Chapters 9. Properties of Point Estimators

Recap

- Population parameter θ. Population distribution $f(x;\theta)$. The form of $f(x;\theta)$ is known except the value of θ.
- Sample: $\{X_1, X_2, \ldots, X_n\}$ iid with distribution $f(x,\theta)$.
- Estimator $\hat{\theta}$: a function of samples $\{X_1, X_2, \ldots, X_n\}$:

$$\hat{\theta} = \hat{\theta}(X_1, X_2, \ldots, X_n).$$

- MSE, unbiased, confidence interval.

Relative efficiency

Two estimators for θ: $\hat{\theta}_1$ and $\hat{\theta}_2$. The relative efficiency of $\hat{\theta}_1$ with respect to $\hat{\theta}_2$ is defined as

$$\text{eff}(\hat{\theta}_1, \hat{\theta}_2) = \frac{\text{MSE}(\hat{\theta}_2)}{\text{MSE}(\hat{\theta}_1)}$$

Remark: When $\hat{\theta}_1$ and $\hat{\theta}_2$ are both unbiased, their relative efficiency reduces to

$$\text{eff}(\hat{\theta}_1, \hat{\theta}_2) = \frac{\text{Var}(\hat{\theta}_2)}{\text{Var}(\hat{\theta}_1)}$$

Remark: When $\text{eff}(\hat{\theta}_1, \hat{\theta}_2) > (<) 1$, $\hat{\theta}_1$ is more (less) efficient than $\hat{\theta}_2$.

Minimal Variance Unbiased Estimator (MVUE)

Goal: Among all the unbiased estimators, find the one with the minimal variance (most efficient unbiased estimator).

Keywords:

1. Estimator: function of samples $\{X_1, X_2, \ldots, X_n\}$
2. Unbiased.
3. Minimal variance.

MVUE: Sufficient Statistics

Definition: A *Statistics* is a function of samples $\{X_1, X_2, \ldots, X_n\}$.

Definition: A statistics $t = t(X_1, X_2, \ldots, X_n)$ is said to be *sufficient* if the *likelihood* of samples $\{X_1, X_2, \ldots, X_n\}$

$$L(x_1, x_2, \ldots, x_n; \theta) = f(x_1; \theta) \times f(x_2; \theta) \times \cdots \times f(x_n; \theta)$$

can be written as

$$L(x_1, x_2, \ldots, x_n; \theta) = g_\theta(t) \times h(x_1, x_2, \ldots, x_n).$$

Examples of sufficient statistics

1. Bernoulii Distribution. $\{X_1, X_2, \ldots, X_n\}$ iid Bernoulli with parameter p (target parameter). Then

$$\sum_{i=1}^{n} X_i$$

is sufficient.

2. Poisson Distribution. $\{X_1, X_2, \ldots, X_n\}$ iid Poisson with parameter λ (target parameter). Then

$$\sum_{i=1}^{n} X_i$$

is sufficient.

3. Uniform Distribution. $\{X_1, X_2, \ldots, X_n\}$ iid uniform on interval $[0, \theta]$ (target parameter θ). Then

$$X_{(n)} = \max\{X_1, X_2, \ldots, X_n\}$$

is sufficient.

4. Normal Distribution. $\{X_1, X_2, \ldots, X_n\}$ iid $N(\mu, \sigma^2)$.

(a) Suppose σ is known, and μ is the target parameter. Then

$$\sum_{i=1}^{n} X_i$$

is sufficient.

(b) Suppose μ and σ are both unknown (target parameters). Then

$$\left(\sum_{i=1}^{n} X_n, \quad \sum_{i=1}^{n} X_i^2 \right)$$

are (jointly) sufficient.

Remark: Sufficient statistics are not unique. Many of them.

Remark: What is the meaning of "sufficiency" — A sufficient statistics contains all the information about θ from the samples $\{X_1, X_2, \ldots, X_n\}$.

> The conditional distribution of $\{X_1, X_2, \ldots, X_n\}$ given a sufficient statistics $t = t(X_1, X_2, \ldots, X_n)$ does NOT depend on θ.

Verify the discrete case ....

MVUE: Rao-Blackwell Theorem

Theorem: Let $\hat{\theta} = \hat{\theta}(X_1, X_2, \ldots, X_n)$ be an unbiased estimator for θ, and t any sufficient statistics. Define

$$\hat{\theta}^* = E[\hat{\theta}(X_1, X_2, \ldots, X_n)|t].$$

Then $\hat{\theta}^*$ is an unbiased estimator for θ and

$$\text{Var}[\hat{\theta}^*] \leq \text{Var}[\hat{\theta}]$$

Remark: $\hat{\theta}^*$ is a function of t only.

Observation: If there is only one function of t, say $h(t)$, such that $h(t)$ is an unbiased estimator for θ, that is

$$E[h(t)] = \theta,$$

then $h(t)$ is the MVUE.

Definition: We say a statistics t is complete if

$$E[g(t)] = 0$$

for every θ implies $g \equiv 0$.

Remark: Suppose t is sufficient and complete, then there will be at most one function of t, say $h(t)$, that is an unbiased estimator for θ.

MVUE: A useful approach

To identify an MVUE,

1. Find a sufficient statistics, say t.
2. Argue this statistics is complete.
3. Find an unbiased estimator $h(t)$ for θ. (One can use any unbiased estimator, say $\hat{\theta}$, and then let $h(t) = E[\hat{\theta}|t]$)
4. This estimator $h(t)$ is MVUE.

MVUE: Examples

1. A coin with $P(\text{H}) = p$ (target parameter). Toss coin n times,

$$X_i = \begin{cases} 1 & , \quad \text{if } i\text{-th toss is heads} \\ 0 & , \quad \text{if } i\text{-th toss is tails} \end{cases}$$

Identify the MVUE for p.

2. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid $N(\mu, \sigma^2)$.

(a) If σ^2 is known, what is the MVUE for μ?

(b) If μ and σ^2 are both unknown, what is the MVUE for μ? for σ^2?

3. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid samples from uniform distribution on $[0, \theta]$. Find an MVUE for θ.

4. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid samples from Poisson distribution with parameter λ. Find an MVUE for θ. What about an MVUE for $e^{-\theta}$?

Maximum Likelihood Estimate (MLE)

MLE: Find θ to maximize $L(x_1, x_2, \ldots, x_n; \theta)$.

[In this maximization problem, $\{x_1, x_2, \ldots, x_n\}$ are regarded as fixed]

Examples

1. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid samples from Poisson distribution with parameter θ. Find the MLE for θ.

2. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid samples from uniform distribution $[0, \theta]$. Find the MLE for θ.

3. Suppose $\{X_1, X_2, \ldots, X_n\}$ are iid samples from $N(\mu, \sigma^2)$.

(a) Find the MLE for μ when σ^2 is known.

(b) Find the MLE for μ and σ^2 when they are both unknown.

Properties of MLE

MLE has the following nice properties under mild regularity conditions.

1. MLE is a function of sufficient statistics.
2. Consistency: An estimator $\hat{\theta} = \hat{\theta}(X_1, X_2, \ldots, X_n)$ is said to be *consistent* if
$$\left|\hat{\theta}(X_1, X_2, \ldots, X_n) - \theta\right| \longrightarrow 0$$
as $n \longrightarrow \infty$.
3. Asymptotic optimality: MLE is asymptotically normal and asymptotically most efficient.
4. Invariance Property: Suppose $\hat{\theta}$ is the MLE for θ, then $h(\hat{\theta})$ is MLE for $h(\theta)$ when h is a one-to-one function.