

Exs. for An Introduction to Probability and Statistics by
Rohatgi and Saleh (Third Edition)

Problems 8.2

- ① * T_n is a sequence of estimators for θ
 * $E(T_n) \rightarrow \theta$ and $\text{Var}(T_n) \rightarrow 0$, $n \rightarrow \infty$
 $\Rightarrow T_n$ is consistent for θ
 * $T_n \xrightarrow{z} \theta$, i.e. $\lim_{n \rightarrow \infty} E[(T_n - \theta)^2] = 0$

II T_n consistent for θ and $|T_n - \theta| \leq A < \infty$

$$E[(T_n - \theta)^2] = \dots = E[(T_n - E(T_n))^2] + [E(T_n - \theta)]^2$$

Variance
Bias²

$$= \text{Var}(T_n) + [E(T_n - \theta)]^2$$

$$\lim_{n \rightarrow \infty} E[(T_n - \theta)^2] = \lim_{n \rightarrow \infty} \text{Var}(T_n) + \lim_{n \rightarrow \infty} [E(T_n - \theta)]^2$$

$\rightarrow 0$

$$= \lim_{n \rightarrow \infty} [E(T_n) - E(\theta)]^2$$

$$= \lim_{n \rightarrow \infty} [E(T_n) - E(\theta)] \cdot \lim_{n \rightarrow \infty} [E(T_n) - E(\theta)]$$

$\rightarrow 0$
 $\rightarrow 0$

$$= 0$$

$$\therefore T_n \xrightarrow{z} \theta$$

?

Resolução do professor Raul:

I T_n consistent for θ and $|T_n - \theta| \leq A < \infty$

Se Y for v.a não negativa,

$$E Y = \int_0^{\infty} y \cdot f_{\theta}(y) dy = \int_0^{\infty} P(Y > \epsilon) d\epsilon$$

$$E |T_n - \theta|^2 \rightarrow 0, n \rightarrow \infty$$

$$E |T_n - \theta|^2 = \int_0^{\infty} P(|T_n - \theta|^2 > \epsilon) d\epsilon$$

$$= \int_0^{\infty} P(|T_n - \theta| > \sqrt{\epsilon}) d\epsilon$$

$$= 2 \cdot \int_0^{\infty} \epsilon \cdot P(|T_n - \theta| > \sqrt{\epsilon}) d\epsilon$$

$$\leq 2 \cdot A \cdot \int_0^A P(|T_n - \theta| > \sqrt{\epsilon}) d\epsilon \rightarrow 0, n \rightarrow \infty$$

$$\therefore E |T_n - \theta|^2 \rightarrow 0, n \rightarrow \infty \Rightarrow T_n \xrightarrow{z} \theta$$

II $|T_n - \theta| \leq A_n < \infty$

Para esse caso, temos:

$$E |T_n - \theta|^2 \leq 2 A_n \int_0^{A_n} P(|T_n - \theta| > \sqrt{\epsilon}) d\epsilon$$

Uma vez que não sabemos o valor, no limite, por causa do fato de A_n estar indexado em n , não há garantia que

$$T_n \xrightarrow{z} \theta.$$

(2) * X_1, \dots, X_n A.A. de $\mathcal{U}[0, \theta], \theta \in \Theta = (0, \infty)$

$$* X_{(n)} = \max \{X_1, \dots, X_n\}$$

* $X_{(n)} \xrightarrow{P} \theta$, se e somente se

$$P(|X_{(n)} - \theta| > \varepsilon) \rightarrow 0, n \rightarrow \infty, \forall \varepsilon > 0$$

o que é equivalente a.

$$P(|X_{(n)} - \theta| \leq \varepsilon) \rightarrow 1, n \rightarrow \infty, \forall \varepsilon > 0$$

$$\begin{aligned} \bullet \quad P(|X_{(n)} - \theta| \leq \varepsilon) &= P(-\varepsilon \leq X_{(n)} - \theta \leq \varepsilon) \\ &= P(\theta - \varepsilon \leq X_{(n)} \leq \theta + \varepsilon) \\ &= F_{X_{(n)}}(\theta + \varepsilon) - F_{X_{(n)}}(\theta - \varepsilon) \end{aligned}$$

$$\begin{aligned} F_{X_{(n)}}(x) &= P(X_{(n)} \leq x) \\ &= P(\max \{X_1, \dots, X_n\} \leq x) \\ &= P(\{X_1 \leq x\} \cap \dots \cap \{X_n \leq x\}) \\ &\stackrel{\text{ind}}{=} \left[P(X_1 \leq x) \right]^n \\ &= \left(\frac{x}{\theta} \right)^n \end{aligned}$$

$$= 1 - \left(\frac{\theta - \varepsilon}{\theta} \right)^n.$$

$\rightarrow 1, n \rightarrow \infty$ e $0 < \varepsilon < \theta$.

