```
In [86]:
            # Import the libraries
               import numpy as np
               import pandas as pd
               import matplotlib.pyplot as plt
               import seaborn as sns
               import warnings #to remove the warnings
               warnings.filterwarnings('ignore')
In [87]:
            # Import the dataset
               Test1 1 = pd. read csv(r'D:\Caroline\Documents\Graduate\ISE 530 Optimizaton for Anal
               print(Test1 1.head(10))
                  Sample code number Clump Thickness Uniformity of Cell Size
               0
                             1000025
                             1002945
               1
                                                     5
                                                                               4
               2
                             1015425
                                                     3
                                                                               1
               3
                             1016277
                                                     6
                                                                               8
               4
                             1017023
                                                     4
                                                                               1
               5
                             1017122
                                                     8
                                                                               10
               6
                             1018099
                                                     1
                                                                               1
               7
                             1018561
                                                     2
                                                                               1
                                                     2
               8
                             1033078
                                                                               1
                             1033078
                  Uniformity of Cell Shape Marginal Adhesion Single Epithelial Cell Size \
               0
                                          1
               1
                                          4
                                                              5
                                                                                            7
               2
                                          1
                                                              1
                                                                                            2
               3
                                          8
                                                                                            3
               4
                                                              3
                                                                                            2
                                          1
                                                                                            7
               5
                                                              8
                                         10
                                                                                            2
               6
                                          1
                                                              1
               7
                                          2
                                                                                            2
                                                              1
                                                                                            2
               8
                                          1
                                                              1
                                                                                            2
               9
                                                              1
                                          1
                  Bare Nuclei Bland Chromatin Normal Nucleoli Mitoses Class
               0
                                              3
                                                                                2
                            1
                                                                1
                                                                         1
                                                                2
                                                                                 2
               1
                           10
                                              3
                                                                         1
               2
                            2
                                              3
                                                                                2
                                                                1
                                                                         1
               3
                                              3
                                                                7
                                                                                2
                            4
                                                                         1
                                              3
                                                                                2
               4
                            1
                                                                1
                                                                         1
               5
                           10
                                              9
                                                                7
                                                                         1
                                              3
                                                                                2
               6
                           10
                                                                1
                                                                         1
                                                                                2
               7
                                              3
                            1
                                                                1
                                                                         1
               8
                             1
                                              1
                                                                1
                                                                         5
                                                                                2
               9
                                              2
                                                                                 2
                             1
                                                                1
                                                                         1
```

```
In [88]:
                # Remove the first column which is Sample Code Number
                     Test1 1. drop('Sample code number', axis=1, inplace=True)
                     X = Test1_1.iloc[:,:-1].values # get columns except for the last one.
                     print("Data of X:", X)
                     Y = Test1_1.iloc[:,-1].values # get the last one column which is class.
                     print("Data of Y:", Y)
                     Data of X: [[ 5 1 1 ... 3 1 1]
                      [5 4 4 ... 3 2 1]
                      [ 3 1 1 ...
                                          3 1 1]
                      [ 5 10 10 ... 8 10 2]
                      [ 4 8 6 ... 10 6 1]
                      [ 4 8 8 ... 10 4
                                                   1]]
                     4\ 4\ 2\ 4\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 4\ 4\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4\ 4\ 2\ 2\ 4
                      2\ 2\ 2\ 4\ 2\ 4\ 2\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 4\ 4\ 2
                      4\ 4\ 2\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 4\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2
                      2 2 2 2 2 2 2 2 2 2 4 2 2 2 2 4 4 4]
In [89]:
                # We don't need to encode the dataset because the data size is similar
                     # Spliting the dataset into training and testing set
                     from sklearn.model_selection import train_test_split
                     X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.2, random_s
```

```
In [90]:
            ▶ # Feature Scaling—Normalization
               # I choose the normalization meathod
               from sklearn.preprocessing import MinMaxScaler
               # Create an instance of MinMaxScaler
               scaler = MinMaxScaler()
               X_train_normal = scaler.fit_transform(X_train)
               X test normal = scaler.fit transform(X test)
               X_train_normal = pd. DataFrame(X_train_normal)
               X_test_normal = pd. DataFrame(X_test_normal)
               print("Normalized X train:", X_train_normal.head(10))
               print("Normalized X test:", X_test_normal.head(10))
               Normalized X train:
                                                         1
                                                                    2
                         6
               0
                  1.000000 0.000000 0.000000 0.000000 0.111111
                                                                      1.000000 0.444444
                  2\quad 0.\ 444444 \quad 0.\ 000000 \quad 0.\ 000000 \quad 0.\ 000000 \quad 0.\ 111111 \quad 0.\ 000000 \quad 0.\ 222222
               3 \quad 0.222222 \quad 0.000000 \quad 0.111111 \quad 0.000000 \quad 0.111111 \quad 0.000000 \quad 0.111111
               4 \quad 0.777778 \quad 0.111111 \quad 0.222222 \quad 0.000000 \quad 0.555556 \quad 0.222222 \quad 0.666667
               5\quad 0.\ 000000\quad 0.\ 000000\quad 0.\ 000000\quad 0.\ 1111111\quad 0.\ 000000\quad 0.\ 222222
                6 \quad 0. \ 111111 \quad 0. \ 000000 \quad 0. \ 000000 \quad 0. \ 000000 \quad 0. \ 111111 \quad 0. \ 000000 \quad 0. \ 222222 
               7
                 0.333333
                            0.000000 0.000000 0.222222 0.000000 0.000000
                                                                                 0.111111
               8
                  0.444444
                            0. 222222
                  0.777778
                            1.000000 1.000000 0.777778 0.555556 0.888889 0.222222
                               8
               0 0.333333 0.0
               1 0.000000 0.0
               2 0.000000 0.0
               3 0.000000 0.0
                 0.000000 0.0
```

