

# PLSC 502 – Autumn 2016

## Estimation and Estimators

October 11, 2016

# Random Variables, Take Two

For:

$$X_i = \mu + u_i$$

and so

$$u_i = X_i - \mu,$$

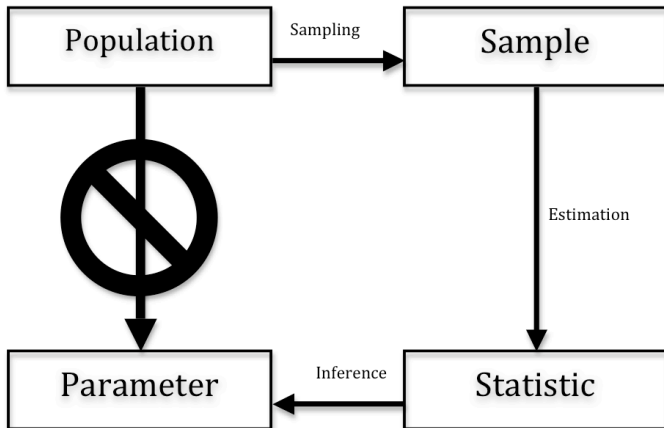
# Random Variables, Take Two

That means

$$\begin{aligned}E(u) &= E(X - \mu) \\&= E(X) - E(\mu) \\&= E(X) - \mu \\&= \mu - \mu \\&= 0\end{aligned}$$

and

$$\begin{aligned}\text{Var}(X) &= E[(X - \mu)^2] \\&= E(u^2) \\[1em]\text{Var}(u) &= E[(u - E(u))^2] \\&= E[(u - 0)^2] \\&= E(u^2).\end{aligned}$$



## Estimation Example: $\bar{X}$

$$\begin{aligned}\bar{X} &= \frac{1}{N} \sum_{i=1}^N X_i \\&= \frac{1}{N} \sum_{i=1}^N (\mu + u_i) \\&= \frac{1}{N} \sum_{i=1}^N (\mu) + \frac{1}{N} \sum_{i=1}^N (u_i) \\&= \frac{1}{N} (N\mu) + \frac{1}{N} \sum_{i=1}^N (u_i) \\&= \mu + \bar{u}\end{aligned}$$

## **Small-Sample Properties**

- Hold irrespective of  $N$
- “Small sample estimators”

## **Large-Sample (Asymptotic) Properties**

- Hold as  $N \rightarrow \infty$
- “More is better”

# Unbiasedness

Means:

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

“Bias”:

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

Example:  $\bar{X}$

$$\begin{aligned} E(\bar{X}) &= E(\mu + \bar{u}) \\ &= E(\mu) + E(\bar{u}) \\ &= \mu + 0 \\ &= \mu \end{aligned}$$

# Multiple Unbiased Estimators

For  $N = 2$ :

$$Z = \lambda_1 X_1 + \lambda_2 X_2.$$

note that

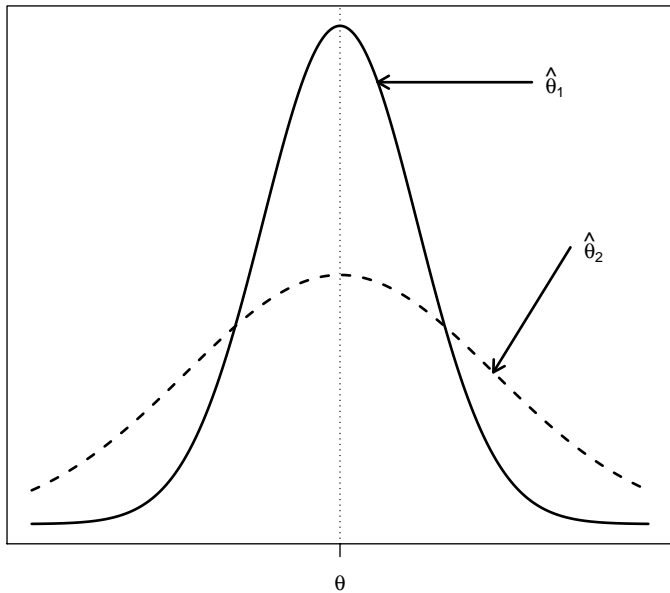
$$\begin{aligned} E(Z) &= E(\lambda_1 X_1 + \lambda_2 X_2) \\ &= E(\lambda_1 X_1) + E(\lambda_2 X_2) \\ &= \lambda_1 E(X_1) + \lambda_2 E(X_2) \\ &= \lambda_1 \mu + \lambda_2 \mu \\ &= (\lambda_1 + \lambda_2) \mu \end{aligned}$$

Means

$$E(Z) = \mu \iff (\lambda_1 + \lambda_2) = 1.0$$



# Efficiency



# Efficiency (continued)

Note:

$$\begin{aligned}\text{Var}(Z) &= \text{Var}(\lambda_1 X_1 + \lambda_2 X_2) \\ &= (\lambda_1^2 + \lambda_2^2)\sigma^2\end{aligned}$$

and:

$$\begin{aligned}\lambda_1^2 + \lambda_2^2 &= \lambda_1^2 + (1 - \lambda_1)^2 \\ &= \lambda_1^2 + (1 - 2\lambda_1 + \lambda_1^2) \\ &= 2\lambda_1^2 - 2\lambda_1 + 1.\end{aligned}$$

Minimize:

$$\begin{aligned}\frac{\partial 2\lambda_1^2 - 2\lambda_1 + 1}{\partial \lambda_1} &= 4\lambda_1 - 2 \\ 4\lambda_1 - 2 &= 0 \\ \lambda_1 &= 0.5\end{aligned}$$

# Mean Squared Error

$$\begin{aligned}\text{MSE}(\hat{\theta}) &= E[(\hat{\theta} - \theta)^2] \\ &= E[B(\hat{\theta})^2] \\ &= \text{Var}(\hat{\theta}) + [B(\hat{\theta})]^2\end{aligned}$$

Among unbiased estimators, the efficient estimator will always have the smallest MSE (because  $B(\hat{\theta}) = [B(\hat{\theta})]^2 = 0$ ).

