

Example 4:-

$$x_1, \dots, x_n \sim N(\theta, \theta^2).$$

$$\begin{aligned} f(x_1, \dots, x_n; \theta) &= \frac{1}{(\theta\sqrt{2\pi})^n} e^{-\frac{1}{2\theta^2} \sum_{i=1}^n (x_i - \theta)^2} \\ &= \frac{1}{(\theta\sqrt{2\pi})^n} e^{-\frac{1}{2\theta^2} \left(\sum_{i=1}^n x_i^2 - 2\theta \sum_{i=1}^n x_i + n\theta^2 \right)} \\ &= e^{-\frac{1}{2\theta^2} \left(\sum_{i=1}^n x_i^2 - 2\theta \sum_{i=1}^n x_i \right)} \times \frac{1}{\theta^n} \times e^{\frac{n\theta^2}{2\theta}} \times \underbrace{\frac{1}{(\sqrt{2\pi})^n}}_{h(x_1, \dots, x_n)}, \\ &\qquad\qquad\qquad g(\theta; T_n(x_1, \dots, x_n)) \end{aligned}$$

Hence, by NFT, $T_n = \left(\sum_{i=1}^n x_i^2, \sum_{i=1}^n x_i \right)$ is jointly sufficient statistic for θ .

Rao-Blackwellization Theorem:-

Statement:-

Let $U_n(x_1, \dots, x_n)$ be an unbiased estimator of $g(\theta)$. And, suppose that $T_n(x_1, \dots, x_n)$ is a sufficient statistic for θ .

Define $\eta(T_n) = E_{U|T_n}[U_n(x_1, \dots, x_n) | T_n(x_1, \dots, x_n)]$, which is indep of θ since $T_n(x_1, \dots, x_n)$ is sufficient statistic for θ .

Then $E_{T_n}[\eta(T_n)] = g(\theta)$ and

$$\text{Var}(\eta(T_n)) \leq \text{Var}(U_n(x_1, \dots, x_n)).$$

Justification of the unliedness of $E(Y)$:-

$$(x, y) \sim f_{X,Y}$$

Result :- $E Y = E_x [E_{Y|X}(Y)]$

$$\begin{aligned} &= \int y f(x, y) dx dy \\ &= \int y \left[f_{Y|X}(y) g_X(x) \right] dx dy \\ &= \int \left[\int y f_{Y|X}(y) dy \right] g_X(x) dx \\ &= \int \left[E_{Y|X}(Y) \right] g_X(x) dx \\ &= E_x [E_{Y|X}(Y)] \end{aligned}$$

Conditioned density \rightarrow Marginal density of X

Note that

$$\eta(T_n) = E_{U_n|T_n} [U_n(x_1, \dots, x_n) | T_n(x_1, \dots, x_n)]$$

$$E_{T_n} [\eta(T_n)] = E_{T_n} \left[E_{U_n|T_n} [U_n(x_1, \dots, x_n) | T_n(x_1, \dots, x_n)] \right]$$

$$= E_{U_n} [U_n(x_1, \dots, x_n)]$$

$$= g(\theta).$$

Hence, $\eta(T_n)$ is an unbiased estimator of $g(\theta)$.

$$P[X=0] = 1-\theta$$

Example!:-

Let $x_1, \dots, x_n \sim \text{Bin}(1, \theta)$, $\theta \in (0, 1)$. $P[X=1] = \theta$

$$\hookrightarrow P[X=x] = \theta^x (1-\theta)^{1-x},$$

$x = 0 \text{ or } 1.$

Note that

$U_n^{(x_1, \dots, x_n)} = X_1$ is an unbiased estimator of θ .

Already, we know $T_n(x_1, \dots, x_n) = \sum_{i=1}^n x_i$ is sufficient statistic for θ .

Observation!:-

$$E[U_n] = \theta \quad \& \quad \text{Var}[U_n] = \theta(1-\theta).$$

$$\eta(T_n) = E[U_n | T_n]$$

$$= E[X_1 | \sum_{i=1}^n x_i = t]$$

$$= 0 \times P[x_1=0 | \sum_{i=1}^n x_i = t] \times 1 \times P[x_1=1 | \sum_{i=1}^n x_i = t]$$
$$= P[x_1=1 | \sum_{i=1}^n x_i = t]$$

$$= \frac{P[x_1 = 1 \cap \sum_{i=1}^n x_i = t]}{P[\sum_{i=1}^n x_i = t]}$$

$x_1, \dots, x_n \stackrel{\text{i.i.d.}}{\sim} \text{Bin}(1, \theta)$
 $x_1 \perp\!\!\!\perp (x_2, \dots, x_n)$.

$$= \frac{P[x_1 = 1 \cap \sum_{i=2}^n x_i = t-1]}{P[\sum_{i=1}^n x_i = t]}$$

$$\xrightarrow{\text{Bin}(n-1, \theta)}$$

$$= \frac{P[x_1 = 1] \times P[\sum_{i=2}^n x_i = t-1]}{P[\sum_{i=1}^n x_i = t]}$$

$$\xdownarrow{\text{Bin}(n, \theta)}$$

$$= \frac{\theta \times \binom{n-1}{t-1} \theta^{t-1} (1-\theta)^{(n-1)-(t-1)}}{\binom{n}{t} \theta^t (1-\theta)^{n-t}}$$

check

$$\frac{\binom{n-1}{t-1}}{\binom{n}{t}} = \frac{t}{n}$$

Hence, the Rao-Blackwellized improved estimator = $\frac{\sum x_i}{n}$.

