

**CASELLA-BERGER  
STATISTICAL INFERENCE SOLUTION:  
CHAPTER 7**

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September 26, 2022

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## 1. EXERCISE 7.1

For each  $x$ , we find  $\theta$  so that  $f(x|\theta)$  is maximised.

$x$	0	1	2	3	4
$\theta$	1	1	Either 2 or 3 works	3	3
$f(x \theta)$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{4}$

Therefore,

$$\hat{\theta}_1(x) = \begin{cases} 1 & \text{if } x = 0, 1, \\ 2 & \text{if } x = 2, \\ 3 & \text{if } x = 3, 4 \end{cases} \quad \hat{\theta}_2(x) = \begin{cases} 1 & \text{if } x = 0, 1, \\ 3 & \text{if } x = 2, 3, 4, \end{cases}$$

are the possible MLEs' for  $\theta$ .

## 2. EXERCISE 7.2

The likelihood function for  $\beta$  is given by

$$\begin{aligned} L(\beta|x_1, \dots, x_n) &= \prod_{i=1}^n f(x_i; \alpha, \beta) \\ &= \prod_{i=1}^n \frac{x_i^{\alpha-1} e^{-\frac{x_i}{\beta}}}{\Gamma(\alpha) \beta^\alpha} \\ &= \frac{\left(\prod_{i=1}^n x_i\right)^{\alpha-1}}{[\Gamma(\alpha)]^n} \cdot \exp \left[ -\frac{\sum_{i=1}^n x_i}{\beta} \right] \cdot \beta^{\alpha n}, \end{aligned}$$

and has derivative

$$\frac{\partial L}{\partial \beta} = \frac{\left(\prod_{i=1}^n x_i\right)^{\alpha-1}}{[\Gamma(\alpha)]^n} \cdot \exp \left[ -\frac{\sum_{i=1}^n x_i}{\beta} \right] \cdot \beta^{-\alpha n - 2} \cdot \left( \sum_{i=1}^n x_i - \alpha n \beta \right).$$

In particular,

$$\begin{aligned} \frac{\partial L}{\partial \beta} = 0 &\iff \sum_{i=1}^n x_i - \alpha n \beta = 0 \\ &\iff \beta = \frac{\sum_{i=1}^n x_i}{\alpha n}. \end{aligned}$$

It remains to show this  $\beta$  maximises  $L$ .

We note that the sign of  $\frac{\partial L}{\partial \beta}$  is completely determined by the sign of the term  $\sum_{i=1}^n x_i - \alpha n \beta$ .

Furthermore,

$$\begin{aligned} \left. \frac{\partial L}{\partial \beta} \right|_{\beta=\hat{\beta}+\varepsilon} &= -\alpha n \varepsilon \\ &= \begin{cases} > 0 & \text{if } \varepsilon < 0, \\ < 0 & \text{if } \varepsilon > 0. \end{cases} \end{aligned}$$

Thus, the First Derivative Test says  $\hat{\beta} = \frac{\sum_{i=1}^n x_i}{\alpha n}$  is the MLE for  $\beta$ .

## 3. EXERCISE 7.3

Pre-calculus.

## 4. EXERCISE 7.6

(a) The joint distribution is given by

$$\begin{aligned} f_{X_1, \dots, X_n}(x_1, \dots, x_n | \theta) &= \prod_{i=1}^n \chi_{[\theta, \infty)}(x_i) \cdot \frac{\theta}{x_i^2} \\ &= \frac{\chi_{[\theta, \infty)}\left(\min_{1 \leq i \leq n} x_i\right)}{\left(\prod_{i=1}^n x_i\right)^2} \cdot \theta^n. \end{aligned}$$

[BC01, Factorization Theorem 6.2.6 on page 276] says the tuple  $\left(\min_{1 \leq i \leq n} X_i, \prod_{i=1}^n X_i\right)$  is a sufficient statistic for  $\theta$ .

(b) Up to a positive multiplier, the likelihood function  $L(\theta | x_1, \dots, x_n)$  is just the monomial  $\theta^n$ . But  $\theta^n$  has no maximum on the interval  $(0, \infty)$ . However, there is also the characteristic function  $\chi_{[\theta, \infty)}\left(\min_{1 \leq i \leq n} x_i\right)$ , which restricts  $\theta$  inside the interval  $\left(0, \min_{1 \leq i \leq n} x_i\right]$ . We summarise this discussion as the following optimisation problem

$$\max_{\theta \in \left(0, \min_{1 \leq i \leq n} x_i\right]} \left[ \frac{\chi_{[\theta, \infty)}\left(\min_{1 \leq i \leq n} x_i\right)}{\left(\prod_{i=1}^n x_i\right)^2} \cdot \theta^n \right],$$

and its solution is  $\hat{\theta} = \min_{1 \leq i \leq n} x_i$ .

(c) We compute the moments

$$\begin{aligned} E_{\theta}[X^n] &= \int_0^{\infty} x^n \cdot f(x | \theta) \, dx \\ &= \int_0^{\infty} \theta x^{n-2} \, dx \\ &= \infty \end{aligned} \quad (\text{since } n \geq 1).$$

Therefore, the desired estimator does not exist.

## 5. EXERCISE 7.7

The likelihood function is given by

$$\begin{aligned}
 L(\theta|x_1, \dots, x_n) &= \prod_{i=1}^n f(x_i|\theta) \\
 &= \begin{cases} \prod_{i=1}^n 1 & \text{if } \theta = 0 \text{ and } 0 < x < 1, \\ \prod_{i=1}^n \frac{1}{2\sqrt{x_i}} & \text{if } \theta = 1 \text{ and } 0 < x < 1, \\ 0 & \text{if else.} \end{cases} \\
 &= \begin{cases} 1 & \text{if } \theta = 0 \text{ and } 0 < x < 1, \\ \prod_{i=1}^n \frac{1}{2\sqrt{x_i}} & \text{if } \theta = 1 \text{ and } 0 < x < 1, \\ 0 & \text{if else.} \end{cases}
 \end{aligned}$$

Therefore, the MLE is

$$\hat{\theta}(x_1, \dots, x_n) = \begin{cases} 0 & \text{if } \prod_{i=1}^n \frac{1}{2\sqrt{x_i}} \leq 1, \\ 1 & \text{if else.} \end{cases}$$

## REFERENCES

- [BC01] Roger Berger and George Casella. *Statistical Inference*. 2nd edition. Florence, AL: Duxbury Press, June 2001.