

Lecture 9: CRLB

Theorem: Cramér-Rao Lower Bound (CRLB)

If $x_n \stackrel{iid}{\sim} f_\theta$ for $\theta \in \Theta$ and if $\hat{\theta}$ is an unbiased est. of $\tau(\theta)$

(*) and if f_θ is nice enough
read: 1-dim'l exp. fams.

$\hookrightarrow \theta$ is 1-dim'l e.g. $\theta \in \mathbb{R}$

then
$$\text{Var}(\hat{\theta}) \geq \left(\frac{\partial \tau}{\partial \theta} \right)^2 / I_N(\theta) = \beta$$

Cramér-Rao lower bound

Notes: (1) If $\tau(\theta) = \theta$ then $\frac{\partial \tau}{\partial \theta} = 1$

So
$$\beta = 1 / I_N(\theta).$$

(2) If I can find some est. θ^* that is

(1) unbiased for $\tau(\theta)$

and (2)
$$\text{Var}(\theta^*) = \beta$$

then θ^* is the UMVUE.

③ If I have an est. $\hat{\theta}$ that is unbiased for $T(\theta)$ but its variance is

$$\text{Var}(\hat{\theta}) > B.$$

I don't know if $\hat{\theta}$ is the UMVUE or not.



Ex. $X_n \stackrel{iid}{\sim} \text{Pois}(\lambda)$ \leftarrow exp. fam

let $\hat{\lambda} = \bar{X}$ and $T(\lambda) = \lambda$

Know $E\hat{\lambda} = \lambda$, $\text{Var}(\bar{X}) = \lambda/N$

\uparrow $\hat{\lambda}$ unbiased for λ

$$I_N(\lambda) = N/\lambda$$

$$\text{so } \text{Var}(\hat{\lambda}) = \lambda/N = 1/I_N(\lambda) = B$$

So $\hat{\lambda}$ achieves the CRLB, and so it is the UMVUE.

Ex. $X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ \leftarrow an exp. fam

$\hat{\mu} = \bar{X}$ then $E\hat{\mu} = \mu$ so it's unbiased for $T(\mu) = \mu$

$$\text{ad } \text{Var}(\bar{X}) = \sigma^2/N$$

$$I_N(\mu) = N/\sigma^2$$

So since $\text{Var}(\bar{X}) = \text{CRLB}$

then \bar{X} is the UMVUE.

Ex. $X_n \stackrel{iid}{\sim} \text{Exp}(\lambda)$ \leftarrow is an exp. fam

$$\text{let } T(\lambda) = 1/\lambda$$

$$\text{let } T = \bar{X} \text{ then } ET = 1/\lambda$$

So T is unbiased for $1/\lambda$

let's get $I_N(\lambda)$

$$\textcircled{1} \text{ get } \log f_\lambda(x) = \log(\lambda e^{-\lambda x})$$

$$= -\lambda x + \log(\lambda)$$

$$\textcircled{2} \frac{\partial \log f_\lambda}{\partial \lambda} = -x + 1/\lambda$$

$$\frac{\partial^2 \log f_\lambda}{\partial \lambda^2} = -1/\lambda^2$$

$$\begin{aligned} \textcircled{3} I(\lambda) &= -E\left[\frac{\partial^2 \log f_{\lambda}(X)}{\partial \lambda^2}\right] \\ &= -E\left[-\frac{1}{\lambda^2}\right] = \frac{1}{\lambda^2} \end{aligned} \quad \left. \begin{array}{l} I_N(\lambda) \\ = N/\lambda^2 \end{array} \right\}$$

$$\text{Var}(T) = \text{Var}(\bar{X}) = \left(\frac{1}{\lambda^2}\right) / N = \frac{1}{\lambda^2 N}$$

$$B = \frac{\left(\frac{\partial I}{\partial \lambda}\right)^2}{I_N(\lambda)} = \frac{\left(-\frac{1}{\lambda^2}\right)^2}{N/\lambda^2} = \frac{\lambda^2}{N\lambda^4} = \frac{1}{N\lambda^2} = \text{Var}(T)$$

$T(\lambda) = 1/\lambda$
 $\frac{\partial T}{\partial \lambda} = -1/\lambda^2$

So $T = \bar{X}$ is the UMVUE for $T(\lambda) = 1/\lambda$.

Ex. let $X_n \stackrel{iid}{\sim} U(0, \theta)$

Want UMVUE for $T(\theta) = \theta$.

① Unbiased est?

Can show that $E[X_{(N)}] = \frac{N}{N+1} \theta$

So if $\hat{\theta} = \frac{N+1}{N} X_{(N)}$ then $E[\hat{\theta}] = \theta$
 so $\hat{\theta}$ is unbiased.

