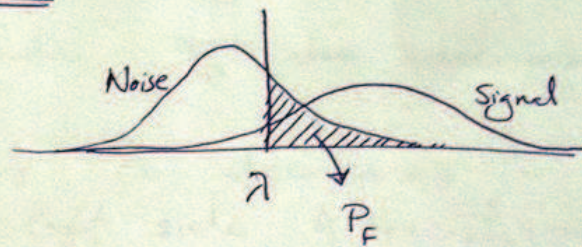


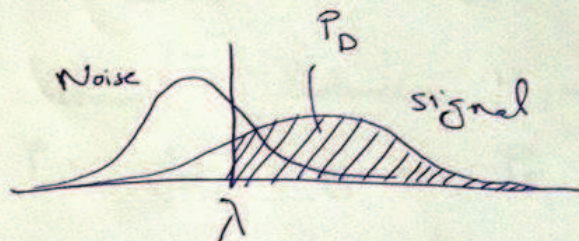
Solutions

Problem (1):

$$\begin{aligned} a) P_F &= \Pr \{ X_n > \lambda \} \\ &= 1 - \Pr \{ X_n \leq \lambda \} \\ &= 1 - F_n(\lambda) \end{aligned}$$



$$\begin{aligned} b) P_D &= \Pr \{ X_s > \lambda \} \\ &= 1 - \Pr \{ X_s \leq \lambda \} \\ &= 1 - F_s(\lambda) \end{aligned}$$



$$c) X_n \sim \mathcal{N}(\mu_n, \sigma_n^2) \quad , \quad X_s \sim \mathcal{N}(\mu_s, \sigma_s^2)$$

$$\mathcal{N}(\mu, \sigma) \Rightarrow f_x(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$\begin{aligned} \therefore P_F &= \Pr \{ X_n > \lambda \} \\ &= \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_n} e^{-\frac{(x-\mu_n)^2}{2\sigma_n^2}} dx \end{aligned}$$

$$\text{let } y = \frac{x - \mu_n}{\sigma_n} \quad dy = \frac{dx}{\sigma_n}$$

$$\Rightarrow P_F = \int_{\frac{\lambda - \mu_n}{\sigma_n}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy$$

$$\boxed{P_F = Q\left(\frac{\lambda - \mu_n}{\sigma_n}\right)}$$

Similarly

$$\boxed{P_D = Q\left(\frac{\lambda - \mu_s}{\sigma_s}\right)}$$

$$d) \lambda = 1.2 \quad X_n \sim \mathcal{N}(0, 1) \quad X_s \sim \mathcal{N}(1.5, 4)$$

$$P_F = Q\left(\frac{1.2 - 0}{1}\right) = Q(1.2) = 0.11507 \text{ (from Table)}$$

$$P_D = Q\left(\frac{1.2 - 1.5}{2}\right) = Q(-0.15) =$$



e) If  $\lambda$  increases (i.e. moves to the right of the figure).

$P_F$  decreases while  $P_D$  also decrease

On the other hand, as  $\lambda$  decreases (i.e. moves to the left side of the figure)

Both  $P_F$  &  $P_D$  increase

However, there exist a certain  $\lambda$  between  $M_n$  and  $M_s$  that achieves the max  $P_D$  for a given  $P_F$ .



Problem (2):

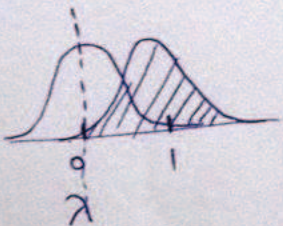
$$\begin{aligned} \text{a) } P_F &= P_r(Y[0] | H_0) \\ &= \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\ &= Q(\lambda) \end{aligned}$$

$$P_F = \alpha \Rightarrow \lambda = Q^{-1}(\alpha)$$

$$\begin{aligned} \text{b) } P_D &= P_r(Y[0] | H_1) \\ &= \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-1)^2}{2}} dx \\ &= Q(\lambda-1) = Q(Q^{-1}(\alpha) - 1) \end{aligned}$$

