

## ISYE 6412 HW-08

① From HW #7,

$$T(X) = \max \left[ -X_{(1)}, \frac{1}{2} X_{(n)} \right]$$

is complete sufficient

We also know from HW #7

$$f_T(t) = \begin{cases} \frac{n}{\theta^n} t^{n-1} & \text{if } 0 \leq t \leq \theta \\ 0 & \text{otherwise.} \end{cases}$$

$$E(T(X)) = \int_0^\theta t \cdot \frac{n}{\theta^n} t^{n-1} dt$$

$$= \frac{n}{\theta^n} \int_0^\theta t^n dt = \frac{n \theta^{n+1}}{(n+1) \theta^n}$$

$$= \left( \frac{n}{n+1} \right) \theta$$

$$\Rightarrow E \left( \left( \frac{n+1}{n} \right) T(X) \right) = \theta$$

$\therefore g(T) = \left( \frac{n+1}{n} \right) T(X)$  is an unbiased estimator of  $\theta$

And  $g(\cdot)$  is fn of  $T$

$\Rightarrow g(T) = \left( \frac{n+1}{n} \right) T(X)$  is the best unbiased estimator

of  $\theta$ .

(2)

Consider  ~~$\delta_0 = \begin{cases} 1 & \text{if } X_1 = X_2 \\ 0 & \text{otherwise} \end{cases}$~~

From HW #7, the ~~unique~~ complete sufficient  $T$  is

$$T = X_{(1)}$$

$$\text{and } f_T(t) = \begin{cases} n e^{-n(\theta-t)} & t > 0 \\ 0 & \text{else} \end{cases}$$

Let  $g(T)$  be the function which is ~~the~~ the best unbiased estimator

$$E(g(T)) = \int_0^{\infty} g(t) n e^{-n(\theta-t)} dt = \theta^r$$

$$\Rightarrow e^{n\theta} \int_0^{\infty} g(t) n e^{-nt} dt = \theta^r$$

Differentiating w.r.t  $\theta$ ,

$$\Rightarrow e^{n\theta} (-g(\theta) n e^{-n\theta}) + e^{n\theta} \left[ n \int_0^{\infty} g(t) n e^{-nt} dt \right] = r \theta^{r-1}$$



$$\Rightarrow -n g(\theta) + n \theta^r = r \theta^{r-1}$$

$$\Rightarrow g(\theta) = \theta^r - \frac{r}{n} \theta^{r-1}$$

$\therefore$  the best unbiased estimator is

~~$g(\theta)$~~

$$g(T) = T^r - \frac{r}{n} T^{r-1}$$

$$\text{where } T = X(1)$$

(2)

$$(a) E(\delta(X_1, \dots, X_{n+1})) = 1 \cdot P(\delta = 1) + 0 \cdot P(\delta = 0)$$

$$= P(\delta = 1) = P\left(\sum_{i=1}^n X_i > X_{n+1}\right) = h(p)$$

$\therefore \delta$  is an unbiased estimator of  $h(p)$

$$(b) P(\delta = 1) = 1 - P\left(\sum_{i=1}^n X_i \leq X_{n+1}\right)$$

$\sum_{i=1}^n X_i \leq X_{n+1}$  is possible only in 2 (disjoint) events:

$$(i) X_1 = X_2 = \dots = X_n = X_{n+1} = 0$$

$$(ii) X_1 = X_2 = \dots = X_n = 0, X_{n+1} = 1$$

$$(iii) \text{ One of } X_1, \dots, X_n = 1$$

$$\text{if } X_{n+1} = 1$$

$$\text{otherwise } P(X_i \leq X_{n+1}) = 0$$

Probability of

- case (i)  $(1-p)^{n+1}$   
 (ii)  $(1-p)^n p$   
 (iii)  ${}^n C_1 p (1-p)^{n-1} \times p$

$\therefore$  terms are  
 iid,

$$= {}^n C_1 p^2 (1-p)^{n-1}$$

$$P(X_1 = 1, X_2 = 1, \dots, X_n = 1, X_{n+1} = 1)$$

$$= P(\underbrace{X_1 = 1, \dots, X_n = 1}_{n C_1 p (1-p)^{n-1}} \mid \underbrace{X_{n+1} = 1}_p)$$