# Comparing Estimators via MSE

$\bar{X}$  has:

- $B(\bar{X}) = 0$
- $\text{Var}(\bar{X}) = \sigma^2/N$ , so
- $\text{MSE}(\bar{X}) = \sigma^2/N + (0)^2 = \sigma^2/N$ .

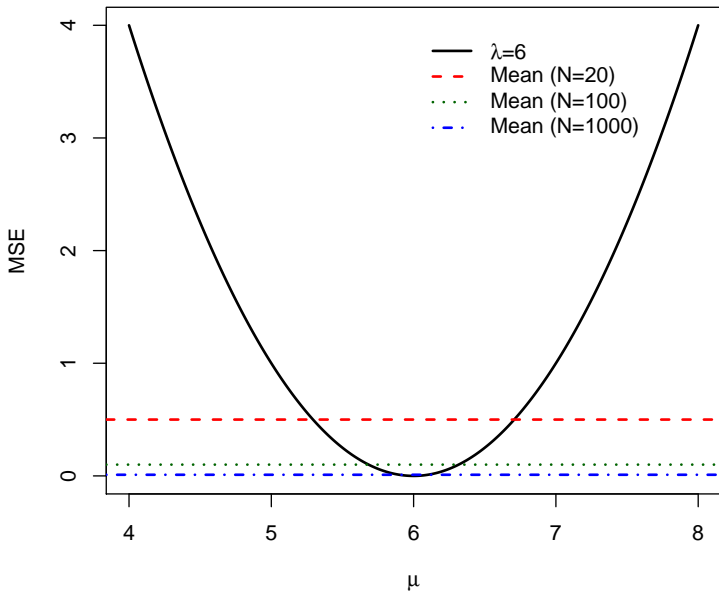
$\lambda = 6$  has:

$$\begin{aligned} B(\lambda) &= E(\lambda - \mu) \\ &= E(6) - E(\mu) \\ &= 6 - \mu, \end{aligned}$$

$$\begin{aligned} \text{Var}(\lambda) &= \text{Var}(6) \\ &= 0 \end{aligned}$$

and so:

$$\begin{aligned} \text{MSE}(\lambda) &= \text{Var}(\lambda) + [B(\lambda)]^2 \\ &= 0 + (6 - \mu)^2 \\ &= 36 - 12\mu + \mu^2 \end{aligned}$$



The black line is the MSE of  $\lambda$ , expressed as a function of the “true” population mean  $\mu$ . The other colored lines are the MSEs for  $\bar{X}$ , under the assumption that  $\sigma^2 = 10$  and  $N = \{20, 100, 1000\}$ , respectively.

# Large-Sample Properties: Consistency

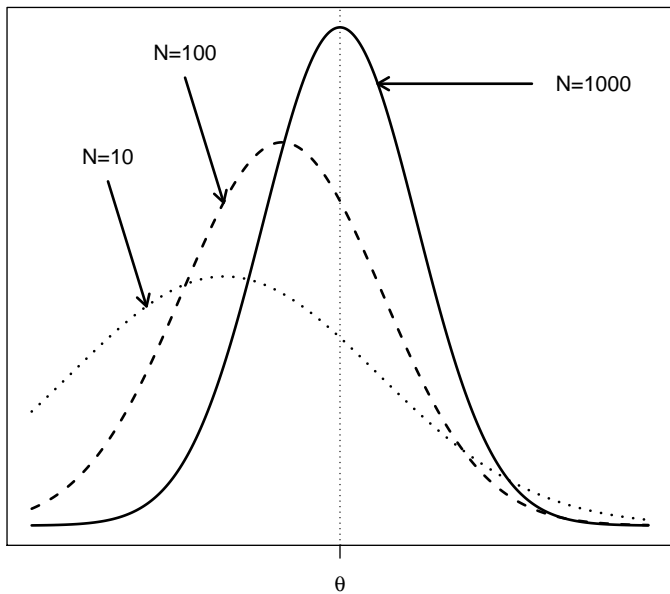
An estimator  $\hat{\theta}$  is *consistent* if:

$$\lim_{N \rightarrow \infty} \Pr[|\hat{\theta} - \theta| < \epsilon] = 1.0$$

for an arbitrarily small  $\epsilon > 0$

Equivalently:

$$E(\hat{\theta}_N) \rightarrow \theta \text{ as } N \rightarrow \infty$$



# Estimation, Generally

- Unbiased  $>$  Consistent  $>$  Biased
- Fully Efficient  $>$  Asymptotically Efficient  $>$  Inefficient
- MSE is one way to trade off bias vs. efficiency