

Then, by setting  $C_{00} = C_{11} = 0$ ,  $C_{01} = 2$ , and  $C_{10} = 1$  in Eq. (8.19), the minimum Bayes' risk  $\bar{C}^*$  can be expressed as a function of  $P(H_0)$  as

$$\begin{aligned}\bar{C}^*[P(H_0)] &= P(H_0) \int_{-\delta}^{\delta} \frac{1}{2} e^{-|x|} dx + 2[1 - P(H_0)] \left[ \int_{-\infty}^{-\delta} e^{2x} dx + \int_{\delta}^{\infty} e^{-2x} dx \right] \\ &= P(H_0) \int_0^{\delta} e^{-x} dx + 4[1 - P(H_0)] \int_{\delta}^{\infty} e^{-2x} dx \\ &= P(H_0)(1 - e^{-\delta}) + 2[1 - P(H_0)]e^{-2\delta}\end{aligned}\quad (8.35)$$

From the definition of  $\delta$  [Eq. (8.34)], we have

$$e^{\delta} = \frac{4[1 - P(H_0)]}{P(H_0)}$$

Thus 
$$e^{-\delta} = \frac{P(H_0)}{4[1 - P(H_0)]} \quad \text{and} \quad e^{-2\delta} = \frac{P^2(H_0)}{16[1 - P(H_0)]^2}$$

Substituting these values into Eq. (8.35), we obtain

$$\bar{C}^*[P(H_0)] = \frac{8P(H_0) - 9P^2(H_0)}{8[1 - P(H_0)]}$$

Now the value of  $P(H_0)$  which maximizes  $\bar{C}^*$  can be obtained by setting  $d\bar{C}^*[P(H_0)]/dP(H_0)$  equal to zero and solving for  $P(H_0)$ . The result yields  $P(H_0) = \frac{2}{3}$ . Substituting this value into Eq. (8.34), we obtain the following minimax test:

$$|x| \underset{H_0}{\overset{H_1}{\leq}} \ln \frac{4(1 - \frac{2}{3})}{\frac{2}{3}} = \ln 2 = 0.69$$

- 8.13.** Suppose that we have  $n$  observations  $X_i$ ,  $i = 1, \dots, n$ , of radar signals, and  $X_i$  are normal iid r.v.'s under each hypothesis. Under  $H_0$ ,  $X_i$  have mean  $\mu_0$  and variance  $\sigma^2$ , while under  $H_1$ ,  $X_i$  have mean  $\mu_1$  and variance  $\sigma^2$ , and  $\mu_1 > \mu_0$ . Determine the maximum likelihood test.

By Eq. (2.52) for each  $X_i$ , we have

$$\begin{aligned}f(x_i | H_0) &= \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2\sigma^2}(x_i - \mu_0)^2\right] \\ f(x_i | H_1) &= \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2\sigma^2}(x_i - \mu_1)^2\right]\end{aligned}$$

Since the  $X_i$  are independent, we have

$$\begin{aligned}f(\mathbf{x} | H_0) &= \prod_{i=1}^n f(x_i | H_0) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_0)^2\right] \\ f(\mathbf{x} | H_1) &= \prod_{i=1}^n f(x_i | H_1) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2\right]\end{aligned}$$

With  $\mu_1 - \mu_0 > 0$ , the likelihood ratio is then given by

$$\Lambda(\mathbf{x}) = \frac{f(\mathbf{x} | H_1)}{f(\mathbf{x} | H_0)} = \exp\left\{\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n 2(\mu_1 - \mu_0)x_i - n(\mu_1^2 - \mu_0^2) \right]\right\}$$

Hence, the maximum likelihood test is given by

$$\exp\left\{\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n 2(\mu_1 - \mu_0)x_i - n(\mu_1^2 - \mu_0^2) \right]\right\} \underset{H_0}{\overset{H_1}{\geq}} 1$$