ASDS Statistics, YSU, Fall 2020

Lecture 22

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Contents

Bias-Variance Decomposition

This is an important result:

Theorem(Bias-Variance Decomposition of the MSE): If $\hat{\theta}$ is an Estimator for θ, then

$$MSE(\hat{\theta}, \theta) = \left(Bias(\hat{\theta}, \theta)\right)^2 + Var_\theta(\hat{\theta}).$$

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Proof: OTB

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Nice Graphical Interpretation: Link, see also the next slide.

Bias-Variance Decomposition/Tradeoff

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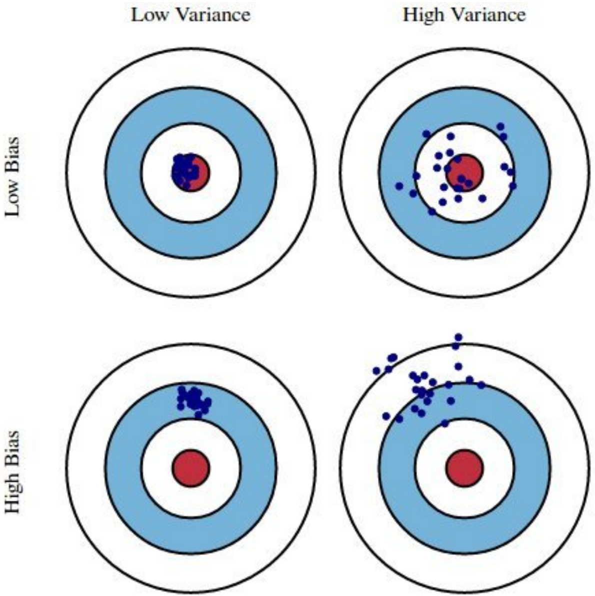

Standard Error and Estimated Standard Error

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And statisticians, when reporting the Estimate, usually report also the Estimated Standard Error, as a measure how precise is the result. If the Standard Error is small (and we are using a nice Estimator, say, it is Unbiased), then this is a sign that the result is close to real/actual one.

Example

Example: Assume we are facing an election with Parties A and B, and we want to estimate the percentage of voters for A in advance. So we do a poll, asking 10 persons to give their preferences. Let the result be:

$$A, B, B, B, A, B, B, A, B, B.$$

Problem: Estimate the percentage of voters for the Party A, and give the Estimated Standard Error.

Solution: OTB.

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Corollary: If $\hat{\theta}_1$ and $\hat{\theta}_2$ are both *Unbiased* Estimators for the unknown Parameter θ, then $\hat{\theta}_1$ is preferable to $\hat{\theta}_2$ if and only if

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Well, in general, there will be a lot of Unbiased Estimators for the same Parameter.Say, if $\hat{\theta}_0$ and $\hat{\theta}_1$ are Unbiased Estimators of θ, then for any $\alpha \in [0, 1]$, the Estimator

$$\hat{\theta}_\alpha = \alpha \cdot \hat{\theta}_1 + (1 - \alpha) \cdot \hat{\theta}_0$$

will be an Unbiased Estimator too.

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- $\hat{\theta}$ is Unbiased Estimator for θ;
- $\hat{\theta}$ has the smallest Variance among all *Unbiased* Estimators of θ, i.e., for any Unbiased Estimator $\tilde{\theta}$,

$$Var_{\theta}(\hat{\theta}) \leq Var_{\theta}(\tilde{\theta}), \qquad \forall \theta \in \Theta.$$

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- **weakly or Mean Square consistent**, if $\hat{\theta}_n \xrightarrow{q.m.} \theta$ for any $\theta \in \Theta$, i.e., if

$$MSE(\hat{\theta}_n, \theta) = \mathbb{E}_\theta((\hat{\theta}_n - \theta)^2) \to 0 \qquad \forall \theta \in \Theta.$$

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Then:

- $\hat{p}$ is a Biased Estimator for p;
- $\hat{p}$ is Consistent Estimator for p.

Proof: OTB

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- If $\hat{\theta}_n$ is an *Asymptotically Unbiased Estimator* for θ and

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  then $\hat{\theta}_n$ is consistent.

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- $\widehat{\sigma^2}$ is Biased;
- $\widehat{\sigma^2}$ is Consistent.

Proof: OTB. Use the relation $\widehat{\sigma^2} = \frac{\sum_{k=1}^{n} (X_k)^2}{n} - \left(\frac{\sum_{k=1}^{n} X_k}{n}\right)^2$.

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And also, the universal measure for goodness is: *an Estimator is good if it has a small MSE*.

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Answer: No, in general. This is because, say,

- we can do a lot of resamplings even when our dataset is not big enough, but one large sample will not be available
- when taking a large sample, we will take each individual just once. But if we are doing resamplings, we can have the same individual in different samples.

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To find the one with the minimal Variance, we can use the Cramer-Rao inequality. But before stating that inequality, we need the notion of the Fisher Information.

Fisher Information

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Definition: The following quantity is called **the Fisher Information** of the parametric family $\mathcal{F}_\theta$:

$$I(\theta) = -\mathbb{E}\left(\frac{\partial^2}{\partial\theta^2} \ln f(X|\theta)\right) = \mathbb{E}\left[\left(\frac{\partial}{\partial\theta} \ln f(X|\theta)\right)^2\right],$$

where $X \sim \mathcal{F}_\theta$.