

2.2.1.

$$H_1: r = s + \eta$$

$$H_0: r = \eta,$$

$$P_s(s) = a e^{-as} \quad s \geq 0,$$

$$= 0 \quad s < 0,$$

$$P_n(n) = b e^{-bn} \quad n \geq 0,$$

$$= 0 \quad n < 0.$$

s and η are independent random variables.

$$(a) \quad f_{r/H_1}(r/H_1) = \int_{\alpha=0}^r P_s(\alpha) \cdot P_n(r-\alpha) d\alpha$$

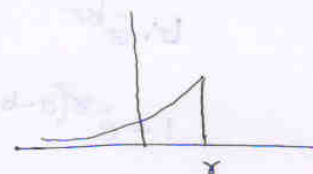
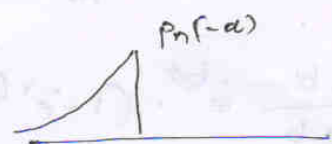
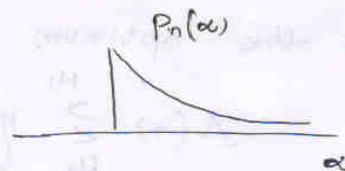
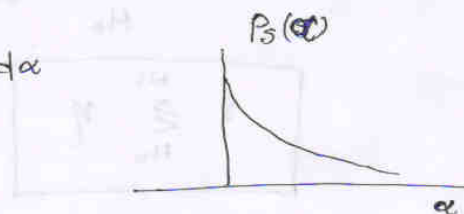
$$= \int_{\alpha=0}^r a \cdot e^{-a\alpha} \cdot b \cdot e^{-b(r-\alpha)} d\alpha$$

$$= ab \cdot \int_0^r e^{-a\alpha} \cdot e^{-b(r-\alpha)} d\alpha$$

$$= ab \cdot e^{-br} \int_0^r \frac{-\alpha(a-b)}{e} d\alpha$$

$$= ab \cdot e^{-br} \cdot \left[\frac{-\alpha(a-b)}{-(a-b)} \right]_0^r$$

$$= \frac{ab}{a-b} \cdot e^{-br} [1 - e^{-r(a-b)}], \quad r \geq 0,$$



$P_s(\alpha) \cdot P_n(r-\alpha)$ is non zero only for $0 \leq \alpha \leq r$.

$$f_{r/H_0}(r/H_0) = b \cdot e^{-br}, \quad r \geq 0$$

$$L(r) = \frac{f_{r/H_1}(r/H_1)}{f_{r/H_0}(r/H_0)} \quad \begin{matrix} H_1 \\ \geq \\ H_0 \end{matrix} \quad \eta'$$

$$\frac{\frac{ab}{a-b} \cdot \frac{e^{-br}}{b} \cdot (1 - e^{-r(a-b)})}{b \cdot e^{-br}}$$

$$\begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta'$$

$$1 - e^{-r(a-b)} \begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta''$$

$$e^{-r(a-b)} \begin{matrix} H_1 \\ \leq \\ \geq \\ H_0 \end{matrix} \eta'' - 1$$

by taking log on both sides

$$-r(a-b) \begin{matrix} H_1 \\ \leq \\ \geq \\ H_0 \end{matrix} \log_e(\eta'' - 1)$$

$$\boxed{\gamma \begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta}$$

(b) for the optimum Bayes test find η ?

$$\Lambda(r) \begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta' = \frac{\pi_0 (C_{10} - C_{00})}{\pi_1 (C_{01} - C_{11})}$$

$$\frac{\frac{ab}{a-b} \cdot \frac{e^{-br}}{b} \cdot (1 - e^{-r(a-b)})}{b \cdot e^{-br}}$$

$$\begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta'$$

$$1 - e^{-r(a-b)} \begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \eta' \left(\frac{a-b}{a} \right)$$

$$e^{-r(a-b)} \begin{matrix} H_1 \\ \leq \\ \geq \\ H_0 \end{matrix} \left(\eta' \left(\frac{a-b}{a} \right) + 1 \right)$$

by taking log on both sides,

$$-r(a-b) \begin{matrix} H_1 \\ \leq \\ \geq \\ H_0 \end{matrix} \log \left(\eta' \left(\frac{a-b}{a} \right) + 1 \right)$$

$$\gamma \begin{matrix} H_1 \\ \geq \\ \leq \\ H_0 \end{matrix} \frac{\log \left(\eta' \left(\frac{a-b}{a} \right) + 1 \right)}{-(a-b)} = \eta$$

(c)

$$P_F \triangleq \Pr(\text{say } H_1 / H_0 \text{ is true}) = \int f_{X/H_0}(x/H_0) dx \quad (2)$$

$$P_F = \int_{\eta}^{\infty} b \cdot e^{-br} \cdot dr$$

$$= \left[b \cdot \frac{e^{-br}}{-b} \right]_{\eta}^{\infty}$$

$$= -[0 - e^{-b\eta}] = e^{-b\eta}$$

$$P_F = e^{-b\eta} \Rightarrow \log P_F = -b\eta$$

$$\Rightarrow \eta = \frac{\log(P_F)}{(-b)}$$

2.2.18

$$f_{X/H_1}(x/H_1) = \sum_{k=1}^M P_k \frac{1}{(\pi\sigma^2)^{M/2}} e^{-\left[\frac{(x-m)^2}{2\sigma^2}\right]} \prod_{i \neq k} \frac{M}{1} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]}$$

$$\sum_{k=1}^M P_k = 1$$

$$f_{X/H_0}(x/H_0) = \prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]} \quad -\infty < x_i < \infty$$

$$\Lambda(x) = \frac{f_{X/H_1}(x/H_1)}{f_{X/H_0}(x/H_0)} \underset{H_0}{\overset{H_1}{>}} \eta$$

$$\frac{\sum_{k=1}^M P_k \cdot \frac{1}{(\pi\sigma^2)^{M/2}} e^{-\left[\frac{x^2}{2\sigma^2}\right]} \cdot e^{-\left[\frac{m^2 - 2mx}{2\sigma^2}\right]} \cdot \prod_{i \neq k} \frac{M}{1} \exp\left[-\frac{x_i^2}{2\sigma^2}\right]}{\prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]}} \underset{H_0}{\overset{H_1}{>}} \eta$$

$$\frac{\prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]}}{\prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]}}$$

$$\frac{\prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]} \sum_{k=1}^M P_k e^{-\left[\frac{m^2 - 2mx}{2\sigma^2}\right]}}{\prod_{i=1}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-\left[\frac{x_i^2}{2\sigma^2}\right]}} \underset{H_0}{\overset{H_1}{>}} \eta$$

$$e^{-\frac{m^2}{2\sigma^2}} \sum_{k=1}^M p_k \cdot e^{\frac{m x_k}{\sigma^2}} \sum_{H_0}^{H_1} \eta$$

