

Question 1:

```
function Lpred = myBayesPredict(Dtrain, Ltrain, Dtest, opt)

%% 1. Use Naive Bayes Function to Make classification
if opt==1
NB = fitcnb(Dtrain,Ltrain); % construct a Naive Bayes model NB
Lpred = predict(NB, Dtest); % apply the trained model NB to predict
class of test samples in Dtest
end

%% 2. Use the discriminant function  $G(x) = \text{likelihood} \times \text{prior}$  for
classification

if opt==2
    C = unique(Ltrain);
    Lpred = [];

    for iC = 1:length(C) % For each class i, calculate  $P(X|W_j)P(W_j)$  for
all testing samples
        cl = C(iC);
        idx = find(Ltrain==cl);
        data = Dtrain(idx,:);
        mu = mean(data); % feature mean vector
        sigma = cov(data); % feature covariance matrix
        P = length(idx)/length(Ltrain);

        % For each testing sample, calculate  $P(X|W_j)P(W_j) = \text{likelihood of}$ 
class i * prior of class i
        for j = 1:size(Dtest,1)
            x = Dtest(j, :);
            likelihood = mvnpdf(x,mu,sigma); % likelihood of the current
class i
            prior = P; % prior of the current class i

            % Record values of the discriminat function G(X)
            % In the following matrix G, each row represent a class, and
            % each column represent a testing sample
            G(iC, j) = likelihood*prior; %  $P(X|W_j)P(W_j)$ 
        end
    end

    % For each testing sample, find the index of the class that have
maximum
    % value of likelihood*prior
    [~, pred] = max(G);
    Lpred = C(pred);
end
```

```

%% 3. Use the derived discriminant function G(x) for classification
% based on the the assumption of Multivariate Normal Distribution for
features
if opt==3
    C = unique(Ltrain);
    Lpred = [];

    for iC = 1:length(C)
        cl = C(iC);
        idx = find(Ltrain==cl);
        data = Dtrain(idx,:);

        mu = mean(data)';
        sigma = cov(data);
        P = length(idx)/length(Ltrain);
        W = -0.5*inv(sigma);
        w = inv(sigma)*mu;
        w0 = -0.5*mu'*inv(sigma)*mu-0.5*log(det(sigma))+log(P);

        for j = 1:size(Dtest,1)
            x = Dtest(j, :)';
            % The closed form of the derived discriminant function G(X)
            G(iC, j) = x'*W*x + w'*x + w0;
        end
    end

    [~, pred] = max(G);
    Lpred = C(pred);

end

```

Results:

Confusion matrix for fold 1

| 1 | 2 | 3 |
|----|----|----|
| 10 | 0 | 0 |
| 0 | 10 | 0 |
| 0 | 0 | 10 |

Confusion matrix for fold 2

| 1 | 2 | 3 |
|----|----|----|
| 10 | 0 | 0 |
| 0 | 10 | 0 |
| 0 | 0 | 10 |

Confusion matrix for fold 3

| 1 | 2 | 3 |
|----|---|----|
| 10 | 0 | 0 |
| 0 | 9 | 1 |
| 0 | 0 | 10 |

Confusion matrix for fold 4

| 1 | 2 | 3 |
|----|---|---|
| 10 | 0 | 0 |
| 0 | 9 | 1 |
| 0 | 1 | 9 |

Confusion matrix for fold 5

| 1 | 2 | 3 |
|----|----|----|
| 10 | 0 | 0 |
| 0 | 10 | 0 |
| 0 | 0 | 10 |

Overall confusion matrix

| 1 | 2 | 3 |
|----|----|----|
| 50 | 0 | 0 |
| 0 | 48 | 2 |
| 0 | 1 | 49 |

Accuracy for 5 folds

| 1 |
|--------|
| 1 |
| 1 |
| 0.9667 |
| 0.9333 |
| 1 |

Overall average accuracy

| 1 | 2 |
|--------|---|
| 0.9800 | |
| | |

Accuracy for Bayesian option 1,2 and 3

| 1 | 2 |
|---|--------|
| 1 | 0.9533 |
| 2 | 0.9800 |
| 3 | 0.9800 |

Question 2:

```
function [Lpred, w] = FishersLDA(Dtrain, Ltrain, Dtest, lambda)
% Binary Classification using Fisher's linear discriminant
if (nargin<3 || isempty(lambda))
    lambda = [0 1; 1 0];
end

%-----Fisher Linear Discriminant-----%
idx1 = find(Ltrain==1); % the index for class 1
idx2 = find(Ltrain==2); % the index for class 2
Dtrain_c1 = Dtrain(idx1, :); % the training samples of class 1
Dtrain_c2 = Dtrain(idx2, :); % the training samples of class 2

N_c1 = length(idx1); % the number of samples in class 1
N_c2 = length(idx2); % the number of samples in class 2

sigma1 = cov(Dtrain_c1);
mu1 = mean(Dtrain_c1);

sigma2 = cov(Dtrain_c2);
mu2 = mean(Dtrain_c2);
Sw = sigma1 + sigma2;

%% The optimal direction w for sample projection:
w = inv(Sw)*(mu1-mu2)';

%-----The Projected Data-----%
Dtrain_new = Dtrain*w; % Projected training data
Ltrain_new = Ltrain; % Training data label
Dtest_new = Dtest*w; % Projected testing data

Dtrain_new_c1 = Dtrain_new(idx1, :); % projected training samples of
class 1
Dtrain_new_c2 = Dtrain_new(idx2, :); % projected training samples of
class 2

mu1_new = mean(Dtrain_new_c1); % mean of projected samples of class 1
mu2_new = mean(Dtrain_new_c2);

sigma1_new = std(Dtrain_new_c1); % standard deviation of projected
samples of class 1
sigma2_new = std(Dtrain_new_c2);

Ntest = size(Dtest, 1);
Lpred = [];

for i = 1:Ntest
    feat = Dtest_new(i);
    prior1 = length(idx1)/length(Ltrain);
```

```

        likelihood1 = normpdf(feat, mu1_new, sigma1_new); % likelihood of
the current class 1
        prior2 = length(idx2)/length(Ltrain);
        likelihood2 = normpdf(feat, mu2_new, sigma2_new); % likelihood of
the current class 2

        if (likelihood1/likelihood2) > (lambda(1,2)-
lambda(2,2))/(lambda(2,1)-lambda(1,1))*(prior2/prior1);
            pred = 1;
        else
            pred = 2;
        end

        Lpred(i,1) = pred;
    end
end

```

Results:**lambda = [0 1; 1 0]**

5 fold accuracy

| 1 |
|--------|
| 0.6087 |
| 0.6250 |
| 0.6957 |
| 0.6522 |
| 0.4783 |

Sensitivity and specificity

| 1 | 2 |
|--------|--------|
| 0.3000 | 0.8462 |
| 0.3636 | 0.8462 |
| 0.5000 | 0.8462 |
| 0.7000 | 0.6154 |
| 0.9091 | 0.0833 |

Overall accuracy

| 1 |
|--------|
| 0.6120 |

lambda = [0 5; 1 0]

Accuracy for 5 folds

| 1 |
|--------|
| 0.5652 |
| 0.5652 |
| 0.5417 |
| 0.5417 |
| 0.5000 |

Sensitivity and specificity

| 1 | 2 |
|--------|--------|
| 0 | 1 |
| 0 | 1 |
| 0 | 1 |
| 0 | 1 |
| 0.4000 | 0.5833 |

Overall accuracy

| 1 |
|--------|
| 0.5428 |