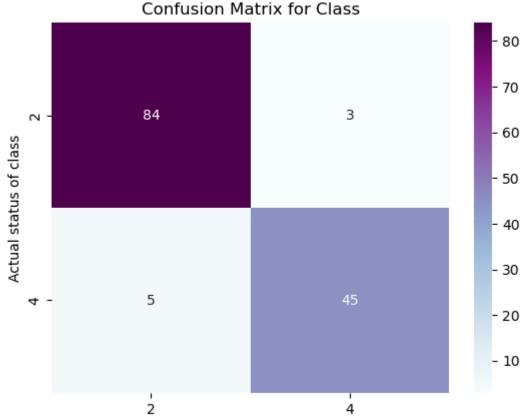
Training the Logistic Regression model on the Training Set

```
In [91]: # Training the Logistic Regression model on the Training Set from sklearn.linear_model import LogisticRegression modelLogistic = LogisticRegression(random_state = 0) modelLogistic.fit(X_train_normal, Y_train) #print the regression coefficients print("The intercept b0= ", modelLogistic.intercept_) print("The coefficient b1= ", modelLogistic.coef_)

The intercept b0= [-4.98497464]
The coefficient b1= [[2.31479863 1.46611995 1.60077767 1.37726984 1.35613885 2.76471853
1.92988752 1.80420999 0.74381706]]
```

Predicting the Test set results

```
In [92]:
                                 y test pred = modelLogistic.predict(X test normal)
                                          print(y test pred)
                                          print (np. concatenate ((y_test_pred.reshape (len(y_test_pred), 1), Y_test.reshape (len(Y_test_pred), 1), Y_
                                           [2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 2\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4
                                             4\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 2\ 2\ 4\ 2\ 2\ 2\ 4\ 4\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 2
                                             2\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 2\ 2\ 4\ 4\ 2\ 4\ 2\ 4\ 2\ 2\ 4\ 2\ 2\ 4\ 2]
                                           [[2 \ 2]]
                                              [2 \ 2]
                                             [4 \ 4]
                                             [4 \ 4]
                                              [2 2]
                                              [2 2]
                                              [2 \ 2]
                                              [4 \ 4]
                                              [2 2]
                                              [2 2]
                                              [4 \ 4]
                                              [2 \ 2]
                                              [4 \ 4]
                                              [2 \ 2]
                                              [2 \ 2]
In [98]:
                                 # Confusion Matrix
                                          from sklearn.metrics import confusion_matrix, accuracy_score
                                          ConfusionMatrix = confusion_matrix(Y_test, y_test_pred)
                                          print(ConfusionMatrix)
                                          ax = sns. heatmap (ConfusionMatrix, annot=True, cmap='BuPu')
                                          ax.set_title('Confusion Matrix for Class');
                                          ax.set_xlabel('Prediction made for Class')
                                          ax.set_ylabel('Actual status of class');
                                          ## Ticket labels - List must be in alphabetical order
                                          ax. xaxis. set_ticklabels(['2','4'])
                                          ax. yaxis. set_ticklabels(['2', '4'])
                                          ## Display the visualization of the Confusion Matrix.
                                          plt.show()
                                          [[84 3]
                                              [ 5 45]]
```