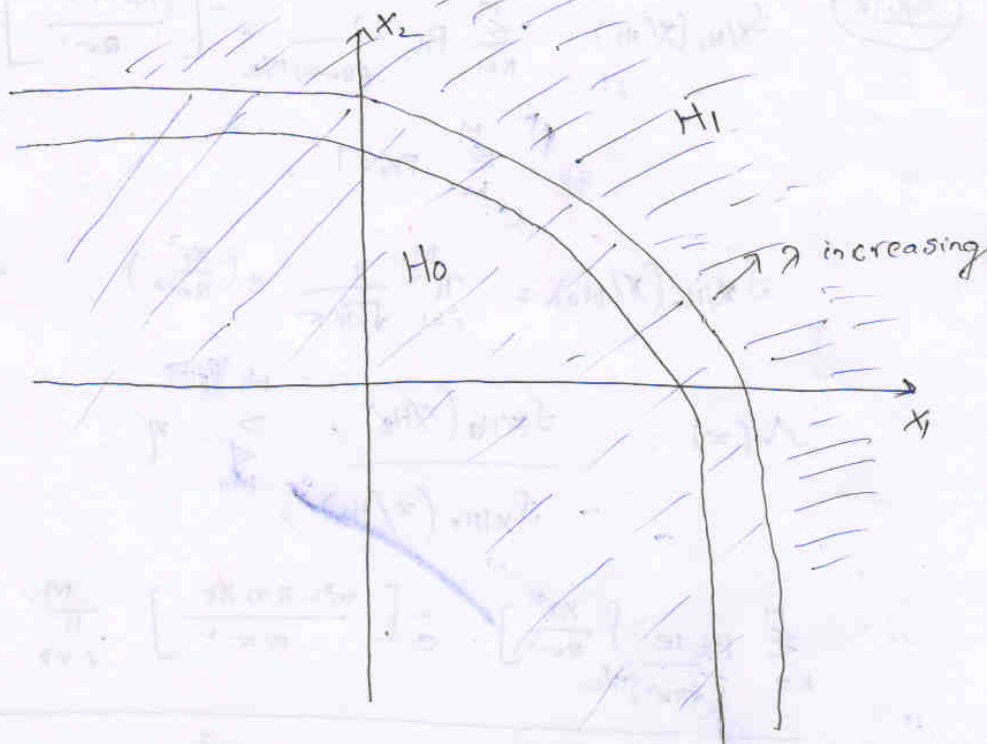
$$\sum_{k=1}^M p_k \cdot e^{\frac{m x_k}{\sigma^2}} \sum_{H_0}^{H_1} \eta'$$

(b) $M=2$, and $p_1=p_2=1/2$

$$\frac{1}{2} \left[e^{\frac{m x_1}{\sigma^2}} + e^{\frac{m x_2}{\sigma^2}} \right] \sum_{H_0}^{H_1} \eta'$$

$$\Rightarrow e^{\frac{m x_1}{\sigma^2}} + e^{\frac{m x_2}{\sigma^2}} \sum_{H_0}^{H_1} 2\eta'$$

$$\Rightarrow e^{K x_1} + e^{K x_2} \sum_{H_0}^{H_1} \eta''' = 10 = 9$$



(3)

(c)

$$e^{KX_1} + e^{KX_2} \underset{H_0}{\overset{H_1}{>}} \eta''' = \gamma$$

$$\text{Let } X_1 \gg X_2$$

$$e^{KX_1} \underset{H_0}{\overset{H_1}{>}} \eta''' = \gamma$$

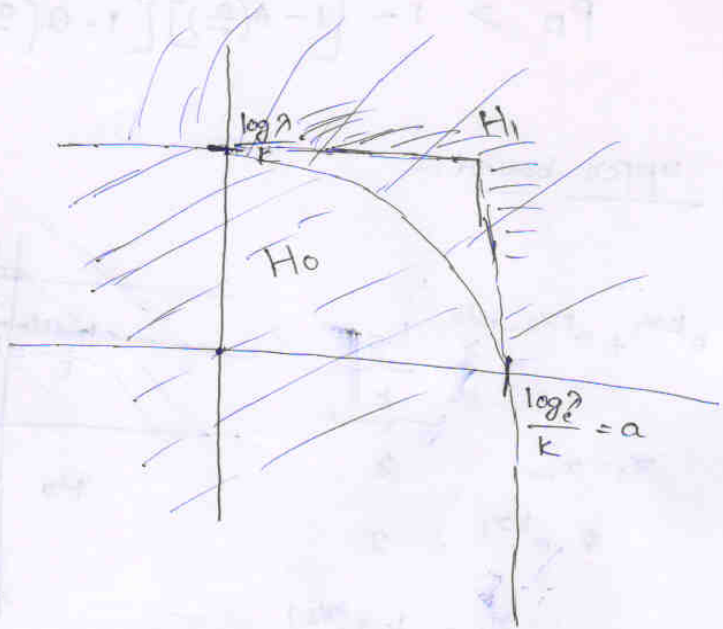
$$KX_1 \underset{H_0}{\overset{H_1}{>}} \log_e \gamma$$

$$X_1 \underset{H_0}{\overset{H_1}{>}} \frac{\log_e \gamma}{K}$$

Similarly

$$X_2 \gg X_1$$

$$X_2 \underset{H_0}{\overset{H_1}{>}} \frac{\log_e \gamma}{K}$$



lower bound;

$$P_{FA} > P(\Lambda(x) > \gamma/H_0)$$

$$= 1 - \int_{-\infty}^a \int_{-\infty}^a p_{x_1 x_2}(x_1, x_2) dx_1 dx_2$$

$$= 1 - \int_{-\infty}^a p_{x_1}(x_1) dx_1 \int_{-\infty}^a p_{x_2}(x_2) dx_2$$

$$= 1 - \int_{-\infty}^a \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x_1^2}{2\sigma^2}} dx_1 \int_{-\infty}^a \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x_2^2}{2\sigma^2}} dx_2$$