(k) Rao Blackwell thm, best unbiased  
 estimator =  $E(\delta | T=b)$

Case (i)  $T=0$

case (ii)  $T=1+p=2$

case (iii)  $T=2+1=3$

case (iv)  $T \geq 3$

(we note  $T \geq 0$   
 always)

$$g(T) = E(\delta | T=b) = P(\delta=1 | T=b)$$

$$= P\left(\sum_{i=1}^n X_i > X_{n+1} \mid T=b\right)$$

$$= 1 - P\left(\sum_{i=1}^n X_i \leq X_{n+1} \mid T=b\right)$$

$$\Rightarrow P\left(\sum_{i=1}^n X_i \leq X_{n+1} \mid T=0\right) = 1$$

$\therefore$  always  $\sum_{i=1}^n X_i = X_{n+1} \Rightarrow$   
 $\sum_{i=1}^n X_i = 0$



$P(\sum_{i=1}^n x_i \leq x_{n+1} | T \geq 3) \Rightarrow$  at least 3  $x_i$ 's are  $> 1 \Rightarrow$  at least 2  $x_i$ 's other than  $x_{n+1} \geq 1 \Rightarrow x \sum_{i=1}^n x_i \geq 2$  but  $x_{n+1} \geq 1 \Rightarrow$  probability is 0

$$P\left(\sum_{i=1}^n x_i \leq x_{n+1} \mid T \geq 3\right) = \frac{P\left(\sum_{i=1}^n x_i \leq x_{n+1}, \sum_{i=1}^{n+1} x_i \geq 1\right)}{P\left(\sum_{i=1}^{n+1} x_i \geq 1\right)}$$

Num. falls under case (ii)

$$= \frac{(1-p)^n p}{\binom{n+1}{1} (1-p)^n p} = \frac{1}{n+1}$$

$$P\left(\sum_{i=1}^n x_i \leq x_{n+1} \mid T = 2\right) = \frac{P\left(\sum_{i=1}^n x_i \leq x_{n+1}, \sum_{i=1}^{n+1} x_i = 2\right)}{P\left(\sum_{i=1}^{n+1} x_i = 2\right)}$$

$P(\sum_{i=1}^n x_i \leq x_{n+1}, \sum_{i=1}^{n+1} x_i = 2)$  falls under case (iii)

$$= \binom{n+1}{2} p^2 (1-p)^{n-1}$$

$$P(\sum_{i=1}^n x_i \geq 2) = \binom{n+1}{2} p^2 (1-p)^{n-1} \quad (\because \text{geometric distribution} \Rightarrow \text{Binomial})$$

$$\Rightarrow P\left(\sum_{i=1}^n x_i \leq x_{n+1} \mid T = 2\right)$$

$$= \frac{\binom{n+1}{2} p^2 (1-p)^{n-1}}{\binom{n+1}{2} p^2 (1-p)^{n-1}} = 1$$

$$\therefore g(T=b) = \begin{cases} 0 & b=0 \\ 1 - \frac{1}{n+1} & b=1 \\ 1 - \frac{2}{n+1} & b=2 \\ 1 - 0 & b \geq 3 \end{cases}$$

$$= \begin{cases} 0 & b=0 \\ \frac{n}{n+1} & b=1 \\ \frac{n-1}{n+1} & b=2 \\ 1 & b \geq 3 \end{cases}$$

④ From class, we showed that  $T(X) = (\bar{X}, S^2)$  is complete and suf

$$U = \frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2 \quad \text{which indep. of } (\bar{X}, \sigma^2)$$

$\Rightarrow \in (UP/2)$  is indep. of  $\mu, \sigma^2 = c_{p,n}$



$$\Rightarrow E\left(\frac{(n-1)^{p/2} S^p}{c_{p,n}}\right) = \sigma^p \quad (1)$$

here  $S$  is the R.V. sample which exp. is taken,  $\sigma^p$  is just a constant

$$\Rightarrow E\left(\frac{(n-1)^{p/2} S^p}{c_{p,n}}\right) = E_{p,n} \sigma^p$$

$\therefore \frac{(n-1)^{p/2} S^p}{c_{p,n}}$  is an unbiased estimator for  $\sigma^p$

But it is also a function of  $T = S^2$ .

