## ENGR 421/DASC 521: Introduction to Machine Learning **Homework 2:** Multivariate Parametric Classification

**Deadline:** April 5, 2023, 11:59 PM

In this homework, you will implement a multivariate parametric classification using Python. Here are the steps you need to follow:

- 1. Read Chapter 5 from the textbook.
- 2. You are given a multivariate classification data set, which contains 5000 data points from a two-dimensional feature space. These data points are from five distinct classes, where we have 1000 data points from each class. You are provided with two data files:
  - a. hw02\_data\_points.csv: two-dimensional data points,
  - b. hw02\_class\_labels.csv: corresponding class labels.
- 3. Calculate the prior probability estimates  $\widehat{\Pr}(y=1), \widehat{\Pr}(y=2), \dots, \widehat{\Pr}(y=5)$  using the training data points. (10 points)

class\_priors = estimate\_prior\_probabilities(y\_train) print(class\_priors)

[0.2 0.2 0.2 0.2 0.2]

**Hint:** You can use the following equation to calculate the prior probability estimates.

$$\widehat{\Pr}(y=c) = \frac{\sum_{i=1}^{N} 1(y_i = c)}{N} = \frac{N_c}{N}$$

4. Calculate the class mean estimates  $\hat{\boldsymbol{\mu}}_1, \hat{\boldsymbol{\mu}}_2, \dots, \hat{\boldsymbol{\mu}}_5$  using the training data points. (20 points)

sample\_means = estimate\_class\_means(X\_train, y\_train) print(sample\_means)

[[ -6.64451313 -26.36348034]

[-42.59684357 -3.08704541]

[-15.33132145 34.74988518]

[ 35.28039812 28.29476758]

[ 29.29228003 -33.59412701]]

**Hint:** You can use the following equation to calculate the class mean estimates.

$$\hat{\boldsymbol{\mu}}_c = rac{\sum\limits_{i=1}^{N} \boldsymbol{x}_i 1(y_i = c)}{\sum\limits_{i=1}^{N} 1(y_i = c)}$$

5. Calculate the class covariance estimates  $\hat{\Sigma}_1, \hat{\Sigma}_2, \dots, \hat{\Sigma}_5$  using the training data points. (20 points)

```
sample_covariances = estimate_class_covariances(X_train, y_train)
print(sample_covariances)
```

```
[[[ 268.24169454 84.38622865]
  [ 84.38622865 165.60007039]]
  [[ 268.36399098 -79.36361871]
  [ -79.36361871 228.81216241]]
  [[ 257.88530822 107.48459802]
  [ 107.48459802 270.90303479]]
  [[ 390.64688372 -143.01194574]
  [-143.01194574 159.85719588]]
  [[ 62.29030005 8.10502983]
  [ 8.10502983 379.25858684]]]
```

**Hint:** You can use the following equation to calculate the class covariance estimates.

$$\hat{\boldsymbol{\Sigma}}_c = \frac{\sum_{i=1}^{N} (\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_c) (\boldsymbol{x}_i - \hat{\boldsymbol{\mu}}_c)^{\top} 1(y_i = c)}{\sum_{i=1}^{N} 1(y_i = c)}$$

6. Calculate the score values for the data points in your training and test sets using the estimated parameters. (30 points)

```
scores_train = calculate_score_values(X_train, sample_means, sample_covariances, class_priors)
print(scores_train)

[[-14.19538107 -22.10065254 -32.17093002 -22.95654712 -9.69739781]
        [-13.31824343 -21.10515229 -30.34378865 -22.68609467 -9.16710182]
        [-15.84197823 -20.97522186 -36.85943093 -35.44103047 -8.93068396]
        ...
        [-21.2864439 -33.52980121 -17.3443919 -9.47618622 -16.51638154]
        [-15.17110159 -24.16805014 -16.72250881 -9.40819221 -11.97010383]
        [-20.31293361 -31.85967687 -16.98927511 -9.1391833 -15.61253304]]
```