$$= 1 - [1 - Q(\frac{a}{\sigma})]^2$$

$$P_D > P(\Lambda(x) > \gamma/H_1)$$

$$= 1 - \int_{-\infty}^a \int_{-\infty}^a \frac{1}{2} \left[\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_1-m)^2}{2\sigma^2}\right) \cdot \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x_2^2}{2\sigma^2}\right) \right.$$

$$\left. + \frac{1}{2} \left[\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_2-m)^2}{2\sigma^2}\right) \cdot \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x_1^2}{2\sigma^2}\right) \right] dx_1 dx_2 \right]$$

$$P_D \geq 1 - \frac{1}{2} \left[\left(1 - Q\left(\frac{a}{\sigma}\right) \right) \left(1 - Q\left(\frac{a-m}{\sigma}\right) \right) + \left(1 - Q\left(\frac{a}{\sigma}\right) \right) \left(1 - Q\left(\frac{a-m}{\sigma}\right) \right) \right]$$

$$P_D > 1 - \left[1 - Q\left(\frac{a}{\sigma}\right) \right] \left[1 - Q\left(\frac{a-m}{\sigma}\right) \right]$$

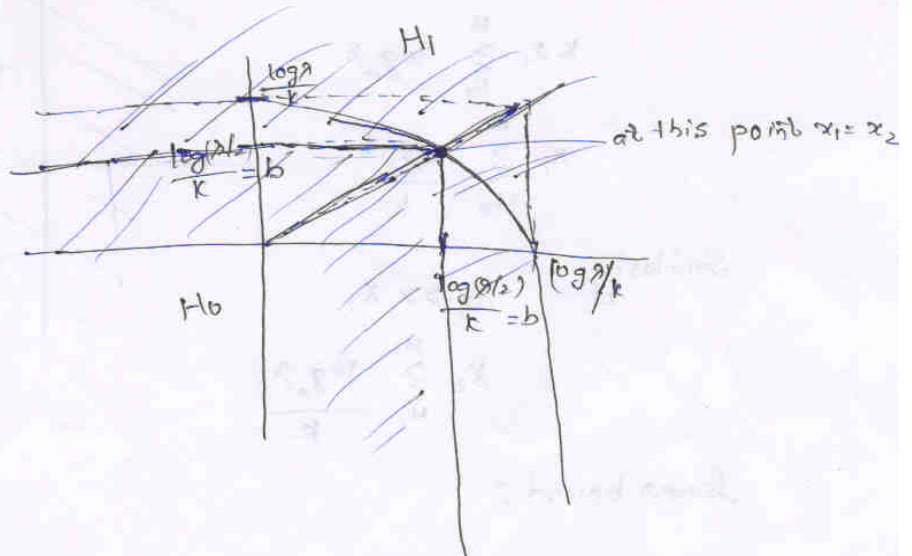
upper bound:-

$$e^{kx_1} + e^{kx_2} \underset{H_0}{\overset{H_1}{>}} \underbrace{\frac{\log \lambda}{k}}_b$$

$$x_1 = x_2$$

$$\text{or } e^{kx_1} = \lambda$$

$$x_1 = \frac{\log(\lambda/2)}{k}$$



$$P_{FA} < 1 - \int_{-\infty}^b \int_{-\infty}^b p_{x_1, x_2}(x_1, x_2) dx_1 dx_2$$

$$= 1 - \left[1 - Q\left(\frac{b}{\sigma}\right) \right]^2$$

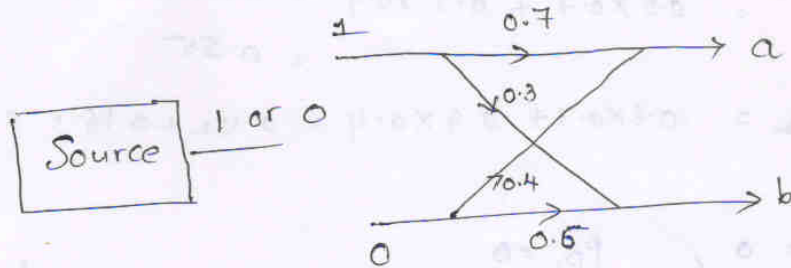
$$P_D < 1 - \left[\left(1 - Q\left(\frac{b}{\sigma}\right) \right) \left(1 - Q\left(\frac{b-m}{\sigma}\right) \right) \right]$$

2.27:

④

$$S_1: \Pr(1) = 0.5, \Pr(0) = 0.5;$$

$$S_2: \Pr(1) = 0.6, \Pr(0) = 0.4.$$



the four possible cases are

$$\left. \begin{array}{l} r=a \rightarrow \text{decide } S_1 \\ r=b \rightarrow \text{decide } S_2 \end{array} \right\} \textcircled{1}$$

$$\left. \begin{array}{l} r=a \rightarrow \text{decide } S_2 \\ r=b \rightarrow \text{decide } S_1 \end{array} \right\} \textcircled{2}$$

$$\left. \begin{array}{l} r=a \rightarrow \text{decide } S_1 \\ r=b \rightarrow \text{decide } S_1 \end{array} \right\} \textcircled{3}$$

$$\left. \begin{array}{l} r=a \rightarrow \text{decide } S_2 \\ r=b \rightarrow \text{decide } S_2 \end{array} \right\} \textcircled{4}$$

$$P_{FA1} = P(\text{decide } S_2 / S_1 \text{ is true})$$

$$= \Pr(r=b / S_1 \text{ is true})$$

$$= 0.5 \times 0.3 + 0.5 \times 0.6$$

$$= 0.15 + 0.30 = 0.45$$

$$P_{D1} = P(\text{decide } S_2 / S_2 \text{ is true})$$

$$= \Pr(r=b / S_2 \text{ is true})$$

$$= 0.6 \times 0.3 + 0.4 \times 0.6 = 0.18 + 0.24 = 0.42$$

$$= 0.6 \times 0.7 + 0.0$$

$$+ 0.16 =$$



2. $2 \times 2 = 4$

$$\text{prob}(1-p)$$

$$P_{FA} = p \times (1-p)$$

$$0.55 \times (1 - p)$$

$$\begin{array}{r} 5 \\ 01 \end{array}$$

2.3.7.