$\Rightarrow \frac{(n-1)^{p/2} S^p}{c_{p,n}}$  is the best unbiased estimator for  $\sigma^p$

for prob. We note,  $E(Y) = n$  where  $Y \sim \chi_n^2$

$$\Rightarrow \int_0^\infty \frac{y^{n/2-1} e^{-y/2}}{2^{n/2} \Gamma(n/2)} dy = 1$$

$$E(U^{p/2}) = \int_0^\infty \frac{u^{n/2-1} u^{p/2} e^{-u/2}}{2^{n/2} \Gamma(n/2)} du$$

(a)

$$p = 1$$

$$E(u^{1/2}) = \int_0^{\infty} \frac{u^{\frac{n}{2}-1} e^{-u/2}}{2^{\frac{n-1}{2}} \Gamma(\frac{n-1}{2})} du$$

$$= 2^{1/2} \left( \frac{\Gamma(n/2)}{\Gamma(n-1/2)} \right) \int_0^{\infty} f(x^2) dx$$

$$= 2^{1/2} \left( \frac{\Gamma(n/2)}{\Gamma(n-1/2)} \right)$$

∴ The best unbiased estimator is

$$\frac{S(n-1)^{1/2}}{n\sqrt{2}} \left( \frac{\Gamma(n-1/2)}{\Gamma(n/2)} \right)$$

(b)  $p = 2$ 

$$E(u) = \int_0^{\infty} \frac{u^{\frac{n+1}{2}-1} e^{-u/2}}{2^{\frac{n-1}{2}} \Gamma(\frac{n-1}{2})} du$$

$$= \frac{2 \Gamma(\frac{n-1}{2} + 1)}{\Gamma(\frac{n-1}{2})} = 2 + \frac{n-1}{2}$$

∴ Best estimator is  $\frac{(n-1)^2 S^2}{(n-1)} = S^2$

for  $\sigma^2$



$$c) \quad p=4 \quad \int_0^{\infty} \frac{u^{\frac{n+3}{2}-1} e^{-u/2}}{2^{\frac{n-1}{2}} \Gamma(\frac{n-1}{2})} du.$$

$$= \frac{2^2 \Gamma(\frac{n+3}{2})}{\Gamma(\frac{n-1}{2})} = \frac{2^2 \left( \Gamma(\frac{n+1}{2}) \cdot \frac{(n+1)}{2} \right)}{\Gamma(\frac{n-1}{2})}$$

$$= \frac{2^2 \frac{(n-1)}{2} \frac{(n+1)}{2}}{(n-1)(n+1)^2}$$

$$\therefore \frac{(n-1)^2 S^4}{(n-1)(n+1)} = \frac{S^4 (n-1)}{(n+1)} \text{ is the}$$

best estimator for  $\sigma^4$ .

$$(5) a) \quad E\left(\frac{1}{X_1}\right) = \int_0^{\infty} \frac{1}{\Gamma(x) \beta^x} x^{x-1} e^{-x/\beta} \times \frac{1}{x} dx$$

$$= \int_0^{\infty} \frac{1}{\Gamma(x) \beta^x} x^{(x-1)-1} e^{-x/\beta} dx$$

$$= \frac{\Gamma(x-1) \beta^{x-1}}{\Gamma(x) \beta^x} \int_0^{\infty} \frac{1}{\Gamma(x-1) \beta^{x-1}} x^{(x-1)-1} e^{-x/\beta} dx$$

Integral is integral of pdf of  $f_{\beta}(x)$  to 1

$$E\left(\frac{1}{X_1}\right) = \frac{q_1}{1-\beta} \frac{1}{(\alpha-1)\beta}$$

$$1 - \frac{P(X+1)}{P(X)} = \beta \quad \text{where } X \text{ is known}$$

$$\Rightarrow E\left(\frac{X-1}{X_1}\right) = \frac{1}{\beta} \quad \text{where } \frac{X-1}{X_1} \text{ is an unbiased estimator of } \frac{1}{\beta}$$

$$b) E\left(\frac{U}{V}\right) = \sum_{x \neq 0} x P\left(\frac{U}{V} = x\right)$$

$$= \sum_{x \neq 0} x \sum_{y \neq 0} P\left(\frac{U}{V} = x \mid \frac{U}{V} = y\right) P\left(\frac{U}{V} = y\right)$$

$$E\left(\frac{U}{V} \times \frac{1}{U}\right)$$

$$E\left(\frac{1}{V}\right) = E\left(\frac{U}{V} \times \frac{1}{U}\right)$$

we note that  $\frac{U}{V}$  and  $V$  are independent

$\Rightarrow \frac{U}{V}$  and  $\frac{1}{U}$  are independent!

