

Day 2, January 2011.

Prob 1 (Solution).

(a). By Central Limit Theorem, one has

$$\sqrt{n}(\bar{X} - \lambda) \xrightarrow{d} N(0, \lambda).$$

Let $g(\lambda) = e^{-\lambda}$. Using delta method, one has

$$\sqrt{n}(g(\bar{X}) - g(\lambda)) \xrightarrow{d} N(0, (g'(\lambda))^2 \cdot \lambda)$$

$$\text{i.e., } \sqrt{n}(e^{-\bar{X}} - e^{-\lambda}) \xrightarrow{d} N(0, \lambda e^{-2\lambda})$$

This is $T_{n,1}$.

~~(b)~~

(b) Let $Y_i = \mathbb{1}(X_i=0)$ for $i=1, \dots, n$.

Then Y_i 's are iid r.v.s and $Y_i \sim \text{Bernoulli}(p = e^{-\lambda})$.

$$E(Y_i) = p = e^{-\lambda}. \quad E(Y_i^2) = E(Y_i) = e^{-\lambda}.$$

$$\text{Var}(Y_i) = e^{-\lambda} - (e^{-\lambda})^2 = e^{-\lambda}(1 - e^{-\lambda}).$$

By using Central Limit Theorem, one has

$$\bar{Y} \overset{\sim}{\sim} N\left(p, \frac{p(1-p)}{n}\right) \quad \text{or} \quad \sqrt{n}(\bar{Y} - p) \xrightarrow{d} N(0, p(1-p))$$

$$\text{i.e., } \sqrt{n}\left(\frac{1}{n} \sum_{i=1}^n \mathbb{1}(X_i=0) - e^{-\lambda}\right) \xrightarrow{d} N(0, e^{-\lambda}(1 - e^{-\lambda}))$$

This is $T_{n,2}$.

Day 2, Problem 1 Solution (continued)

(c) Consider the ratio of the asymptotic variances of $T_{n,1}$ and $T_{n,2}$,

$$\frac{\lambda e^{-2\lambda}}{e^{-\lambda} \cdot (1 - e^{-\lambda})} = \frac{\lambda}{e^{\lambda} - 1} < 1$$

Since $\lambda > 0$, $e^{\lambda} - 1 > \lambda$ always holds.

Thus, $T_{n,1}$ has a smaller asymptotic variance. Notice that

both estimators are asymptotically unbiased, so $T_{n,1}$ is more efficient than $T_{n,2}$ ~~in~~ ⁱⁿ estimating $e^{-\lambda}$

when sample size is large.

Day 2 Prob 2 $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} f(x|\lambda) = \lambda e^{-\lambda x}, x > 0.$

$X_{(1)} < X_{(2)} < \dots < X_{(n)}$ are the o.s.

$$D_i = (n-i+1)(X_{(i)} - X_{(i-1)}), \quad D_1 = 0.$$

ⓐ Joint Dist of the D_i 's

First the jpdf of the $X_{(1)}, \dots, X_{(n)}$ is

$$\begin{aligned} f(x_{(1)}, \dots, x_{(n)}) &= n! \prod_{i=1}^n \lambda e^{-\lambda x_{(i)}}, \quad 0 < x_{(1)} < \dots < x_{(n)} < \infty. \\ &= n! \lambda^n e^{-\lambda \sum_{i=1}^n x_{(i)}}. \end{aligned}$$

Observe that

$$X_{(1)} = \frac{D_1}{n}$$

$$X_{(2)} = \frac{D_2}{n-1} + X_{(1)} = \frac{D_1}{n} + \frac{D_2}{n-1}$$

$$X_{(3)} = \frac{D_3}{n-2} + X_{(2)} = \frac{D_1}{n} + \frac{D_2}{n-1} + \frac{D_3}{n-2}$$

$$\vdots$$

$$X_{(k)} = \sum_{j=1}^k \frac{D_j}{n-j+1}$$

$$\vdots$$

$$X_{(n)} = \sum_{j=1}^n \frac{D_j}{n-j+1}.$$

Day 2, Problem 2

(2)

Also, note that $P_i \geq 0 \quad \forall i$. The Jacobian of transformation is

$$|J| = \begin{vmatrix} \frac{1}{n} & 0 & \cdots & 0 \\ \frac{1}{n} & \frac{1}{n-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{n} & \frac{1}{n-1} & \frac{1}{n-2} & \cdots & 1 \end{vmatrix} = \frac{1}{n!}$$

Therefore,

$$f_{D_1, \dots, D_n}(d_1, \dots, d_n) = n! \cdot \frac{1}{n!} e^{-\lambda \sum_{j=1}^n \left(\sum_{i=j}^n \frac{d_i}{n-j+1} \right)} \cdot \frac{1}{n!}, \quad d_i \geq 0$$

$$= \lambda^n \exp \left\{ -\lambda \sum_{j=1}^n \left(\sum_{i=j}^n \frac{d_i}{n-j+1} \right) \right\}, \quad d_i \geq 0$$

$$= \lambda^n \exp \left\{ -\lambda \sum_{j=1}^n (n-j+1) \frac{d_j}{n-j+1} \right\}$$

$$= \lambda^n \exp \left\{ -\lambda \sum_{j=1}^n d_j \right\}, \quad d_j \geq 0$$

\therefore

$$D_1, D_2, \dots, D_n \stackrel{iid}{\sim} \text{Exp}(\lambda).$$

Day 2, Problem 2

(3)

(b) Since $X_{(n)} = \sum_{j=1}^n \frac{D_j}{n-j+1}$, then

$$E(X_{(n)}) = \frac{1}{\lambda} \sum_{j=1}^n \frac{1}{n-j+1}$$

(c) The TTT statistic based on $X_{(1)}, \dots, X_{(k)}$ is $X_{(j)} \geq X_{(k)}$ for $j > k$ is

$$T = \sum_{j=1}^k X_{(j)} + (n-k)X_{(k)}$$

$$= \sum_{j=1}^k \left(\sum_{i=1}^j \frac{D_i}{n-i+1} \right) + (n-k) \sum_{i=1}^k \frac{D_i}{n-i+1}$$

$$= \sum_{i=1}^k \sum_{j=i}^k \frac{D_i}{n-i+1} + (n-k) \sum_{i=1}^k \frac{D_i}{n-i+1}$$

$$= \sum_{i=1}^k \frac{D_i}{n-i+1} \cdot (k-i+1) + (n-k) \sum_{i=1}^k \frac{D_i}{n-i+1}$$

$$= \sum_{i=1}^k \frac{D_i}{n-i+1} [k-i+1+n-k]$$

$$= \sum_{i=1}^k D_i$$

Day 2, Problem 2

(4)

Now, since $D_i \stackrel{iid}{\sim} \text{EXP}(\lambda)$, then

$$T \sim \text{Gamma}(k, \lambda). \quad \text{We know } E(T) = \frac{k}{\lambda}.$$

Consider an estimator of form

$$S_c = \frac{c}{T}, \quad \text{for } c \text{ constant.}$$

Then

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

$$= c \int_0^{\infty} \frac{1}{t} \cdot \frac{\lambda^k}{\Gamma(k)} t^{k-1} e^{-\lambda t} dt$$

$$= c \frac{\lambda^k}{\Gamma(k)} \int_0^{\infty} t^{(k-1)-1} e^{-\lambda t} dt$$

$$= c \frac{\lambda^k}{\Gamma(k)} \frac{\Gamma(k-1)}{\lambda^{k-1}}$$

$$= c \frac{\lambda}{k-1}.$$

Taking $c = k-1$, we find that

$$S_{k-1} = \frac{k-1}{T} \quad \text{is unbiased for } \lambda, \text{ for } k > 1.$$

Day 2, Problem 2

(5)

① Variance of $\hat{\sigma}_{k-1} = \frac{k-1}{T}$. We have

$$E\left(\left(\frac{k-1}{T}\right)^2\right) = (k-1)^2 E\left(\frac{1}{T^2}\right)$$

$$= (k-1)^2 \int_0^{\infty} \frac{1}{t^2} \frac{\lambda^k}{\Gamma(k)} t^{k-1} e^{-\lambda t} dt$$

$$= (k-1)^2 \frac{\lambda^k}{\Gamma(k)} \int_0^{\infty} t^{(k-2)-1} e^{-\lambda t} dt$$

$$= (k-1)^2 \frac{\lambda^k}{\Gamma(k)} \frac{\Gamma(k-2)}{\lambda^{k-2}}$$

$$= \frac{(k-1)^2 \lambda^2}{(k-1)(k-2)} = \left(\frac{k-1}{k-2}\right) \lambda^2$$

\therefore

$$\text{Var}\left(\frac{k-1}{T}\right) = \left(\frac{k-1}{k-2}\right) \lambda^2 - \lambda^2$$

$$= \lambda^2 \left\{ \frac{(k-1) - (k-2)}{k-2} \right\}$$

$$= \frac{\lambda^2}{k-2}$$

$k > 2$.

since unbiased

Day 2, Prb 3

$X \sim \text{POI}(\mu), Y \sim \text{POI}(\nu), X \perp\!\!\!\perp Y.$

Ⓐ $P(X=x | S=X+Y=s)$

$$= \frac{P(X=x, Y=s-x)}{P(S=s)}$$

$\int_{S < 0}$
Prb is 0.

$$= \frac{P(X=x)P(Y=s-x)}{P(S=s)}$$

$$P(S=s) = \sum_{x=0}^s P(X=x)P(Y=s-x)$$

$$= \sum_{x=0}^s \frac{e^{-\mu} \mu^x}{x!} \frac{e^{-\nu} \nu^{s-x}}{(s-x)!}$$

$$= e^{-(\mu+\nu)} \frac{1}{s!} \sum_{x=0}^s \binom{s}{x} \mu^x \nu^{s-x}$$

$$= \frac{e^{-(\mu+\nu)} (\mu+\nu)^s}{s!}$$

So $S \sim \text{POI}(\mu+\nu).$

Day 2, Problem 3

(2)

$$\begin{aligned}
 P(X=x|S=s) &= \frac{\frac{e^{-\mu} \mu^x}{x!} \frac{e^{-\nu} \nu^{s-x}}{(s-x)!}}{\frac{e^{-(\mu+\nu)} (\mu+\nu)^s}{s!}} \\
 &= \binom{s}{x} \left(\frac{\mu}{\mu+\nu}\right)^x \left(1 - \frac{\mu}{\mu+\nu}\right)^{s-x} \\
 &= \binom{s}{x} p^x (1-p)^{s-x}, \quad x=0, 1, \dots, s.
 \end{aligned}$$

$$X|S=s \sim \text{BIN}(s, p = \frac{\mu}{\mu+\nu}).$$

(b) Under $H_0: \mu = \nu, \nu \in \mathbb{R}_+$,
 $X|S=s \sim \text{BIN}(s, p = \frac{1}{2})$

Under $H_1: \mu = 2\nu, \nu \in \mathbb{R}_+$,

$$X|S=s \sim \text{BIN}(s, p = \frac{2}{3}). \quad \frac{\mu}{\mu+\nu} = \frac{2\nu}{2\nu+\nu} = \frac{2}{3}$$

Given $S=s$, the MP test of H_0 vs H_1 would be of form $\frac{2}{3}$

and

$$\begin{aligned} \delta_S &= \frac{\alpha - B(S, k_S - 1)}{b(S, k_S)} \\ &= \frac{\alpha - \sum_{j=1}^{k_S - 1} \binom{S}{j} \left(\frac{1}{2}\right)^S}{\binom{S}{k_S} \left(\frac{1}{2}\right)^S} \end{aligned}$$

(d) Power of test in (c).

$$\pi(\mu, \nu) = E\left(\delta_S(X) \mid \begin{matrix} \mu, \nu \\ M=2\nu \end{matrix}\right)$$

$$= E\left\{ E\left[\delta_S(X) \mid S, \begin{matrix} \mu, \nu \\ M=2\nu \end{matrix}\right] \right\}$$

$$= E\left\{ P\left(X < k_S \mid P = \frac{2}{3}, S\right) + \frac{1}{S} P\left(X = k_S \mid P = \frac{2}{3}, S\right) \right\}$$

Day 2, Problem 3

$$= \sum_{s=0}^{\infty} \frac{e^{-(\mu+\nu)} (\mu+\nu)^s}{s!} \left\{ \sum_{j=0}^{k_s-1} \binom{s}{j} \left(\frac{2}{3}\right)^j \left(\frac{1}{3}\right)^{s-j} + \gamma_s \binom{s}{k_s} \left(\frac{2}{3}\right)^{k_s} \left(\frac{1}{3}\right)^{s-k_s} \right\} \quad (5)$$

where the k_s and γ_s are as defined in part (c).

Day 2,
Problem 3

$$S_S(x) = \begin{cases} 1 & \text{if } R_S(x) > k_S \\ \alpha_S & = \\ 0 & < \end{cases} \quad (3)$$

where

$$R_S(x) = \frac{\binom{S}{x} \left(\frac{2}{3}\right)^x \left(\frac{1}{3}\right)^{S-x}}{\binom{S}{x} \left(\frac{1}{2}\right)^x \left(\frac{1}{2}\right)^{S-x}}$$

$$= \left(\frac{2}{3}\right)^x \left(\frac{2}{3}\right)^{S-x} 2^{S-x}$$

$$= \left(\frac{2}{3}\right)^S 2^{S-x}$$

$$\frac{\left(\frac{2}{3}\right)^x \left(\frac{1}{3}\right)^{S-x}}{\left(\frac{1}{2}\right)^S}$$

$$\left(\frac{1}{2}\right)^S$$

$$= 2^x \cdot 3^{-x} \cdot 3^{x-S} \cdot 2^S$$

$$= 2^{S+x} 3^{-S}$$

$$= \left(\frac{2}{3}\right)^S \cdot 2^x$$

Since this is ~~decreasing~~ increasing in x ,

$$S_S(x) = \begin{cases} 1 & \text{if } x \geq k_S \\ \alpha_S & = \\ 0 & < \end{cases}$$

where we choose

cdf of $\text{Bin}(S, \frac{1}{2})$.

$$k_S = \max \left\{ m : B(S, m) \leq \frac{1}{2} \right\}$$

$$= \max \left\{ m : \sum_{j=0}^m \binom{S}{j} \left(\frac{1}{2}\right)^S \leq \frac{1}{2} \right\}$$