Mathematical Statistics

Anna Janicka

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PROPERTIES OF ESTIMATORS, PART II

Plan for Today

1. Fisher information
2. Information inequality
3. Estimator efficiency
4. Asymptotic estimator properties
   - consistency
   - *asymptotic normality*
   - *asymptotic efficiency*

Comparing estimators – reminder

$\hat{g}_1(X)$ is **better** than (dominates) $\hat{g}_2(X)$, if

$$\forall \theta \in \Theta \qquad MSE(\theta, \hat{g}_1) \leq MSE(\theta, \hat{g}_2)$$

and

$$\exists \theta \in \Theta \qquad MSE(\theta, \hat{g}_1) < MSE(\theta, \hat{g}_2)$$

an estimator will be better than a different estimator only if its plot of the MSE never lies above the MSE plot of the other estimator; if the plots intersect, estimators are **incomparable**

Comparing estimators – cont.

A lot of estimators are incomparable $\rightarrow$ comparing any old thing is pointless; we need to constrain the class of estimators

If we compare two unbiased estimators, the one with the smaller variance will be better

Minimum-variance unbiased estimator - reminder

We constrain comparisons to the class of unbiased estimators. In this class, one can usually find the best estimator:

$g^*(X)$ is a **minimum-variance unbiased estimator (MVUE)** for $g(\theta)$, if

- $g^*(X)$ is an unbiased estimator of $g(\theta)$,
- for any unbiased estimator $\hat{g}(X)$ we have

$$Var_\theta g^*(X) \leq Var_\theta \hat{g}(X) \quad \text{for } \theta \in \Theta$$

How can we check if the estimator has a minimum variance?

- In general, it is not possible to freely minimize the variance of unbiased estimators – for many statistical models there exists a limit of variance minimization. It depends on the distribution and on the sample size.

Fisher information

If a statistical model with obs. $X_1, X_2, \ldots, X_n$ and probability f_θ fulfills regularity conditions, i.e.:

1. Θ is an open 1-dimensional set.
2. The support of the distribution {x: $f_\theta(x)>0$} does not depend on θ.
3. The derivative $\frac{df_\theta}{d\theta}$ exists.

we can define **Fisher information (Information)** for sample $X_1, X_2, \ldots, X_n$:

$$I_n(\theta) = E_\theta\left(\tfrac{d}{d\theta}\ln f_\theta(X_1, X_2, \ldots, X_n)\right)^2$$

we do not assume independence of $X_1, X_2, \ldots, X_n$

Fisher information – what does it mean?

- It is a measure of how much a sample of size *n* can tell us about the value of the unknown parameter θ (on average).
- If the density around θ is flat, then information from a single observation or a small sample will not allow to differentiate among possible values of θ. If the density around θ is steep, the sample contributes a lot of info leading to θ identification.

Fisher Information – cont.

Some formulae:

- if the distribution is continuous

$$I_n(\theta) = \int_{\mathfrak{X}} \left(\frac{\frac{df_\theta(x)}{d\theta}}{f_\theta(x)} \right)^2 f_\theta(x)dx$$

- if the distribution is discrete

$$I_n(\theta) = \sum_{x \in \mathfrak{X}} \left(\frac{\frac{dP_\theta(x)}{d\theta}}{P_\theta(x)} \right)^2 P_\theta(x)$$

- if f_θ is twice differentiable

$$I_n(\theta) = -E_\theta\left(\frac{d^2}{d\theta^2} \ln f_\theta(X_1, X_2, \ldots, X_n) \right)$$

Fisher information – cont. (2)

- If the sample consists of independent random variables from the same distribution, then

$$I_n(\theta) = nI_1(\theta)$$

where $I_1(\theta)$ is Fisher information for a single observation

Fisher Information – examples

- Exponential distribution exp(λ)

$$I_1(\lambda) = \ldots = \frac{1}{\lambda^2}$$

- Poisson distribution Poiss(θ)

$$I_1(\theta) = \ldots = \frac{1}{\theta}$$

Information Inequality (Cramér-Rao)

Let $X=(X_1, X_2, \ldots, X_n)$ be observations from a joint distribution with density $f_\theta(x)$, where $\theta \in \Theta \subseteq \mathbb{R}$. If:

- $T(X)$ is a statistic with a finite expected value, and $E_\theta T(X)=g(\theta)$
- Fisher information is well defined, $I_n(\theta) \in (0,\infty)$
- All densities f_θ have the same support
- The order of differentiating ($d/d\theta$) and integrating $\int \ldots dx$ may be reversed.

Then, for any θ:

$$\mathrm{Var}_\theta T(X) \geq \frac{(g'(\theta))^2}{I_n(\theta)}$$

Information inequality – implications

- The MSE of an unbiased estimator (= the variance) cannot be lower than a given function of n and θ.
- If the MSE of an estimator is equal to the lower bound of the information inequality, then the estimator is MVUE.
- If $\hat{\theta}(X)$ is an unbiased estimator of θ, then

$$\mathrm{Var}_{\theta}\hat{\theta}(X) \geq \frac{1}{I_n(\theta)}$$

Information inequality – examples

$Var_\theta(\overline{X}) = \frac{\theta}{n}$

- In the Poisson model, $\hat{\theta} = \overline{X}$ is MVUE(θ)
- In the exponential model, $\overline{X}$ is MVUE(1/λ)

$Var_\lambda(\overline{X}) = \frac{1}{n\lambda^2}$

- The Cramér-Rao inequality is not always optimal. In the exponential model, $\hat{\lambda} = 1/\overline{X}$ is a biased estimator of λ.

$$\tilde{\lambda} = \frac{n-1}{n\overline{X}}$$

  is an unbiased estimator, which is also MVUE(λ), although its variance is *higher* than the bound in the Cramér-Rao inequality.

