

#4.1.1.

(a)

$$\beta(\theta) \equiv E_{\theta}[\int_c(x) = 1] = P_{\theta}[M_n \geq c] = 1 - P_{\theta}[M_n \leq c] = 1 - \left[\int_0^c \frac{1}{\theta} dx \right]^n = 1 - \left[\frac{c}{\theta} \right]^n$$

$$\text{Since } \beta'(\theta) = -n \cdot \left[\frac{c}{\theta} \right]^{n-1} \cdot \left[-\frac{c}{\theta^2} \right] = n \frac{c^n}{\theta^{n+1}} > 0, \quad \forall \theta > 0.$$

$\beta(\theta)$ is a monotone increasing fct of θ . //

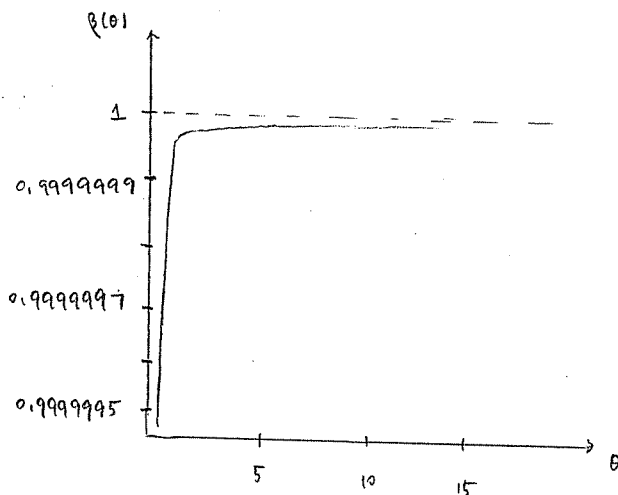
(b)

$$\alpha = \sup_{\theta > 0} \beta(\theta) = \beta\left(\frac{1}{2}\right) \quad \text{by (a)}$$

$$= 1 - (2c)^n \stackrel{\text{set } = 0.05}{}$$

$$\therefore c = \frac{1}{2} (0.95)^{\frac{1}{n}} //$$

(c)



(d)

$$\beta(\theta) = 1 - \left[\frac{c}{\theta} \right]^n = 1 - \left[\frac{1}{2} (0.95)^{\frac{1}{n}} \cdot \frac{4}{3} \right]^n = 1 - 0.95 \left(\frac{2}{3} \right)^n \stackrel{\text{set}}{=} 0.98$$

$$\begin{cases} c = \frac{1}{2} (0.95)^{\frac{1}{n}} \\ \theta = \frac{3}{4} \end{cases}$$

$$\Rightarrow n = \frac{\log 0.02 - \log 0.95}{\log 2 - \log 3} = 9.52 \quad \therefore n = 10 \quad //$$

(e)

$$P = \sup_{\theta_0} (M_{20} \geq 0.48) = \sup_{\theta} \left\{ 1 - \left[\frac{0.48}{\theta} \right]^{20} : \theta \leq \frac{1}{2} \right\} = 1 - (2 \times 0.48)^{20} = 0.558 \quad //$$

#4.1.3.

(a)

sol)

For any fixed $\theta_1 \leq \theta_0$ and $\theta_2 > \theta_0$,

$$\frac{f_{\theta_2}(z)}{f_{\theta_1}(z)} = \frac{\frac{n}{\pi} \frac{e^{-\theta_2} \theta_2^{\frac{n}{\pi} z}}{z!}}{\frac{n}{\pi} \frac{e^{-\theta_1} \theta_1^{\frac{n}{\pi} z}}{z!}} = \frac{e^{-n\theta_2} \theta_2^{\frac{n}{\pi} z}}{e^{-n\theta_1} \theta_1^{\frac{n}{\pi} z}} = e^{-n(\theta_2 - \theta_1)} \left[\frac{\theta_2}{\theta_1} \right]^{\frac{n}{\pi} z} \triangleq g_{\theta_1, \theta_2}(T(z))$$

where $T(z) = \frac{n}{\pi} z$.

