

Group member

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Solution 4.1

We know the decision rule for a MAP classifier is $w_{opt} = \arg \max_{w_k} P(w_k | x)$ and discriminant function is

$$\begin{aligned} g_i(x) &= P(w_i | x) \\ &= P(x | w_i) P(w_i) \end{aligned}$$

We can use log function as it is increasing monotonically

$$g_i(x) = \log P(x | w_i) + \log P(w_i)$$

For two class decision boundary is

$$g_i(x) = g_j(x)$$

$$\therefore \log P(x | w_i) + \log P(w_i) = \log P(x | w_j) + \log P(w_j)$$

if $\log P(w_i) = \log P(w_j)$, we get

$$\log P(x | w_i) = \log P(x | w_j)$$

$$\Rightarrow \log P(x | w_i) - \log P(x | w_j) = 0$$

$$\Rightarrow \log \frac{P(x | w_i)}{P(x | w_j)} = 0$$

So, The special required condition is the prior probability have to be equal.

Solution - 4.2

Here,

$$\omega_1 = \{ (3, 8), (2, 6), (3, 4), (4, 6) \}$$

$$\omega_2 = \{ (3, 0), (3, -4), (1, -2), (5, -2) \}$$

$$\mu_1 = \begin{pmatrix} 3 \\ 6 \end{pmatrix}, \quad \Sigma_1 = \begin{pmatrix} 1/2 & 0 \\ 0 & 2 \end{pmatrix}, \quad \Sigma_1^{-1} = \begin{pmatrix} 2 & 0 \\ 0 & 1/2 \end{pmatrix}$$

$$\mu_2 = \begin{pmatrix} 3 \\ -2 \end{pmatrix}, \quad \Sigma_2 = \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix}, \quad \Sigma_2^{-1} = \begin{pmatrix} 1/2 & 0 \\ 0 & 1/2 \end{pmatrix}$$

Here, $\Sigma = \frac{1}{2n} \sum_i^n (x_i - \bar{x})(y_i - \bar{y})$

$$\det \Sigma_1 = 1, \quad \det \Sigma_2 = 4$$

Discriminant function's

$$g_1(x) = \ln p(x|\omega_1) + \ln(\omega_1)$$

$$g_2(x) = \ln p(x|\omega_2) + \ln(\omega_2)$$

and $g_1(x) = g_2(x)$

$$\Rightarrow \ln p(x|\omega_1) = \ln p(x|\omega_2) \quad [\because \ln(\omega_1) = \ln(\omega_2)]$$

We know for multivariate normal density

$$p(x|\omega) = \frac{1}{\sqrt{(2\pi)^2 \cdot |\Sigma|}} e^{-\frac{1}{2} (x-\mu)^T \cdot \Sigma^{-1} \cdot (x-\mu)}$$

$$\ln p(x|\omega) = -1/2 \ln[(2\pi)^2 \cdot \det(\Sigma)] - \frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu) \cdot \ln e$$

$$\begin{aligned} \therefore \ln p(x|\omega_1) &= -1/2 \left\{ \ln[(2\pi)^2] + \ln(1) + (x-\mu_1)^T \Sigma_1^{-1} (x-\mu_1) \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 3 \\ 6 \end{pmatrix} \right)^T \begin{pmatrix} 2 & 0 \\ 0 & 1/2 \end{pmatrix} \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 3 \\ 6 \end{pmatrix} \right) \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + \left(2(x_1-3) + \frac{1}{2}(x_2-6) \right) \begin{pmatrix} x_1-3 \\ x_2-6 \end{pmatrix} \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + 2(x_1-3)^2 + \frac{1}{2}(x_2-6)^2 \right\} \end{aligned}$$

Again,

$$\begin{aligned} \ln p(x|\omega_2) &= -1/2 \left\{ \ln(2\pi)^2 + \ln(4) + (x-\mu_2)^T \Sigma_2^{-1} (x-\mu_2) \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + \ln(4) + \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 3 \\ -2 \end{pmatrix} \right)^T \begin{pmatrix} 1/2 & 0 \\ 0 & 1/2 \end{pmatrix} \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 3 \\ -2 \end{pmatrix} \right) \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + \ln(4) + \left(\frac{1}{2}(x_1-3) + \frac{1}{2}(x_2+2) \right) \begin{pmatrix} x_1-3 \\ x_2+2 \end{pmatrix} \right\} \\ &= -1/2 \left\{ \ln(2\pi)^2 + \ln(4) + \frac{1}{2}(x_1-3)^2 + \frac{1}{2}(x_2+2)^2 \right\} \end{aligned}$$

$$\ln p(x|w_1) = \ln p(x|w_2)$$

$$\Rightarrow -1/2 \left\{ \ln(2\pi)^2 + 2(x_1-3)^2 + \frac{1}{2}(x_2-6)^2 \right\} = -1/2 \left\{ \ln(2\pi)^2 + \ln(u) + \frac{1}{2}(x_1-3)^2 + \frac{1}{2}(x_2+2)^2 \right\}$$

$$\Rightarrow 2(x_1-3)^2 + \frac{1}{2}(x_2-6)^2 = \ln(u) + \frac{1}{2}(x_1-3)^2 + \frac{1}{2}(x_2+2)^2$$