

1. Under H_0 ,

$$\begin{aligned} p(y|H_0) &= \frac{p(y, H_0)}{p(H_0)} \\ &= \frac{\int_0^B \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta}{\int_0^B \alpha e^{-\alpha \theta} d\theta} \end{aligned}$$

Under H_1 ,

$$\begin{aligned} p(y|H_1) &= \frac{p(y, H_1)}{p(H_1)} \\ &= \frac{\int_B^\infty \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta}{\int_B^\infty \alpha e^{-\alpha \theta} d\theta} \end{aligned}$$

The likelihood ratio can be written as

$$\begin{aligned} L(y) &= \frac{p(y|H_1)}{p(y|H_0)} \\ &= \frac{\int_B^\infty \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta}{\int_0^B \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta} \cdot \frac{\int_0^B \alpha e^{-\alpha \theta} d\theta}{\int_B^\infty \alpha e^{-\alpha \theta} d\theta} \end{aligned}$$

The threshold is

$$T = \frac{\pi_{H_0} ((c_{10} - c_{00})}{\pi_{H_1} ((c_{01} - c_{11})} = \frac{p(H_0)}{p(H_1)} = \frac{\int_0^P \alpha e^{-\alpha \theta} d\theta}{\int_B^P \alpha e^{-\alpha \theta} d\theta}$$

Therefore, $L(y) \geq T \Leftrightarrow \frac{\int_B^P \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta}{\int_0^P \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta} \geq 1$,

which is equivalent to

$$\frac{e^{-\beta(\alpha+y)}}{1 - e^{-\beta(\alpha+y)}} \left((\alpha+y)\beta + 1 \right) \geq 1$$

Let y' be the solution of $e^{-\beta(\alpha+y)} \left((\alpha+y)\beta + 1 \right) = \frac{1}{2}$,
the decision rule is

$$S_\beta(y) = \begin{cases} 1 & \text{if } y \leq y' \\ 0 & \text{if } y > y' \end{cases}$$

The Bayes risk is

$$\begin{aligned} R(\delta_B) &= \pi_0 C_{10} p(E_1 | H_0) + \pi_1 C_{01} p(E_0 | H_1) \\ &= C_{10} p(E_1, H_0) + C_{01} p(E_0, H_1) \\ &= \int_0^{\eta'} \int_0^B \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta dy \\ &\quad + \int_{\eta'}^B \int_B^B \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta dy \end{aligned}$$

2. Under H_0 ,

$$f(y|H_0) = \frac{\int_0^B \theta^n e^{-\theta \sum y_i} \alpha e^{-\alpha \theta} d\theta}{\int_0^B \alpha e^{-\alpha \theta} d\theta}$$

Under H_1 ,

$$f(y|H_1) = \frac{\int_B^\infty \theta^n e^{-\theta \sum y_i} \alpha e^{-\alpha \theta} d\theta}{\int_B^\infty \alpha e^{-\alpha \theta} d\theta}$$

$$L(y) \geq 1 \Leftrightarrow F(y) \geq 1 \quad \text{where}$$

$$F(y) = \frac{\int_B^\infty \theta^n e^{-\theta \sum y_i} \alpha e^{-\alpha \theta} d\theta}{\int_0^\infty \theta^n e^{-\theta \sum y_i} \alpha e^{-\alpha \theta} d\theta}$$

The likelihood ratio test can be written as

$$\delta_F(y) = \begin{cases} 1 & \text{if } F(y) \geq 1 \\ 0 & \text{if } F(y) < 1 \end{cases}$$

The Bayes Risk can be written as

$$R(\delta_B) = \pi_0 C_{10} p(C_1 | H_0) + \pi_1 C_{01} p(C_0 | H_1)$$

$$= \int_{\{y: F(y) \geq 1\}} \int_0^B \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta dy$$

$$+ \int_{\{y: F(y) < 1\}} \int_B^\infty \theta e^{-\theta y} \alpha e^{-\alpha \theta} d\theta dy$$