$$H_0: r = m_0 + n,$$

$$H_1: r = m_1 + n,$$

$$H_2: r = m_2 + n,$$

$$r \triangleq \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix}$$

$$m_i \triangleq \begin{bmatrix} m_{i1} \\ m_{i2} \\ m_{i3} \end{bmatrix}$$

$$n \triangleq \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix}$$

the components of n are statistically independent,

$$A_1 = \frac{\int r/H_1}{\int r/H_0}$$

$$r \stackrel{H_1}{\sim} N(m_1, \sigma^2 I_{3 \times 3})$$

$$\stackrel{H_0}{\sim} N(m_0, \sigma^2 I)$$

$$\stackrel{H_2}{\sim} N(m_2, \sigma^2 I)$$

$$A_1 = \frac{\frac{1}{(\sqrt{2\pi}\sigma)^3} \exp\left(-\sum_{i=1}^3 \frac{(r_i - m_{1i})^2}{2\sigma^2}\right)}{\frac{1}{(\sqrt{2\pi}\sigma)^3} \exp\left(-\sum_{i=1}^3 \frac{(r_i - m_{0i})^2}{2\sigma^2}\right)}$$

$$= \frac{\exp\left(\sum_{i=1}^3 \left(\frac{(r_i^2 + m_{0i}^2 - 2m_{0i}r_i)}{2\sigma^2} - \frac{(r_i^2 + m_{1i}^2 - 2m_{1i}r_i)}{2\sigma^2} \right)\right)}{1}$$

$$l_1 \triangleq \log(A_1(r))$$

$$= \sum_{i=1}^3 r_i (m_{1i} - m_{0i})$$

$$l_2 \triangleq \sum_{i=1}^3 r_i (m_{2i} - m_{0i})$$

(b)

$$C_{00} = C_{11} = C_{22} = 0$$

$$C_{12} = C_{21} = C_{01} = C_{10} = \frac{1}{2} C_{02} = \frac{1}{2} C_{20} > 0$$

$$\pi_1 (C_{01} - C_{11}) \Delta_1 \begin{matrix} \xrightarrow{H_1 \text{ or } H_2} \\ \xleftarrow{H_0 \text{ or } H_2} \end{matrix} \pi_0 (C_{10} - C_{00}) + \pi_2 (C_{12} - C_{02}) \Delta_2$$

$$\pi_1 \cdot C_{01} \Delta_1 \begin{matrix} \xrightarrow{H_1 \text{ or } H_2} \\ \xleftarrow{H_0 \text{ or } H_2} \end{matrix} \pi_0 \cdot C_{10} + \pi_2 (C_{01} - 2 C_{01}) \Delta_2$$

$$\pi_1 \cdot \Delta_1 \geq \pi_0 - \pi_2 \Delta_2 \quad \text{--- (1)}$$

$$\pi_2 (C_{02} - C_{22}) \Delta_2 \begin{matrix} \xrightarrow{H_2 \text{ or } H_1} \\ \xleftarrow{H_0 \text{ or } H_1} \end{matrix} \pi_0 (C_{20} - C_{00}) + \pi_1 (C_{21} - C_{01}) \Delta_1$$

$$\pi_2 \cdot 2 C_{01} \Delta_2 \geq \pi_0 \cdot 2 C_{01} + \pi_1 (0) \cdot \Delta_1$$

$$\pi_2 \Delta_2 \geq \pi_0 \quad \text{--- (2)}$$

$$\pi_2 (C_{12} - C_{22}) \Delta_2 \begin{matrix} \xrightarrow{H_2 \text{ or } H_0} \\ \xleftarrow{H_1 \text{ or } H_0} \end{matrix} \pi_0 (C_{20} - C_{10}) + \pi_1 (C_{21} - C_{11}) \Delta_1$$

$$\pi_2 \cdot C_{12} \Delta_2 \geq \pi_0 \cdot C_{10} + \pi_1 \cdot C_{21} \cdot \Delta_1$$

$$\pi_2 \Delta_2 \geq \pi_0 + \pi_1 \cdot \Delta_1 \quad \text{--- (3)}$$

$$\pi_1 \cdot \Delta_1 + \pi_2 \Delta_2 \begin{matrix} \xrightarrow{H_1 \text{ or } H_2} \\ \xleftarrow{H_0 \text{ or } H_2} \end{matrix} \pi_0 \quad \text{--- (4)}$$

$$\Delta_2 \begin{matrix} \xrightarrow{H_2 \text{ or } H_1} \\ \xleftarrow{H_0 \text{ or } H_1} \end{matrix} \pi_0 / \pi_2 \quad \text{--- (5)}$$

$$-\pi_1 \Delta_1 + \pi_2 \Delta_2 \begin{matrix} \xrightarrow{H_2 \text{ or } H_0} \\ \xleftarrow{H_1 \text{ or } H_0} \end{matrix} \pi_0 \quad \text{--- (6)}$$

6

$$\log(\mathcal{L}_1) = l_1 + \gamma_1 \quad \Rightarrow \quad \mathcal{L}_1 = e^{l_1} \cdot e^{\gamma_1}$$

$$\gamma_1 = \sum_{i=1}^3 (m_{0i}^2 - m_{1i}^2)$$

$$\log(\mathcal{L}_2) = l_2 + \gamma_2$$

$$\gamma_2 = \sum_{i=1}^3 (m_{0i}^2 - m_{1i}^2)$$

$$\pi_1 \cdot \mathcal{L}_1 + \pi_2 \cdot \mathcal{L}_2 \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}}{>} \pi_0$$

