

Unbiased estimators

Recap: Cramer-Rao lower bound

Let X_1, \dots, X_n be a sample from a distribution with probability function $f(x|\theta)$, and let $\hat{\theta}$ be an unbiased estimator of $\theta \in \mathbb{R}$. Then, under regularity conditions,

$$\text{Var}(\hat{\theta}) \geq \frac{1}{\mathcal{I}(\theta)} \quad \left. \vphantom{\frac{1}{\mathcal{I}(\theta)}} \right\} \begin{array}{l} \text{Cramér-Rao lower} \\ \text{bound (CRLB)} \end{array}$$

Example

Suppose that $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$.

Calculate the Cramer-Rao lower bound for the variance of an unbiased estimator of σ^2 . Does the sample variance $s^2 = \frac{1}{n-1} \sum_i (X_i - \bar{X})^2$ attain the Cramer-Rao lower bound?

want $\hat{l}(\sigma^2)$

$$l(\mu, \sigma^2) = \log \left(\left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \right\} \right)$$
$$= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2$$

$$\frac{\partial l}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (x_i - \mu)^2$$

$$\text{var}(u(\sigma^2)) = \text{var} \left(\frac{1}{2\sigma^4} \sum_{i=1}^n (x_i - \mu)^2 \right) \left(\frac{1}{2\sigma^4} \right)^2 \sum_{i=1}^n \text{var}((x_i - \mu)^2)$$

or

$$\frac{\partial^2 l}{\partial \sigma^4} = \frac{n}{2\sigma^4} - \frac{1}{\sigma^6} \sum_{i=1}^n (x_i - \mu)^2$$

$$-E \left[\frac{\partial^2 l}{\partial \sigma^4} \right] = - \left(\frac{n}{2\sigma^4} - \frac{n}{\sigma^4} \right) = \frac{n}{2\sigma^4} = \hat{l}(\sigma^2)$$

$$\text{CRLB} = \frac{2\sigma^4}{n}$$

$$\text{var}(s^2) = \frac{2\sigma^4}{n-1} > \frac{2\sigma^4}{n}$$

Attaining the CRLB

Let X_1, \dots, X_n be iid with probability function $f(x|\theta)$, and suppose the regularity conditions for the CRLB hold. Let $\hat{\theta}$ be an unbiased estimator of θ . Then $\hat{\theta}$ attains the CRLB if and only if

$$u(\theta) = a(\theta) [\hat{\theta} - \theta]$$

(for some function $a(\theta)$).

If: Proof of the CRLB uses the fact that

$$[\text{Cov}(\hat{\theta}, u(\theta))]^2 \leq \text{Var}(\hat{\theta}) \text{Var}(u(\theta))$$

The CRLB is attained when this inequality is an equality, i.e.

$$[\text{Cov}(\hat{\theta}, u(\theta))]^2 = \text{Var}(\hat{\theta}) \text{Var}(u(\theta))$$

Lemma: $(\text{Cov}(X, Y))^2 = \text{Var}(X) \text{Var}(Y)$ (i.e. $|\text{Corr}(X, Y)| = 1$)
if and only if $X - \mathbb{E}[X] = c(Y - \mathbb{E}[Y])$

so, $[\text{Cov}(\hat{\theta}, u(\theta))]^2 = \text{Var}(\hat{\theta}) \text{Var}(u(\theta))$ if and only if
 $u(\theta) - \mathbb{E}[u(\theta)] = a(\theta) [\hat{\theta} - \mathbb{E}[\hat{\theta}]] \Leftrightarrow u(\theta) = a(\theta) [\hat{\theta} - \theta]$

Example: $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$

$$\begin{aligned} U(\sigma^2) &= -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (X_i - \mu)^2 \\ &= \frac{n}{2\sigma^4} \left(\sum_{i=1}^n \frac{(X_i - \mu)^2}{n} - \sigma^2 \right) \end{aligned}$$

If $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2$ then $E[\hat{\sigma}^2] = \sigma^2$

and $a(\sigma^2) = \frac{n}{2\sigma^4}$ then $U(\sigma^2) = a(\sigma^2) (\hat{\sigma}^2 - \sigma^2)$

$\Rightarrow \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2$ attains the CRLB if μ is known

If μ is unknown, then CRLB cannot be attained

Sufficient statistics

Given an unbiased estimator, can I improve its variance?

Def: Let X_1, \dots, X_n be a sample from a distribution $f(x|\theta)$. Let $T \equiv T(X_1, \dots, X_n)$ be a statistic. If the conditional distribution of $X_1, \dots, X_n | T$ does not depend on θ , then T is a sufficient statistic for θ .

Ex: Suppose $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\lambda)$. Let $T = \sum_{i=1}^n X_i$
 $T \sim \text{Poisson}(n\lambda)$

$$f(X_1, \dots, X_n | T, \lambda) = \frac{f(X_1, \dots, X_n, T | \lambda)}{f(T | \lambda)} = \frac{f(X_1, \dots, X_n | \lambda)}{f(T | \lambda)}$$

$$= \frac{\cancel{e^{-n\lambda}} \cancel{\lambda^{x_1}} \dots \cancel{\lambda^{x_n}} / \prod_i x_i!}{\cancel{e^{-n\lambda}} (n\lambda)^T / T!} = \frac{T! \cdot n^T}{\prod_i x_i!} \quad \begin{array}{l} \text{(does not depend on } \lambda) \\ \Rightarrow T \text{ is sufficient} \end{array}$$

Rao-Blackwell

Let θ be a parameter of interest, and $\tau(\theta)$ some function of θ . Let $\hat{\tau}$ be some unbiased estimator of $\tau(\theta)$, and T a sufficient statistic for θ .

Let $\tau^* = E[\hat{\tau} | T]$. Then:

$$\textcircled{1} \quad E[\tau^*] = \tau \quad (\text{unbiased})$$

$$\textcircled{2} \quad \text{Var}(\tau^*) \leq \text{Var}(\hat{\tau})$$

Example

Let $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\lambda)$.