**Hint:** You can use the following equation to calculate the score values.

$$g_c(\boldsymbol{x}) = \log \hat{p}(\boldsymbol{x}|y=c) + \log \widehat{\Pr}(y=c)$$

$$= -\frac{D}{2}\log(2\pi) - \frac{1}{2}\log(|\hat{\boldsymbol{\Sigma}}_c|) - \frac{1}{2}(\boldsymbol{x} - \hat{\boldsymbol{\mu}}_c)^{\top} \hat{\boldsymbol{\Sigma}}_c^{-1}(\boldsymbol{x} - \hat{\boldsymbol{\mu}}_c) + \log \widehat{\Pr}(y=c)$$

7. Calculate the confusion matrix for the training data points using the calculated score values. (10 points)

```
confusion_train = calculate_confusion_matrix(y_train, scores_train)
  print(confusion_train)
  [[829 136
                      37]
               0
   [ 46 785 147
                   0
                       0]
   [ 0 79 791 135
                       07
   0
           0 62 865
                       0]
   [125
                   0 963]]
               0
           0
8. Calculate the shared covariance estimate \hat{\Sigma}_1 = \hat{\Sigma}_2 = \cdots = \hat{\Sigma}_5 = \hat{\Sigma} using the training
  data points. (10 points)
  sample_covariances = estimate_shared_class_covariance(X_train, y_train)
  print(sample_covariances)
  [[1088.7724787
                    -46.85767937]
    [ -46.85767937 1009.14155144]]
   [[1088.7724787
                     -46.85767937]
    [ -46.85767937 1009.14155144]]
   [[1088.7724787
                    -46.85767937]
    [ -46.85767937 1009.14155144]]
   [[1088.7724787
                     -46.85767937]
    [ -46.85767937 1009.14155144]]
                     -46.85767937]
   [[1088.7724787
    [ -46.85767937 1009.14155144]]]
  scores_train = calculate_score_values(X_train, sample_means,
                                           sample_covariances, class_priors)
  print(scores_train)
  [[-11.46793996 -13.90222671 -13.76045065 -12.04097548 -10.48248827]
   [-11.32991837 - 13.62530355 - 13.50637918 - 11.94332728 - 10.45947009]
   [-11.34232183 -13.92476829 -14.67342885 -13.22089383 -10.49857077]
   [-13.6968323 -14.84896905 -12.0931904 -10.47805967 -12.95656273]
   [-12.1627728 -13.33771435 -11.61361575 -10.46378924 -11.7028491 ]
   [-13.43558046 -14.56759373 -11.96475973 -10.44324505 -12.75521448]]
  confusion_train = calculate_confusion_matrix(y_train, scores_train)
  print(confusion_train)
  [[833 142
               0
                   0
                       3]
   [ 26 836 174
                       0]
   [ 0 22 804 148
                       0]
          0 22 852 69]
   [ 38
   [103
                   0 928]]
               0
           0
```

Hint: You can use the following equations to calculate the shared covariance estimate.

$$\hat{oldsymbol{\mu}} = rac{\sum\limits_{i=1}^{N} oldsymbol{x}_i}{N} \ \hat{oldsymbol{\Sigma}}_1 = \hat{oldsymbol{\Sigma}}_2 = \dots = \hat{oldsymbol{\Sigma}}_5 = \hat{oldsymbol{\Sigma}} = rac{\sum\limits_{i=1}^{N} (oldsymbol{x}_i - \hat{oldsymbol{\mu}}) (oldsymbol{x}_i - \hat{oldsymbol{\mu}})^ op}{N}$$

What to submit: You need to submit your source code in a single file (.py file). You are provided with a template file named as 0099999.py, where 99999 should be replaced with your 5-digit student number. You are allowed to change the template file between the following lines.

- # your implementation starts below
- # your implementation ends above

How to submit: Submit the file you edited to Blackboard by following the exact style mentioned. Submissions that do not follow these guidelines will not be graded.

Late submission policy: Late submissions will not be graded.

Cheating policy: Very similar submissions will not be graded.