Prediction made for Class

```
In [99]: ▶ print(accuracy_score(Y_test, y_test_pred))
```

0.9416058394160584

The accuracy rate of 94.16% is very high, meaning the logistic regression model is the good and fitted model.

Try Standardization

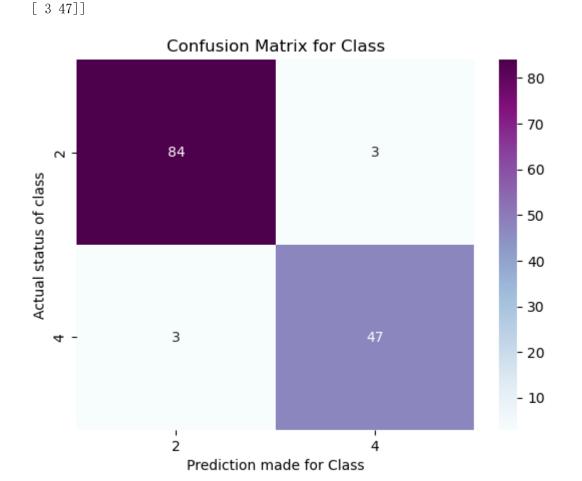
```
[94]:
                 # Try Standardization
                        from sklearn.preprocessing import StandardScaler
                        scaler2 = StandardScaler()
                        X_train_stand = scaler2.fit_transform(X_train)
                        X_test_stand = scaler2.fit_transform(X_test)
                        X_train_stand = pd.DataFrame(X_train_stand)
                        X test stand = pd. DataFrame(X test stand)
                        print("Standized X train:", X_train_stand.head(10))
                        print("Standized X test:", X_test_stand. head(10))
                        Standized X train:
                                                                                                            1
                                                                                                                                                                                                   5
                              1. 988395 -0. 697811 -0. 741526 -0. 633637 -0. 548720 1. 815536 0. 619074
                        0
                        1 \;\; -1.\; 224684 \;\; -0.\; 697811 \;\; -0.\; 741526 \;\; -0.\; 633637 \;\; -0.\; 997897 \;\; -0.\; 682796 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\; -0.\; 188607 \;\;
                        2\quad 0.\ 203351\ -0.\ 697811\ -0.\ 741526\ -0.\ 633637\ -0.\ 548720\ -0.\ 682796\ -0.\ 188607
                        3 - 0.510666 - 0.697811 - 0.404973 - 0.633637 - 0.548720 - 0.682796 - 0.592447
                        4 \quad 1.274378 \quad -0.372444 \quad -0.068420 \quad -0.633637 \quad 1.247988 \quad -0.127611 \quad 1.426754
                        5 - 1.224684 - 0.697811 - 0.741526 - 0.633637 - 0.548720 - 0.682796 - 0.188607
                        7 \ \ -0.\ 153658 \ \ -0.\ 697811 \ \ -0.\ 741526 \quad \  0.\ 075309 \ \ -0.\ 997897 \ \ -0.\ 682796 \ \ -0.\ 592447
                             0. 203351 1. 254392 1. 277791 -0. 633637 0. 798811
                                                                                                                                          1. 260351 -0. 188607
                              1. 274378 2. 230493 2. 287450 1. 847676 1. 247988 1. 537943 -0. 188607
                                              7
                        0 0.345321 -0.338637
                        1 -0.621578 -0.338637
                        2 -0.621578 -0.338637
                        3 -0.621578 -0.338637
                        4 -0.621578 -0.338637
                        5 -0.621578 -0.338637
                        6 -0.621578 -0.338637
                        7 -0.621578 -0.338637
                        8 0.345321 -0.338637
                        9 2. 279119 4. 765854
                                                                                                                                                                                                 5
                        Standized X test:
                        6 \
                        0 \;\; -1.\; 208343 \;\; -0.\; 720172 \;\; -0.\; 743031 \;\; -0.\; 663180 \;\; -0.\; 583582 \quad \  \, 0.\; 296005 \;\; -1.\; 012067 \\
                        1 \ \ -0.\ 515694 \ \ -0.\ 720172 \ \ -0.\ 743031 \ \ -0.\ 663180 \ \ -0.\ 583582 \ \ -0.\ 764196 \ \ -0.\ 582800
                        2 0. 176954 0. 604171 0. 570456 -0. 331590 0. 779214
