

Examples for 10/19/2020 (2) and 10/23/2020 (2) and 10/30/2020 (3) (continued)

1. Let $\beta > 0$ and let X_1, X_2, \dots, X_n be a random sample from the distribution with probability density function

$$f(x; \beta) = \frac{\beta^2 \ln x}{x^{\beta+1}}, \quad x > 1, \quad \text{zero otherwise.}$$

Recall: $W = \ln X$ has a Gamma($\alpha = 2, \theta = \frac{1}{\beta}$) distribution.

$$\Rightarrow Y = \sum_{i=1}^n \ln X_i = \sum_{i=1}^n W_i \text{ has a Gamma}(\alpha = 2n, \theta = \frac{1}{\beta}) \text{ distribution.}$$

n) Find a sufficient statistic $u(X_1, X_2, \dots, X_n)$ for β .

o) Find the Fisher information $I(\beta)$.

(After you are done with part (o), glance back at part (m).)

Recall: $\hat{\beta} = \frac{2n-1}{\sum_{i=1}^n \ln X_i}$ is an unbiased estimator for β .

p) Is $\hat{\beta}$ an efficient estimator of β ? If $\hat{\beta}$ is not efficient, find its efficiency.

① Find $\text{Var}(\hat{\beta})$. (“Hint”: Recall 1(e) of Examples for 10/19/2020 (2).)

② Find the Rao-Cramér lower bound.

③ Is $\hat{\beta}$ an efficient estimator of β ? Does $\text{Var}(\hat{\beta})$ attain the R.C.L.B.?
If $\hat{\beta}$ is not efficient, find its efficiency.

Answers:

1. Let $\beta > 0$ and let X_1, X_2, \dots, X_n be a random sample from the distribution with probability density function

$$f(x; \beta) = \frac{\beta^2 \ln x}{x^{\beta+1}}, \quad x > 1, \quad \text{zero otherwise.}$$

Recall: $W = \ln X$ has a Gamma($\alpha = 2, \theta = \frac{1}{\beta}$) distribution.

$$\Rightarrow Y = \sum_{i=1}^n \ln X_i = \sum_{i=1}^n W_i \text{ has a Gamma}(\alpha = 2n, \theta = \frac{1}{\beta}) \text{ distribution.}$$

- n) Find a sufficient statistic $u(X_1, X_2, \dots, X_n)$ for β .

$$f(x_1, x_2, \dots, x_n; \beta) = f(x_1; \beta) f(x_2; \beta) \dots f(x_n; \beta)$$

$$= \prod_{i=1}^n \frac{\beta^2 (\ln x_i)}{x_i^{\beta+1}} = \left[\beta^{2n} \cdot \left(\prod_{i=1}^n x_i \right)^{-\beta-1} \right] \cdot \left(\prod_{i=1}^n \ln x_i \right).$$

By Factorization Theorem, $Y = \sum_{i=1}^n X_i$ is a sufficient statistic for β .

$$\prod_{i=1}^n \frac{1}{X_i} \text{ is also a sufficient statistic for } \beta.$$

OR

$$f(x; \beta) = \exp\{-\beta \cdot \ln x + 2 \ln \beta + \ln \ln x - \ln x\}. \quad K(x) = \ln x.$$

$$\Rightarrow Y = \sum_{i=1}^n K(X_i) = \sum_{i=1}^n \ln X_i \text{ is a sufficient statistic for } \beta.$$

o) Find the Fisher information $I(\beta)$.

(After you are done with part (o), glance back at part (m).)

$$\ln f(x; \beta) = -\beta \cdot \ln x + 2 \ln \beta + \ln \ln x - \ln x.$$

$$\frac{\partial}{\partial \beta} \ln f(x; \beta) = -\ln x + \frac{2}{\beta}.$$

$$\frac{\partial^2}{\partial \beta^2} \ln f(x; \beta) = -\frac{2}{\beta^2}.$$

$$I(\beta) = \text{Var} \left[\frac{\partial}{\partial \beta} \ln f(X; \beta) \right]$$

$$= \text{Var} \left[-\ln X + \frac{1}{\beta} \right]$$

$$= \text{Var}(W)$$

$$= \alpha \theta^2 = \frac{2}{\beta^2}.$$

$$I(\beta) = -E \left[\frac{\partial^2}{\partial \beta^2} \ln f(X; \beta) \right]$$

$$= -E \left[-\frac{2}{\beta^2} \right]$$

$$= \frac{2}{\beta^2}.$$

Glancing back at part (m):

$\hat{\beta}$ is the maximum likelihood estimator for β .

$$\sqrt{n} \left(\hat{\beta} - \beta \right) \xrightarrow{D} N\left(0, \frac{1}{I(\beta)}\right) = N\left(0, \frac{\beta^2}{2}\right).$$



Recall: $\hat{\beta} = \frac{2n-1}{\sum_{i=1}^n \ln X_i}$ is an unbiased estimator for β .

p) Is $\hat{\beta}$ an efficient estimator of β ? If $\hat{\beta}$ is not efficient, find its efficiency.

① Find $\text{Var}(\hat{\beta})$. (“Hint”: Recall **1** (e) of Examples for 10/19/2020 (2).)

② Find the Rao-Cramér lower bound.

③ Is $\hat{\beta}$ an efficient estimator of β ? Does $\text{Var}(\hat{\beta})$ attain the R.C.L.B.?
If $\hat{\beta}$ is not efficient, find its efficiency.

$$\text{Recall: } \text{Var}\left(\frac{1}{Y}\right) = \frac{\beta^2}{(2n-1)(2n-2)} - \left(\frac{\beta}{2n-1}\right)^2 = \frac{\beta^2}{(2n-1)^2(2n-2)}.$$

$$\text{Var}(\hat{\beta}) = \text{Var}\left(\frac{2n-1}{Y}\right) = (2n-1)^2 \text{Var}\left(\frac{1}{Y}\right) = \frac{\beta^2}{2n-2}.$$

$$\text{Rao-Cramer lower bound} = \frac{1}{n \cdot I(\beta)} = \frac{\beta^2}{2n}.$$

$$\text{Var}(\hat{\beta}) = \frac{\beta^2}{2n-2} > \frac{\beta^2}{2n}.$$

$\text{Var}(\hat{\beta})$ does NOT attain its Rao-Cramer lower bound.

$\Rightarrow \hat{\beta}$ is NOT an efficient estimator of β ,

$$\text{its efficiency} = \frac{2n-2}{2n} = \frac{n-1}{n} \rightarrow 1 \text{ as } n \rightarrow \infty.$$

$\Rightarrow \hat{\beta}$ is an asymptotically efficient estimator of β .