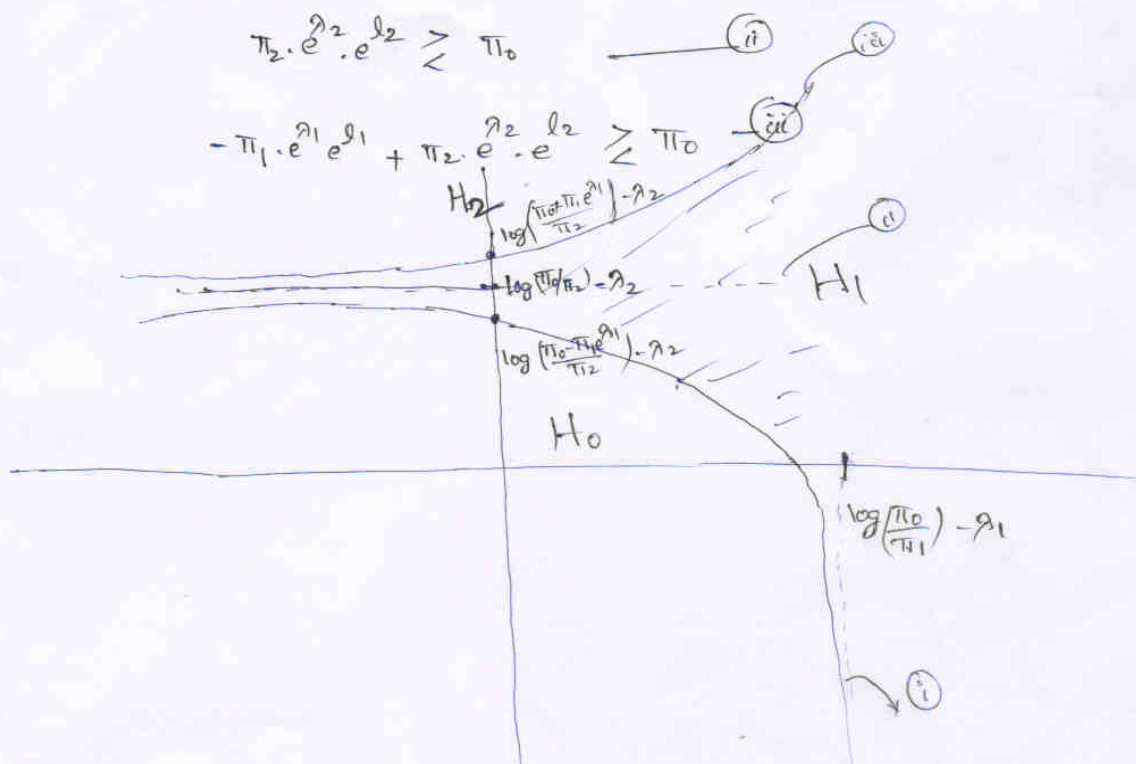
$$\pi_2 \cdot \mathcal{L}_2 \underset{H_0 \text{ or } H_1}{\overset{H_2 \text{ or } H_1}}{>} \pi_0$$

$$-\pi_1 \mathcal{L}_1 + \pi_2 \mathcal{L}_2 \underset{H_1 \text{ or } H_0}{\overset{H_2 \text{ or } H_0}}{>} \pi_0$$

$$\pi_1 \cdot e^{\gamma_1} \cdot e^{l_1} + \pi_2 \cdot e^{\gamma_2} \cdot e^{l_2} \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}}{>} \pi_0 \quad \text{--- (i)}$$

$$\pi_2 \cdot e^{\gamma_2} \cdot e^{l_2} \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}}{>} \pi_0 \quad \text{--- (ii)}$$

$$-\pi_1 \cdot e^{\gamma_1} \cdot e^{l_1} + \pi_2 \cdot e^{\gamma_2} \cdot e^{l_2} \underset{H_0 \text{ or } H_2}{\overset{H_1 \text{ or } H_2}}{>} \pi_0 \quad \text{--- (iii)}$$



2.2.6.

(7)

$$H_1: r = b m_1 + n$$

$$H_0: r = n$$

b and n are independent zero-mean Gaussian Variables with Variances σ_b^2 and σ_n^2

$$b \sim \mathcal{N}(0, \sigma_b^2)$$

$$n \sim \mathcal{N}(0, \sigma_n^2)$$

$$f_{r/H_1}(r/H_1) \sim \mathcal{N}(0, \underbrace{m_1^2 \sigma_b^2 + \sigma_n^2}_{\sigma_{r_1}^2})$$

$$f_{r/H_0}(r/H_0) \sim \mathcal{N}(0, \sigma_n^2)$$

$$\frac{f_{r/H_1}(r/H_1)}{f_{r/H_0}(r/H_0)} \underset{H_0}{\overset{H_1}{>}} \eta$$

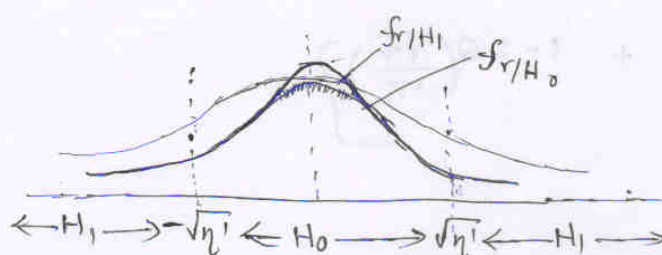
$$\frac{\frac{1}{\sqrt{2\pi} \sigma_{r_1}} e^{-\frac{r^2}{2\sigma_{r_1}^2}}}{\frac{1}{\sqrt{2\pi} \sigma_n} e^{-\frac{r^2}{2\sigma_n^2}}} \underset{H_0}{\overset{H_1}{>}} \eta$$

$$\frac{\sigma_n}{\sigma_{r_1}} e^{\frac{1}{2} \left[\frac{1}{\sigma_n^2} - \frac{1}{\sigma_{r_1}^2} \right] r^2} \underset{H_0}{\overset{H_1}{>}} \eta$$

$$\Rightarrow r^2 \underset{H_0}{\overset{H_1}{>}} \eta'$$

$$(\because \sigma_{n_1}^2 > \sigma_n^2)$$

$$\Rightarrow |r| \underset{H_0}{\overset{H_1}{>}} \sqrt{\eta'}$$



$$P_F = \int_{\sqrt{\eta'}}^{\infty} f_{A/H_0} dA + \int_{-\infty}^{-\sqrt{\eta'}} f_{A/H_0} dA$$

$$= \int_{\sqrt{\eta'}}^{\infty} \frac{1}{\sqrt{2\pi} \sigma_n} e^{-\frac{r^2}{2\sigma_n^2}} dr + \int_{-\infty}^{-\sqrt{\eta'}} \frac{1}{\sqrt{2\pi} \sigma_n} e^{-\frac{r^2}{2\sigma_n^2}} dr$$

$$= Q\left(\frac{\sqrt{\eta'}}{\sigma_n}\right) + Q\left(\frac{\sqrt{\eta'}}{\sigma_n}\right)$$

$$= 2Q\left(\frac{\sqrt{\eta'}}{\sigma_n}\right) \Rightarrow \sqrt{\eta'} = \sigma_n Q^{-1}(P_F/2)$$

