

2.3. minimax criterion
zero-one loss function $\pi_{11} = \pi_{22} = 0$ $\pi_{12} = \pi_{21} = 1$.

(a) prove $\int_{R_2} p(x|w_1) dx = \int_{R_1} p(x|w_2) dx$.

Answer: priors: $P(w_1), P(w_2) = 1 - P(w_1)$.

$$R(P(w_1)) = P(w_1) \int_{R_2} p(x|w_1) dx + (1 - P(w_1)) \int_{R_1} p(x|w_2) dx.$$

Obtain the prior with minimum risk:

$$\frac{d}{dP(w_1)} R(P(w_1)) = \int_{R_2} p(x|w_1) dx - \int_{R_1} p(x|w_2) dx = 0$$

$$\Rightarrow \int_{R_2} p(x|w_1) dx = \int_{R_1} p(x|w_2) dx$$

(b) The solution is not unique

i.e. Quadratic in x_0

2.5. Generalize the minimax decision rule.

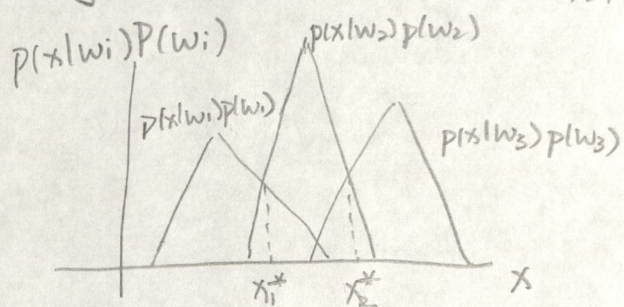
$$p(x|w_i) = T(\mu_i, \delta_i) \equiv \begin{cases} (\delta_i - |x - \mu_i|) / \delta_i^2 & \text{for } |x - \mu_i| < \delta_i \\ 0 & \text{otherwise} \end{cases}$$

where $\delta_i > 0$ is the half-width of a distribution ($i = 1, 2, 3$)

Assume that $\mu_1 < \mu_2 < \mu_3$

$$(a) p(w_1)p(x|w_1) = p(w_2)p(x|w_2)$$

$$p(w_2)p(x|w_2) = p(w_3)p(x|w_3)$$



$$\Rightarrow \begin{cases} x_1^* = 0 \\ x_2^* = 0 \end{cases}$$

$$\begin{aligned}
 (b) \quad R &= \int_{R_2} p(w_1) p(x|w_1) dx + \int_{R_1} p(w_2) p(x|w_2) dx \\
 &+ \int_{R_3} p(w_2) p(x|w_2) dx + \int_{R_4} p(w_3) p(x|w_3) dx \\
 &= P(w_1) \frac{1}{2\sigma_1^2} (\mu_1 + \sigma_1 - x_1^*)^2 + P(w_2) \frac{1}{2\sigma_2^2} [(\sigma_2 - \mu_2 + x_1^*)^2 + \\
 &\quad (\mu_2 + \sigma_2 - x_2^*)^2] + [1 - P(w_1) - P(w_2)] \frac{1}{2\sigma_3^2} (\sigma_3 - \mu_3 + x_2^*)^2
 \end{aligned}$$

$$\frac{\partial E}{\partial P(w_1)} = \frac{\partial E}{\partial P(w_2)} = 0 \Rightarrow x_i^* = \frac{b_i + \sqrt{C_i}}{a_i} \quad i=1,2$$

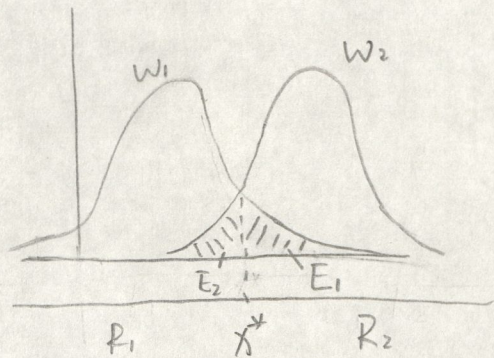
(c) (d) \uparrow

$$2.7. \quad p(x|w_i) = \frac{1}{\pi b} \cdot \frac{1}{1 + \left(\frac{x-a_i}{b}\right)^2} \quad i=1,2$$

Assume zero-one error loss, $a_2 > a_1$, same "width" b , and equal priors.

(a) maximum acceptable error rate for classifying a pattern that is actually in w_1 as if it were in w_2 is \bar{E}_1 .

$$\begin{aligned}
 E_1 &= \int_{R_2} p(x|w_1) p(w_1) dx \\
 &= \frac{1}{2} \int_{x^*}^{+\infty} \frac{1}{\pi b} \frac{1}{1 + \left(\frac{x-a_1}{b}\right)^2} dx
 \end{aligned}$$



$$(b) E_2 = \int_{R_1} p(x|w_2) p(w_2) dx$$

$$(c) E = \bar{E}_1 + \bar{E}_2$$

(d) \uparrow

(e) For the Bayes case, the decision point is midway between the peaks of the two distribution.