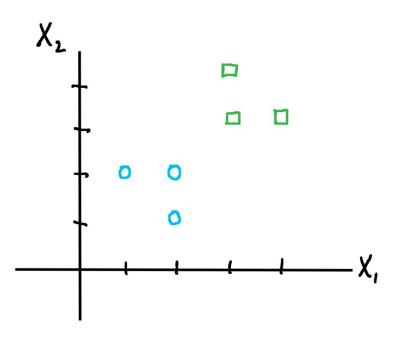
Solution Set: Linear Discriminant Analysis

1. Here is a graph of the data points:



The number of features p is 2, the number of classes K is 2, the total number of data points N is 6, the number  $N_1$  of data points in class  $k_1$  is 3, and the number  $N_2$  of data points in class  $k_2$  is 3.

First, we will find estimates for  $\pi_1$  and  $\pi_2$ , the prior probabilities that  $Y = k_1$  and  $Y = k_2$ , respectively.

Then, we will find estimates for  $\mu_1$  and  $\mu_2$ , the class-specific mean vectors.

We can then calculate the estimate for the covariance matrix  $\Sigma$ .

Finally, using the estimates  $\widehat{\pi_1}$ ,  $\widehat{\pi_2}$ ,  $\widehat{\mu_1}$ ,  $\widehat{\mu_2}$ ,  $\widehat{\Sigma}$ , we can find the estimates for the linear discriminant functions  $\delta_1(x)$  and  $\delta_2(x)$ .

$$\widehat{\pi_1} = \frac{N_1}{N} = \frac{3}{6} = \frac{1}{2}$$

$$\widehat{\pi_2} = \frac{N_2}{N} = \frac{3}{6} = \frac{1}{2}$$

$$\widehat{\mu_1} = \frac{1}{N_1} \sum_{i:y_i=1}^{N} x_i = \frac{1}{3} [x_1 + x_2 + x_3] = \begin{bmatrix} \frac{5}{3} \\ \frac{5}{3} \\ \frac{5}{3} \end{bmatrix}$$

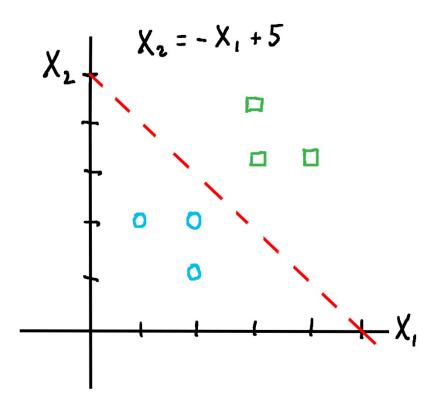
$$\begin{aligned} \widehat{\mu_2} &= \frac{1}{N_2} \sum_{i:y_i=2} x_i = \frac{1}{3} [x_4 + x_5 + x_6] = \begin{bmatrix} \frac{10}{3} \\ \frac{10}{3} \end{bmatrix} \\ \widehat{\Sigma} &= \frac{1}{N - K} \sum_{k=1}^{K} \sum_{i:y_i=k} (x_i - \widehat{\mu_k}) (x_i - \widehat{\mu_k})^T \\ &= \frac{1}{6-2} \begin{bmatrix} 12/9 & -6/9 \\ -6/9 & 12/9 \end{bmatrix} = \begin{bmatrix} 1/3 & -1/6 \\ -1/6 & 1/3 \end{bmatrix} \\ \implies \qquad \widehat{\Sigma}^{-1} &= \begin{bmatrix} 4 & 2 \\ 2 & 4 \end{bmatrix} \end{aligned}$$

$$\widehat{\delta_1}(x) = x^T \widehat{\Sigma}^{-1} \widehat{\mu_1} - \frac{1}{2} \widehat{\mu_1}^T \widehat{\Sigma}^{-1} \widehat{\mu_1} + \log \widehat{\pi_1}$$
$$= x^T \begin{bmatrix} 10\\10 \end{bmatrix} - \frac{1}{2} \begin{pmatrix} 100\\3 \end{pmatrix} + \log \frac{1}{2}$$
$$= 10X_1 + 10X_2 - \frac{50}{3} + \log \frac{1}{2}$$