3.a) The likelihood ratio can be written as

$$L(y) = \frac{\prod_{k=1}^n \frac{1}{\sqrt{2\pi}\sigma_1} e^{-(y_k - \mu_1)^2/2\sigma_1^2}}{\prod_{k=1}^n \frac{1}{\sqrt{2\pi}\sigma_0} e^{-(y_k - \mu_0)^2/2\sigma_0^2}}$$

$$= \left(\frac{\sigma_0}{\sigma_1}\right)^n e^{\sum_{k=1}^n \left(\frac{\mu_0^2}{\sigma_0^2} - \frac{\mu_1^2}{\sigma_1^2}\right)} e^{\left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2}\right) \sum_{k=1}^n y_k^2} \\ e^{\left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_0}{\sigma_0^2}\right) \sum_{k=1}^n y_k},$$

which is of the desired form

b) If $\mu_0 = \mu_1$, $\sigma_1^2 > \sigma_0^2$,

$$L(y) = \left(\frac{\sigma_0}{\sigma_1}\right)^n e^{\sum_{k=1}^n (y_k - \mu)^2 \left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2}\right)}$$

$$L(y) \geq T \Leftrightarrow \sum_{k=1}^n (y_k - \mu)^2 \geq T'$$

In other words, we compare $\sum_{k=1}^n (y_k - \mu)^2$ with some threshold.

If $\sigma_0^2 = \sigma_1^2$, $u_1 > u_0$,

$$L(y) = e^{\sum_{k=1}^n (y_k - u_0)^2 - \sum_{k=1}^n (y_k - u_1)^2}$$

$$= e^{2(u_1 - u_0) \sum_{k=1}^n y_k} \cdot e^{n(u_0^2 - u_1^2)}$$

$$L(y) \geq T \Leftrightarrow \sum_{k=1}^n y_k \geq T''$$

In other words, we compare $\sum_{k=1}^n y_k$ with some threshold.

c) For $n=1$, $u_1 = u_0 = u$ and $\sigma_1^2 > \sigma_0^2$, the NP test is

$$\delta_{NP}(y) = \begin{cases} 1 & \text{if } (y-u)^2 \geq T' \\ 0 & \text{if } (y-u)^2 < T' \end{cases}$$

The false alarm probability is

$$P_F(\delta_{NP}) = \cancel{P_0((y-u)^2 \geq T')}$$

$$= 2[1 - \phi(\frac{\sqrt{T'}}{\sigma_0})]$$

where $\phi(\cdot)$ is the CDF of normal distribution.

Therefore, the appropriate τ' for α is

$$\tau' = \left[\sigma_0 \phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right]^2$$

The detection probability is

$$P_D(\delta_{NP}) = 1 - P_1((y-u)^2 < \tau')$$

$$= 2 \left[1 - \phi \left(\frac{\delta_0}{\sigma_1} \phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right) \right], \quad 0 < \alpha < 1$$

4. If $\eta = \eta_1 > \eta_0 = 0$ and $\delta^2 = \delta_0^2 = \delta_1^2 > 0$,

$$L(y) = e^{2u} \sum_{k=1}^n y_k e^{-\eta u^2}$$

The NP test is

$$S_{NP}(y) = \begin{cases} 1 & \text{if } \sum y_i \geq T'' \\ 0 & \text{if } \sum y_i < T' \end{cases}$$

$$P_F = P_0 \left(\sum y_i \geq T'' \right)$$

$$= 1 - \phi \left(\frac{T''}{\sqrt{n}\delta} \right)$$

Therefore, the appropriate T'' for α is

$$T'' = \phi^{-1}(1-\alpha) \sqrt{n} \delta$$

If δ is unknown, there does not exist a UMP for any δ .

$$P_D = P_1 \left(\sum y_i \geq T'' \right)$$

$$= 1 - \phi \left(\frac{T'' - \eta u}{\sqrt{n}\delta} \right)$$

5.a) From chapter 2.5 of the lecture notes, with the error probability criterion, the decision becomes a MAP computer.

Under equal priors, it reduces to a maximum likelihood problem.

The decision rule is

$$\delta(y) = \begin{cases} 1 & \text{if } y > 1 \\ 2 & \text{if } y < -1 \\ V_1 & \text{if } y \in [0, 1] \\ V_2 & \text{if } y \in [-1, 0] \end{cases}$$

where V_1 can be 0 or 1 with any probability,

V_2 can be 0 or 2 with any probability,

without changing the error probability.

b) Take $V_1=0$ and $V_2=0$ as an example, the error probability is

$$\frac{1}{3} \times P_0(C_1 \cup C_2) + \frac{1}{3} P_1(C_0 \cup C_2) + \frac{1}{3} P_2(C_0 \cup C_1)$$

$$= 0 + \frac{1}{3} \times \frac{1}{2} + \frac{1}{3} \times \frac{1}{2}$$

$$= \frac{1}{3}$$