

Output Analysis - Part II (Criteria of Good Estimators)

W. M. Song 桑慧敏
Tsing Hua Univ. 清華大學

2015.11.25

- 1 Notations
- 2 Criteria of Good Estimators
- 3 Comparing X_1 , and $\bar{X}_{(n)}, n > 1$
- 4 Comparing $S^2, \frac{n-1}{n}S^2$, and $\frac{n-1}{n+1}S^2$
- 5 Why use Common Random Numbers (CRN)?

Notations

Recall the midterm-exam problem: Identify a common property for each part.

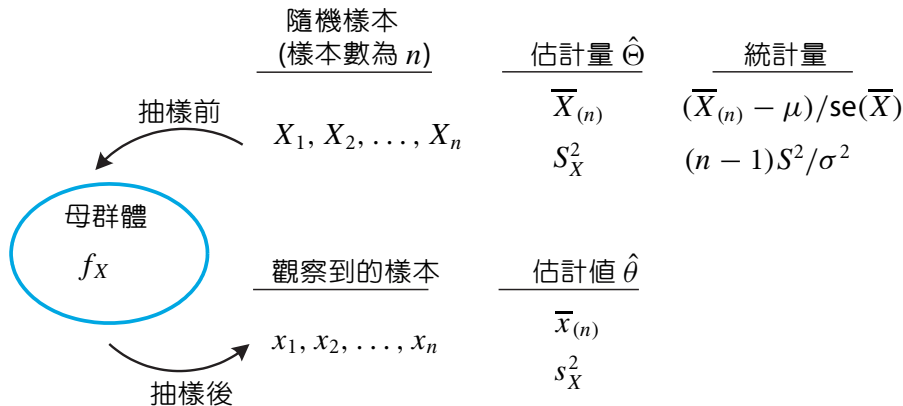
Notations

- 1. $E(X)$ and \bar{X}
- 2. $\text{Var}(X)$ and S^2
- 3. $E(X)$ and $\text{Var}(X)$
- 4. \bar{X} and S^2
- 5. \bar{x} and s^2
- 6. σ_X and σ_Y
- 7. $E(X > 10)$ and $\text{Var}(X < 10)$
- 8. $\{X > 10\}$ and $\{X < 10\}$
- 9. $P(X > 10)$ and $P(\bar{X} < 10)$
- 10. $E(X)$, $\text{Var}(X)$, \bar{x} , s^2

Common Property

- 1. About centering
- 2. About variability
- 3. Population Property
- 4. Sample Property, or R.V.
- 5. Sample Property, or constants
- 6. Population Prop., or constants
- 7. Meaningless
- 8. Events
- 9. Constants in $[0,1]$
- 10. Constants

Notations



- Distinguish before and after sampling
- Distinguish capital X and lower case x

Notations

r.v.	pdf or pmf	分配的屬性		
		平均數	變異數	標準差或標準誤
X	f_X	$E(X)$ 或 μ_X	$V(X)$ 或 σ_X^2	σ_X 或 $\text{sd}(X)$
\bar{X}	$f_{\bar{X}}$	$E(\bar{X})$ 或 $\mu_{\bar{X}}$	$V(\bar{X})$ 或 $\sigma_{\bar{X}}^2$	$\sigma_{\bar{X}}$ 或 $\text{se}(\bar{X})$
S^2	f_{S^2}	$E(S^2)$ 或 μ_{S^2}	$V(S^2)$ 或 $\sigma_{S^2}^2$	σ_{S^2} 或 $\text{se}(S^2)$
$\hat{\Theta}$	$f_{\hat{\Theta}}$	$E(\hat{\Theta})$ 或 $\mu_{\hat{\Theta}}$	$V(\hat{\Theta})$ 或 $\sigma_{\hat{\Theta}}^2$	$\sigma_{\hat{\Theta}}$ 或 $\text{se}(\hat{\Theta})$

- Goal: To estimate θ
- Estimator of θ : $\hat{\Theta}$
- Distinguish θ , $\hat{\Theta}$, and $\hat{\theta}$

Criteria of Good Estimators

- Goal: To estimate θ

Estimates

- $\hat{\theta}_1$ and $\hat{\theta}_2$
- Q: Which estimate is better?
- **A: No way to know**

Estimators

- $\hat{\Theta}_1$ and $\hat{\Theta}_2$
- Q: Which estimator is better?
- **A: Bias, Var, and MSE**

- Bias, Var, and MSE of $\hat{\Theta}_1$ and $\hat{\Theta}_2$

Bias ($\hat{\Theta}$) and Var($\hat{\Theta}$)

- Goal: estimate θ
- estimator: $\hat{\Theta}, \hat{\Theta}_1, \hat{\Theta}_2$

Bias (偏度)

$$\text{Bias}(\hat{\Theta}): E(\hat{\Theta}) - \theta$$

Variance(變異)

$$\text{Var}(\hat{\Theta}) = E(\hat{\Theta} - \mu_{\hat{\Theta}})^2$$

Which estimator is a better?