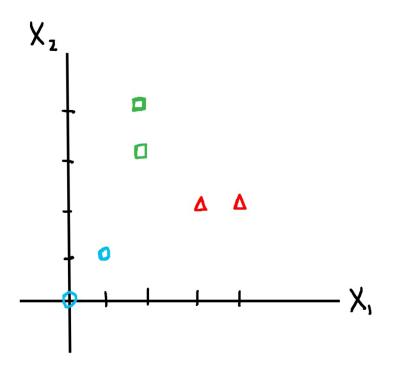
$$\begin{split} \widehat{\delta_2}(x) &= x^T \widehat{\Sigma}^{-1} \widehat{\mu_2} - \frac{1}{2} \widehat{\mu_2}^T \widehat{\Sigma}^{-1} \widehat{\mu_2} + \log \widehat{\pi_2} \\ &= x^T \begin{bmatrix} 20 \\ 20 \end{bmatrix} - \frac{1}{2} \Big( \frac{400}{3} \Big) + \log \frac{1}{2} \\ &= 20X_1 + 20X_2 - \frac{200}{3} + \log \frac{1}{2} \end{split}$$

Setting 
$$\widehat{\delta_1}(x) = \widehat{\delta_2}(x)$$
  
 $\Rightarrow \quad 10X_1 + 10X_2 - \frac{50}{3} + \log \frac{1}{2} = 20X_1 + 20X_2 - \frac{200}{3} + \log \frac{1}{2}$   
 $\Rightarrow \quad \frac{150}{3} = 10X_1 + 10X_2$   
 $\Rightarrow \quad 50 = 10X_1 + 10X_2$   
 $\Rightarrow \quad 5 = X_1 + X_2$   
 $\Rightarrow \quad -X_1 + 5 = X_2$ 

So, the line that decides between the two classes is given by  $X_2 = -X_1 + 5$ . Here is a graph of the decision line:



If  $\widehat{\delta_1}(x) > \widehat{\delta_2}(x)$ , then we classify x as of class  $k_1$ . So if x is below the line  $X_2 = -X_1 + 5$ , then we classify x as of class  $k_1$ . Conversely, if  $\widehat{\delta_1}(x) < \widehat{\delta_2}(x)$ , then we classify x as of class  $k_2$ . This corresponds to x being above the line  $X_2 = -X_1 + 5$ . The point (4, 5) is above the line; so we classify it as of class  $k_2$ . 2. Here is a graph of the data points:



The number of features p is 2, the number of classes K is 3, the total number of data points N is 6, the number  $N_1$  of data points in class  $k_1$  is 2, the number  $N_2$  of data points in class  $k_2$  is 2, and the number  $N_3$  of data points in class  $k_3$  is 2.

First, we will find estimates for  $\pi_1$ ,  $\pi_2$ ,  $\pi_3$ , the prior probabilities that  $Y = k_1$ ,  $Y = k_2$ ,  $Y = k_3$ , respectively.

Then, we will find estimates for  $\mu_1$ ,  $\mu_2$ ,  $\mu_3$ , the class-specific mean vectors.

We can then calculate the estimate for the covariance matrix  $\Sigma$ .

Finally, using the estimates  $\widehat{\pi_1}, \widehat{\pi_2}, \widehat{\pi_3}, \widehat{\mu_1}, \widehat{\mu_2}, \widehat{\mu_3}, \widehat{\Sigma}$ , we can find the estimates for the linear discriminant functions  $\delta_1(x), \delta_2(x)$ , and  $\delta_3(x)$ .

$$\begin{aligned} \widehat{\pi_1} &= \frac{N_1}{N} = \frac{2}{6} = \frac{1}{3} \\ \widehat{\pi_2} &= \frac{N_2}{N} = \frac{2}{6} = \frac{1}{3} \\ \widehat{\pi_3} &= \frac{N_3}{N} = \frac{2}{6} = \frac{1}{3} \end{aligned}$$

$$\widehat{\mu_1} &= \frac{1}{N_1} \sum_{i:y_i=1} x_i = \frac{1}{2} [x_1 + x_2] = \begin{bmatrix} 1/2\\1/2 \end{bmatrix}$$

$$\widehat{\mu_2} &= \frac{1}{N_2} \sum_{i:y_i=2} x_i = \frac{1}{2} [x_3 + x_4] = \begin{bmatrix} 2\\7/2 \end{bmatrix}$$

$$\widehat{\mu_{3}} = \frac{1}{N_{3}} \sum_{i:y_{i}=3} x_{i} = \frac{1}{2} [x_{5} + x_{6}] = \begin{bmatrix} 7/2 \\ 2 \end{bmatrix}$$

$$\widehat{\Sigma} = \frac{1}{N - K} \sum_{k=1}^{K} \sum_{i:y_{i}=k} (x_{i} - \widehat{\mu_{k}}) (x_{i} - \widehat{\mu_{k}})^{T}$$

$$= \frac{1}{6-3} \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/6 \\ 1/6 & 1/3 \end{bmatrix}$$

$$\implies \widehat{\Sigma}^{-1} = \begin{bmatrix} 4 & -2 \\ -2 & 4 \end{bmatrix}$$

$$\widehat{\delta_{1}}(x) = x^{T} \widehat{\Sigma}^{-1} \widehat{\mu_{1}} - \frac{1}{2} \widehat{\mu_{1}}^{T} \widehat{\Sigma}^{-1} \widehat{\mu_{1}} + \log \widehat{\pi_{1}}$$
$$= x^{T} \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \frac{1}{2} (1) + \log \frac{1}{3}$$
$$= X_{1} + X_{2} - \frac{1}{2} + \log \frac{1}{3}$$

$$\widehat{\delta_2}(x) = x^T \widehat{\Sigma}^{-1} \widehat{\mu_2} - \frac{1}{2} \widehat{\mu_2}^T \widehat{\Sigma}^{-1} \widehat{\mu_2} + \log \widehat{\pi_2}$$
$$= x^T \begin{bmatrix} 1\\10 \end{bmatrix} - \frac{1}{2} (37) + \log \frac{1}{3}$$
$$= X_1 + 10X_2 - \frac{37}{2} + \log \frac{1}{3}$$

$$\widehat{\delta_3}(x) = x^T \widehat{\Sigma}^{-1} \widehat{\mu_3} - \frac{1}{2} \widehat{\mu_3}^T \widehat{\Sigma}^{-1} \widehat{\mu_3} + \log \widehat{\pi_3}$$
$$= x^T \begin{bmatrix} 10\\1 \end{bmatrix} - \frac{1}{2} (37) + \log \frac{1}{3}$$
$$= 10X_1 + X_2 - \frac{37}{2} + \log \frac{1}{3}$$

Setting 
$$\widehat{\delta_1}(x) = \widehat{\delta_2}(x)$$
  
 $\Rightarrow \quad X_1 + X_2 - \frac{1}{2} + \log \frac{1}{3} = X_1 + 10X_2 - \frac{37}{2} + \log \frac{1}{3}$   
 $\Rightarrow \quad 18 = 9X_2$   
 $\Rightarrow \quad 2 = X_2$ 

So, the line that decides between classes  $k_1$  and  $k_2$  is given by  $X_2 = 2$ .

Setting 
$$\widehat{\delta_1}(x) = \widehat{\delta_3}(x)$$
  

$$\Rightarrow \quad X_1 + X_2 - \frac{1}{2} + \log \frac{1}{3} = 10X_1 + X_2 - \frac{37}{2} + \log \frac{1}{3}$$

$$\Rightarrow \quad 18 = 9X_1$$

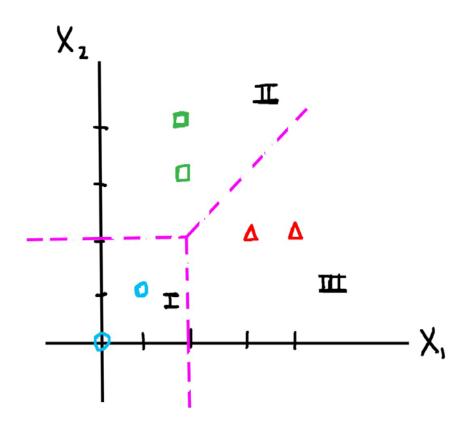
$$\Rightarrow \quad 2 = X_1$$

So, the line that decides between classes  $k_1$  and  $k_3$  is given by  $X_1 = 2$ .

Setting 
$$\widehat{\delta_2}(x) = \widehat{\delta_3}(x)$$
  
 $\Rightarrow \quad X_1 + 10X_2 - \frac{37}{2} + \log \frac{1}{3} = 10X_1 + X_2 - \frac{37}{2} + \log \frac{1}{3}$   
 $\Rightarrow \quad 9X_2 = 9X_1$   
 $\Rightarrow \quad X_2 = X_1$ 

So, the line that decides between classes  $k_2$  and  $k_3$  is given by  $X_2 = X_1$ .

Here is a graph of the decision lines:



The lines divide the plane into 3 regions.

If x is in region I, then we classify x as of class  $k_1$ . Similarly, points in region II get classified as of  $k_2$ , and points in region III get classified as of  $k_3$ .

The point (3, 0) is in region III; so we classify it as of class  $k_3$ .