$E(XY) = E(X)E(Y)$  for independent  $X, Y$

$$\Rightarrow E\left(\frac{1}{V}\right) = E\left(\frac{U}{V}\right) E\left(\frac{1}{U}\right)$$

$$\Rightarrow E\left(\frac{U}{V}\right) = \frac{E\left(\frac{1}{V}\right)}{E\left(\frac{1}{U}\right)}$$



$$c) \quad T = \sum_{i=1}^n X_i$$

Since  $\beta$  is scale parameter,  
consider  $Z_i = \frac{X_i}{T}$

$$\Rightarrow f(z) = \frac{1}{\Gamma(\alpha)} x^{\alpha-1} e^{-x} \text{ indep of } \beta$$

$$\therefore \sum_{i=1}^n X_i = \sum_{i=1}^n Z_i T = T \sum_{i=1}^n Z_i$$

$$\frac{X_i}{T} = Z_i \Rightarrow \frac{X_i/\beta}{T/\beta} = \frac{Z_i/\beta}{Z_i/\beta}$$

$$\Rightarrow \sum_{i=1}^n \frac{X_i}{T} = \sum_{i=1}^n Z_i \text{ which is independent of } \beta!$$

$\therefore \frac{T}{\sum X_i}$  is an ancillary statistic;  $T$ 's comp. sufficient

$\Rightarrow$  By Basu's thm,  
 $\frac{T}{\sum X_i}$  is independent of  $T$

$$E\left(\frac{1}{\sum X_i} \mid T\right) = E\left(\frac{T}{\sum X_i} \cdot \frac{1}{T} \mid T\right) = \frac{E(T)}{E(\sum X_i)}$$

$$E\left(\frac{1}{T} | T\right) = \frac{1}{T}$$

$$\Rightarrow E\left(\frac{1}{x_i} | T\right) = E\left(\frac{T}{x_i} \cdot \frac{1}{T} | T\right) = E\left(\frac{1}{T} | T\right) \quad \text{(independence of } x_i \text{ as per hint)}$$

$$= \frac{E\left(\frac{1}{x_i}\right)}{E\left(\frac{1}{T}\right)} = \frac{1}{T}$$

$$V = \frac{T}{n} E g(w) = \frac{1}{T} \quad \text{(here)}$$

$$\Rightarrow E\left(\frac{1}{x_i} | T\right) = \frac{E\left(\frac{1}{x_i}\right)}{E\left(\frac{1}{T}\right)} = \frac{1}{T}$$

d) Rao Blackwell theorem : unbiased estimator =  $\frac{(n-1)}{x_i}$

$$\Rightarrow \text{Best unbiased estimator} = E\left(\frac{n-1}{x_i} | T\right)$$

$$= \frac{E\left(\frac{n-1}{x_i}\right)}{E\left(\frac{1}{T}\right)} = \frac{1}{T}$$

we are given  $T \sim \text{Gamma}(n\alpha, \beta)$

$$\therefore E\left(\frac{1}{x_i} | T\right) = \frac{\frac{n-1}{(n-1)\beta}}{\frac{1}{(n\alpha-1)\beta}} = \frac{1}{T} \quad \text{(using part (a))}$$

$$= \frac{(n\alpha-1)}{n\alpha-1} \cdot \frac{1}{T}$$

$$\therefore \left(\frac{1}{T}\right) \left(\frac{n\alpha-1}{n\alpha-1}\right) \text{ is the best unbiased estimator } \frac{1}{\beta}$$



(6) ~~the~~ find

factor

$$P(X=x|\theta) = \frac{\theta^x e^{-\theta}}{x!} = e^{x \log \theta - \theta} \frac{1}{x!}$$

$$\Rightarrow h(x) = \frac{1}{x!} \quad w_1(\theta) = \log \theta$$

$$c(\theta) = e^{-\theta} \quad t_2(x) = x$$

$\theta \in (0, \infty)$  - open set in  $\mathbb{R}^1$

$\therefore$  By thm 6.2.25,  $\sum_{i=1}^n t_1(x_i) = \sum_{i=1}^n x_i$

is a complete sufficient statistic

(a)  $\phi_1(\theta) = e^{-\theta}$

(b)  $\phi_2 = \theta e^{-\theta}$

$\delta = \begin{cases} 1 & \text{if } X_1 = 1 \\ 0 & \text{otherwise} \end{cases}$

