

CS4044D Machine Learning Assignment 1

Submitted by: Namburi Soujanya, B180491CS

[Repo Link](#)

Question 1:

The below formula is implemented this way:

$$g_i(\mathbf{x}) = -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_i)^T \boldsymbol{\Sigma}_i^{-1}(\mathbf{x} - \boldsymbol{\mu}_i) - \frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\boldsymbol{\Sigma}_i| + \ln P(\omega_i).$$

```
def discriminant(x, mean, covariance, dimension, probability):
    #Check if it is univariate
    if dimension == 1:
        dis = (-0.5*(x - mean) * (1 / covariance))* (x-mean) -
0.5*log(2*pi) - 0.5*log(covariance)
    else:
        temp = np.matmul(-0.5*(x - mean), np.linalg.inv(covariance))
        dis = np.matmul(temp, (x-mean).T) -0.5*dimension*log(2*pi) -
0.5*log(np.linalg.det(covariance))
    if(probability == 0):
        return dis
    else:
        dis += log(probability)
    return dis
```

Initial check has been done to get rid of numpy errors (inverse of scalar quantities) when the data is has the dimension 1 (single feature), other errors can also be avoided with above conditions.

Other variables should also be initialised along with the data

```
dataclass = [
    [[-5.01, -8.12, -3.68], [-5.43, -3.48, -3.54], [1.08, -5.52,
1.66], [0.86, -3.78, -4.11], [-2.67, 0.63, 7.39], [4.94, 3.29, 2.08],
[-2.51, 2.09, -2.59], [-2.25, -2.13, -6.94], [5.56, 2.86, -2.26], [1.03,
-3.33, 4.33]],
    [[-0.91, -0.18, -0.05], [1.30, -2.06, -3.53], [-7.75, -4.54,
-0.95], [-5.47, 0.50, 3.92], [6.14, 5.72, -4.85], [3.60, 1.26, 4.36],
[5.37, -4.63, -3.65], [7.18, 1.46, -6.66], [-7.39, 1.17, 6.30], [-7.50,
-6.32, -0.31]],
    [[5.35, 2.26, 8.13], [5.12, 3.22, -2.66], [-1.34, -5.31,
-9.87], [4.48, 3.42, 5.19], [7.11, 2.39, 9.21], [7.17, 4.33, -0.98], [5.75,
3.97, 6.65], [0.77, 0.27, 2.41], [0.90, -0.43, -8.71], [3.52, -0.36, 6.43]]
```

```

    ]
    n = len(dataclasses)          # number of classes
    d = len(dataclasses[0][0])   # number of features

    #Assuming each class is equally probable
    probability = [1/n] * n

    #Find mean and covariance
    means = []                   # d-component mean vector
    covariance = []              # d by d covariance matrix for each set

    #Finding means in each column
    for sing in dataclasses:
        means.append(sing.mean(axis=0))
        covariance.append(np.cov(sing.T))

```

(Numpy functions can be used to find mean and covariance)

We can find the g vector using the code below and classify x to the class where g is maximum. Make sure to change the lists to numpy arrays.

```

for dataclass in dataclasses:
    k+=1
    print("The following data should be classified as: ", k)
    missed = 0
    count = 0
    for data in dataclass:
        gi = [0] * n           # each gi
        for i in range(n):
            gi[i] = discriminant(data, means[i], covariance[i], d,
probability[i])

        #find maximum g[i]
        maximum_indices = gi.index(max(gi)) + 1
        count+=1
        if(maximum_indices != k):
            missed += 1
        print(data, "\t classified as: \t", maximum_indices )
    print("Success: \t", ((count - missed) / count)*100 , "%")
    print("Failure: \t", ((missed) / count)*100 , "%")

