

MATH 557 - ASSIGNMENT 2
SOLUTIONS

1 (a) The joint pdf for X_1, \dots, X_n is

$$f_{\underline{X}|\theta}(\underline{x}|\theta) = \frac{1}{\theta^n} \exp \left\{ -\frac{1}{\theta} \sum_{i=1}^n (x_i - \theta) \right\} I_{(x_{(1)}, \infty)}(\theta) \quad -\infty < \theta < \infty$$

where $x_{(1)} = \min\{x_1, \dots, x_n\}$. Thus

$$\underline{T}(\underline{X}) = \left(\sum_{i=1}^n X_i, X_{(1)} \right)^T = (T_1(\underline{X}), T_2(\underline{X}))^T,$$

say, is a sufficient statistic for θ . To demonstrate that this is a minimal sufficient statistic, note that for two vectors \underline{x} and \underline{y}

$$\frac{f_{\underline{X}|\theta}(\underline{x}|\theta)}{f_{\underline{X}|\theta}(\underline{y}|\theta)} = \exp \left\{ -\frac{1}{\theta} (T_1(\underline{x}) - T_1(\underline{y})) \right\} \frac{I_{(T_2(\underline{x}), \infty)}(\theta)}{I_{(T_2(\underline{y}), \infty)}(\theta)}$$

which does not depend on θ if and only if

$$T_1(\underline{x}) = T_1(\underline{y}) \quad \text{and} \quad T_2(\underline{x}) = T_2(\underline{y})$$

Hence $\underline{T}(\underline{X})$ is minimal sufficient.

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(b) Note first that for $i = 1, \dots, n$,

$$X_i \stackrel{d}{=} Z_i + \theta$$

where $Z_i \sim \text{Exp}(1/\theta)$ constitute a random sample. Thus

$$T_1(\underline{X}) = \sum_{i=1}^n X_i \stackrel{d}{=} \sum_{i=1}^n Z_i + n\theta$$

and

$$E_{f_{T_1(\underline{X})}}[T_1(\underline{X})] = \sum_{i=1}^n E_{f_{Z_i}}[Z_i] + n\theta = n\theta + n\theta = 2n\theta$$

by properties of the Exponential distribution. Secondly

$$T_2(\underline{X}) = \min\{X_1, \dots, X_n\} \stackrel{d}{=} \min\{Z_1, \dots, Z_n\} + \theta$$

By results related to order statistics from MATH 556, we have that

$$F_{Z_{(1)}}(z) = 1 - \{1 - F_{Z_1}(z)\}^n = 1 - \exp\{-nz/\theta\} \quad z > 0$$

so that $Z_{(1)} \sim \text{Exp}(n/\theta)$. Hence

$$E_{f_{T_2(\underline{X})}}[T_2(\underline{X})] = E_{f_{Z_{(1)}}}[Z_{(1)}] + \theta = \frac{\theta}{n} + \theta = \frac{(n+1)\theta}{n}.$$

Thus if we take function g to be

$$g(t_1, t_2) = \frac{1}{2n}t_1 - \frac{n}{n+1}t_2$$

and it follows that $\underline{T}(\underline{X})$ is **not** complete, as

$$E_{f_{\underline{T}(\underline{X})}}[g(T_1(\underline{X}), T_2(\underline{X}))] = 0$$

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2 (a) The expectation of random variable X from this distribution is

$$E_{f_{X|\theta}}[X] = \int_{-1}^1 x \frac{1+\theta x}{2} dx = \left[\frac{x^2}{4} + \theta \frac{x^3}{6} \right]_{-1}^1 = \frac{\theta}{3}$$

By, for example, the strong law of large numbers

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{a.s.} E_{f_{X|\theta}}[X] = \frac{\theta}{3}$$

and hence by the continuous mapping theorem

$$\tilde{\theta}_n(\underline{X}) = 3\bar{X}_n \xrightarrow{a.s.} \theta$$

as $n \rightarrow \infty$, and is a consistent estimator of θ .

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(b) By the central limit theorem (which may be applied as the support of the pdf is bounded, and hence the variance of the distribution is finite), we have that

$$n^{1/2}(\bar{X}_n - \theta/3) \xrightarrow{d} Z \sim N(0, \sigma^2)$$

and thus by the Delta method applied with function $g(t) = 3t$, we have that

$$n^{1/2}(\tilde{\theta}_n(\underline{X}) - \theta) \xrightarrow{d} Z \sim N(0, 9\sigma^2)$$

Here

$$E_{f_{X|\theta}}[X^2] = \int_{-1}^1 x^2 \frac{1+\theta x}{2} dx = \left[\frac{x^3}{6} + \theta \frac{x^4}{8} \right]_{-1}^1 = \frac{1}{3}$$

so that

$$\sigma^2 = \text{Var}_{f_{X|\theta}}[X] = \frac{1}{3} - \frac{\theta^2}{9} = \frac{3 - \theta^2}{9}$$

and the asymptotic variance of $\tilde{\theta}_n(\underline{X})$ is $(3 - \theta^2)$.

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3 For any finite n , we have that

$$\sum_{i=1}^n I_{\{0\}}(X_i) \sim \text{Binomial}(n, \phi)$$

and thus, by results from lectures, properties of the Binomial distribution, and the Central Limit Theorem (CLT), the asymptotic variance of $\tilde{\phi}_{n1}(\underline{X})$ is

$$\sigma_1^2 = \phi(1 - \phi)$$

Also by the CLT, we have for a random sample from a $Poisson(\theta)$ distribution that as $n \rightarrow \infty$,

$$n^{1/2}(\bar{X}_n - \theta) \xrightarrow{d} Z \sim N(0, \theta).$$

Using the Delta method with mapping $g(t) = e^{-t}$, so that $\dot{g}(t) = -e^{-t}$, it follows that

$$n^{1/2}(\tilde{\phi}_{n2}(\underline{X}) - \phi) \xrightarrow{d} Z \sim N(0, e^{-2\theta}\theta),$$

so the asymptotic variance of $\tilde{\phi}_{n2}(\underline{X})$ is

$$\sigma_2^2 = -\phi^2 \log \phi$$

Thus the asymptotic relative efficiency is

$$\frac{\sigma_1^2}{\sigma_2^2} = \frac{(\phi - 1)}{\phi \log \phi}.$$

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