Since $g_{\theta_1, \theta_2}(t) = e^{-n(\theta_2 - \theta_1)} \left[\frac{\theta_2}{\theta_1} \right]^t = e^{-n(\theta_2 - \theta_1) + t(\log \theta_2 - \log \theta_1)}$ and

$$\frac{dg}{dt} = (\log \theta_2 - \log \theta_1) e^{-n(\theta_2 - \theta_1) + t(\log \theta_2 - \log \theta_1)} > 0, \quad \forall t,$$

g_{θ_1, θ_2} is nondecreasing in $\frac{n}{\pi} z$, for $z \in \{z \in \mathbb{N} : f_{\theta_1}(z) + f_{\theta_2}(z) > 0\}$.

$\therefore f_{\theta}$ has MLR in IX_z .

Then, a UMP α -test is given by

$$\phi(x) = \begin{cases} 1 & \text{If } \frac{1}{T} \sum x_i > c \\ \gamma & \text{If } \frac{1}{T} \sum x_i = c \\ 0 & \text{If } \frac{1}{T} \sum x_i < c \end{cases} \quad \text{equiv.} \quad \Leftrightarrow \quad \begin{cases} 1 & \text{If } \bar{x} > \frac{c}{n} \\ \gamma & \text{If } \bar{x} = \frac{c}{n} \\ 0 & \text{If } \bar{x} < \frac{c}{n} \end{cases}$$

where c and γ are determined by

$$\alpha = \max_{\theta_0} E_{\theta_0} \phi(x) = \max_{\theta_0} [P_{\theta_0}(\bar{x} > \frac{c}{n}) + \gamma \cdot P_{\theta_0}(\bar{x} = \frac{c}{n})]$$

$$= \max_{\theta_0} [P_{\theta_0}(\frac{1}{T} \sum x_i > c) + \gamma \cdot P_{\theta_0}(\frac{1}{T} \sum x_i = c)]$$

$$= \sum_{y=c+1}^{\infty} \frac{e^{-n\theta_0} \cdot (n\theta_0)^y}{y!} + \gamma \cdot \frac{e^{-n\theta_0} \cdot (n\theta_0)^c}{c!}$$

as $Y \equiv \sum_{i=1}^n x_i \sim \text{Poisson}(n\theta)$.

//

(b)

$$\beta(\theta) \equiv E_{\theta} \phi(x) = \sum_{y=c+1}^{\infty} \frac{e^{-n\theta} (n\theta)^y}{y!} + \gamma \cdot \frac{e^{-n\theta} (n\theta)^c}{c!}$$

$$= 1 - \sum_{y=0}^{c-1} \frac{e^{-n\theta} (n\theta)^y}{y!} + (\gamma-1) \frac{e^{-n\theta} (n\theta)^c}{c!}$$

$$\Rightarrow \beta'(\theta) = - \sum_{y=0}^{c-1} \frac{1}{y!} [-n e^{-n\theta} (n\theta)^y + e^{-n\theta} \cdot y (n\theta)^{y-1} \cdot n] + (\gamma-1) \frac{1}{c!} [-n e^{-n\theta} (n\theta)^c + e^{-n\theta} c (n\theta)^{c-1} \cdot n]$$

$$= - \sum_{y=0}^{c-1} \frac{1}{y!} n e^{-n\theta} (n\theta)^{y-1} [y - n\theta] + \frac{\gamma-1}{c!} n e^{-n\theta} (n\theta)^{c-1} [c - n\theta] > 0$$

for θ is not too small (as $y - n\theta < 0$ and $\gamma \in (0, 1)$).

$\therefore \beta(\theta)$ is increasing in θ .