```

This should be the following output:

```

~/Doc/ml_ass/Q1  P main !1 ?1  python main.py
The following data should be classified as:  1
[-5.01 -8.12 -3.68]      classified as:      1
[-5.43 -3.48 -3.54]      classified as:      1
[ 1.08 -5.52  1.66]      classified as:      1
[ 0.86 -3.78 -4.11]      classified as:      1
[-2.67  0.63  7.39]      classified as:      2
[4.94  3.29  2.08]       classified as:      3
[-2.51  2.09 -2.59]      classified as:      1
[-2.25 -2.13 -6.94]      classified as:      1
[ 5.56  2.86 -2.26]      classified as:      3
[ 1.03 -3.33  4.33]      classified as:      1
Success:      70.0 %
Failure:      30.0 %
The following data should be classified as:  2
[-0.91 -0.18 -0.05]      classified as:      2
[ 1.3  -2.06 -3.53]      classified as:      3
[-7.75 -4.54 -0.95]      classified as:      2
[-5.47  0.5   3.92]      classified as:      2
[ 6.14  5.72 -4.85]      classified as:      2
[3.6   1.26  4.36]       classified as:      3
[ 5.37 -4.63 -3.65]      classified as:      2
[ 7.18  1.46 -6.66]      classified as:      2
[-7.39  1.17  6.3 ]      classified as:      2
[-7.5  -6.32 -0.31]      classified as:      2
Success:      80.0 %
Failure:      20.0 %
The following data should be classified as:  3
[5.35  2.26  8.13]       classified as:      3
[ 5.12  3.22 -2.66]      classified as:      3
[-1.34 -5.31 -9.87]      classified as:      3
[4.48  3.42  5.19]       classified as:      3
[7.11  2.39  9.21]       classified as:      3
[ 7.17  4.33 -0.98]      classified as:      3
[5.75  3.97  6.65]       classified as:      3
[0.77  0.27  2.41]       classified as:      1
[ 0.9  -0.43 -8.71]      classified as:      3
[ 3.52 -0.36  6.43]      classified as:      3
Success:      90.0 %
Failure:      10.0 %
~/Doc/ml_ass/Q1  P main !1 ?1

```

Question 2:

Part a and b:

Change the probability from $[1/n, 1/n, 1/n]$ to $[0.5, 0.5, 0]$ Change the inputs accordingly. (Remove other features except x_1)

Failure percentage is the percentage of points misclassified This is the expected output:

```

~/Doc/ml_ass/Q2  main 12 ?1  python ab.py
The following data should be classified as:  1
[-5.01]      classified as:  1
[-5.43]      classified as:  2
[1.08]       classified as:  1
[0.86]       classified as:  1
[-2.67]      classified as:  1
[4.94]       classified as:  2
[-2.51]      classified as:  1
[-2.25]      classified as:  1
[5.56]       classified as:  2
[1.03]       classified as:  1
Success:      70.0 %
Failure:      30.0 %
The following data should be classified as:  2
[-0.91]      classified as:  1
[1.3]        classified as:  1
[-7.75]      classified as:  2
[-5.47]      classified as:  2
[6.14]       classified as:  2
[3.6]        classified as:  1
[5.37]       classified as:  2
[7.18]       classified as:  2
[-7.39]      classified as:  2
[-7.5]       classified as:  2
Success:      70.0 %
Failure:      30.0 %
The following data should be classified as:  3
[5.35]       classified as:  2
[5.12]       classified as:  2
[-1.34]      classified as:  1
[4.48]       classified as:  2
[7.11]       classified as:  2
[7.17]       classified as:  2
[5.75]       classified as:  2
[0.77]       classified as:  1
[0.9]        classified as:  1
[3.52]       classified as:  1
Success:      0.0 %
Failure:     100.0 %

```

Part C:

Change the inputs accordingly. (Remove other features except x_1 and x_2)

Failure percentage is the percentage of points misclassified This is the expected output:

```

~/Doc/ml_ass/Q2  main !2 ?2  python c.py
The following data should be classified as: 1
[-5.01 -8.12]    classified as:      1
[-5.43 -3.48]    classified as:      2
[ 1.08 -5.52]    classified as:      1
[ 0.86 -3.78]    classified as:      1
[-2.67  0.63]    classified as:      2
[4.94  3.29]     classified as:      2
[-2.51  2.09]    classified as:      2
[-2.25 -2.13]    classified as:      1
[5.56  2.86]     classified as:      2
[ 1.03 -3.33]    classified as:      1
Success:         50.0 %
Failure:         50.0 %
The following data should be classified as: 2
[-0.91 -0.18]    classified as:      1
[ 1.3  -2.06]     classified as:      1
[-7.75 -4.54]    classified as:      2
[-5.47  0.5 ]     classified as:      2
[6.14  5.72]     classified as:      2
[3.6   1.26]     classified as:      1
[ 5.37 -4.63]    classified as:      2
[7.18  1.46]     classified as:      2
[-7.39  1.17]    classified as:      2
[-7.5  -6.32]    classified as:      1
Success:         60.0 %
Failure:         40.0 %
The following data should be classified as: 3
[5.35  2.26]     classified as:      2
[5.12  3.22]     classified as:      2
[-1.34 -5.31]    classified as:      1
[4.48  3.42]     classified as:      1
[7.11  2.39]     classified as:      2
[7.17  4.33]     classified as:      2
[5.75  3.97]     classified as:      2
[0.77  0.27]     classified as:      1
[ 0.9  -0.43]    classified as:      1
[ 3.52 -0.36]    classified as:      1
Success:         0.0 %
Failure:        100.0 %