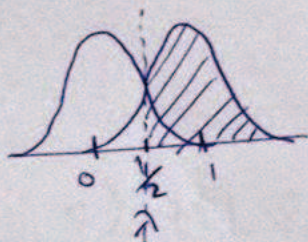
$$\text{c) } * \alpha = 0.5 \xrightarrow{\text{table}} \lambda = Q^{-1}(0.5) = 0$$

$$P_D = Q(0-1) = Q(-1) = 1 - Q(1) = 1 - 0.15866 = 0.84134$$



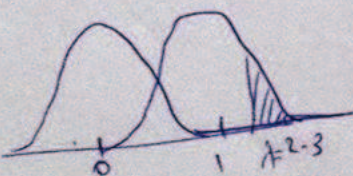
$$* \alpha = 0.3 \xrightarrow{\text{table}} \lambda = Q^{-1}(0.3) \approx 0.5$$

$$P_D = Q(0.5-1) = P(-0.5) = 1 - Q(0.5) = 1 - 0.3 = 0.7$$



$$* \alpha = 0.01 \xrightarrow{\text{table}} \lambda = Q^{-1}(0.01) \approx 2.3$$

$$P_D = Q(2.3-1) = P(1.3) = 0.09680$$



As  $P_F$  decrease from 0.5, we can achieve  $P_D > 0.5$  as long as  $\lambda$  is greater than 0 & less than 1. If  $\lambda$  is further increased  $P_D$  will be less than  $1/2$  which is not



Problem (3):

$$H_1: Y[n] \sim \mathcal{N}(0, \alpha_0^2)$$

$$H_0: Y[n] \sim \mathcal{N}(0, \alpha_1^2), \quad (\alpha_1^2 > \alpha_0^2)$$

$n$  are i.i.d.

a) Since the  $N$  samples are i.i.d., the joint density of  $\underline{Y}$  is simply the product of the individual probabilities

$$P(\underline{Y} | H_0) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi} \alpha_0} e^{-\frac{(Y[n])^2}{2\alpha_0^2}}$$

$$\& P(\underline{Y} | H_1) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi} \alpha_1} e^{-\frac{(Y[n])^2}{2\alpha_1^2}}$$

b) Maximum likelihood ratio

$$\frac{P(\underline{Y} | H_1)}{P(\underline{Y} | H_0)} = \frac{\prod_{n=1}^N \frac{1}{\sqrt{2\pi} \alpha_1} e^{-\frac{(Y[n])^2}{2\alpha_1^2}}}{\prod_{n=1}^N \frac{1}{\sqrt{2\pi} \alpha_0} e^{-\frac{(Y[n])^2}{2\alpha_0^2}}}$$

$$= \left(\frac{\alpha_0}{\alpha_1}\right)^N \frac{e^{-\frac{1}{2\alpha_1^2} \left[ \sum_{n=1}^N (Y[n])^2 \right]}}{e^{-\frac{1}{2\alpha_0^2} \left[ \sum_{n=1}^N (Y[n])^2 \right]}}$$

$$= \left(\frac{\alpha_0}{\alpha_1}\right)^N e^{-\frac{1}{2} \left( \frac{1}{\alpha_1^2} - \frac{1}{\alpha_0^2} \right) \left[ \sum_{n=1}^N (Y[n])^2 \right]}$$

c) MLT:

$$\frac{P(\underline{Y} | H_1)}{P(\underline{Y} | H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma$$

$$\left(\frac{\alpha_0}{\alpha_1}\right)^N e^{-\frac{1}{2} \left( \frac{1}{\alpha_1^2} - \frac{1}{\alpha_0^2} \right) \left[ \sum_{n=1}^N (Y[n])^2 \right]} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma$$



d) Because the ~~log~~ function is monotonic and both sides are positive. we take take the ~~log~~ of the MLT without affecting the test

$$\log \frac{P(Y|H_1)}{P(Y|H_0)} \stackrel{H_1}{\geq} \sum_{H_0} \ln \gamma$$

$$N \ln \frac{\sigma_0}{\sigma_1} - \frac{1}{2} \left( \frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2} \right) \sum_{n=1}^N (Y[n])^2 \stackrel{H_1}{\geq} \sum_{H_0} \ln \gamma$$

since  $\frac{1}{\sigma_1^2} < \frac{1}{\sigma_0^2}$ , we have

$$N \ln \frac{\sigma_0}{\sigma_1} + \frac{1}{2} \left( \frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right) \sum_{n=1}^N (Y[n])^2 \stackrel{H_1}{\geq} \sum_{H_0} \ln \gamma$$