Lecture 09: Sufficiency, Completeness and Unbiasedness

Mathematical Statistics II, MATH 60062/70062

Thursday February 17, 2022

Reference: Casella & Berger, 7.3.3

Recap: Uniformly minimum-variance unbiased estimator

An estimator $W^* = W^*(X)$ is a uniformly minimum-variance unbiased estimator (UMVUE) of $\tau(\theta)$ if

- ② $Var_{\theta}(W^*) \le Var_{\theta}(W)$ for all $\theta \in \Theta$, where W is any other unbiased estimator of $\tau(\theta)$.

We will discuss two approaches to find UMVUEs:

- **1** (Cramér-Rao Inequality) Determine a lower bound on the variance of any unbiased estimator of $\tau(\theta)$. If we can find an unbiased estimator whose variance attains this lower bound, we have found the UMVUE.
- (Rao-Blackwell Theorem) Relate the property of UMVUEs with the notation of sufficiency and completeness.

Rao-Blackwell Theorem

Let $W=W(\boldsymbol{X})$ be an unbiased estimator of $\tau(\theta)$, and let $T=T(\boldsymbol{X})$ be a sufficient statistic for θ . Define

$$\phi(T) = E(W \mid T).$$

Then

- $2 \operatorname{Var}_{\theta}(\phi(T)) \leq \operatorname{Var}_{\theta}(W) \text{ for all } \theta \in \Theta.$

That is, $\phi(T) = E(W \mid T)$ is a uniformly better unbiased estimator than W.

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We can improve an unbiased estimator by conditioning on a sufficient statistic; in the search for UMVUE, we can restrict attention to those estimators that are functions of a sufficient statistic.

Proof of the Rao-Blackwell Theorem

By the law of total expectation, we know $\phi(T) = E(W \mid T)$ is an unbiased for $\tau(\theta)$,

$$E_{\theta}[\phi(T)] = E_{\theta}[E(W \mid T)] = E_{\theta}(W) = \tau(\theta).$$

By the law of total variance,

$$\operatorname{Var}_{\theta}(W) = E_{\theta}[\operatorname{Var}(W \mid T)] + \operatorname{Var}_{\theta}[E(W \mid T)]$$
$$= E_{\theta}[\operatorname{Var}(W \mid T)] + \operatorname{Var}_{\theta}[\phi(T)]$$
$$\geq \operatorname{Var}_{\theta}[\phi(T)].$$

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There was no mention of sufficiency in the proof. It might seem that conditioning on any statistic will result in an improvement.

However, if T is not sufficient, $\phi(T) = E(W \mid T)$ may not be an estimator.

Conditioning on an insufficient statistic

Let X_1, X_2 be iid $\mathcal{N}(\theta, 1)$. The statistic $\bar{X} = (X_1 + X_2)/2$ is an unbiased estimator of θ ,

$$E_{\theta}[\bar{X}] = \theta, \quad \operatorname{Var}_{\theta}[\bar{X}] = \frac{1}{2}.$$

Consider conditioning on X_1 , which is not sufficient. Let $\phi(X_1) = E(\bar{X} \mid X_1), \ E_{\theta}[\phi(X_1)] = \theta$ and $\mathrm{Var}_{\theta}[\phi(X_1)] \leq \mathrm{Var}_{\theta}[\bar{X}].$

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However, $\phi(X_1)$ is *not* an estimator since

$$\phi(X_1) = E(\bar{X} \mid X_1)$$

$$= \frac{1}{2}E(X_1 \mid X_1) + \frac{1}{2}E(X_2 \mid X_1)$$

$$= \frac{1}{2}X_1 + \frac{1}{2}\theta$$

depends on θ .

Uniqueness of UMVUE

If W is an UMVUE of $\tau(\theta)\text{, then }W$ is unique.

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If W is an UMVUE of $\tau(\theta)$, then W is unique.

Suppose that W' is another UMVUE. It suffices to show that W=W'. Consider an estimator

$$W^* = \frac{1}{2}(W + W').$$

Note that W^* is an unbiased estimator

$$E_{\theta}(W^*) = \frac{1}{2} [E_{\theta}(W) + E_{\theta}(W')] = \tau(\theta), \quad \forall \theta \in \Theta.$$

The variance of W^* is

$$\operatorname{Var}_{\theta}(W^{*}) = \operatorname{Var}_{\theta} \left[\frac{1}{2} (W + W') \right]$$

$$= \frac{1}{4} \operatorname{Var}_{\theta}(W) + \frac{1}{4} \operatorname{Var}_{\theta}(W') + \frac{1}{2} \operatorname{Cov}_{\theta}(W, W')$$

$$\leq \frac{1}{4} \operatorname{Var}_{\theta}(W) + \frac{1}{4} \operatorname{Var}_{\theta}(W') + \frac{1}{2} \left[\operatorname{Var}_{\theta}(W) \operatorname{Var}_{\theta}(W') \right]^{1/2}$$

$$= \operatorname{Var}_{\theta}(W),$$

where the inequality is an application of Cauchy-Schwartz and the last equality holds because $Var_{\theta}(W) = Var_{\theta}(W')$ by assumption.

