

1. (a) Bayes decision rule for minimum-error-rate classification

(two categories)

: Decide w_1 if $IP(w_1|x) > IP(w_2|x)$

$$\Leftrightarrow \frac{IP(x|w_1) \cdot IP(w_1)}{IP(x)} > \frac{IP(x|w_2) \cdot IP(w_2)}{IP(x)}$$

$$\Leftrightarrow \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-1)^2\right] \cdot \frac{1}{2} > \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-3)^2\right] \cdot \frac{2}{2}$$

Since \ln -fn is increasing function,
without flipping the inequality sign,

$$\Leftrightarrow \ln \exp\left[-\frac{1}{2}(x-1)^2\right] > \ln\left(\exp\left[-\frac{1}{2}(x-3)^2\right] \cdot 2\right)$$

$$\Leftrightarrow -\frac{1}{2}(x-1)^2 > -\frac{1}{2}(x-3)^2 + \ln 2$$

$$\Leftrightarrow -\cancel{\frac{1}{2}x^2} + x - \frac{1}{2} > -\cancel{\frac{1}{2}x^2} + 3x - \frac{9}{2} + \ln 2$$

$$\Leftrightarrow 2x < 4 - \ln 2 \quad \Leftrightarrow x < 2 - \frac{1}{2}\ln 2$$

$$\therefore \text{Decide } \begin{cases} w_1 & \text{if } x < 2 - \frac{1}{2}\ln 2 \\ w_2 & \text{if } x \geq 2 - \frac{1}{2}\ln 2 \end{cases}$$

1. (b) Bayes decision rule for minimum risk classification:

$$\text{Decide } w_1 \text{ if } \sum_{j=1}^2 \lambda(x|w_j) p(w_j|x) < \sum_{j=1}^2 \lambda(x|w_j) p(w_j|x)$$

$$\Leftrightarrow 2p(w_2|x) < p(w_1|x)$$

$$\Leftrightarrow 2 \cdot p(x|w_2) \cdot p(w_2) < p(x|w_1) p(w_1)$$

$$\Leftrightarrow 2 \cdot \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-3)^2\right] \cdot \frac{2}{3} < \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-1)^2\right] \cdot \frac{1}{3}$$

Similarly, take log on both sides and get

$$\Leftrightarrow -\frac{1}{2}(x-3)^2 + \log 4 < -\frac{1}{2}(x-1)^2$$

$$\Leftrightarrow 3x - \frac{9}{2} + \log 4 < x - \frac{1}{2}$$

$$\Leftrightarrow 2x < 4 - \log 4 \quad \Leftrightarrow x < 2 - \log 2$$

Decide	w_1	if	$x < 2 - \log 2$
	w_2	if	$x \geq 2 - \log 2$

2. The minimum probability rate is achieved by deciding a category with greater posterior probability

⇒ set the discriminant function as

$$g_j(\vec{x}) = \ln [P(\vec{x} | w_j) \cdot P(w_j)]$$

(∵ log-fn is increasing fn)

Note that

$$\begin{aligned} P(x_i = 1 | w_j) &= P_{ij} &] \text{ (} \because P(x_i = 0 \text{ or } x_i = 1) = 1 \text{)} \\ P(x_i = 0 | w_j) &= 1 - P_{ij} \end{aligned}$$

So $P(x_i | w_j)$ can be written as

$$P(x_i | w_j) = P_{ij}^{x_i} (1 - P_{ij})^{1-x_i}$$

Hence, $g_j(x) = \ln P(\vec{x} | w_j) + \ln P(w_j)$

$$= \ln \prod_{i=1}^d P(x_i | w_j) + \ln P(w_j)$$

$$= \sum_{i=1}^d \ln P(x_i | w_j) + \ln P(w_j)$$

$$= \sum_{i=1}^d [x_i \ln P_{ij} + (1-x_i) \ln (1-P_{ij})] + \ln P(w_j)$$

$$= \sum_{i=1}^d \left[\left(\ln \frac{P_{ij}}{1-P_{ij}} \right) x_i \right] + \sum_{i=1}^d \ln (1-P_{ij}) + \ln P(w_j)$$

Therefore, c_{ij} and b_j can be expressed as

$$\boxed{c_{ij} = \ln \frac{P_{ij}}{1-P_{ij}} \quad b_j = \sum_{i=1}^d \ln (1-P_{ij}) + \ln P(w_j)}$$