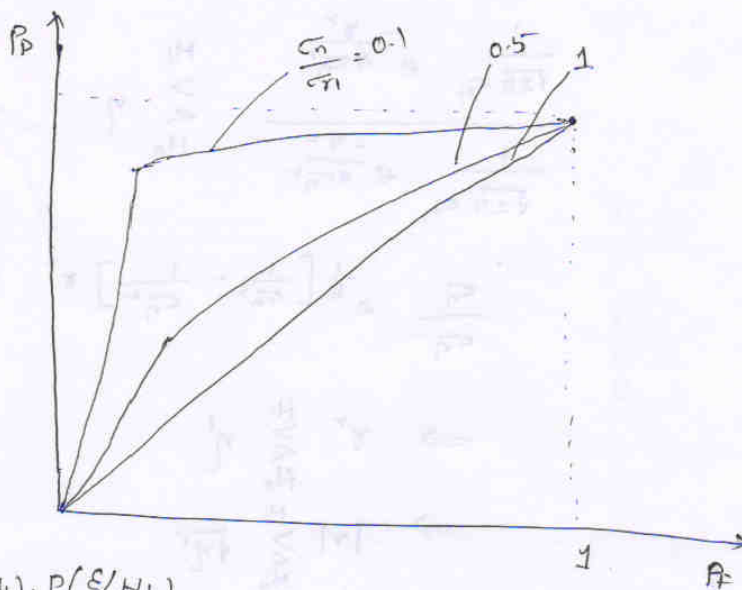
$$P_D = 2Q\left(\frac{\sqrt{\eta'}}{\sigma_n}\right)$$

$$= 2Q\left(\frac{\sigma_n}{\sigma_{r1}} Q^{-1}\left(\frac{P_F}{2}\right)\right)$$

(c) two hypothesis are equally likely,
use ML detector,

$$e^{\frac{1}{2} \left[\frac{1}{\sigma_n^2} - \frac{1}{\sigma_{r1}^2} \right] r^2} \underset{H_0}{\overset{H_1}{>}} \frac{\sigma_{r1}}{\sigma_n}$$

$$r^2 \underset{H_0}{\overset{H_1}{>}} \frac{\log\left(\frac{\sigma_{r1}}{\sigma_n}\right)}{\frac{1}{2} \left[\frac{1}{\sigma_n^2} - \frac{1}{\sigma_{r1}^2} \right]} = \eta$$



$$P(E) = P(H_0) \cdot P(E/H_0) + P(H_1) \cdot P(E/H_1)$$

$$= \frac{1}{2} \left[2Q\left(\frac{\sqrt{\eta}}{\sigma_n}\right) + 1 - 2Q\left(\frac{\sqrt{\eta}}{\sigma_{r1}}\right) \right]$$

2.2.13

(8)

$$\Lambda(r) = \frac{f_{r/H_1}(r/H_1)}{f_{r/H_0}(r/H_0)}$$

$$\begin{aligned} 1. \quad E[\Lambda^{n+1}/H_0] &= \int \Lambda^{n+1} f_{r/H_0}(r/H_0) dr \\ &= \int \Lambda^n \cdot \frac{f_{r/H_1}(r/H_1)}{f_{r/H_0}(r/H_0)} \cdot f_{r/H_0}(r/H_0) dr \end{aligned}$$

$$= E[\Lambda^n/H_1]$$

$$2. \quad E[\Lambda/H_0] = E[\Lambda^0/H_1] = E[1/H_1] = 1.$$

$$\begin{aligned} 3. \quad \text{Var}[\Lambda/H_0] &= E[\Lambda^2/H_0] - [E[\Lambda/H_0]]^2 \\ &= E[\Lambda^2/H_1] - 1^2 \\ &= E[\Lambda^2/H_1] - E[\Lambda/H_0]^2 \end{aligned}$$

2.2.19

$$f_{R_i/H_k}(R_i/H_k) = \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left[-\frac{(R_i - m_k)^2}{2\sigma_k^2}\right] \quad \begin{matrix} i=1, 2, \dots, N \\ k=0, 1. \end{matrix}$$

$$\Lambda(r) = \frac{f_{Y/H_1}(Y/H_1)}{f_{Y/H_0}(Y/H_0)} \quad \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \quad \eta$$

$$\frac{\left(\frac{1}{\sqrt{2\pi}\sigma_1}\right)^N \cdot \exp\left[-\sum_{i=1}^N \frac{(R_i - m_1)^2}{2\sigma_1^2}\right]}{\left(\frac{1}{\sqrt{2\pi}\sigma_0}\right)^N \cdot \exp\left[-\sum_{i=1}^N \frac{(R_i - m_0)^2}{2\sigma_0^2}\right]} \quad \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \quad \eta$$

$$\left(\frac{\sigma_0}{\sigma_1}\right)^N \exp \left[\sum_{i=1}^N \frac{(R_i - m_0)^2}{2\sigma_0^2} - \frac{(R_i - m_1)^2}{2\sigma_1^2} \right] \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta$$

$$\sum_{i=1}^N \left\{ R_i^2 \left[\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2} \right] + R_i \left[\frac{m_1}{\sigma_1^2} - \frac{m_0}{\sigma_0^2} \right] \right\} \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta'$$

$$\text{let } l_\alpha = \sum_{i=1}^N R_i$$

$$l_\beta = \sum_{i=1}^N R_i^2$$

$$l_\beta \left[\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2} \right] + l_\alpha \left[\frac{m_1}{\sigma_1^2} - \frac{m_0}{\sigma_0^2} \right] \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta'$$

(b) decision regions in l_α, l_β -plane for

$$2m_0 = m_1 > 0$$

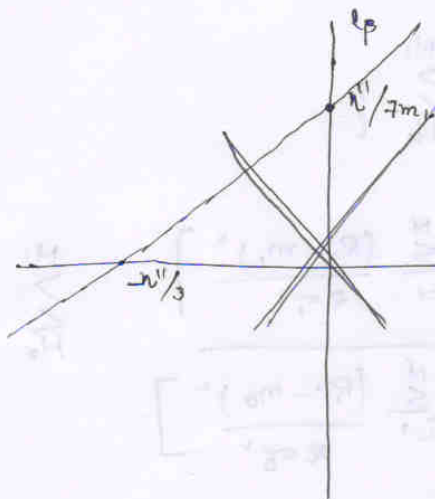
$$2\sigma_1 = \sigma_0$$

$$l_\beta \left[\frac{1}{8\sigma_1^2} - \frac{1}{2\sigma_1^2} \right] + l_\alpha \left[\frac{m_1}{\sigma_1^2} - \frac{m_1/2}{4\sigma_1^2} \right] \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta'$$

$$l_\beta \left[\frac{-3}{8\sigma_1^2} \right] + l_\alpha \left[\frac{7m_1}{8\sigma_1^2} \right] \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta'$$