$$\therefore X_{(n)} \xrightarrow{P} \theta$$

$$\bullet \quad Y_n = z \bar{X}, \quad \bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

$$E(Y_n) = E(z \bar{X}) = z \cdot E(\bar{X}) = \frac{z}{n} \cdot n \cdot \theta = \theta$$

$$\begin{aligned} \text{Var}(y_n) &= \text{Var}(2\bar{x}) = 4 \cdot \text{Var}(\bar{x}) \stackrel{\text{i.i.d.}}{=} 4 \cdot \frac{1}{n^2} \cdot n \cdot \frac{\sigma^2}{12} \\ &= \frac{4 \cdot \sigma^2}{12 \cdot n} = \frac{\sigma^2}{3n} \end{aligned}$$

$$\rightarrow 0, n \rightarrow \infty.$$

Pelo Teorema 2, uma vez que $E(y_n) = \theta$ e $\text{Var}(y_n) \rightarrow 0$, $n \rightarrow \infty$, y_n é consistente para θ .

(3)

* X_1, X_2, \dots, X_n i.i.d. v.a.'s

* $E(X_i) = \mu$, $E(|X_i|^2) < \infty$

* $T(X_1, \dots, X_n) = \frac{2}{n(n+1)} \cdot \sum_{i=1}^n i \cdot X_i$

$$\begin{aligned} E[T(X_1, \dots, X_n)] &= \frac{2}{n(n+1)} \sum_{i=1}^n i \cdot E(X_i) \\ &= \frac{2\mu}{n(n+1)} \sum_{i=1}^n i \\ &= \frac{2\mu}{n(n+1)} \cdot \frac{(1+n) \cdot n}{2} \\ &= \mu. \end{aligned}$$

$$\begin{aligned} \text{Var}(T(X_1, \dots, X_n)) &= \left[\frac{2}{n(n+1)} \right]^2 \cdot \text{Var}\left(\sum_{i=1}^n i X_i\right) \\ &\stackrel{\text{i.i.d.}}{=} \left[\frac{2}{n(n+1)} \right]^2 \sum_{i=1}^n i^2 \cdot \text{Var}(X_i) \\ &= \left[\frac{2}{n(n+1)} \right]^2 \cdot \sigma_X^2 \cdot \sum_{i=1}^n i^2 \\ &= \left[\frac{2}{n(n+1)} \right]^2 \sigma_X^2 \cdot \frac{n \cdot (n+1) \cdot (2n+1)}{6} \\ &= \frac{4}{n \cdot (n+1)} \cdot \frac{(2n+1)}{6} \cdot \sigma_X^2 \end{aligned}$$

$$= \left(\frac{2n+1}{n^2+n} \right) \cdot \frac{2}{3} \cdot \sqrt{\frac{2}{x}}$$

$$\longrightarrow 0, \quad n \rightarrow \infty$$

Pelo Teorema 2, uma vez $E(T_n) \rightarrow \mu$ e $\text{Var}(T_n) \rightarrow 0, n \rightarrow \infty$,

T_n é consistente para μ .

(4) * X_1, X_2, \dots, X_n amostra de $U[0, \theta]$

$$* T_n = \left(\prod_{i=1}^n X_i \right)^{1/n}$$

$$* \psi(\theta) = \frac{\theta}{e}$$

$$Y_n = \ln(T_n) \quad (T_n = e^{Y_n})$$

$$= \frac{1}{n} \cdot \ln \left(\prod_{i=1}^n X_i \right)$$

$$= \frac{1}{n} \sum_{i=1}^n \ln(X_i)$$

$$E(\ln(X_i)) = \int_0^\theta \ln(x) \cdot \frac{1}{\theta} \cdot dx.$$

$$= \frac{1}{\theta} \int_0^\theta \ln(x) dx.$$

$$\int_0^\theta \ln(x) dx = \ln(x) \cdot x \Big|_0^\theta - \int_0^\theta x \cdot \frac{1}{x} dx$$

$$= \ln(x) \cdot x \Big|_0^\theta - \int_0^\theta 1 dx$$

$$= \ln(\theta) \cdot \theta - \theta$$

$$= \frac{1}{\theta} \cdot [\ln(\theta) \cdot \theta - \theta]$$

$$= \ln(\theta) - 1$$

Pela Lei Forte dos Grandes Números.