$E(\delta) = P(\delta=1) = P(X_1=1) = \theta e^{-\theta}$

$\delta$  is an unbiased estimate <sup>best</sup>

Reason: this  $\Rightarrow E(\delta|T)$  is the best unbiased

$E(\delta|T) = P(F=1|T)$

$= P(X_1=1 | \sum_{i=1}^n x_i = b)$

$= \frac{P(X_1=1, \sum_{i=1}^n x_i = b)}{P(\sum_{i=1}^n x_i = b)}$

$P(\sum_{i=1}^n x_i = b)$

Sum of  $n$  iid Poisson  $X_i(\theta) \sim \text{Poisson}(n\theta)$

$$= \frac{P(X_1 = 1, \sum_{i=2}^n X_i = b-1)}{P(\sum_{i=1}^n X_i = b)}$$

$$= \frac{P(X_1 = 1) P(\sum_{i=2}^n X_i = b-1)}{P(\sum_{i=1}^n X_i = b)}$$

( $\because X_1$  and  $X_2, \dots, X_n$  are independent)

$$P(\sum_{i=1}^n X_i = b)$$

$$= \frac{\theta e^{-\theta} ((n-1)\theta)^{b-1} e^{-(n-1)\theta}}{1! (b-1)!}$$

$$\frac{(n\theta)^b e^{-n\theta}}{b!}$$

$$= b \left( \frac{(n-1)^{b-1}}{n^b} \right) \quad \forall b \geq 0$$

$\therefore g(T=b) = b \left( \frac{(n-1)^{b-1}}{n^b} \right)$  is the best unbiased estimator for  $\theta$   $\forall \theta \in \mathbb{C}$

$$b) \delta_2 = \begin{cases} 1 & \text{if } X_1 > 0 \\ 0 & \text{else} \end{cases}$$

$$E(\delta_2) = P(X_1 > 0) = 1 - e^{-\theta}$$

$\therefore \delta_2$  is unbiased estimator of  $\phi_2$



Rao-Blackwell then says  $\hat{\theta}(\delta, T)$  is the best unbiased estimator.

$$\hat{\theta}(\delta, T) = P(\delta, T) \sum_{i=1}^n X_i = b$$

$$= P(X_1 = 0 \mid \sum_{i=1}^n X_i = b)$$

$$= \frac{P(X_1 = 0, \sum_{i=1}^n X_i = b)}{P(\sum_{i=1}^n X_i = b)}$$

$$P(\sum_{i=1}^n X_i = b)$$

$$= \frac{P(X_1 = 0, \sum_{i=2}^n X_i = b)}{P(\sum_{i=2}^n X_i = b)}$$

$$P(\sum_{i=2}^n X_i = b)$$

$$e^{-\theta} \left( \frac{b}{(n-1)\theta} \right)^{b-(n-1)\theta} e^{-(n-1)\theta}$$

$$\frac{n^b \theta^b e^{-(n\theta)}}{n^b \theta^b e^{-(n\theta)}}$$

$$= \frac{(n-1)^b}{n^b} = \left( \frac{n-1}{n} \right)^b$$

$\therefore \left( \frac{n-1}{n} \right)^b$  is the best estimate for  $\phi(\theta) = e^{-\theta}$

c) (i)  $e^{-\theta}$  : best estimate =  $\left(\frac{n-1}{n}\right)^b$

$$= \left(\frac{n-1}{n}\right)^{\sum y_i}$$

$$T = b - 6 = 7 = \sum y_i = 10 + 7 + 8 + 13 + 8 + \dots + 3 + 5$$

$$d = 74 = 104 \times 0.79 =$$

$$n = 15$$

$$\therefore P(\text{no mutant colony}) = \left(\frac{14}{15}\right)^{104} \approx 7.653 \times 10^{-4}$$

$$= 7.653 \times 10^{-4}$$

(ii) Best estimate:  $b \left(\frac{(n-1)^{b-1}}{n^b}\right)$

$$\Rightarrow P(1 \text{ mutant colony}) = 0.5685 \times 10^{-3}$$