

5 - Rao - Blackwell Theorem.

Let $\hat{\theta}$ be an unbiased estimator and T is the sufficient statistic of θ iff.

$$\tilde{\theta} = E(\hat{\theta}/T)$$

Then

① $\tilde{\theta}$ is a function of suff. statistic.

② $E(\tilde{\theta}) = \theta$ (unbiased)

③ $V(\tilde{\theta}) \leq V(\hat{\theta})$ (minimum variance)

*Ex 1/ let $X_i \sim P(\theta)$; $i=1, \dots, n$ if $\hat{\theta} = X_1$ is unbiased estimator for θ . Can we find a better estimator for θ by R-B Theorem?

Sol/

1 - $\hat{\theta} = X_1$ is unbiased est. for θ where since $X_1 \sim P(\theta)$
Then $E(\hat{\theta}) = E(X_1) = \theta$

2 - By Factorization Theorem

$$f(x_1, \dots, x_n, \theta) = \frac{e^{-n\theta} \theta^{\sum x_i}}{(\prod_{i=1}^n x_i)!}$$

where

$$g(t, \theta) = e^{-n\theta} \theta^{\sum x_i} \quad \text{and} \quad h(x_1, \dots, x_n) = \frac{1}{(\prod_{i=1}^n x_i)!}$$

That means $T = \sum_{i=1}^n x_i$ is S.S. for θ

3 - By Rao - Blackwell Theorem $\tilde{\theta} = E(\hat{\theta}/T)$ is better estimator with minimum variance and unbiased estimator for θ such that.

$\tilde{\theta} = E(\hat{\theta} | T) = E(x_1 | \sum_{i=1}^n x_i = t) = \dots$ ← لأن التوزيع متقطع فالتوقع متوقعه هو
 كما نؤمن التوقع المتقطع $E(x|y)$

$= \sum x \cdot P(x|y)$ ← متقطع
 Now $\int_{-\infty}^{\infty} x \cdot P(x|y)$ ← متصلة
 $= \sum_{x_1} x_1 P(x_1 = x_1 | \sum_{i=1}^n x_i = t) \sum x \cdot P(x, y)$ ← حالة شريطة

$P(x_1 = x_1 | \sum_{i=1}^n x_i = t) = \frac{P(x_1 = x_1, \sum_{i=1}^n x_i = t)}{P(\sum_{i=1}^n x_i = t)}$ ← joint Marginal

$= \frac{P(x_1 = x_1, \sum_{i=2}^n x_i = t - x_1)}{P(\sum_{i=1}^n x_i = t)} = \frac{P(x_1 = x_1) \cdot P(\sum_{i=2}^n x_i = t - x_1)}{P(\sum_{i=1}^n x_i = t)}$

where

$P(x_1 = x_1) = \frac{e^{-\theta} \theta^{x_1}}{(x_1)!}$

$\sum_{i=1}^n x_i = t \sim P(n, \theta) \rightarrow P(\sum_{i=1}^n x_i = t) = \frac{e^{-n\theta} (n\theta)^t}{t!}$ ← $\frac{n!}{x!(n-x)!}$ \rightarrow $\frac{n!}{x!(n-x)!}$ \rightarrow $\frac{n!}{x!(n-x)!}$

$\sum_{i=2}^n x_i = t - x_1 \sim P((n-1), \theta)$

$P(\sum_{i=2}^n x_i = t - x_1) = \frac{e^{-(n-1)\theta} ((n-1)\theta)^{t-x_1}}{(t-x_1)!}$ ← $\frac{n!}{x!(n-x)!}$ \rightarrow $\frac{n!}{x!(n-x)!}$

$\therefore P(x_1 = x_1 | \sum_{i=1}^n x_i = t)$

$= \frac{\theta^{x_1} e^{-\theta} e^{-(n-1)\theta} ((n-1)\theta)^{t-x_1}}{x_1! (t-x_1)!} \cdot \frac{t!}{e^{-n\theta} (n\theta)^t}$

$= \frac{(n-1)^{t-x_1} t!}{n^t x_1! (t-x_1)!} = C_{x_1}^t \frac{(n-1)^{t-x_1}}{n^{t-x_1+x_1}}$ ← $\frac{n!}{x!(n-x)!}$ \rightarrow $\frac{n!}{x!(n-x)!}$

$= C_{x_1}^t \left(\frac{n-1}{n}\right)^{t-x_1} \left(\frac{1}{n}\right)^{x_1} \sim b\left(t, \frac{1}{n}\right)$
 P.d.f binomial.



7

$$\therefore E \left[X_1 / \sum_{i=1}^n X_i = t \right] = \sum X_i P(X_i / \sum X_i = t)$$

توزيع ثنائي فوجي

$$= \sum X_i C_{X_i}^t \left(\frac{1}{n}\right)^{X_i} \left(1 - \frac{1}{n}\right)^{t - X_i}$$

bin

$$= t = \frac{1}{n} = \frac{\sum X_i}{n} = \bar{X}$$

$$\therefore \tilde{\theta} = \bar{X}$$

① $\tilde{\theta}$ is a function of S.S

② $E(\tilde{\theta}) = E(\bar{X}) = \theta$ (unbiased)

③ $V(\tilde{\theta}) = V(\bar{X}) = \frac{n\theta}{n^2} = \frac{\theta}{n}$

$$\left. \begin{aligned} E(\bar{X}) &= E\left(\frac{\sum X_i}{n}\right) \\ &= \frac{1}{n} \sum E(X_i) \\ &= \frac{1}{n} \cdot n \cdot \theta \end{aligned} \right\} \begin{array}{l} \text{توزيع} \\ P(\theta) \end{array}$$

$$V(\hat{\theta}) = V(X_1) = \theta$$

$$\therefore V(\tilde{\theta}) \leq V(\hat{\theta}) \quad (\text{minimum variance})$$