

$$8.14(d) \quad f(x_1, x_2, \dots, x_n | \sigma) = \prod_{i=1}^n \left[ \frac{1}{2\sigma} e^{-\frac{|x_i|}{\sigma}} \right] = \left(\frac{1}{2\sigma}\right)^n \cdot e^{-\frac{1}{\sigma} \sum_{i=1}^n |x_i|}$$

$$g[T(x_1, \dots, x_n), \sigma] = \left(\frac{1}{2\sigma}\right)^n e^{-\frac{1}{\sigma} \sum_{i=1}^n |x_i|} \quad T(x_1, \dots, x_n) = \sum_{i=1}^n |x_i|$$

$$h(x_1, \dots, x_n) = 1$$

sufficient statistic for  $\sigma$  is  $\sum_{i=1}^n |x_i|$

$$8.16(d) \quad f(x_1, x_2, \dots, x_n | \alpha) = \prod_{i=1}^n \left[ \frac{\Gamma(3\alpha)}{\Gamma(\alpha)\Gamma(2\alpha)} x_i^{\alpha-1} (1-x_i)^{2\alpha-1} \right]$$

$$= \left( \frac{\Gamma(3\alpha)}{\Gamma(\alpha)\Gamma(2\alpha)} \right)^n \left[ \prod_{i=1}^n x_i (1-x_i)^2 \right]^{\alpha} \cdot \prod_{i=1}^n \frac{1}{x_i (1-x_i)}$$

$$h(x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{x_i (1-x_i)}$$

$$T(x_1, \dots, x_n) = \prod_{i=1}^n [x_i (1-x_i)^2]$$

Sufficient Statistic for  $\alpha$  is  $\prod_{i=1}^n [x_i (1-x_i)^2]$

8.17(c) Let  $T(x_1, x_2, \dots, x_n)$  be any unbiased estimate of  $\mu$ , from Cramer-Rao Inequality  $\text{Var}(T) \geq \frac{1}{n I(\mu)}$

$$I(\mu) = E \left[ - \frac{\partial^2 \ln f(x; \mu)}{\partial \mu^2} \right] = E \left[ - \frac{\partial^2}{\partial \mu^2} \left[ \ln n - \ln n \sqrt{\frac{\pi}{2}} - \frac{1}{2} \frac{(x-\mu)^2}{\sigma^2} \right] \right]$$

$$= E \frac{1}{\sigma^2} = \frac{1}{\sigma^2}$$

$$\text{Var}(T) \geq \frac{\sigma^2}{n} = \text{Var}(\bar{X})$$

So, There is no other unbiased estimate of  $\mu$  have smaller variance than  $\bar{X}$

8.54 (a) we know  $T = \sum_{i=1}^n X_i \sim \text{Poisson}(n\lambda)$

$P(X_1=k_1, X_2=k_2, \dots, X_n=k_n | T=t)$  when  $\sum_{i=1}^n k_i \neq t$   
 this probability is 0 (doesn't depend on  $\lambda$ )

So, we assume  $\sum_{i=1}^n k_i = t$

$$P(X_1=k_1, X_2=k_2, \dots, X_n=k_n | T=t) = \frac{P(X_1=k_1, \dots, X_n=k_n, T=t)}{P(T=t)} = \frac{P(X_1=k_1, \dots, X_n=k_n)}{P(T=t)}$$

$$= \frac{\frac{e^{-\lambda} \lambda^{k_1}}{k_1!} \times \dots \times \frac{e^{-\lambda} \lambda^{k_n}}{k_n!}}{\frac{e^{-n\lambda} (n\lambda)^t}{t!}} = \frac{t!}{k_1! \dots k_n! \cdot n^t} \quad (\text{doesn't depend on } \lambda)$$

so  $T = \sum_{i=1}^n X_i$  is sufficient for  $\lambda$

(b)  $P(X_2=k_2 | X_1=k_1) = P(X_2=k_2) = \frac{e^{-\lambda} \lambda^{k_2}}{k_2!}$  (depend on  $\lambda$ )  
 so  $X_1$  is not sufficient for  $\lambda$

(c)  $P(X_1=x_1, \dots, X_n=x_n | \lambda) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} = e^{-n\lambda} \cdot \lambda^{\sum_{i=1}^n x_i} \prod_{i=1}^n \frac{1}{x_i!}$

$h(x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{x_i!}$ ;  $g(T(x_1, \dots, x_n), \lambda) = e^{-n\lambda} \cdot \lambda^{\sum_{i=1}^n x_i}$

$T(x_1, \dots, x_n) = \sum_{i=1}^n x_i$  is sufficient for  $\lambda$

55  $f(x_1, \dots, x_n | p) = \prod_{i=1}^n p(1-p)^{x_i-1} = \left(\frac{p}{1-p}\right)^n \cdot (1-p)^{\sum_{i=1}^n x_i}$

$h(x_1, \dots, x_n) = 1$   $T(x_1, \dots, x_n) = \sum_{i=1}^n x_i$  is sufficient for  $p$

57  $f(x_1, \dots, x_n | \theta) = \prod_{i=1}^n \frac{\theta}{(1+x_i)^{\theta+1}} = \theta^n \left[ \prod_{i=1}^n \frac{1}{1+x_i} \right]^{\theta+1}$

$= \theta^n \left[ \prod_{i=1}^n (1+x_i) \right]^{-\theta} \cdot \left[ \prod_{i=1}^n (1+x_i) \right]^{-1}$

$h(x_1, \dots, x_n) = \left[ \prod_{i=1}^n (1+x_i) \right]^{-1}$ ;  $T(x_1, \dots, x_n) = \prod_{i=1}^n (1+x_i)$  is a sufficient

statistic for  $\theta$