$$Y_n = \frac{\ln(x_1) + \dots + \ln(x_n)}{n} \xrightarrow{q.c.} E(\ln(x_1)) = \ln(\theta) - 1$$

Pelo Teorema da Aplicação Contínua

$$Y_n \xrightarrow{q.c.} \ln(\theta) - 1 \Rightarrow$$

$$T_n = e^{Y_n} \xrightarrow{q.c.} \exp(\ln(\theta) - 1) = \theta \cdot e^{-1}$$

Uma vez que $T_n \xrightarrow{q.c.} \psi(\theta) = \theta \cdot e^{-1}$, então $T_n \xrightarrow{P} \psi(\theta)$

$\therefore T_n$ é estimador consistente para $\psi(\theta) = \theta \cdot e^{-1}$

(5) $* T(\underline{X}) = X_{(n)}$

$$F_{X_{(n)}}(x) = \begin{cases} 0, & x < 0 \\ \left(\frac{x}{\theta}\right)^n, & 0 \leq x < \theta \\ 1, & x \geq \theta \end{cases}$$

\Rightarrow

$$f_{X_{(n)}}(x) = \begin{cases} 0, & x \notin (0, \theta) \\ \frac{d}{dx} \left(\frac{x}{\theta}\right)^n = \frac{n \cdot x^{n-1}}{\theta^n}, & x \in (0, \theta) \end{cases}$$

$\theta \qquad n-1$

$$\begin{aligned}
 E X_{(n)} &= \int_0^{\theta} x \cdot \frac{n \cdot x^{n-1}}{\theta^n} \cdot dx \\
 &= \frac{n}{\theta^n} \cdot \int_0^{\theta} x^n dx \\
 &= \frac{n}{\theta^n} \cdot \left[\frac{x^{n+1}}{n+1} \right]_0^{\theta} \\
 &= \frac{n}{\theta^n} \cdot \frac{\theta^{n+1}}{n+1} = \left(\frac{n}{n+1} \right) \cdot \theta
 \end{aligned}$$

Sabemos que $\{T_n\}$ é assintoticamente não viesado p/ θ , se.

$$\lim_{n \rightarrow \infty} E_{\theta} T_n(\underline{X}) = \theta$$

? No enunciado diz "biased"!

⑥ * $T(\underline{X}) = e X_{(n)}$

* $T_{\theta}(\underline{X}) = \frac{(n+2)}{(n+1)} X_{(n)}$

Problems 8.3

①

(a) * $X \sim B(\alpha, \beta)$

(i) α desconhecido, β conhecido

$$\begin{aligned} f(x_1, \dots, x_n) &= \prod_{i=1}^n \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} \cdot x_i^{\alpha-1} (1-x_i)^{\beta-1} \\ &= \underbrace{\frac{1}{[\Gamma(\beta)]^n} \prod_{i=1}^n (1-x_i)^{\beta}}_{h(x_1, x_2, \dots, x_n)} \cdot \underbrace{\left[\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)} \right]^n \left(\prod_{i=1}^n x_i \right)^{\alpha}}_{g_{\alpha}(\prod x_i)} \end{aligned}$$

$\therefore \prod x_i$ é estatística suficiente para α .

(ii) α conhecido, β desconhecido

$$\begin{aligned} f(x_1, \dots, x_n) &= \underbrace{\frac{1}{[\Gamma(\alpha)]^n} \cdot \frac{\prod x_i^{\alpha}}{\prod x_i (1-x_i)}}_{h(x_1, \dots, x_n)} \cdot \underbrace{\left[\frac{\Gamma(\alpha + \beta)}{\Gamma(\beta)} \right]^n (\prod (1-x_i))^{\beta}}_{g_{\beta}(\prod (1-x_i))} \end{aligned}$$

$\therefore \prod (1-x_i)$ é estatística suficiente para β .

(iii) α, β desconhecidos.

$$\theta = (\alpha, \beta)$$

$$\begin{aligned} f(x_1, \dots, x_n) &= \underbrace{\prod_{i=1}^n \frac{1}{x_i (1-x_i)}}_{h(x_1, \dots, x_n)} \cdot \underbrace{\left[\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} \right]^n (\prod x_i)^{\alpha} (\prod (1-x_i))^{\beta}}_{g_{\theta}(\prod x_i, \prod (1-x_i))} \end{aligned}$$

$\therefore T(x_i)$ e $T(1-x_i)$ são estatísticas suficientes para α e β .