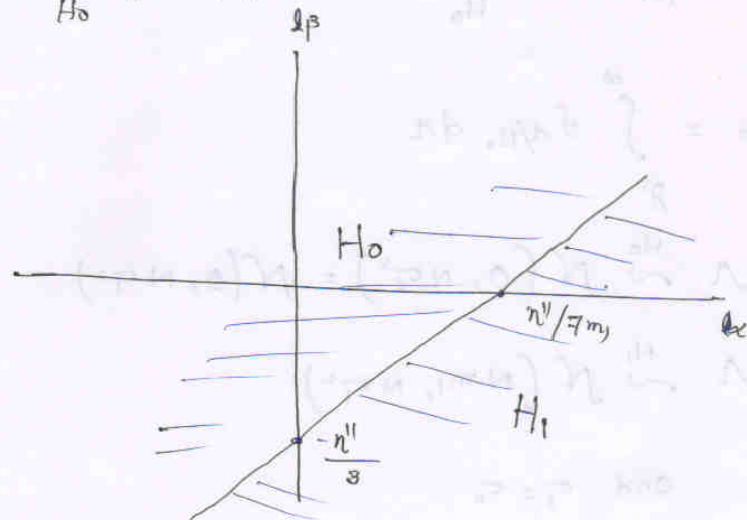
$$(-3) l_\beta + (7m_1) l_\alpha \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \eta''$$

$$(-3) l_\beta + (7m_1) l_\alpha = \eta''$$



$$(7m_1) \ln \alpha + (-3) \ln \beta \quad \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \quad \eta'' = 3\sigma_1^2 \eta'$$

9



2.8.20

1. $m_0 = 0$
 $\sigma_0 = \sigma_1$

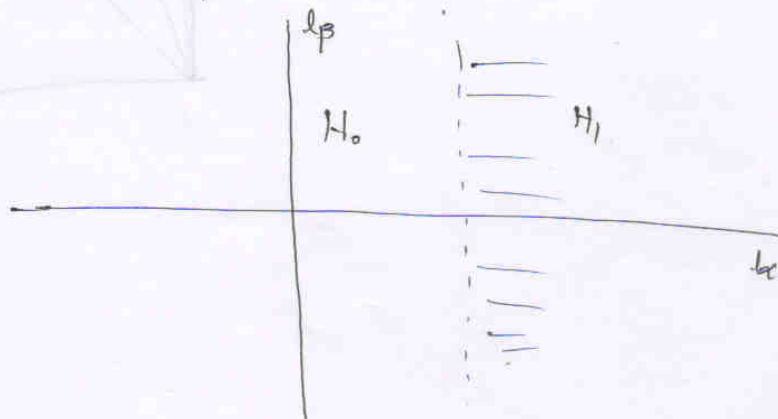
decision regions and Roc.

$$2 \ln \left[\frac{m_1}{\sigma_1^2} - \frac{m_0}{\sigma_0^2} \right] + \ln \left[\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right] \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \quad \eta$$

$$m_0 = 0, \quad \sigma_0 = \sigma_1$$

$$2 \ln \cdot \frac{m_1}{\sigma_1^2} + \ln(0) \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \quad \eta$$

$$\ln \begin{matrix} H_1 \\ > \\ H_0 \end{matrix} \quad \eta - \frac{\sigma_1^2}{2m_1} = \eta'$$



$$\Lambda = \sum_{i=1}^N R_i \cdot \begin{matrix} H_1 \\ \geq \\ H_0 \end{matrix} \lambda^1$$

$$P_F = \int_{\lambda^1}^{\infty} f_{\Lambda/H_0} d\Lambda$$

$$\Lambda \underset{H_0}{\sim} \mathcal{N}(0, N\sigma_0^2) = \mathcal{N}(0, N\sigma^2)$$

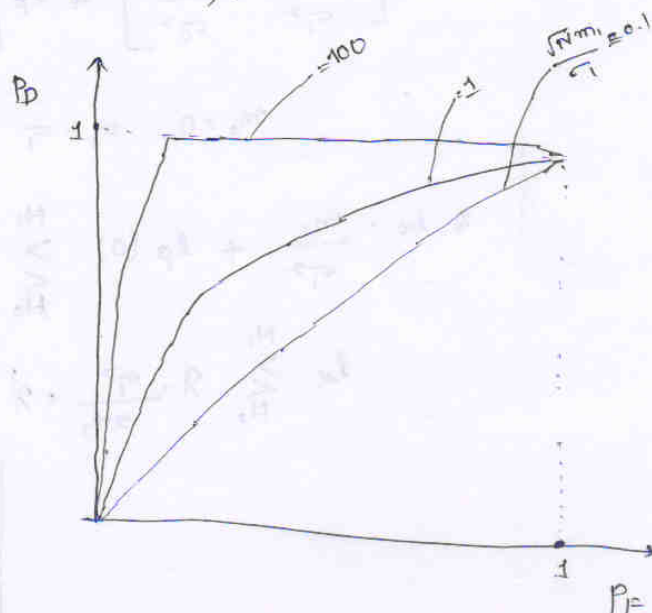
$$\Lambda \underset{H_1}{\sim} \mathcal{N}(Nm_1, N\sigma^2)$$

$$\text{and } \sigma_1 = \sigma_0$$

$$P_F = Q\left(\frac{\lambda^1}{\sqrt{N}\sigma}\right) \Rightarrow \frac{\lambda^1}{\sqrt{N}\sigma} = Q^{-1}(P_F)$$