                                                                                                                                          1.621257
                                                                                                                                                              0.275733
                        3 -0.169370 1.266343 1.555572 0.000000 0.324949
                                                                                                                                          1.621257
                                                                                                                                                               2.422067
                        4 - 1.208343 - 0.720172 - 0.743031 - 0.663180 - 0.583582 - 0.764196 - 1.012067
                         6 \quad 0.\ 176954 \ -0.\ 058000 \ -0.\ 743031 \ -0.\ 331590 \ -0.\ 583582 \ -0.\ 764196 \ -0.\ 582800 
                        7 1. 215927 2. 259601 2. 212316 2. 321129 1. 687745 0. 296005 0. 275733
                        8 \ -1.\ 208343 \ -0.\ 720172 \ -0.\ 743031 \quad 0.\ 000000 \ -1.\ 037847 \ -0.\ 234096 \ -1.\ 012067
                        9 \;\; -1.\; 208343 \;\; -0.\; 720172 \;\; -0.\; 743031 \;\; -0.\; 663180 \;\; -0.\; 583582 \;\; -0.\; 764196 \;\; -0.\; 582800
                                              7
                        0 -0.579728 -0.392731
                        1 -0.579728 -0.392731
                             0. 129403 -0. 392731
                        3 -0.579728 -0.392731
                        4 -0.579728 -0.392731
                        5 -0.579728 -0.392731
                        6 -0.579728 -0.392731
                        7 1.902231 3.361046
                        8 -0.579728 -0.392731
                        9 -0.579728 -0.392731
```

```
from sklearn.linear_model import LogisticRegression
                 modelLogistic2 = LogisticRegression(random state = 0)
                 modelLogistic2.fit(X_train_stand, Y_train)
                 #print the regression coefficients
                 print("The intercept b0= ", modelLogistic2.intercept_)
print("The coefficient b1= ", modelLogistic2.coef_)
                 The intercept b0= [-1.15196112]
                 The coefficient b1= [[1.14397509 0.19849412 0.58494288 0.64708178 0.51186677 1.3
                 058281
                   0. 98532234 0. 78902716 0. 43939809]]
In [96]:
             y_test_pred2 = modelLogistic2.predict(X_test_stand)
                 print(y_test_pred2)
                 print (np. concatenate ((y_test_pred2.reshape (len(y_test_pred2), 1), Y_test.reshape (len
                 [2\ 2\ 4\ 4\ 2\ 2\ 2\ 4\ 2\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4\ 4\ 4\ 2\ 2\ 2\ 4
                  4\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 2\ 2\ 4\ 2\ 2\ 2\ 4\ 4\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 4\ 2\ 2\ 2\ 2\ 2
                  2\ 2\ 4\ 2\ 2\ 2\ 2\ 2\ 2\ 4\ 2\ 2\ 4\ 4\ 2\ 4\ 2\ 4\ 2\ 2\ 4\ 2\ 2\ 4\ 2]
                 [[2 2]
                  [2 \ 2]
                  [4 \ 4]
                  [4 \ 4]
                  \begin{bmatrix} 2 & 2 \end{bmatrix}
                  [2 2]
                  [2 \ 2]
                  [4 \ 4]
                  [2 2]
                  \begin{bmatrix} 2 & 2 \end{bmatrix}
                  [4 \ 4]
                  [2 \ 2]
                  [4 \ 4]
```

🔰 # Training the Logistic Regression model on the Standized Training Set

In [95]:

[2 2] [2 2]



After standization, the accurcacy rate is higer than the normalization data, meaning the standardization is better than the normalization. (There are other possible factors that influence on the result, but I am not going to analyze so deeply here.)