

$$P(x|\mu_i, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i)\right)$$

$$\Sigma = I$$

Let the discriminant function be

$$g_i(x) = \log(P(x|\mu_i, \Sigma))$$

$$g_i(x) = \log\left[\frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i)\right)\right]$$

$$= -\frac{1}{2}(x-\mu_i)^T \Sigma^{-1} (x-\mu_i) - \frac{d}{2} \log(2\pi) - \frac{1}{2} \log(|\Sigma|)$$

$$g_1(x) = -\frac{1}{2} \left[ \begin{bmatrix} 0.5 \\ 0.25 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \right]^T \cdot I \cdot \left[ \begin{bmatrix} 0.5 \\ 0.25 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \right] -$$

this is same for all discriminant so can be ignored

$$\frac{3}{2} \log(2\pi) - \frac{1}{2} \log(1)$$

$$= -\frac{1}{2} \begin{bmatrix} -0.5 & 0.25 & 1 \end{bmatrix} \begin{bmatrix} -0.5 \\ 0.25 \\ 1 \end{bmatrix} - \frac{3}{2} \log(2\pi)$$

$$= -0.65625 - 2.75681 = -3.413$$

$$g_2(x) = -\frac{1}{2} \begin{bmatrix} 0.5 & -0.75 & 1 \end{bmatrix} \begin{bmatrix} 0.5 \\ -0.75 \\ 1 \end{bmatrix} - \frac{3}{2} \log(2\pi)$$

$$= -0.90625 - 2.75681 = -3.663$$

$g_1(x) > g_2(x)$ , Hence  $X$  belongs to class 1

Sol<sup>c</sup> ② The likelihood ratio test is given by

$$\frac{p(x|\omega_1)}{p(x|\omega_2)} > \frac{\lambda_{12} - \lambda_{22}}{\lambda_{21} - \lambda_{11}} \frac{p(\omega_2)}{p(\omega_1)} = 0.25$$

If LHS > RHS, then  $x \in \omega_1$  else  $x \in \omega_2$

$$\text{Now, } p(x|\omega_1) \sim N(x|\mu_1, I)$$

$$p(x|\omega_2) \sim N(x|\mu_2, I)$$

$$\text{MVG, } N(x|\mu, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right\}$$

$$\text{RHS : } \frac{\lambda_{12} - \lambda_{22}}{\lambda_{21} - \lambda_{11}} \frac{p(\omega_2)}{p(\omega_1)}$$

$$= \frac{2-0}{1-0} \frac{\cancel{1/2}}{\cancel{1/2}} \quad (\because \text{priors are equal})$$

$$= 2 \quad \frac{1}{(2\pi)^{d/2} |I|^{1/2}} \exp \left\{ -\frac{1}{2} (x-\mu_1)^T I^{-1} (x-\mu_1) \right\}$$

$$\text{LHS : } \frac{p(x|\omega_1)}{p(x|\omega_2)} = \frac{\cancel{\frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x-\mu_1)^T \Sigma^{-1} (x-\mu_1) \right\}}}{\cancel{\frac{1}{(2\pi)^{d/2} |I|^{1/2}} \exp \left\{ -\frac{1}{2} (x-\mu_2)^T I^{-1} (x-\mu_2) \right\}}}$$

$$= \exp \left\{ -\frac{1}{2} \left[ (\mathbf{x} - \boldsymbol{\mu}_1)^T (\mathbf{x} - \boldsymbol{\mu}_1) - (\mathbf{x} - \boldsymbol{\mu}_2)^T (\mathbf{x} - \boldsymbol{\mu}_2) \right] \right\}$$

where  $\mathbf{x} - \boldsymbol{\mu}_1 = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.5 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 1/4 \\ 1/4 \\ 1/2 \end{bmatrix}$

$$\mathbf{x} - \boldsymbol{\mu}_2 = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.5 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.75 \\ -0.75 \\ -0.5 \end{bmatrix} = \begin{bmatrix} -3/4 \\ -3/4 \\ -1/2 \end{bmatrix}$$

LHS then becomes

$$\begin{aligned} \text{LHS} &: \exp \left\{ -\frac{1}{2} \left[ \left(\frac{1}{4}\right)^2 + \left(\frac{1}{4}\right)^2 + \left(\frac{1}{2}\right)^2 - \left(\left(-\frac{3}{4}\right)^2 + \left(-\frac{3}{4}\right)^2 + \left(-\frac{1}{2}\right)^2\right) \right] \right\} \\ &= \exp \left\{ -\frac{1}{2} \times \frac{1}{2} \left[ \left(\frac{1}{4}\right)^2 - \left(\frac{3}{4}\right)^2 \right] \right\} \\ &= \exp \left\{ \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2 \right\} \\ &= \exp \left\{ \left(\frac{3}{4} + \frac{1}{4}\right) \left(\frac{3}{4} - \frac{1}{4}\right) \right\} \\ &= \exp \left( \frac{1}{2} \right) \quad \text{--- } 0.75 \end{aligned}$$

$$\therefore \exp \left( \frac{1}{2} \right) < 2 \quad \text{i.e. LHS} < \text{RHS}$$

$$\Rightarrow \mathbf{x} \in \omega_2$$

Q.3) Discriminant for class  $i$  is

$$g_i^*(x) = \ln P(x | \mu_i^*, \Sigma) + \ln P(\mu_i^* | \mu_0, \Sigma_0).$$

Given,  $p(x | \mu_i^*, \Sigma) \sim N(\mu_i^*, I)$  1/2

$$P(\mu_i^* | \mu_0, \Sigma_0) \sim N(\mu_0, \Sigma_0).$$

$$\text{So, } g_i^*(x) = -\frac{1}{2} \left\{ (x - \mu_i^*)^T \Sigma^{-1} (x - \mu_i^*) \right\} \\ - \frac{1}{2} \left\{ (\mu_i^* - \mu_0)^T \Sigma_0^{-1} (\mu_i^* - \mu_0) \right\}$$

$$= -\frac{1}{2} \cdot \left\{ x^T \Sigma^{-1} x - 2\mu_i^* T \Sigma^{-1} x + \mu_i^* T \Sigma^{-1} \mu_i^* \right\} \\ - \frac{1}{2} \cdot \left\{ \mu_i^* T \Sigma_0^{-1} \mu_i^* - 2\mu_0^* T \Sigma_0^{-1} \mu_i^* + \mu_0^* T \Sigma_0^{-1} \mu_0^* \right\}$$