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$$= \operatorname{Var}_{\theta}(W),$$

where the inequality is an application of Cauchy-Schwartz and the last equality holds because $Var_{\theta}(W) = Var_{\theta}(W')$ by assumption.

The inequality cannot be strict because W is UMVUE by assumption. So, it must be true that $\mathrm{Var}_{\theta}(W^*) = \mathrm{Var}_{\theta}(W)$ and (because the equality holds)

$$W' = a(\theta)W + b(\theta).$$

Using properties of covariance, we have

$$Cov_{\theta}(W, W') = Cov_{\theta}[W, a(\theta)W + b(\theta)] = a(\theta)Var_{\theta}(W),$$

and we have just shown that $\mathrm{Cov}_{\theta}(W,W')=\mathrm{Var}_{\theta}(W).$ Hence, $a(\theta)=1.$

Finally, since both W and W' are unbiased and

$$E_{\theta}(W') = E_{\theta}[a(\theta)W + b(\theta)] = E_{\theta}(W) + b(\theta),$$

we must have $b(\theta) = 0$.

Therefore, W = W'. W is unique.

Suppose $E_{\theta}(W) = \tau(\theta)$ for all $\theta \in \Theta$. W is the UMVUE of $\tau(\theta)$ if and only if W is uncorrelated with all unbiased estimators of 0.

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Necessity: Suppose that $E_{\theta}(W) = \tau(\theta)$ for all $\theta \in \Theta$ and W is the UMVUE of $\tau(\theta)$. Suppose that U is an unbiased estimator of 0, i.e., $E_{\theta}(U) = 0$. It suffices to show that $\mathrm{Cov}_{\theta}(W,U) = 0$ for all $\theta \in \Theta$.

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Necessity: Suppose that $E_{\theta}(W)=\tau(\theta)$ for all $\theta\in\Theta$ and W is the UMVUE of $\tau(\theta)$. Suppose that U is an unbiased estimator of 0, i.e., $E_{\theta}(U)=0$. It suffices to show that $\mathrm{Cov}_{\theta}(W,U)=0$ for all $\theta\in\Theta$. Consider an estimator

$$\phi_a = W + aU,$$

where a is a constant. The estimator is unbiased for $\tau(\theta)$ since

$$E_{\theta}(\phi_a) = E_{\theta}(W + aU) = E_{\theta}(W) + aE_{\theta}(U) = \tau(\theta).$$

The variance of ϕ_a is

$$Var_{\theta}(\phi_a) = Var_{\theta}(W + aU)$$

= $Var_{\theta}(W) + 2aCov_{\theta}(W, U) + a^2Var_{\theta}(U),$

which is minimized when

$$a = -\frac{\operatorname{Cov}_{\theta}(W, U)}{\operatorname{Var}_{\theta}(U)}.$$

The best unbiased estimator in this class is

$$W - \frac{\operatorname{Cov}_{\theta}(W, U)}{\operatorname{Var}_{\theta}(U)} U,$$

which cannot be W if $Cov_{\theta}(W,U) \neq 0$. Therefore, we must have

$$Cov_{\theta}(W, U) = 0.$$

Sufficiency: Suppose $E_{\theta}(W) = \tau(\theta)$ for all $\theta \in \Theta$ and W is uncorrelated with any unbiased estimators of 0. That is $\mathrm{Cov}_{\theta}(W,U) = 0$ for any U that satisfies $E_{\theta}(U) = 0$, for all $\theta \in \Theta$. Let W' be any other unbiased estimator of $\tau(\theta)$. It suffices to show that $\mathrm{Var}_{\theta}(W) \leq \mathrm{Var}_{\theta}(W')$.

