STAT 517:Sufficiency Measures of Quality of Estimators

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- So far, we considered consistency and unbiasedness
- Recall that MLE's are not always unbiased although they tend to be asymptotically unbiased under a set of regularity conditions
- The model : $X_1, \ldots, X_n \sim f(x; \theta)$ for $\theta \in \Omega$
- For a given n > 0, Y = u(X₁,...,X_n) is a minimum variance unbiased estimator (MVUE) of θ if Y is unbiased and the variance of Y is less than or equal to the variance of every other unbiased estimator of θ

- Let $X_1, \ldots, X_n \sim N(\theta, \sigma^2)$
- Since $\bar{X} \sim N\left(\theta, \frac{\sigma^2}{n}\right) \bar{X}$ is an unbiased estimator of θ ...but so it X_1
- ► Clearly, Var X̄ < Var X₁ for any n > 1...but X̄ is not a minimum variance unbiased estimator!!

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- Any function $\delta(Y)$ is a **decision function** or a **decision rule**
- A specific values $\delta(y)$ is a **decision**
- To measure how different δ(y) is from θ, use the loss function L(θ, δ(y))
- > The loss function is random...better to use the risk function

$$R(\theta,\delta) = \mathbb{E} \left\{ L(\theta,\delta(y)) \right\} = \int_{-\infty}^{\infty} L(\theta,\delta(y)) f_{Y}(y;\theta) \, dy$$

Problem: uniform minimization of risk function over all possible θ may be impossible

- Model: $X_1, \ldots, X_n \sim N(\theta, 1)$ and let $Y = \bar{X}$
- Choose the mean squared error loss $L(\theta, \delta(y)) = [\theta \delta(y)]^2$
- ► How to choose between δ(y) = y and δ₂(y) = 0? The risk functions are

$$R(heta, \delta_1) = \mathbb{E} \left[(heta - Y)
ight]^2 = rac{1}{n}$$

and

$$R(\theta, \delta_1) = \mathbb{E}\left[(\theta - 0)^2\right] = \theta^2$$

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Example

- If θ = 0, then the 2nd choice is better...but if θ is far from zero, δ₂ = 0 is a bad choice!
- If considering only $\delta(y) : \mathbb{E}[(\delta(Y)] = 0$, then δ_2 is not allowed
- ► Under the latter restriction, we are looking for an MVUE which is, actually, X̄ (to be shown later)
- Yet another possible alternative is to use the minimax criterion: δ₀(y) is a minimax decision function if, for all θ ∈ Θ,

$$\max_{\theta} R[\theta, \delta_0(y)] \leq \max_{\theta} R[\theta, \delta(y)]$$

for any other decision function $\delta(y)$

- Note R(θ, δ₂) = θ² which is unbounded if −∞ < θ < ∞ and so has to be excluded according to the minimax criterion
- Actually (not proven by us here..) δ_1 is the best choice according to the minimax decision function

- ► Another possibility is simply to define δ(X₁,..., X_n) without using a statistic Y will not do it here
- Besides the squared error loss function, can also consider e.g. the absolute-error loss function

$$L(\theta, \delta) = \begin{cases} 0 & |\theta - \delta| \le a \\ b & |\theta - \delta| > a \end{cases}$$

for some a, b > 0

This is sometimes called the goalpost loss function

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- A scientist A observes 10 independent trials with prob. of success 0 < θ < 1 and has only 1 success</p>
- ► A scientist *B* observes all trials until the first success which happens to be the 10th
- First model: $Y \sim B(10, \theta)$ with observed number of successes y = 1; the second model is $g(z) = (1 \theta)^{z-1}\theta$ with z = 10
- A sensible estimate in both cases is the relative frequency: $\hat{\theta} = \frac{y}{n} = \frac{1}{z} = \frac{1}{10}$
- $\hat{\theta}$ is unbiased in the first case but not in the second!

Likelihood principle

The first likelihood is

$$L_1(heta) = {10 \choose y} heta^y (1- heta)^{10-y}$$

The second likelihood is

$$L_2(\theta) = (1-\theta)^{z-1}\theta$$

- ▶ When z = 10 and y = 1, both are proportional to $(1 \theta)^9 \theta$...and both give the same answer $\hat{\theta} = \frac{1}{10}$
- To a true believer in the likelihood principle the fact that one of them is unbiased does not matter!

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