plt.title('Prediction of test data')
         plt.xlabel('Prediction')
         plt.ylabel('Number of data')
         plt.show()
         Shap of y_pred: (355,)
```



In [51]: