

03/04 final exam

a. $Y_1 \sim N(4-\theta, \sigma^2)$, $Y_2 \sim N(2+2\theta, \sigma^2)$

$$L(y_1, y_2; \theta, \sigma^2) = \frac{1}{2\pi\sigma^2} \exp \left\{ -\frac{1}{2\sigma^2} [(y_1 + \theta - 4)^2 + (y_2 - 2\theta - 2)^2] \right\}$$

$$\log L = \log C - \frac{1}{2\sigma^2} [(y_1 + \theta - 4)^2 + (y_2 - 2\theta - 2)^2]$$

$$\frac{\partial}{\partial \theta} \log L = -\frac{1}{2\sigma^2} [2(y_1 + \theta - 4) + 2(-2)(y_2 - 2\theta - 2)] = 0$$

$$\Rightarrow 2y_1 - 4y_2 + 10\theta = 0$$

$$\Rightarrow \hat{\theta} = \frac{-y_1 + 2y_2}{5}$$

b. $E(\hat{\theta}) = E\left(-\frac{y_1}{5} + \frac{2y_2}{5}\right) = -\frac{1}{5}(4-\theta) + \frac{2}{5}(2+2\theta) = \theta$

$\Rightarrow \hat{\theta}$ is an unbiased estimator for θ .

c. $\text{Var}(\hat{\theta}) = \frac{1}{25}\sigma^2 + \frac{4}{25}\sigma^2 = \frac{1}{5}\sigma^2$

d. $E(W) = E(Y_1 + Y_2 - 6) = 4 - \theta + (2 + 2\theta) - 6 = \theta$,
So, W is unbiased.

$$\text{Var}(Y_1 + Y_2 - 6) = \sigma^2 + \sigma^2 = 2\sigma^2$$

So, $\hat{\theta}$ is more efficient since $\frac{\sigma^2}{5} = \text{Var}(\hat{\theta}) < \text{Var}(W) = 2\sigma^2$.

$$2a) X \sim \text{gamma}(2, \theta)$$

$$L(X, \theta) = \prod_{i=1}^n \theta^2 x_i e^{-\theta x_i} = \theta^{2n} e^{-\theta \sum_{i=1}^n x_i} \cdot \prod_{i=1}^n x_i$$

$$\log L(X, \theta) = 2n \log \theta - \theta \sum_{i=1}^n x_i + \sum_{i=1}^n \log x_i$$

$$\Rightarrow \frac{\partial \log L(X, \theta)}{\partial \theta} = \frac{2n}{\theta} - \sum_{i=1}^n x_i \Rightarrow \hat{\theta} = \frac{2n}{\sum_{i=1}^n x_i}$$

$$E(X) = \frac{2}{\theta}, \quad \text{Var}(X) = \frac{2}{\theta^2}. \quad \text{MLE for Variance is } \frac{2}{\hat{\theta}^2} = \frac{(\sum x_i)^2}{2n^2}$$

$$b). \quad \frac{\partial^2 \log L(X, \theta)}{\partial \theta^2} = -\frac{2n}{\theta^2} \quad \therefore \text{CRLB for } \frac{1}{\theta} = -\frac{(-\frac{1}{\theta^2})^2}{-\frac{2n}{\theta^2}} = \frac{1}{2n\theta^2}$$

$$f(x, \theta) = \theta^2 x e^{-\theta x} = \exp(2 \log \theta + \log x + (-\theta x))$$

$$a(\theta) = 2 \log \theta, \quad b(x) = \log x, \quad c(\theta) = -\theta, \quad d(x) = x$$

$$\Rightarrow \sum_{i=1}^n x_i \text{ is complete and sufficient.}$$

$$\text{and } E(\bar{X}) = \frac{2}{\theta} \Rightarrow \frac{\bar{X}}{2} \text{ is UMVUE for } \frac{1}{\theta}$$

$$\text{Var}(\frac{\bar{X}}{2}) = \frac{1}{4} \text{Var}(\bar{X}) = \frac{1}{4} \cdot \frac{1}{n^2} \cdot \text{Var}(\sum x_i) = \frac{1}{4} \cdot \frac{1}{n^2} \cdot n \cdot \frac{2}{\theta^2} = \frac{1}{2n\theta^2}$$

$$\Rightarrow \text{Var}(\frac{\bar{X}}{2}) = \text{CRLB}$$

$$c). \quad S = \sum_{i=1}^n x_i \sim \text{gamma}(2n, \theta)$$

$$E(\frac{1}{S}) = \int_0^\infty \frac{1}{s} \frac{\theta^{2n} s^{2n-1} e^{-\theta s}}{\Gamma(2n)} ds$$

$$= \int_0^\infty \frac{\theta^{2n}}{\Gamma(2n)} \cdot s^{2n-2} e^{-\theta s} ds$$

$$= \int_0^\infty \frac{\Gamma(2n-1)}{\theta^{2n-1}} \cdot \frac{\theta^{2n}}{\Gamma(2n)} \cdot \frac{\theta^{2n-1}}{\Gamma(2n-1)} \cdot s^{2n-2} \cdot e^{-\theta s} ds$$

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

$$\Rightarrow \text{UMVUE for } \theta = \frac{2n-1}{\sum_{i=1}^n x_i}$$

$$\text{CRLB} = -\frac{1}{-2n/\theta^2} = \frac{\theta^2}{2n}$$

$$\therefore \text{UMVUE for } \theta > \text{CRLB}$$

$$3a. \hat{\theta} = X_{(n)} = Y_n$$

$$b. P(Y_n < y) = [P(X_i < y)]^n = \left[\int_0^y \frac{2x}{\theta^2} dx \right]^n = \left[\frac{1}{\theta^2} x^2 \Big|_0^y \right]^n = \left(\frac{y}{\theta} \right)^{2n}$$

$$f(y) = \frac{d}{dy} P(Y_n < y) = \frac{2ny^{2n-1}}{\theta^{2n}}$$

$$\begin{aligned} E(X_{(n)}) &= E(Y_n) = \int_0^\theta y \cdot \frac{2ny^{2n-1}}{\theta^{2n}} dy \\ &= \int_0^\theta \frac{2ny^{2n}}{\theta^{2n}} dy = \frac{2n}{\theta^{2n}} \cdot \frac{y^{2n+1}}{2n+1} \Big|_0^\theta \\ &= \frac{2n}{2n+1} \theta \end{aligned}$$

$$\Rightarrow E\left(\frac{2n+1}{2n} X_{(n)}\right) = \theta$$

$$\begin{aligned} c. E(X_{(n)}^2) &= E(Y_n^2) = \int_0^\theta y^2 \cdot \frac{2ny^{2n-1}}{\theta^{2n}} dy \\ &= \int_0^\theta \frac{2ny^{2n+1}}{\theta^{2n}} dy = \frac{2n}{\theta^{2n}} \cdot \frac{y^{2n+2}}{2n+2} \Big|_0^\theta \\ &= \frac{2n}{2n+2} \theta^2 \end{aligned}$$

$$\Rightarrow E\left(\frac{2n+2}{2n} X_{(n)}^2\right) = \theta^2$$

$$E\left(\frac{n+1}{n} X_{(n)}^2\right) = \theta^2$$

4. a) X_1, \dots, X_n is a random sample from $\exp(\theta)$

$$\begin{cases} H_0: \theta = \theta_0 \\ H_1: \theta = \theta_a \quad (\theta_0 < \theta_a) \end{cases} \quad f_X(x, \theta) = \theta^n e^{-\theta \sum_{i=1}^n x_i}$$

By N-P theorem $C_1 = \{X : \frac{f_X(X, \theta_0)}{f_X(X, \theta_a)} \leq K\}$

$$\frac{f_X(X, \theta_0)}{f_X(X, \theta_a)} \leq K \Rightarrow \frac{\theta_0^n e^{-\theta_0 \sum_{i=1}^n x_i}}{\theta_a^n e^{-\theta_a \sum_{i=1}^n x_i}} \leq K$$

$$\Rightarrow n \log \theta_0 - \theta_0 \sum_{i=1}^n x_i - n \log \theta_a + \theta_a \sum_{i=1}^n x_i \leq \log K$$

$$\Rightarrow (\theta_a - \theta_0) \sum_{i=1}^n x_i \leq K' \Rightarrow \sum_{i=1}^n x_i \geq K''$$

the critical region $C_1 = \{X : \sum_{i=1}^n x_i \geq K''\}$

b) Yes. Because C_1 above doesn't contain θ_a .

c) Yes. suppose it is at significant level α .

$$\begin{cases} \text{in } H_0: \theta = \theta_0 \\ H_a: \theta \geq \theta_a \end{cases} \quad X \sim \exp(\theta) \Rightarrow \sum_{i=1}^n x_i \sim \text{gamma}(n, \theta) \\ \Rightarrow 2\theta \sum_{i=1}^n x_i \sim \chi_{2n}^2$$

$$\text{then } C_1 = \{X : \sum_{i=1}^n x_i \geq k\} \Rightarrow 2\theta_0 k = \chi_{2n, \alpha}^2 \Rightarrow k = \frac{\chi_{2n, \alpha}^2}{2\theta_0}$$

$$\begin{aligned} \beta(\theta) &= \Pr\left(\sum_{i=1}^n x_i \geq \frac{\chi_{2n, \alpha}^2}{2\theta_0}\right) = \Pr\left(2\theta \sum_{i=1}^n x_i \geq \frac{\theta}{\theta_0} \chi_{2n, \alpha}^2\right) \\ &= \Pr\left(\chi_{2n}^2 \geq \frac{\theta}{\theta_0} \chi_{2n, \alpha}^2\right), Y \sim \chi_{2n}^2 \end{aligned}$$

It is obviously that when $\theta = \theta_0$, $\beta(\theta)$ is max. ($\theta \geq \theta_0$)

$\Rightarrow C_1$ is UMP test for $H_0: \theta \leq \theta_0$
 $H_1: \theta > \theta_0$

d) $n=10, \alpha=0.05$. $\begin{cases} H_0: \theta=5 \\ H_a: \theta=2 \end{cases} \Rightarrow \theta_0=5$

$$K = \frac{\chi_{2n, \alpha}^2}{2\theta_0} = \frac{\chi_{20, 0.05}^2}{10} = 3.141$$

$$\Rightarrow C_1 = \left\{X : \sum_{i=1}^{10} x_i > 3.141\right\}$$

Q5. (a) joint p.d.f. = $\prod_{i=1}^m \frac{e^{-\theta_1} \theta_1^{x_i}}{x_i!} \prod_{j=1}^n \frac{e^{-\theta_2} \theta_2^{y_j}}{y_j!}$
 $= e^{-(\theta_1 + \theta_2)} \prod_{i=1}^m \frac{\theta_1^{x_i}}{x_i!} \prod_{j=1}^n \frac{\theta_2^{y_j}}{y_j!}$

log likelihood = $-(m\theta_1 + n\theta_2) + \sum_{i=1}^m x_i \log \theta_1 - \sum_{i=1}^m \log x_i! + \sum_{j=1}^n y_j \log \theta_2 - \sum_{j=1}^n \log y_j!$

Under $H_0: \theta_1 = \theta_2 = \theta_0$

$\frac{\partial \log \text{likelihood}}{\partial \theta} = -\frac{(m+n)}{\theta_0} + \frac{1}{\theta_0} \sum_{i=1}^m x_i + \frac{1}{\theta_0} \sum_{j=1}^n y_j = 0 \Rightarrow \hat{\theta}_0 = \frac{\sum_{i=1}^m x_i + \sum_{j=1}^n y_j}{m+n} = \frac{m\bar{x} + n\bar{y}}{m+n}$

Under θ ,

$\hat{\theta}_1 = \frac{\sum_{i=1}^m x_i}{m}, \hat{\theta}_2 = \frac{\sum_{j=1}^n y_j}{n}$

$\lambda(x) = \frac{e^{-(m\hat{\theta}_0 + n\hat{\theta}_0)} \prod_{i=1}^m \frac{\hat{\theta}_0^{x_i}}{x_i!} \prod_{j=1}^n \frac{\hat{\theta}_0^{y_j}}{y_j!}}{e^{-(m\hat{\theta}_1 + n\hat{\theta}_2)} \prod_{i=1}^m \frac{\hat{\theta}_1^{x_i}}{x_i!} \prod_{j=1}^n \frac{\hat{\theta}_2^{y_j}}{y_j!}}$
 $= \frac{\hat{\theta}_0^{(\sum_{i=1}^m x_i + \sum_{j=1}^n y_j)}}{\hat{\theta}_1^{\sum_{i=1}^m x_i} \hat{\theta}_2^{\sum_{j=1}^n y_j}}$
 $= \frac{\left(\frac{m\bar{x} + n\bar{y}}{m+n}\right)^{(m\bar{x} + n\bar{y})}}{\bar{x}^{m\bar{x}} \bar{y}^{n\bar{y}}}$
 $= \left(\frac{m\bar{x} + n\bar{y}}{(m+n)\bar{x}}\right)^{m\bar{x}} \left(\frac{m\bar{x} + n\bar{y}}{(m+n)\bar{y}}\right)^{n\bar{y}}$

(b) $r = 2 - 1 = 1$,

~~$-2 \log \lambda(x) = \dots$~~ $-2 \log \lambda(x)$

$-2 \log \lambda(x) = -2 \{ m\bar{x} \log(m\bar{x} + n\bar{y}) - m\bar{x} \log((m+n)\bar{x}) + n\bar{y} \log(m\bar{x} + n\bar{y}) - n\bar{y} \log((m+n)\bar{y}) \}$

$= -2 \{ m\bar{x} \log((m+n)\bar{x}) - \dots \}$

$= -2 \{ (m\bar{x} + n\bar{y}) \log(m\bar{x} + n\bar{y}) - (m\bar{x} + n\bar{y}) \log((m+n)\bar{x}) \}$

$\Rightarrow C_1 = \{ x : -2 \log \lambda(x) \geq \chi_1^2 \}$

6: X_1, \dots, X_n is random sample from $U(0, \theta)$

$$\begin{cases} H_0: \theta = 1.6 \\ H_a: \theta = 2 \end{cases}$$

a) i) $n=1$
 $Q(\theta) = \Pr(X > k | \theta)$

$$Q(2) = \Pr(X > k | 2) = 0.9 = 1 - \beta$$

$$\Rightarrow \int_k^2 \frac{1}{2} dx = 0.9 \Rightarrow 1 - \frac{k}{2} = 0.9 \Rightarrow k = 0.2$$

ii) $\alpha = Q(1.6) = \Pr(X > 0.2 | 1.6) = \int_{0.2}^{1.6} \frac{1}{1.6} dx = 0.875$

b) i) $n=1$

$$\alpha = Q(1.6) = \Pr(X > k | 1.6) = 0.05$$

$$\Rightarrow \int_k^{1.6} \frac{1}{1.6} dx = 0.05 \Rightarrow k = 1.52$$

ii) $Q(2) = \Pr(X > 1.52 | 2) = \int_{1.52}^2 \frac{1}{2} dx = 0.24$

c) $n=8$

$$C_1 = \{X : Y_n \geq k\} \quad Y_n = f_Y(y) = ny^{n-1} / \theta^n$$

$$Q(\theta) = \Pr(Y \geq k)$$

$$= 1 - \int_0^k \frac{ny^{n-1}}{\theta^n} dy$$

$$= 1 - \frac{n}{\theta^n} \int_0^k y^{n-1} dy$$

$$= 1 - \frac{k^n}{\theta^n} \quad (n=8)$$

$$Q(1.6) = 1 - \frac{k^8}{1.6^8} = 0.05 \Rightarrow k = 1.5898$$

$$\Rightarrow C_1 = \{X : Y \geq 1.5898\}$$