```

Part D:

Change the inputs accordingly. Use all features. This is the expected output:

```

~/Doc/ml_ass/Q2  P main 12 ?2  python d.py
The following data should be classified as: 1
[-5.01 -8.12]    classified as:      1
[-5.43 -3.48]    classified as:      2
[ 1.08 -5.52]    classified as:      1
[ 0.86 -3.78]    classified as:      1
[-2.67  0.63]    classified as:      2
[4.94  3.29]     classified as:      2
[-2.51  2.09]    classified as:      2
[-2.25 -2.13]    classified as:      1
[5.56  2.86]     classified as:      2
[ 1.03 -3.33]    classified as:      1
Success:         50.0 %
Failure:         50.0 %
The following data should be classified as: 2
[-0.91 -0.18]    classified as:      1
[ 1.3  -2.06]    classified as:      1
[-7.75 -4.54]    classified as:      2
[-5.47  0.5 ]    classified as:      2
[6.14  5.72]     classified as:      2
[3.6   1.26]     classified as:      1
[ 5.37 -4.63]    classified as:      2
[7.18  1.46]     classified as:      2
[-7.39  1.17]    classified as:      2
[-7.5  -6.32]    classified as:      1
Success:         60.0 %
Failure:         40.0 %
The following data should be classified as: 3
[5.35  2.26]     classified as:      2
[5.12  3.22]     classified as:      2
[-1.34 -5.31]    classified as:      1
[4.48  3.42]     classified as:      1
[7.11  2.39]     classified as:      2
[7.17  4.33]     classified as:      2
[5.75  3.97]     classified as:      2
[0.77  0.27]     classified as:      1
[ 0.9  -0.43]    classified as:      1
[ 3.52 -0.36]    classified as:      1
Success:         0.0 %
Failure:        100.0 %

```

Part E:

Comparing all the outputs, it is evident that using x1 is better than the other 2 cases. Reason could be higher covariance

Part F:

Similar to the questions above, we could consider 3 cases:

1. Only x_1 is considered
2. Both x_1 and x_2 are considered
3. All the features are considered

We use the covariance and mean matrices of the data given above

```
ix = [[1, 2, 1], [5, 3, 2], [0, 0, 0], [1, 0, 0]]
```

```
for ip in ix:
    print("Case 1: Considering 1 feature: ")
    d = 1
    for i in range(n):
        g[i] = discriminant(ip[0], means[i][0], covariance[i][0][0], d,
probability[i])
    maximum_indices = g.index(max(g)) + 1
    print(ip, "\t classified as: \t", maximum_indices )
    print("Case 2: Considering 2 features: ")
    d = 2
    for i in range(n):
        g[i] = discriminant(ip[0:2], means[i][0:2], covariance[i][0:2,
0:2], d, probability[i])
    maximum_indices = g.index(max(g)) + 1
    print(ip, "\t classified as: \t", maximum_indices )
    print("Case 3: Considering 3 features: ")
    d = 3
    for i in range(n):
        g[i] = discriminant(ip, means[i], covariance[i], d, probability[i])
    maximum_indices = g.index(max(g)) + 1
    print(ip, "\t classified as: \t", maximum_indices )
```

This is the output:

```
python f.py
Case 1: Considering 1 feature:
[1, 2, 1]      classified as:      3
Case 2: Considering 2 features:
[1, 2, 1]      classified as:      1
Case 3: Considering 3 features:
[1, 2, 1]      classified as:      2
-----
Case 1: Considering 1 feature:
[5, 3, 2]      classified as:      3
Case 2: Considering 2 features:
[5, 3, 2]      classified as:      3
Case 3: Considering 3 features:
[5, 3, 2]      classified as:      3
-----
Case 1: Considering 1 feature:
[0, 0, 0]      classified as:      3
Case 2: Considering 2 features:
[0, 0, 0]      classified as:      1
Case 3: Considering 3 features:
[0, 0, 0]      classified as:      1
-----
Case 1: Considering 1 feature:
[1, 0, 0]      classified as:      3
Case 2: Considering 2 features:
[1, 0, 0]      classified as:      3
Case 3: Considering 3 features:
[1, 0, 0]      classified as:      3
-----
```