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Write

$$W' = W + (W' - W),$$

and calculate

$$\operatorname{Var}_{\theta}(W') = \operatorname{Var}_{\theta}(W) + \operatorname{Var}_{\theta}(W' - W) + 2\operatorname{Cov}_{\theta}(W, W' - W),$$

where the covariance $Cov_{\theta}(W, W' - W) = 0$ because W' - W is an unbiased estimator of 0. Therefore,

$$\operatorname{Var}_{\theta}(W') = \operatorname{Var}_{\theta}(W) + \underbrace{\operatorname{Var}_{\theta}(W' - W)}_{>0} \ge \operatorname{Var}_{\theta}(W).$$

Characterizing the unbiased estimators of 0 is not an easy task, and requires conditions on the PDFs/PMFs with which we are working.

If a family of PDFs/PMFs has the property that there are no unbiased estimators of 0 (other than zero function itself), then our search would be ended, since any statistic W satisfies $\mathrm{Cov}_{\theta}(W,0)=0$.

Recall: Complete statistic

Let $\{f_T(t \mid \theta); \theta \in \Theta\}$ be a family of PDFs (or PMFs) for a statistic $T = T(\boldsymbol{X})$. The family is called **complete** if the following condition holds:

$$E_{\theta}(g(T)) = 0, \ \forall \theta \in \Theta \implies P_{\theta}(g(T) = 0) = 1, \ \forall \theta \in \Theta.$$

In other words, g(T)=0 almost surely for all $\theta\in\Theta$. Equivalently, $T(\boldsymbol{X})$ is called a **complete statistic**.

This means, the only function of T that is an unbiased estimator of zero is the function that is zero itself (with probability 1).

Sufficiency, completeness and best unbiasedness

Let T be a complete sufficient statistic for a parameter θ , and let $\phi(T)$ be any estimator based only on T. Then $\phi(T)$ is the unique UMVUE of its expected value.

To find the UMVUE for $\tau(\theta)$.

- ${\rm 1 \hskip -5.5pt 1}$ Find a complete sufficient statistic T for θ
- **②** Find a function of T, say $\phi(T)$, that satisfies

$$E_{\theta}[\phi(T)] = \tau(\theta).$$

Then $\phi(T)$ is the UMVUE for $\tau(\theta)$.

Poisson UMVUE

Suppose that X_1, \ldots, X_n are iid $\operatorname{Pois}(\theta)$, where $\theta > 0$.

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Suppose that X_1, \ldots, X_n are iid $Pois(\theta)$, where $\theta > 0$.

The Poisson PMF is a member of the Exponential family since

$$f_X(x \mid \theta) = \frac{e^{-\theta} \theta^x}{x!} I(x = 0, 1, 2, \dots)$$

$$= \frac{I(x = 0, 1, 2, \dots)}{x!} e^{-\theta} \exp[\log \theta \cdot x]$$

$$= h(x)c(\theta) \exp[w_1(\theta)t_1(x)].$$

Therefore,

$$T = T(X) = \sum_{i=1}^{n} t_1(X_i) = \sum_{i=1}^{n} X_i$$

is a sufficient statistic. Since $d=k=1,\,T$ is complete.

The expectation of T is

$$E_{\theta}(T) = E_{\theta}\left(\sum_{i=1}^{n} X_i\right) = n\theta.$$

So, $\bar{X} = T/n$ is an unbiased estimator of θ .

Since \bar{X} unbiased and is a function of T, which is a complete and sufficient statistic, we know that \bar{X} is UMVUE for θ .

Gamma UMVUE

Suppose that X_1, \ldots, X_n are iid $\operatorname{Gamma}(\alpha_0, \beta)$, where α_0 is known and $\beta > 0$.

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Suppose that X_1, \ldots, X_n are iid $\operatorname{Gamma}(\alpha_0, \beta)$, where α_0 is known and $\beta > 0$.

The $\operatorname{Gamma}(\alpha_0,\beta)$ PDF is part of the full Exponential family

$$f_X(x \mid \beta) = \frac{1}{\Gamma(\alpha_0)\beta^{\alpha_0}} x^{\alpha_0 - 1} e^{-x/\beta}$$

$$= \frac{x^{\alpha_0 - 1} I(x > 0)}{\Gamma(\alpha_0)} \frac{1}{\beta^{\alpha_0}} \exp[(-1/\beta)x]$$

$$= h(x)c(\beta) \exp[w_1(\beta)t_1(x)].$$

Therefore,

$$T = T(\mathbf{X}) = \sum_{i=1}^{n} t_1(X_i) = \sum_{i=1}^{n} X_i$$

is a complete and sufficient statistic.

The expectation of T is

$$E_{\beta}(T) = E_{\beta}\left(\sum_{i=1}^{n} X_i\right) = n\alpha_0\beta.$$

So,

$$\phi(T) = \frac{T}{n\alpha_0}$$

is an unbiased estimator of β .

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What if we want to find UMVUE for $1/\beta$?