- Q: Which estimator is better?
- A: In terms of Bias, $\text{Bias}(\hat{\Theta}_1) < \text{Bias}(\hat{\Theta}_2)$
- In terms of variance, $\text{Var}(\hat{\Theta}_1) > \text{Var}(\hat{\Theta}_2)$
- So, we need an “integrated criterion” to include $\text{Bias}(\hat{\Theta})$ and $\text{Var}(\hat{\Theta})$

Criteria of Good Estimators

- Goal: estimating θ ; estimator: $\hat{\Theta}$
- Estimator: $\hat{\Theta}$

Bias (偏度)

$$\text{Bias}(\hat{\Theta}): E(\hat{\Theta}) - \theta$$

Variance(變異)

$$\text{Var}(\hat{\Theta}) = E(\hat{\Theta} - \mu_{\hat{\Theta}})^2$$

Mean Squared Error (MSE)(均方誤)

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

- Distinguish $E(\hat{\Theta} - \theta)^2$ and $E(\hat{\Theta} - \mu_{\hat{\Theta}})^2$

Comparing X_1 , $\bar{X}_{(2)}$, and $\bar{X}_{(100)}$

Goal: to estimate $\theta = \mu_X$

- $\hat{\Theta}_1 = X_1$
- $\hat{\Theta}_2 = \bar{X}_{(2)}$
- $\hat{\Theta}_3 = \bar{X}_{(100)}$

Performance

- $\text{Bias}(X_1) = \text{Bias}(\bar{X}_{(2)}) = \text{Bias}(\bar{X}_{(100)}) = 0$
- $\text{Var}(X_1) > \text{Var}(\bar{X}_{(2)}) > \text{Var}(\bar{X}_{(100)})$
- $\text{Bias}(\bar{X}_{(n)}) = \mu_X$
- $\text{Var}(\bar{X}_{(n)}) = \text{Var}(X)/n$
- Which estimator (among $\hat{\Theta}_i$, $i = 1, 2, 3$) is the best?

Comparing $S^2, \frac{n-1}{n}S^2$, and $\frac{n-1}{n+1}S^2$

Goal: estimating $\theta = \sigma_X^2$

- $\hat{\Theta}_1 = \sum_{i=1}^n (X_i - \bar{X})^2 / (n - 1) = S^2$
- $\hat{\Theta}_2 = \sum_{i=1}^n (X_i - \bar{X})^2 / n = \frac{n-1}{n}S^2$
- $\hat{\Theta}_3 = \sum_{i=1}^n (X_i - \bar{X})^2 / (n + 1) = \frac{n-1}{n+1}S^2$

Performance

- $\text{Bias}(\hat{\Theta}_1) = 0$
- $\text{Mse}(\hat{\Theta}_3) < \text{Mse}(\hat{\Theta}_2) < \text{Mse}(\hat{\Theta}_1)$
- $\text{mse}(\hat{\Theta}_1) = \frac{2\sigma^4}{n-1}; \text{mse}(\hat{\Theta}_2) = \frac{(2n-1)\sigma^4}{n^2}; \text{mse}(\hat{\Theta}_3) = \frac{2\sigma^4}{n+1}$

- Which estimator (among $\hat{\Theta}_i, i = 1, 2, 3$) is the best?

Why use CRN?

- **Motivation:** Estimating $\theta_1 - \theta_2$ (Recall the MM2 systems with 1 and 2 queues)
- **Crude Estimator:** $\hat{\Theta} \equiv \hat{\Theta}_1 - \hat{\Theta}_2$ with arbitrary random numbers
- **CRN-estimator:** Apply common random numbers (CRN) for $\hat{\Theta}_1$ and $\hat{\Theta}_2$ so that $\text{Cov}(\hat{\Theta}_1, \hat{\Theta}_2) > 0$

Result 1 : $E(\hat{\Theta}) = E(\hat{\Theta}_1) - E(\hat{\Theta}_2) = \theta_1 - \theta_2$,
if Θ_1 and Θ_2 are unbiased

Result 2: $\text{Var}(\hat{\Theta}) = \text{Var}(\hat{\Theta}_1) + \text{Var}(\hat{\Theta}_2) - 2\text{Cov}(\hat{\Theta}_1, \hat{\Theta}_2)$
 $< \text{Var}(\hat{\Theta}_1) + \text{Var}(\hat{\Theta}_2)$ if $\text{Cov}(\hat{\Theta}_1, \hat{\Theta}_2) > 0$

- **We expect CRN-estimator performs better than Crude Estimator**

CRN Used as a Block Variable in DOE

- We expect to use “Random numbers” as a block variable, used in design of experiment (DOE)
- HW: DOE and block variable. One-page report