Removing terms that do not impact discriminant for different classes.

$$= \mu_i^* T \Sigma^{-1} x - \frac{1}{2} \mu_i^* T \Sigma^{-1} \mu_i^* - \frac{1}{2} \mu_i^* T \Sigma_0^{-1} \mu_i^* 1/2 \\ + \mu_0^* T \Sigma_0^{-1} \mu_i^*.$$

Given,  $\Sigma = I, \Rightarrow \Sigma^{-1} = I$

$$= \mu_i^* T I x - \frac{1}{2} \mu_i^* T I \mu_i^* - \frac{1}{2} \mu_i^* T \Sigma_0^{-1} \mu_i^* \\ + \mu_0^* T \Sigma_0^{-1} \mu_i^*.$$

$$\therefore w = I \mu_i^* = \mu_i^*.$$

$$b = -\frac{1}{2} \mu_i^* T \cancel{\mu_i^*} - \frac{1}{2} \mu_i^* T \Sigma_0^{-1} \mu_i^* + \mu_0^* T \Sigma_0^{-1} \mu_i^*.$$

$$\therefore g_i^*(x) = w^T x + b. 1/2$$

$$Q4.) P(x|w_1) = \alpha P(x|u_1, \sigma^2) + \beta P(x|u_2, \sigma^2)$$

$$P(x|w_2) = \beta P(x|u_1, \sigma^2) + \alpha P(x|u_2, \sigma^2)$$

To find D.B.  $\rightarrow$

We equate the posteriors.

$$P(w_1|x) = P(w_2|x)$$

$$\Rightarrow P(w_1)(P(x|w_1)) = P(w_2)(P(x|w_2))$$

$$\Rightarrow P(x|w_1) = P(x|w_2)$$

$$\Rightarrow \alpha P(x|u_1, \sigma^2) + \beta P(x|u_2, \sigma^2) = \beta P(x|u_1, \sigma^2) + \alpha P(x|u_2, \sigma^2)$$

$$\Rightarrow \alpha P(x|u_1, \sigma^2)[\alpha - 1] = P(x|u_2, \sigma^2)[\alpha - \beta]$$

$$\Rightarrow P(x|u_1, \sigma^2) = P(x|u_2, \sigma^2)$$

$$\Rightarrow P(x|u_1, \sigma^2) = P(x|u_2, \sigma^2)$$

$$\Rightarrow \text{Given } u_1 = 1, u_2 = -1 \text{ & } \sigma^2 = 1$$

$$\Rightarrow \frac{1}{\sqrt{2\pi\sigma^2}} \times e^{-\frac{1}{2}(x-u_1)^2} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x-u_2)^2}$$

$$\Rightarrow e^{-\frac{1}{2}(x-1)^2} = e^{-\frac{1}{2}(x+1)^2}$$

$$\Rightarrow (x-1)^2 = (x+1)^2$$

$$\Rightarrow x^2 - 2x + 1 = x^2 + 2x + 1$$

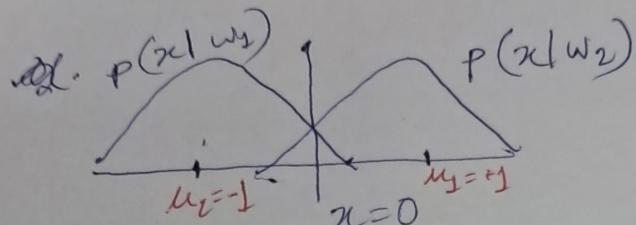
$$\therefore x = 0$$

The D.B. lies at  $x=0$

$$P(\text{error}(x)) = \min(P(w_1|x), P(w_2|x))$$

$$P(x|w_1) \approx b \phi(x|\mu_1, \sigma^2) \quad b \ll a$$

$$P(x|w_2) \approx a \phi(x|\mu_2, \sigma^2)$$



(0.5)  $P(\text{error}) = \frac{1}{2} \int_{-\infty}^0 P(x|w_2) dx + \frac{1}{2} \int_0^{\infty} P(x|w_1) dx$

$$= \frac{1}{2} \int_{-\infty}^0 a \phi(x|\mu_1, \sigma^2) + b \phi(x|\mu_2, \sigma^2) dx$$

$$+ \frac{1}{2} \int_0^{\infty} a \phi(x|\mu_2, \sigma^2) + b \phi(x|\mu_1, \sigma^2) dx$$

$$= \frac{1}{2} \left[ a \int_{-\infty}^0 \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu_1)^2}{2}} dx + b \int_{-\infty}^0 \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu_2)^2}{2}} dx \right]$$

$$+ \frac{1}{2} \left[ a \int_0^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu_2)^2}{2}} dx + b \int_0^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu_1)^2}{2}} dx \right]$$

$$= \frac{1}{2} \left( 1 + \operatorname{erf}\left(\frac{\mu_1}{\sqrt{2}}\right) \right)$$