$$P_D = Q\left(\frac{\lambda^1 - Nm_1}{\sqrt{N}\sigma}\right)$$

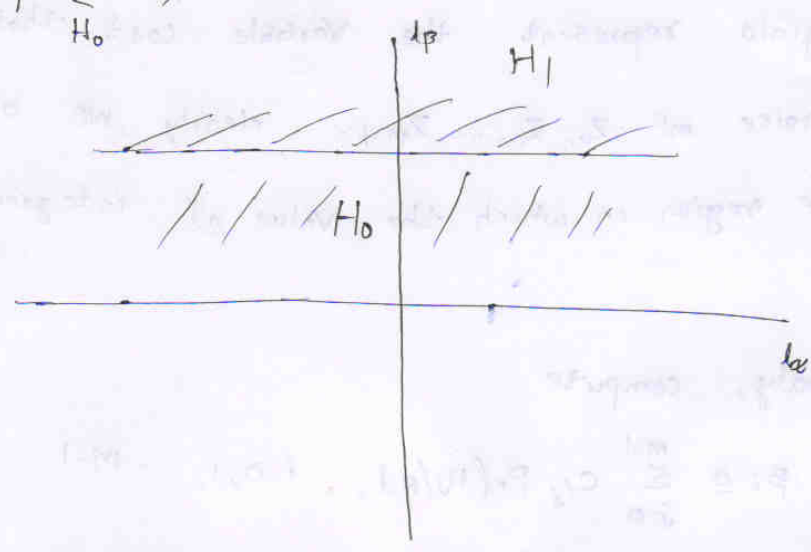
$$= Q\left(\frac{\lambda^1}{\sqrt{N}\sigma} - \frac{\sqrt{N}m_1}{\sigma}\right) = Q\left(Q^{-1}(P_F) - \frac{\sqrt{N}m_1}{\sigma}\right)$$



2. $m_0 = m_1 = 0$
 $\sigma_1^2 = \sigma_s^2 + \sigma_n^2$
 $\sigma_0 = \sigma_n$

$$l_p \cdot \left[\frac{1}{\sigma_n^2} - \frac{1}{\sigma_s^2 + \sigma_n^2} \right] \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \lambda$$

$$l_p \cdot \sum_{H_0}^{H_1} \lambda''$$



2.3.2

$$R = \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} P_j c_{ij} \int_{Z_i} P_{r/H_j}(R/H_j) dR$$

Here, $P_{r/H_j} = f_{r/H_j}$

$$= \sum_{i=0}^{M-1} \int_{Z_i} \sum_{j=0}^{M-1} c_{ij} P_j P_{r/H_j}(R/H_j) dR$$

divide by $P_r(r)$

$$= \sum_{i=0}^{M-1} \int_{Z_i} \sum_{j=0}^{M-1} c_{ij} \frac{P_j P_{r/H_j}(R/H_j)}{P_r(r)} dR$$

$$= \sum_{i=0}^{M-1} \int_{Z_i} \sum_{j=0}^{M-1} C_{ij} P(H_j/R) dR$$

$$= \int_{Z_0} \sum_{j=0}^{M-1} C_{0j} P_{H_j/R}(H_j/R) dR + \dots$$

$$\dots + \int_{Z_{M-1}} \sum_{j=0}^{M-1} C_{M-1,j} P_{H_j/R}(H_j/R) dR$$

the integrals represent the variable cost that depends on our choice of $Z_0, Z_1, \dots, Z_{M-1}$. clearly, we assign each R to the region in which the value of integrand is the smallest.

So clearly, compute

$$P_i \triangleq \sum_{j=0}^{M-1} C_{ij} P_r(H_j/R), \quad i=0, 1, \dots, M-1$$

and Bayes test is choose the smallest.

(b)

$$C_{ii} = 0, \quad i=0, 1, \dots, M-1$$

$$C_{ij} = C \quad i \neq j, \quad i, j=0, 1, \dots, M-1$$

$$P_i = \sum_{j=0}^{M-1} C_{ij} P_r(H_j/R)$$

$$= \sum_{\substack{j=0 \\ j \neq i}}^{M-1} \underbrace{C_{ij}}_C P_r(H_j/R)$$

$$= \sum_{\substack{j=0 \\ j \neq i}}^{M-1} C P_r(H_j/R)$$

$$\text{and we know } \sum_{j=0}^{M-1} P(H_j/R) = 1$$

decision rule is $\underset{i}{\arg \min} \beta_i$

$$= \underset{i}{\arg \min} \sum_{\substack{j=0 \\ j \neq i}}^{M-1} P_r(H_j/R)$$

$$= \underset{i}{\arg \min} (1 - P(H_i/R))$$

$$= \underset{i}{\arg \max} P(H_i/R)$$

finally compute $P(H_i/R)$ $i = 0, 1, 2, \dots, M-1$

choose largest.

2.3.3.

$$f_{r/H_k}(r/H_k) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(R-m_k)^2}{2\sigma^2}\right) \quad -\infty < R < \infty$$

$$k = 1, 2, \dots, 5$$

$$m_1 = -2\sigma$$

$$m_2 = -\sigma$$

$$m_3 = 0$$

$$m_4 = \sigma$$

$$m_5 = 2\sigma$$

Since prior probabilities are equal, ML detector is the optimal detector

Applying ML-detection, the detected index d is

$$d = \underset{i}{\arg \max} f(r/H_i)$$

$$= \underset{i}{\arg \max} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(R-m_k)^2}{2\sigma^2}\right)$$

$$= \underset{i}{\arg \min} \frac{(R-m_k)^2}{2\sigma^2}$$

$$= \underset{i}{\arg \min} (R-m_k)^2$$

The following are the decision regions:

$$H_0: -\frac{m}{2} < R < \frac{m}{2}$$

$$H_1: R < -\frac{3m}{2}$$

$$H_2: -\frac{3m}{2} < R < -\frac{m}{2}$$

$$H_4: \frac{m}{2} < R < \frac{3m}{2}$$

$$H_5: R > \frac{3m}{2}$$

$$\text{error probability } P(\varepsilon) = P(\varepsilon/H_0)P(H_0) + P(\varepsilon/H_1)P(H_1) + \dots + P(\varepsilon/H_5)P(H_1)$$

$$= \frac{1}{5} \left[Q\left(\frac{m}{2\sigma}\right) + 2 \cdot Q\left(\frac{m}{2\sigma}\right) + 2 \cdot Q\left(\frac{m}{2\sigma}\right) + 2 \cdot Q\left(\frac{m}{2\sigma}\right) + Q\left(\frac{m}{2\sigma}\right) \right]$$

$$= \frac{8}{5} Q\left(\frac{m}{2\sigma}\right)$$