Observation:-

$$\begin{aligned} \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right) &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) \\ &\quad + \frac{1}{n^2} \sum_{i \neq j} \text{Cov}(x_i, x_j). \\ &= \frac{1}{n^2} \sum_{i=1}^n \theta(1-\theta) + \frac{1}{n^2} \sum_{i \neq j} 0 \\ &= \frac{1}{n^2} \times n \theta(1-\theta) - \frac{\theta(1-\theta)}{n}. \end{aligned}$$

Hence, for any $n \geq 1$, $\text{Var}(n(T_n)) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right)$

$$\leq \text{Var}(x_1) = \text{Var}[U_n].$$

Remark:-

However, Rao-Blackwellization does NOT give us uniformly minimum variance estimator. It helps us to lower the variance only.

Another concept!—

Complete statistic!—

Defⁿ: A statistic $T_n(x_1, x_2, \dots, x_n)$ is said to be complete

if ~~if~~ for any function g , we have

$$\mathbb{E} [g(T_n)] = 0 \quad \forall \theta \in \Theta.$$

$\Rightarrow g(T_n) = 0$ almost everywhere

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$$P[g(T_n) \neq 0] = 0$$

If a complete statistic is sufficient, then it is called complete sufficient statistic.

A few examples:-

Example:- x_1, x_n i.i.d. $\sim \text{Bin}(1, \theta)$, $\theta \in (0, 1)$.

Already we known $T_n = \sum_{i=1}^n x_i$ is sufficient for θ .

Want to check whether T_n is complete sufficient stat
(css) or NOT.

Tak~~us~~ any arbitrary $f \stackrel{n}{\equiv} g$.

Suppose $E g(T_n) = 0 \forall \theta \in \Theta = (0, 1)$.

Further, note that $T_n \sim \text{Bin}(n, \theta)$.

$$E g(T_n) = 0 \quad \forall \theta \in \mathbb{H}$$

$$\Leftrightarrow \sum_{t=1}^n g(t) \binom{n}{t} \theta^t (1-\theta)^{n-t} = 0 \quad \forall \theta \in \mathbb{H}$$

$$\Leftrightarrow (1-\theta)^n \sum_{t=1}^n g(t) \binom{n}{t} \left(\frac{\theta}{1-\theta}\right)^t = 0 \quad \forall \theta \in \mathbb{H}$$

$$\Leftrightarrow \sum_{t=1}^n g(t) \binom{n}{t} \left(\frac{\theta}{1-\theta}\right)^t = 0 \quad \forall \theta \in \mathbb{H}$$

$$\Leftrightarrow \sum_{t=1}^n g(t) \binom{n}{t} s^t = 0, \text{ where } s \in (0, \infty)$$

Hence, $g(t) \binom{n}{t} = 0$ $\frac{1}{1-\theta}$.

$$\Rightarrow g(t) = 0 \quad \text{Hence, } T_n = \sum_{i=1}^n x_i \text{ since } \binom{n}{t} > 0.$$

Example:-

Not all sufficient statistic is complete.

$$X_1, \dots, X_n \sim N(\theta, \theta^2).$$

$$T_n = \left(\sum_{i=1}^n X_i, \sum_{i=1}^n X_i^2 \right) \text{ is "jointly" sufficient for } \theta.$$

Note that $E(T_{1,n}^2) = \theta^2 (n-1)/n \Rightarrow E\left(\frac{T_{1,n}^2}{n(n-1)}\right) = \theta^2.$ ①

& $E(T_{2,n}) = 2n\theta^2 \Rightarrow E\left(\frac{T_{2,n}}{2n}\right) = \theta^2$ ②

$$\textcircled{1} - \textcircled{2} \Rightarrow E\left(\frac{\frac{T_{1,n}^2}{n(n-1)} - \frac{T_{2,n}}{2n}}{2}\right) = \theta^2 - \theta^2 = 0$$

Hence, $\frac{T_{1,n}^2}{n(n-1)} - \frac{T_{2,n}}{2n} \neq 0 \text{ a.e.}$ Hence $T_n = (T_{1,n}, T_{2,n})$ is NOT CSS