//

CU)

By CLT, $Z \equiv \frac{\sqrt{n}(\bar{x} - \theta_0)}{\sqrt{\theta_0}} \xrightarrow{d} N(0,1)$ as $n \rightarrow \infty$,

$$\Rightarrow P(\bar{x} > \frac{c}{n}) = P(\bar{x} > k) = P\left(\frac{\sqrt{n}(\bar{x} - \theta_0)}{\sqrt{\theta_0}} > \frac{\sqrt{n}}{\sqrt{\theta_0}}(k - \theta_0)\right) \stackrel{\text{set}}{=} \alpha$$

\uparrow
 $\text{let } \frac{c}{n} = k$

$$\therefore k = \theta_0 + \frac{\sqrt{\theta_0}}{\sqrt{n}} z_{1-\alpha} \quad (\Leftrightarrow c = n\theta_0 + \sqrt{n\theta_0} z_{1-\alpha})$$

where $\Phi(z_{1-\alpha}) = 1 - \alpha$ with a standard normal cdf, Φ . //

4.2.1.

$\underline{x} = (x_1, \dots, x_n) \sim N(\mu, \sigma^2)$, σ^2 : known

$H_0: \mu = 0$ vs. $H_1: \mu = \nu$ where ν is a known signal.

By N-P lemma, we can construct the following test as

$$S(x) = \begin{cases} 1 & \text{if } \frac{f(z|H_1)}{f(z|H_0)} > k \\ 0 & \text{o.w.} \end{cases} \quad \text{for some } k$$

where

$$\frac{f(z|H_1)}{f(z|H_0)} = \frac{(2\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2} \sum_1^n (x_i - \nu)^2\right\}}{(2\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2} \sum_1^n x_i^2\right\}} = \exp\left[-\frac{1}{2\sigma^2} \sum_1^n x_i^2 + n\nu^2\right]$$

equiv.

$$\Leftrightarrow S(x) = \begin{cases} 1 & \text{if } \bar{x} > c \\ 0 & \text{o.w.} \end{cases} \quad \text{for some } c$$

$$\Rightarrow \begin{cases} P(S(x) = 1 | H_0) = P(\bar{x} > c | H_0) \leq 0.05 \\ P(S(x) = 0 | H_1) = P(\bar{x} \leq c | H_1) \leq 0.05 \end{cases}$$

$$\Rightarrow \begin{cases} \frac{\sqrt{n}c}{\sigma} \geq z_{1-\alpha} = 1.645 \\ \frac{\sqrt{n}(c-\mu)}{\sigma} \leq z_{\alpha} = -1.645 \end{cases}$$

$$\Rightarrow 1.645 - \frac{\sqrt{n}\mu}{\sigma} \leq \frac{\sqrt{n}c}{\sigma} - \frac{\sqrt{n}\mu}{\sigma} \leq -1.645 \quad \therefore \sqrt{n} \geq 3.29 \frac{\sigma}{\mu} \Rightarrow n \geq (3.29)^2 \left(\frac{\sigma}{\mu}\right)^2$$

$$\textcircled{1} \text{ The first system: } n \geq (3.29)^2 \cdot \left(\frac{1}{2}\right)^2 = 2.17 \quad \therefore n=3$$

$$\textcircled{2} \text{ The second system: } n \geq (3.29)^2 = 10.98 \quad \therefore n=11$$

$$\Rightarrow \textcircled{1} \text{ Cost for 1st system: } 10^6 + 3 \times 100 \times 10^3 = 1.3 \times 10^6$$

$$\textcircled{2} \text{ Cost for 2nd system: } 10^6 + 11 \times 100 \times 10^3 = 1.2 \times 10^6$$

\therefore The 2nd system is cheaper. //

#4.2.3.