Efficiency

The efficiency of an unbiased estimator $\hat{g}(X)$ of $g(\theta)$ is:

$$\mathrm{ef}(\hat{g}) = \frac{\left(g'(\theta)\right)^2}{\mathrm{Var}_\theta(\hat{g}) \cdot I_n(\theta)}$$

Relative efficiency of unbiased estimators $\hat{g}_1(X)$ and $\hat{g}_2(X)$:

$$\mathrm{ef}(\hat{g}_1, \hat{g}_2) = \frac{\mathrm{Var}_\theta(\hat{g}_2)}{\mathrm{Var}_\theta(\hat{g}_1)} = \frac{\mathrm{ef}(\hat{g}_1)}{\mathrm{ef}(\hat{g}_2)}$$

Efficiency and the information inequality

- If the information inequality holds, then for any unbiased estimator
$$\mathrm{ef}(\hat{g}) \leq 1$$
- If $\hat{g}$ = MVUE(g), then it is possible that $\mathrm{ef}(\hat{g}) = 1$, but it is also possible that
$$\mathrm{ef}(\hat{g}) < 1$$
- If $\mathrm{ef}(\hat{g}) = 1$, then the estimator is **efficient**.

Efficiency – examples

- In the Poisson model, $\hat{\theta} = \overline{X}$ is efficient.
- In the exponential model, $\overline{X}$ is an efficient estimator of $1/\lambda$.
- In the exponential model, $\hat{\lambda} = \frac{n-1}{n\overline{X}}$

is not an efficient estimator of λ, although it is MVUE(λ).

- In a uniform model U(0, θ), for the MLE(θ) we get ef >1 (that is because the assumptions of the information inequality are not fulfilled)

Asymptotic poperties of estimators

- Limit theorems describing estimator properties when $n \to \infty$
- In practice: information on how the estimators behave for large samples, *approximately*
- Problem: usually, there is no answer to the question what sample is large enough (for the approximation to be valid)

Consistency

Let X_1, X_2, ..., X_n ,... be an IID sample (of independent random variables from the same distribution) . Let $\hat{g}(X_1, X_2, ..., X_n)$ be a sequence of estimators of the value $g(\theta)$.

$\hat{g}$ is a **consistent** estimator, if for all $\theta \in \Theta$, for any $\varepsilon > 0$:

$$\lim_{n \to \infty} P_\theta(|\hat{g}(X_1, X_2, ..., X_n) - g(\theta)| \leq \varepsilon) = 1$$

(i.e. $\hat{g}$ converges to $g(\theta)$ in probability)

Strong consistency

Let $X_1, X_2, \ldots, X_n, \ldots$ be an IID sample (of independent random variables from the same distribution). Let $\hat{g}(X_1, X_2, \ldots, X_n)$ be a sequence of estimators of the value $g(\theta)$.

$\hat{g}$ is **strong consistent**, if for any $\theta \in \Theta$:

$$P_\theta\left(\lim_{n\to\infty} \hat{g}(X_1, X_2, \ldots, X_n) = g(\theta)\right) = 1$$

(i.e. $\hat{g}$ converges to $g(\theta)$ almost surely)

Consistency – note

From the Glivenko-Cantelli theorem it follows that empirical CDFs converge almost surely to the theoretical CDF. Therefore, we should expect (strong) consistency from all sensible estimators.

Consistency = minimal requirement for a sensible estimator.

Consistency – how to verify?

- From the definition: for example with the use of a version of the Chebyshev inequality:

$$P(|\hat{g}(X)-g(\theta)|\geq\varepsilon)\leq\frac{E(\hat{g}(X)-g(\theta))^2}{\varepsilon^2}$$

Given that the MSE of an estimator is

$$MSE(\theta,\hat{g})=E_{\theta}(\hat{g}(X)-g(\theta))^2$$

we get a sufficient condition for consistency:

$$\lim_{n\to\infty} MSE(\theta,\hat{g})=0$$

- From the LLN

Consistency – examples

- For any family of distributions with an expected value: the sample mean $\overline{X}_n$ is a consistent estimator of the expected value $\mu(\theta)=E_\theta(X_1)$. Convergence from the SLLN.
- For distributions having a variance:

  $S_n^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X})^2$ and $\hat{S}_n^2 = \frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2$

  are consistent estimators of the variance $\sigma^2(\theta)=\mathrm{Var}_\theta(X_1)$. Convergence from the SLLN.

Consistency – examples/properties

- An estimator may be unbiased but unconsistent; eg. $T_n(X_1, X_2, \ldots, X_n) = X_1$ as an estimator of $\mu(\theta) = E_\theta(X_1)$.

- An estimator may be biased but consistent; eg. the biased estimator of the variance or any unbiased consistent estimator + 1/n.