

M378K: October 28th, 2024.

More on Estimators.

Def'n. The bias of an estimator $\hat{\theta}$ for θ is

$$\text{bias}(\hat{\theta}) = E[\hat{\theta} - \theta]$$

If $\text{bias}(\hat{\theta}) = 0$, we say that $\hat{\theta}$ is **unbiased**.

Def'n. The mean squared error of $\hat{\theta}$ is

$$\text{MSE}(\hat{\theta}) = E[(\hat{\theta} - \theta)^2]$$

Then,

$$\text{MSE}(\hat{\theta}) = \text{Var}[\hat{\theta}] + (\text{bias}(\hat{\theta}))^2$$

Def'n. An estimator $\hat{\theta}$ is **UMVUE** of θ if:

- $\hat{\theta}$ is unbiased
- $\text{MSE}[\hat{\theta}] \leq \text{MSE}[\hat{\theta}']$ for all other $\hat{\theta}'$ unbiased estimators of θ

Example. These are **UMVUE**:

- \bar{Y} for μ where (Y_1, \dots, Y_n) is a random sample from $N(\mu, 1)$
- \bar{Y} for p where (Y_1, \dots, Y_n) is a random sample from $B(p)$
- $S^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2$ for σ^2 where (Y_1, Y_2, \dots, Y_n) from $N(\mu, \sigma^2)$ (both unknown)

Def'n. An estimator $\hat{\theta}$ is said to be **linear** if it's of the form

$$\hat{\theta} = \alpha_1 Y_1 + \alpha_2 Y_2 + \dots + \alpha_n Y_n$$

where $\alpha_1, \dots, \alpha_n$ are all constants

Example. \bar{Y} is a linear estimator

Def'n. A linear estimator $\hat{\theta}$ is said to be the best linear unbiased estimator (BLUE) if

- $\hat{\theta}$ is unbiased
- $MSE[\hat{\theta}] \leq MSE[\hat{\theta}']$ for all $\hat{\theta}'$ unbiased linear estimators of θ

Example 9.2.9. ← Look @ @ home

Problem 13.2. Suppose that the two estimators $\hat{\theta}_1$ and $\hat{\theta}_2$ are unbiased. We know that $\text{Var}[\hat{\theta}_1] = \sigma_1^2$ and $\text{Var}[\hat{\theta}_2] = \sigma_2^2$.

Consider the estimator all the estimators that can be obtained as convex combinations of $\hat{\theta}_1$ and $\hat{\theta}_2$, i.e., all the estimators of the form

$$\hat{\theta} = \alpha\hat{\theta}_1 + (1-\alpha)\hat{\theta}_2.$$

What can you say about the bias of estimators $\hat{\theta}$ of the form above? Assuming that $\hat{\theta}_1$ and $\hat{\theta}_2$ are independent, for which weight α is the variance minimal?

$$\rightarrow: \mathbb{E}[\hat{\theta}] = \mathbb{E}[\alpha\hat{\theta}_1 + (1-\alpha)\hat{\theta}_2] = \alpha \underbrace{\mathbb{E}[\hat{\theta}_1]}_{\theta} + (1-\alpha) \underbrace{\mathbb{E}[\hat{\theta}_2]}_{\theta} = \theta$$

$$\Rightarrow \hat{\theta} \text{ unbiased}$$

$$\text{Var}[\hat{\theta}] \longrightarrow \min$$

$$\text{Var}[\alpha\hat{\theta}_1 + (1-\alpha)\hat{\theta}_2] \longrightarrow \min$$

independence

$$\text{Var}[\alpha\hat{\theta}_1] + \text{Var}[(1-\alpha)\hat{\theta}_2] \longrightarrow \min$$

$$\alpha^2 \text{Var}[\hat{\theta}_1] + (1-\alpha)^2 \text{Var}[\hat{\theta}_2] \longrightarrow \min$$

$$\alpha^2 \sigma_1^2 + (1-\alpha)^2 \sigma_2^2 \xrightarrow{\alpha} \min$$

PARABOLA 

$$2\alpha \sigma_1^2 + 2(1-\alpha)(-\sigma_2^2) = 0$$

$$\alpha \sigma_1^2 + \alpha \sigma_2^2 - \sigma_2^2 = 0$$

$$\alpha^* = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$



Problem 13.3. Let Y_1, Y_2, \dots, Y_n be a random sample from a continuous distribution with probability density function

$$f_Y(y) = \frac{\alpha y^{\alpha-1}}{\theta^\alpha} \mathbf{1}_{[0,\theta]}(y)$$

with a known parameter $\alpha > 0$ and an unknown parameter $\theta > 0$. We propose the estimator $\hat{\theta} = \max(Y_1, \dots, Y_n)$. Is this estimator unbiased? If not, how would you modify it to create an unbiased estimator? What is the mean-squared error of the unbiased estimator you obtained?

→: $\hat{\theta} = \max(Y_1, \dots, Y_n) = Y_{(n)}$

$E[\hat{\theta}] = E[Y_{(n)}] = ?$

$$g_{(n)}(y) = n \cdot f_Y(y) (F_Y(y))^{n-1}$$

$$E[Y_{(n)}] = \int_0^\theta y \cdot g_{(n)}(y) dy$$

$$F_Y(y) = \int_0^y f_Y(u) du$$

$$= \int_0^y \frac{\alpha u^{\alpha-1}}{\theta^\alpha} du = \left(\frac{y}{\theta}\right)^\alpha$$

$$y \in [0, \theta]$$

$$E[Y_{(n)}] = \int_0^\theta y \cdot n \cdot \frac{\alpha y^{\alpha-1}}{\theta^\alpha} \cdot \left(\left(\frac{y}{\theta}\right)^\alpha\right)^{n-1} dy$$

$$= \frac{1}{\theta^{\alpha n}} \cdot n \cdot \alpha \int_0^\theta y^{\alpha n} dy = \frac{n \alpha}{\theta^{\alpha n}} \cdot \frac{\theta^{\alpha n+1}}{\alpha n + 1}$$

$$= \frac{\alpha n}{\alpha n + 1} \cdot \theta$$

Not Unbiased!

Let's define:

$$\hat{\theta}' = \frac{\alpha_{n+1}}{\alpha_n} \hat{\theta}$$

$$\begin{aligned} \text{MSE}[\hat{\theta}'] &= \text{Var}[\hat{\theta}'] + (\underbrace{\text{bias}(\hat{\theta}')})^2 = \text{Var}[\hat{\theta}'] = \\ &= \text{Var}\left[\frac{\alpha_{n+1}}{\alpha_n} \hat{\theta}\right] = \left(\frac{\alpha_{n+1}}{\alpha_n}\right)^2 \underbrace{\text{Var}[\hat{\theta}]}_? \end{aligned}$$

$$\begin{aligned} \text{Var}[\hat{\theta}] &= \underbrace{\mathbb{E}[\hat{\theta}^2]}_{\int_0^\infty y^2 g_{\hat{\theta}|\theta}(y) dy} - (\mathbb{E}[\hat{\theta}])^2 \\ &= \dots \end{aligned}$$