(a)

To test $H_0: \theta_1 = \theta_2 = \theta_3 = \theta_4 = 0.17, \theta_5 = 0.14, \theta_6 = 0.18$ vs. $H_1: \theta_1 = \theta_2 = \dots = \theta_6 = \frac{1}{6}$,

we can use N-P Lemma as follows.

$$f(x) = \begin{cases} 1 \\ 0 \end{cases} \quad \text{if } \frac{f(x|H_1)}{f(x|H_0)} > \frac{1}{2} \\ \text{o.w.} \end{cases}$$

for some k

where

$$\frac{f(z|H_1)}{f(z|H_0)} = \frac{\frac{n!}{x_1! x_2! \dots x_6!} \left(\frac{1}{6}\right)^n}{\frac{n!}{x_1! x_2! \dots x_6!} (0.17)^{n-x_5-x_6} (0.14)^{x_5} (0.18)^{x_6}}$$

$$= \frac{1}{(1.02)^{n-x_5-x_6} (0.84)^{x_5} (1.08)^{x_6}}$$

$n = \frac{6}{1} x_5$

(b)

For $n=2$,

$$\Leftarrow \alpha = P(S(x) = 1 | H_0) = P(x = (0, 0, 0, 0, 2, 0) | H_0) = \frac{2!}{2!} (0.14)^2 = 0.0196$$

$$\Rightarrow \alpha = P(S(x) = 1 | H_0) = P\left(\frac{f(z|H_1)}{f(z|H_0)} > k | H_0\right) \stackrel{\text{Set}}{=} 0.0196$$

Note)

$(x_5, x_6, n-x_5-x_6)$	$(2, 0, 0)$	$(1, 0, 1)$	$(0, 0, 2)$...
$\frac{f(z H_1)}{f(z H_0)}$	$\frac{1}{0.84^2}$	$\frac{1}{(0.84)(1.02)}$	$\frac{1}{(1.02)^2}$...

i) For $\frac{1}{(0.84)(1.02)} < k < \frac{1}{0.84^2}$, $\alpha = P(2, 0, 0 | H_0) = \frac{2!}{2!} (0.14)^2 = 0.0196$

ii) For $\frac{1}{(1.02)^2} < k < \frac{1}{(0.84)(1.02)}$, $\alpha = P(2, 0, 0 | H_0) + P(1, 0, 1 | H_0)$

$$= \frac{2!}{2!} (0.14)^2 + \frac{2!}{1!1!} (0.14)(0.17) = 0.0672$$

The most powerful level 0.0196 test rejects H_0

when two 5s are obtained.

(c)

Under H_0 , $(x_5, x_6, Y) \sim \text{Multinom}(n, 0.18, 0.14, 0.68)$ where $Y = \sum_{i=1}^4 x_i$

$$R(x) \equiv \frac{f(x|H_1)}{f(x|H_0)} = \frac{1}{(1.02)^y (0.84)^{x_5} (1.08)^{x_6}}$$

$$\Rightarrow \log R(x) = -x_5 \log 0.84 - x_6 \log 1.08 - y \log 1.02$$

$$\stackrel{\text{let}}{=} a_1 x_5 + a_2 x_6 + a_3 y \sim N(n\mu, n\sigma^2)$$

$$\text{where } a_1 = -\log 0.84, \quad a_2 = -\log 1.08, \quad a_3 = -\log 1.02,$$

$$n\mu = n [a_1 \theta_1 + a_2 \theta_2 + a_3 \theta_3], \quad \text{and}$$

$$n\sigma^2 = n [(a_1 - \mu)^2 \theta_1 + (a_2 - \mu)^2 \theta_2 + (a_3 - \mu)^2 \theta_3]$$

$$\Rightarrow \alpha = P(\log R(x) > k | H_0)$$

$$\Rightarrow \frac{k - n\mu}{\sqrt{n\sigma^2}} = z_{1-\alpha} \quad \text{where } \Phi(z_{1-\alpha}) = 1 - \alpha \quad \text{with a standard normal cdf, } \Phi.$$

$$\therefore k = n\mu + \sqrt{n\sigma^2} z_{1-\alpha}.$$

//

4.1.5

As H is a sample.

$$\alpha(T) = \sup_{\theta_0} P_{\theta_0}(T > k) = P_{\theta_0}(T > k) = 1 - F_T(k)$$

Since T is continuous r.v., $F_T(k) \sim U(0,1)$

and $\alpha(T) = 1 - F_T(k) \sim U(0,1)$.

