ECE531 Screencast 1.4: Minimum Variance Unbiased Estimators

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Minimum Variance Unbiased Estimators

Definition

A minimum-variance unbiased estimator $\hat{\theta}_{\mathsf{mvu}}(y)$ is an unbiased estimator satisfying

$$\hat{\theta}_{\mathsf{mvu}}(y) = \arg\min_{\hat{\theta}(y) \in \Omega} R_{\theta}(\hat{\theta}(y))$$

for all $\theta \in \Lambda$ where Ω is the set of all unbiased estimators.

Remarks:

- Finding an MVU estimator is a multi-objective optimization problem. You have to find **one** estimator to minimize the variance at all θ ∈ Λ.
- The estimator can not be a function of θ .
- ▶ MVU estimators do not always exist (see Example 2.3 in Kay I).
- ▶ We will see, however, that lots of problems do yield MVU estimators.

Example: Estimating a Constant in White Gaussian Noise

Suppose we have random observations given by

$$Y_k = \theta + W_k \qquad k = 0, \dots, n-1$$

where $W_k \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2)$ with $\theta \in \mathbb{R}$.

Suppose we go with an estimator that performs the sample mean:

$$\hat{\theta}(y) = \frac{1}{n} \sum_{k=0}^{n-1} y_k$$

- Is this estimator unbiased? Yes (easy to check).
- ► Is this estimator MVU? The variance of the estimator can be calculated as $\operatorname{var}_{\theta} \left[\hat{\theta}(Y) \right] = \frac{\sigma^2}{n}$. But answering the question as to whether this estimator is MVU or not will require more work.

Example: Estimating Mean and Variance

Suppose we have random observations given by

$$Y_k = \theta_1 + W_k \qquad k = 0, \dots, n-1$$

where $W_k \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \theta_2)$. Note that both θ_1 and $\theta_2 > 0$ are unknown. This is called a vector parameter estimation problem.

We already know an unbiased estimator for θ_1 : the sample mean $\hat{\theta}_1(y) = \frac{1}{n} \sum_{k=0}^{n-1} y_k$. This estimator is still valid in this case because the sample mean does not depend on any unknown parameters.

How about this estimator for θ_2 (sample variance):

$$\hat{\theta}_2(y) = \frac{1}{n} \sum_{k=0}^{n-1} (y_k - \hat{\theta}_1(y))^2$$

- Is this estimator unbiased?
- Is this estimator MVU?

Example: Estimating Mean and Variance

To check if the estimator for θ_2 is unbiased, we can calculate the mean:

$$\begin{split} \mathbf{E}_{\theta}[\hat{\theta}_{2}(Y)] &= \mathbf{E}_{\theta} \left[\frac{1}{n} \sum_{\ell=0}^{n-1} \left(Y_{\ell} - \hat{\theta}_{1}(Y) \right)^{2} \right] \\ &= \frac{1}{n} \sum_{\ell=0}^{n-1} \mathbf{E}_{\theta} \left[\left(Y_{\ell} - \hat{\theta}_{1}(Y) \right)^{2} \right] \\ &= \frac{1}{n} \sum_{\ell=0}^{n-1} \mathbf{E}_{\theta} \left[\left(Y_{\ell} - \left(\frac{1}{n} \sum_{k=0}^{n-1} Y_{k} \right) \right)^{2} \right] \\ &= \frac{1}{n} \sum_{\ell=0}^{n-1} \mathbf{E}_{\theta} \left[\left(\theta_{1} + W_{\ell} - \left(\frac{1}{n} \sum_{k=0}^{n-1} (\theta_{1} + W_{k}) \right) \right)^{2} \right] \\ &= \frac{1}{n^{3}} \sum_{\ell=0}^{n-1} \mathbf{E}_{\theta} \left[\left((n-1)W_{\ell} - \sum_{\substack{k=0\\k \neq \ell}}^{n-1} W_{k} \right)^{2} \right] \\ &= \frac{1}{n^{3}} \sum_{\ell=0}^{n-1} \left[(n-1)^{2} + n - 1 \right] \theta_{2} = \frac{n-1}{n} \theta_{2} \end{split}$$

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Example: Estimating Mean and Variance

Since

$$\mathbf{E}_{\theta}[\hat{\theta}_2(Y)] = \frac{n-1}{n}\theta_2 \neq \theta_2$$

this estimator is biased.

We can use this result to make an unbiased estimator for θ_2 , however:

$$\hat{\theta}_2(y) = \frac{1}{n-1} \sum_{k=0}^{n-1} (y_k - \hat{\theta}_1(y))^2$$

You can confirm this estimator is unbiased by computing the mean ${\rm E}_{\theta}[\hat{\theta}_2(Y)]$ as we did before.

Finding MVU Estimators

There is no "plug-and-chug" method that you can always follow to find an MVU estimator. We will cover two common approaches that work in many cases:

- 1. The Cramer-Rao lower bound (Kay I: Chapters 3-4)
 - Guess at a good estimator and check if the variance achieves the theoretical minimum (CRLB).
 - ► Take advantage of special cases, e.g. linear model
- 2. The Rao-Blackwell-Lehmann-Sheffe (RBLS) theorem (Kay I: Chapter 5)
 - Finding a "complete sufficient statistic" for the observations.
 - Performing a conditional expectation to get the MVU estimator.