(2) Calc. var. $\text{Var}(\hat{\theta}) = \frac{\theta^2}{N(N+2)}$

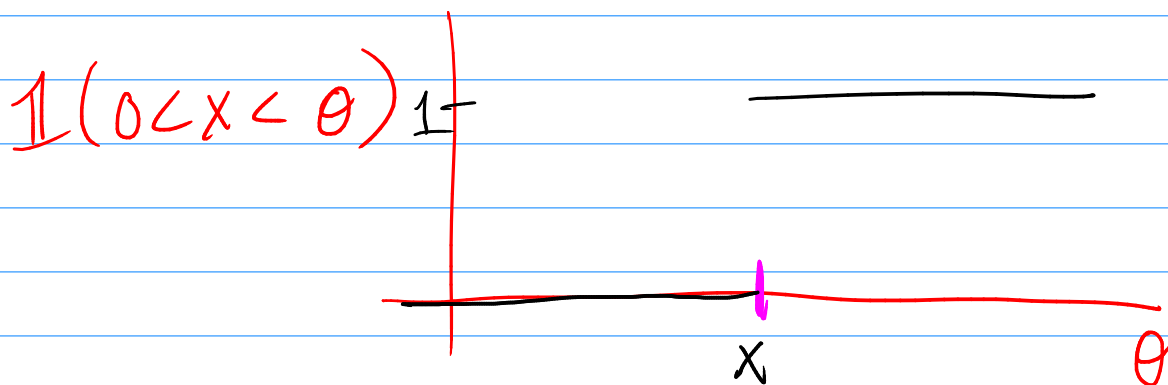
(3) Show $\text{Var}(\hat{\theta}) = B$.

Need $I(\theta)$

$$f_{\theta}(x) = \frac{1}{\theta} \mathbb{1}(0 < x < \theta)$$

$$\log f_{\theta}(x) = -\log(\theta) + \log \mathbb{1}(0 < x < \theta)$$

$\frac{\partial}{\partial \theta}$ $u(0, \theta)$ Not exp. fam.



Review:

Theorem: Iterated Expectation

Background. $E[X | Y=y] = \int x f(x|y) dx = g(y)$

Can plug Y into g to get $g(Y)$

notation: $g(Y) = E[X | Y]$ a random variable

Iterated Expectation

$$E[X] = E_Y[E[X|Y]]$$

$$= E_Y[g(Y)]$$

Law of Total Variance

$$\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]).$$

Ex. $X|Y=y \sim \text{Bin}(y, p)$ $p \in [0, 1]$

$$Y \sim \text{Pois}(\lambda), \lambda > 0$$

$E X$? ① $E[X|Y=y] = yp$

② $E[X|Y] = Yp$

③ $E[E[X|Y]] = E[Yp] = pEY = p\lambda$

$\text{Var}(X)? = E \text{Var}(X|Y) + \text{Var} E[X|Y]$

① $\text{Var}(X|Y=y) = yp(1-p)$

② $\text{Var}(X|Y) = Yp(1-p)$

③ $E \text{Var}(X|Y) = p(1-p)EY = p(1-p)\lambda$

$$\begin{aligned} \text{Var}(Yp) &= p^2 \text{Var}(Y) \\ &= p^2 \lambda \end{aligned}$$

$$\text{Var}(X) = p(1-p)\lambda + p^2\lambda = p\lambda$$

Some facts:

① If $\hat{\theta}$ is unbiased for $\tau(\theta)$
 $E\hat{\theta} = \tau(\theta)$

Let W be some function of \underline{X}
 (could be a stat - maybe not)

Consider $\varphi = \varphi(W) = E[\hat{\theta} | W]$ ← is a RV and is a fn of W

notice that

$$E_W \varphi = E_W [E[\hat{\theta} | W]] = E[\hat{\theta}] = \tau(\theta)$$
↙ iterated expectation

If φ is a stat (no θ in formula) then
 φ is unbiased for $\tau(\theta)$.

② $\text{Var}(\varphi) \leq \text{Var}(\hat{\theta})$

$$\text{Var}(\hat{\theta}) = \text{Var}(\underbrace{E[\hat{\theta} | W]}_{\varphi}) + \underbrace{E(\text{Var}(\hat{\theta} | W))}_{\geq 0}$$

$$\text{Var}(\hat{\theta}) = \text{Var}(\varphi) + \text{something } \geq 0$$

$$\text{So } \text{Var}(\hat{\theta}) \geq \text{Var}(\varphi)$$

Ex. $X_n \stackrel{\text{iid}}{\sim} N(\theta, 1)$

$$\text{Let } \hat{\theta} = \frac{1}{2}(X_1 + X_2)$$

Note: $E\hat{\theta} = \frac{1}{2}(EX_1 + EX_2) = \frac{1}{2}(\theta + \theta) = \theta$

so $\hat{\theta}$ is unbiased for $\tau(\theta) = \theta$.

$$\begin{aligned}\text{Var}(\hat{\theta}) &= \frac{1}{4}(\text{Var} X_1 + \text{Var} X_2) = \frac{1}{4}(1 + 1) \\ &= 1/2\end{aligned}$$

$$\text{Let } W = X_1$$

$$\varphi = E[\hat{\theta} | W] = E\left[\frac{1}{2}(X_1 + X_2) | X_1\right]$$

$$E[Z | Z=5] = 5$$

$$E[Z | Z=3] = 3$$

$$E[Z | Z] = Z$$

$$= \frac{1}{2}E[X_1 | X_1] + \frac{1}{2}E[X_2 | X_1]$$

$$= \frac{1}{2}X_1 + \frac{1}{2}E[X_2]$$

$$= \frac{1}{2}X_1 + \theta/2$$

$$E[\varphi] = \frac{1}{2}EX_1 + \theta/2 = \theta/2 + \theta/2 = \theta = E[\hat{\theta}]$$

$$\text{Var}(\varphi) = \frac{1}{4}\text{Var}(X_1) = \frac{1}{4}(1) = \frac{1}{4}$$

Consider instead $W = \overline{X}$.

$$\varphi = E[\hat{\theta} | W] = ?$$