⊙ Let $U = F_T(k)$,

$$\left(\begin{aligned} P(U \leq u) &= P(F_T(k) \leq u) = P(k \leq F_T^{-1}(u)) = F_T(F_T^{-1}(u)) = u \quad \text{where } u \in (0,1). \\ \therefore f_U(u) &= 1, \quad 0 < u < 1. \quad \therefore F_T(k) \sim U(0,1). \end{aligned} \right.$$

4.1.6.

By conclusion from 4.1.5, $\alpha(T_j) \stackrel{i.i.d.}{\sim} U(0,1)$, $j=1, \dots, k$

$$\Rightarrow -\log \alpha(T_j) \stackrel{i.i.d.}{\sim} \text{Exp}(1) \stackrel{d}{=} \text{Gamma}(1,1)$$

⊙ claim: $X \sim U(0,1) \Rightarrow -\log X \sim \text{Exp}(1)$

$$\Rightarrow -2 \log \alpha(T_j) \stackrel{i.i.d.}{\sim} \text{Gamma}(1,2)$$

$$\left(\begin{aligned} \text{Let } Y = -\log X &\Rightarrow X = e^{-Y}, \quad |J| = e^{-Y} \\ f_Y(y) &= e^{-y}, \quad 0 < y < \infty \end{aligned} \right.$$

$$\Rightarrow -2 \sum_{j=1}^k \log \alpha(T_j) \sim \text{Gamma}(k,2) \stackrel{d}{=} \chi_{2k}^2$$

//

$$\therefore Y = -\log X \sim \text{Exp}(1)$$

#4.2.4.

(a)

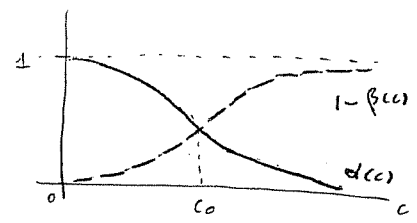
$$P(\text{Type I error}) = P_{\theta_0}(L(X, \theta_0, \theta_1) \geq c) \equiv \alpha(c) \quad \text{is decreasing in } c$$

$$P(\text{Type II error}) = 1 - P_{\theta_1}(L(X, \theta_0, \theta_1) \geq c) = 1 - \beta(c) \quad \text{is increasing in } c.$$

→ The fcts of $\alpha(c)$ and $1 - \beta(c)$ will cross at c_0 , i.e.,

c_0 is the solution of the equation

$$P_{\theta_0}(L(X, \theta_0, \theta_1) \geq c_0) = 1 - P_{\theta_1}(L(X, \theta_0, \theta_1) \geq c_0).$$



$$\Rightarrow \max(\alpha(c), 1 - \beta(c)) = \begin{cases} \alpha(c) & \text{if } c \leq c_0 \\ 1 - \beta(c) & \text{if } c \geq c_0 \end{cases}$$

$$\therefore \min_c [\max(\alpha(c), 1 - \beta(c))] = \alpha(c_0)$$

∴ The likelihood ratio test with critical value c is best in this sense!

(b)

$$P_{\theta_0}(L(X, \theta_0, \theta_1) \geq c) = P_{\theta_0}\left(\frac{\sqrt{n}\bar{X}}{\sigma} > \frac{\sqrt{n}c}{\sigma}\right)$$

$$P_{\theta_1}(L(X, \theta_0, \theta_1) \geq c) = P_{\theta_1}\left(\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} > \frac{\sqrt{n}(c - \mu)}{\sigma}\right)$$

$$\text{From } P_{\theta_0}(L(X, \theta_0, \theta_1) \geq c) = 1 - P_{\theta_1}(L(X, \theta_0, \theta_1) \geq c), \quad c = - (c - \mu) \quad \therefore c = \frac{\mu}{2}$$

$$\therefore \delta(x) = \begin{cases} 1 & \text{if } \bar{x} > \frac{\mu}{2} \\ 0 & \text{if } \bar{x} \leq \frac{\mu}{2} \end{cases}$$

