

المقدمة - الجيد
خواص
Properties of good Estimator :-

عند القير
1 - Unbiasedness :-

* def. -

Let $x_1, x_2, \dots, x_n$ be a random sample from a population having p.d.f. $f(x; \theta)$ with unknown parameter θ . Let $\hat{\theta}$ be an estimator of θ , therefore $\hat{\theta}$ is said to be unbiased estimator of θ if and only if :

$$E(\hat{\theta}) = \theta$$

Otherwise the bias, B , of an estimator $\hat{\theta}$ can be defined as :-

$$B = E(\hat{\theta}) - \theta$$

Generally, we can say that $T(x)$ is an unbiased estimator of $g(\theta)$ if and only if :-

$$E(T(x)) = g(\theta) \quad \forall \theta$$

* Example:- ①

Let $x_1, x_2, \dots, x_n$ be a r.s. from $N(\mu, \sigma^2)$.
Show that $\bar{x}$ is an unbiased estimator of μ

Solu:

We say that $\bar{x}$ is an unbiased estimator of μ if:

$$E(\bar{x}) = \mu$$

∴ نقول بـ $E(x)$ بـ μ

$$E(\bar{x}) = E\left[\frac{\sum_{i=1}^n x_i}{n}\right] = \frac{\sum_{i=1}^n E(x_i)}{n}$$

Since $E(x_i) = \mu$ for all $i = 1, 2, \dots, n$, which comes from the property of a random sample that $\bar{x}$ have identical distribution. Then

$$E(\bar{x}) = \frac{n\mu}{n} = \mu$$

Hence $\bar{x}$ is an unbiased estimator of μ .

* Example:- ②

Let $y_1, y_2, \dots, y_n$ be a r.s. from $N(\mu, \sigma^2)$ with $E(y_i) = \mu$ and variance $(y_i) = \sigma^2$. Show that $S^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$ is a biased estimator of σ^2 .

Solu:

$$S^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2$$

$$E S^2 = E \left[\frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2 \right] = \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \bar{Y})^2 \right]$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \mu - \bar{Y} + \mu)^2 \right] \quad \mu \text{ إضافة وطرح}$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n \{ (Y_i - \mu) - (\bar{Y} - \mu) \}^2 \right]$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \mu)^2 - 2(\bar{Y} - \mu) \sum_{i=1}^n (Y_i - \mu) + n(\bar{Y} - \mu)^2 \right]$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \mu)^2 - 2(\bar{Y} - \mu)(n\bar{Y} - n\mu) + n(\bar{Y} - \mu)^2 \right]$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \mu)^2 - 2n(\bar{Y} - \mu)^2 + n(\bar{Y} - \mu)^2 \right]$$

$$= \frac{1}{n} E \left[\sum_{i=1}^n (Y_i - \mu)^2 - n(\bar{Y} - \mu)^2 \right]$$

$$= \frac{1}{n} \left[\sum_{i=1}^n E(Y_i - \mu)^2 - n E(\bar{Y} - \mu)^2 \right]$$

$$= \frac{1}{n} \left[\sum_{i=1}^n \text{Var}(Y_i) - n \text{Var}(\bar{Y}) \right]$$

$$= \frac{1}{n} \left[n\sigma^2 - n \frac{\sigma^2}{n} \right]$$

$$= \frac{1}{n} [n\sigma^2 - \sigma^2]$$

$$= \frac{1}{n} \sigma^2 (n-1)$$

$$\therefore E S^2 = \frac{n-1}{n} \sigma^2$$

Hence $S^2 = \frac{1}{n} \sum (Y_i - \bar{Y})^2$ is a biased estimator of σ^2
 but $\frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2$ is an unbiased estimator of σ^2 .

* H.W.

prove that $\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$ is an unbiased estimator of σ^2 .

* Example:

If $ES^2 = \frac{n-1}{n} \sigma^2$ where $S^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$,
What is the unbiased estimate for σ^2 .

Solu:

$$\therefore ES^2 = \frac{n-1}{n} \sigma^2 \Rightarrow \frac{n}{n-1} ES^2 = \sigma^2$$

$$\Rightarrow \frac{n}{n-1} \left[\frac{n-1}{n} \sigma^2 \right] = \sigma^2$$

$$\therefore \frac{n}{n-1} S^2 = \frac{n}{n-1} \cdot \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n-1}$$

is an unbiased estimate for σ^2 .

* Example (2) σ^2 هو المقدار المطلوب μ σ^2

$$S^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$$

$$= \frac{1}{n} \sum_{i=1}^n [y_i^2 - 2y_i\bar{y} + \bar{y}^2]$$

$$= \frac{1}{n} \left[\sum_{i=1}^n y_i^2 - 2\bar{y} \sum_{i=1}^n y_i + n\bar{y}^2 \right]$$

$$= \frac{1}{n} \left[\sum_{i=1}^n y_i^2 - 2n\bar{y}^2 + n\bar{y}^2 \right]$$

$$= \frac{1}{n} \left[\sum_{i=1}^n y_i^2 - n\bar{y}^2 \right]$$

$$\begin{aligned}
 \Rightarrow ES^2 &= E\left[\frac{1}{n}\left\{\sum_{i=1}^n Y_i^2 - n\bar{Y}^2\right\}\right] \\
 &= \frac{1}{n}\left[\sum_{i=1}^n E Y_i^2 - n E \bar{Y}^2\right] \\
 &= \frac{1}{n}\left[n E Y_i^2 - n E \bar{Y}^2\right] \\
 &= E Y_i^2 - E \bar{Y}^2
 \end{aligned}$$

$$\begin{aligned}
 \therefore \text{Var}(Y_i) &= E Y_i^2 - (E Y_i)^2 \\
 \sigma^2 &= E Y_i^2 - \mu^2
 \end{aligned}$$

$$\Rightarrow E Y_i^2 = \sigma^2 + \mu^2$$

$$\begin{aligned}
 \text{and } \text{Var}(\bar{Y}) &= E \bar{Y}^2 - (E \bar{Y})^2 \\
 \frac{\sigma^2}{n} &= E \bar{Y}^2 - \mu^2
 \end{aligned}$$

$$\Rightarrow E \bar{Y}^2 = \frac{\sigma^2}{n} + \mu^2$$

$$\begin{aligned}
 \Rightarrow ES^2 &= \sigma^2 + \mu^2 - \frac{\sigma^2}{n} - \mu^2 \\
 &= \sigma^2 - \frac{\sigma^2}{n} \\
 &= \frac{n\sigma^2 - \sigma^2}{n} \\
 &= \frac{(n-1)\sigma^2}{n}
 \end{aligned}$$

$$\therefore ES^2 = \frac{n-1}{n} \sigma^2$$

$\therefore S^2$ is a biased estimator of σ^2 .

if $Y_i \sim N(\mu, \sigma^2)$
 $\Rightarrow \bar{Y} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$