② * $\underline{X} = (X_1, \dots, X_n)$ amostra de $N(\alpha\sigma, \sigma^2)$, $\alpha \in \mathbb{R}$ conhecido

* $T(\underline{X}) = (\sum X_i, \sum X_i^2)$

I Demonstrar que $T(\underline{X})$ é suficiente para σ

$$\begin{aligned} f_{\sigma}(x_1, \dots, x_n) &= \frac{1}{(\sqrt{2\pi})^n} \cdot \frac{1}{\sigma^n} \cdot \exp\left(-\frac{\sum (x_i - \alpha\sigma)^2}{2\sigma^2}\right) \\ &= \frac{1}{(\sqrt{2\pi})^n} \cdot \frac{1}{\sigma^n} \cdot \exp\left(-\frac{\sum x_i^2}{2\sigma^2} + \alpha \frac{\sum x_i}{\sigma} - \frac{n\alpha^2\sigma^2}{2\sigma^2}\right) \\ &= \underbrace{\frac{1}{(\sqrt{2\pi})^n} \cdot \frac{1}{\sigma^n}}_{h(x_1, \dots, x_n)} \cdot \underbrace{\exp\left(-\frac{\sum x_i^2}{2\sigma^2} + \frac{\alpha \sum x_i}{\sigma} - \frac{n\alpha^2}{2}\right)}_{g_{\sigma}(\sum x_i, \sum x_i^2)} \end{aligned}$$

$\therefore T(\underline{X}) = (\underbrace{\sum X_i}_{T_1}, \underbrace{\sum X_i^2}_{T_2})$ é estatística suficiente para σ

II Demonstrar que a família de distribuições $T(\underline{X})$ é não completa.

$$E_{\sigma} \left\{ 2\left(\sum X_i\right)^2 - (n+1) \sum X_i^2 \right\} = 0, \forall \sigma$$

Vamos supor que $P\{2T_1^2 - (n+1)T_2 = 0\} = 1$.

$$2T_1^2 - (n+1)T_2 = 0 \Rightarrow T_2 = \frac{2}{(n+1)} T_1^2$$

?

- ③
- * $X_1, \dots, X_n \sim N(\mu, \sigma^2)$
 - * $\underline{X} = (X_1, \dots, X_n)$ clearly sufficient for $N(\mu, \sigma^2)$, $\mu \in \mathbb{R}$, $\sigma > 0$.

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- * X_1, X_2 amostra de $P(\lambda)$
 - * $T(X_1, X_2) = X_1 + \alpha X_2$, $\alpha > 1$ inteiro

Saber-se que $T = T(\underline{X})$ é suficiente para θ se, e somente se, a distribuição condicional de \underline{X} , dado $T = t$ não depende de θ .

$$P(X_1 = 0, X_2 = 1 \mid X_1 + \alpha X_2 = \alpha) = \frac{P(X_1 = 0, X_2 = 1)}{P(X_1 + \alpha X_2 = \alpha)}$$

I Calcular numerador.

$$\begin{aligned} P(X_1 = 0, X_2 = 1) &= e^{-\lambda} \cdot e^{-\lambda} \lambda \\ &= \lambda \cdot e^{-2\lambda} \end{aligned}$$

II Calcular denominador

$$\begin{aligned} P(X_1 + \alpha X_2 = \alpha) &= P(X_1 + \alpha X_2 = \alpha, X_2 = 1) + P(X_1 + \alpha X_2 = \alpha, X_2 = 0) \\ &= P(X_1 + \alpha X_2 = \alpha | X_2 = 1) \cdot P(X_2 = 1) + \\ &\quad P(X_1 + \alpha X_2 = \alpha | X_2 = 0) \cdot P(X_2 = 0) \\ &= P(X_1 = 0) \cdot P(X_2 = 1) + P(X_1 = \alpha) \cdot P(X_2 = 0) \\ &= \lambda \cdot e^{-2\lambda} + \frac{e^{-\lambda} \cdot \lambda^\alpha}{\alpha!} \cdot e^{-\lambda} \\ &= \lambda e^{-2\lambda} \left(1 + \frac{\lambda^{\alpha-1}}{\alpha!} \right) \end{aligned}$$

III Cálculo final

$$P(X_1 = 0, X_2 = 1 | X_1 + \alpha X_2 = \alpha) = \left[1 + \frac{\lambda^{\alpha-1}}{\alpha!} \right]^{-1}$$

$\therefore X_1 + \alpha X_2$ não é estatística suficiente para λ