//

4.2.5

$$H_0: \begin{bmatrix} X \\ Y \end{bmatrix} \sim N_2 \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0.1b \\ 0.1b & 1 \end{bmatrix} \right) \quad \text{vs.} \quad H_1: \begin{bmatrix} X \\ Y \end{bmatrix} \sim N_2 \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 & 0.1b \\ 0.1b & 1 \end{bmatrix} \right)$$

Let $T = X + Y$. Then, $T \stackrel{\text{under } H_0}{\sim} N(0, 3.2)$ $T \stackrel{\text{under } H_1}{\sim} N(2, 3.2)$

$$\Rightarrow L(T, \theta_0, \theta_1) = \frac{e^{-\frac{1}{2(3.2)}(T-2)^2}}{e^{-\frac{1}{2(3.2)}T^2}} = e^{-\frac{1}{6.4} \{ (T-2)^2 - T^2 \}}$$

$$\Rightarrow \log L(T, \theta_0, \theta_1) = -\frac{1}{6.4} (T-2)^2 + \frac{1}{6.4} T^2 = \frac{T-1}{1.6}$$

$$\Rightarrow f(X, Y) = \begin{cases} 1 & \text{if } T \geq 1.6c + 1 \\ 0 & \text{o.w.} \end{cases}$$

where $k \equiv 1.6c + 1$ is determined s.t.

$$\alpha(k) = P_{\theta_0}(T \geq k) = 1 - P_{\theta_1}(T \geq k) = 1 - \beta(k)$$

$$\Rightarrow 1 - \Phi\left(\frac{k}{\sqrt{3.2}}\right) = 1 - \left[1 - \Phi\left(\frac{k-2}{\sqrt{3.2}}\right) \right]$$

$$\Rightarrow 1 - \Phi\left(\frac{k}{\sqrt{3.2}}\right) = \Phi\left(\frac{k-2}{\sqrt{3.2}}\right)$$

$$\Rightarrow k = -k + 2 \quad \therefore k = 1$$

we,

$$f(X, Y) = \begin{cases} 1 & \text{if } T \geq 1 \\ 0 & \text{if } T < 1. \end{cases}$$

//

#3.

Since $X \sim \text{Poisson}(\lambda)$ and $\lambda \sim \text{Exp}(1)$,

$$f(\lambda|x) \propto f(x|\lambda) \cdot g(\lambda) \propto e^{-\lambda} \lambda^x \cdot e^{-\lambda} = \lambda^x e^{-2\lambda}$$

$\therefore \lambda|x \sim \text{Gamma}(x+1, \frac{1}{2})$

a kernel of Gamma dist. family

$$\Rightarrow \phi(x) = \begin{cases} 1 & \text{if } P(\lambda > 2|x) > 0.5 \\ 0 & \text{o.w.} \end{cases}$$

where $P(\lambda > 2|x) = 1 - P(\lambda \leq 2|x) = 1 - \int_0^2 \frac{1}{\Gamma(x+1) (\frac{1}{2})^{x+1}} \lambda^x e^{-2\lambda} d\lambda$ //

#4.

Since $X \sim \text{Bin}(5,p)$ and $p \sim \text{Beta}(2,1)$,

$$g(p|x) \propto f(x|p) g(p) \propto p^x (1-p)^{5-x} p^1 (1-p)^0 = p^{x+1} (1-p)^{5-x}$$

a kernel of Beta dist. family

$$\therefore p|x \sim \text{Beta}(x+2, 6-x)$$

$$\Rightarrow \phi(x) = \begin{cases} 1 & \text{if } P(p < 0.4) + P(p > 0.6) > 0.5 \\ 0 & \text{o.w.} \end{cases}$$

where $P(p < 0.4) + P(p > 0.6) = 1 - \int_{0.4}^{0.6} \frac{\Gamma(8)}{\Gamma(x+2) \Gamma(6-x)} p^{x+1} (1-p)^{5-x} dp$ //

