

$$7.3.5. (a) T = \frac{1}{n} \sum X_i^2 \quad (b) T = \frac{1}{n} \sum X_i \quad (c) T = \frac{n+1}{n} Y_n$$

are unbiased for 7.2.1, 7.2.2, 7.2.3 respectively

$$7.4.5. f(x_1, \dots, x_n; \theta) = e^{n\theta} \cdot e^{-\sum X_i} I(\theta < \min(x_i)) \\ = (e^{-\sum X_i}) \cdot e^{n\theta} I(\theta < \min(x_i))$$

$\Rightarrow Y_1 = \min(x)$ is sufficient.

$$\text{Notice } f_{Y_1}(y) = n e^{-n(y-\theta)} I(y > \theta)$$

$$\Rightarrow E u(Y_1) = \int_0^{+\infty} u(y) n \cdot e^{-ny} \cdot e^{n\theta} dy = 0$$

$$\Leftrightarrow \int_0^{+\infty} u(y) e^{-ny} dy = 0$$

$\Leftrightarrow u(y) = 0 \quad \forall y > 0$ since above is a Laplace transform of $u(y)$.

$\Rightarrow Y_1$ is complete.

By the fact that $E Y_1 = \theta + \frac{1}{n} \Rightarrow Y_1 - \frac{1}{n}$ is MVUE

$$7.5.2. f(x_1, \dots, x_n; \theta) = \theta^n e^{-\theta \sum X_i}$$

$\Rightarrow Y = \sum X_i$ is sufficient

$f(x) = \theta \cdot e^{-\theta x}$ belongs to the exponential family

$\Rightarrow \sum X_i$ is complete

Notice $Y \sim \text{Gamma}(n, \frac{1}{\theta})$

$$E \frac{n-1}{Y} = n-1 \cdot \int \frac{\theta^n}{(n-1)!} y^{n-2} e^{-\theta y} dy$$

$$= \theta \int \frac{\theta^{n-1}}{(n-2)!} y^{n-2} e^{-\theta y} dy = \theta$$

$\Rightarrow \frac{n-1}{Y}$ is MVUE

7.5.3. Sufficient is obvious.

complete comes from the fact of exponential family

$$(b). \ell = \sum \log f(x_i; \theta) = n \log \theta + (\theta - 1) \sum \log x_i$$

$$\frac{\partial \ell}{\partial \theta} = \frac{n}{\theta} + \sum \log x_i$$

$$\Rightarrow \hat{\theta} = -\frac{n}{\sum \log x_i} = -\frac{1}{\log T}$$

7.5.10. Sufficient is obvious.

exponential family \Rightarrow complete

Notice $X \sim \text{Gamma}(2, \frac{1}{\theta})$

$$\Rightarrow Y = \sum X_i \sim \text{Gamma}(2n, \frac{1}{\theta})$$

$$\Rightarrow \frac{2n-1}{Y} \text{ is UMVUE (see 7.5.2).}$$

7.5.13. $\ell(\theta) = (\sum X_i) \log \theta + n \log(1-\theta)$. Let $Y = \sum X_i$

$$\Rightarrow \frac{\partial \ell}{\partial \theta} = \frac{Y}{\theta} - \frac{n}{1-\theta} \Rightarrow \hat{\theta} = \frac{Y}{n+Y}$$

(b). same as 7.5.10.

(c). $Y = \sum X_i \sim \text{Negative binomial}(n, p)$.

Consider $u(x) = \begin{cases} 1 & \text{if } x_i = 0 \\ 0 & \text{e.w.} \end{cases} \Rightarrow E u(x) = 1-\theta$

$\Rightarrow 1-u(x)$ is unbiased

Let $T = E(1-u(x) | Y)$ is MVUE

$$= 1 - P(X_i = 0 | \sum X_i = y) = 1 - \frac{P(X_i = 0, \sum X_i = y)}{P(\sum X_i = y)}$$

$$= 1 - \frac{\binom{n+\frac{y}{\theta}-2}{\frac{y}{\theta}}}{\binom{n+\frac{y}{\theta}-1}{\frac{y}{\theta}}} = 1 - \frac{n-1}{y+n-1} = \frac{y}{y+n-1} = \frac{\sum X_i}{\sum X_i + n - 1}$$