

Kleine toevoeging aan Statistical Inference

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1 The Cramér-Rao Inequality

Stelling 1 (Cramér-Rao Inequality). *Zij $\mathbf{g} : \mathbb{R}^d \rightarrow \mathbb{R}^m$ voldoende braaf in $\boldsymbol{\theta}$ en zij \mathbf{T} een schatter voor $\mathbf{g}(\boldsymbol{\theta})$. Noteer met Φ de totale afgeleide van $E\mathbf{T}$ naar $\boldsymbol{\theta}$ in $\boldsymbol{\theta}$:*

$$\Phi_{ij} = \frac{\partial ET_i}{\partial \theta_j}(\boldsymbol{\theta}). \quad (1)$$

Zij $I_n(\boldsymbol{\theta})$ positief-definiet. Dan is

$$\mathcal{V}(\mathbf{T}) - \Phi I_n^{-1} \Phi^T \quad (2)$$

positief-definiet.

Bewijs. We tonen aan dat $\Phi = E(\mathbf{T}\mathbf{S}_n^T)$:

$$\begin{aligned} \Phi_{ij} &= \frac{\partial}{\partial \theta_j} ET_i = \frac{\partial}{\partial \theta_j} \int_{\mathbb{R}} T_i(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}, \boldsymbol{\theta}) d\mathbf{x} \\ &= \int_{\mathbb{R}} T_i(\mathbf{x}) \frac{\partial}{\partial \theta_j} f_{\mathbf{X}}(\mathbf{x}, \boldsymbol{\theta}) d\mathbf{x} = \int_{\mathbb{R}} T_i(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}, \boldsymbol{\theta}) \frac{\partial}{\partial \theta_j} \ln(f_{\mathbf{X}}(\mathbf{x}, \boldsymbol{\theta})) d\mathbf{x} \\ &= E\left(T_i(\mathbf{x}) \frac{\partial}{\partial \theta_j} \ln(f_{\mathbf{X}}(\mathbf{x}, \boldsymbol{\theta}))\right) = E(T_i(\mathbf{x}) S_{nj}(\mathbf{x}, \boldsymbol{\theta})) = E(\mathbf{T}\mathbf{S}_n^T)_{ij}. \end{aligned} \quad (3)$$

Definieer $\mathbf{Y} := \mathbf{T} - \Phi I_n^{-1} \mathbf{S}_n \in \mathbb{R}^m$. Merk op dat $E\mathbf{S}_n = \mathbf{0}$, zodat $E\mathbf{Y} = E\mathbf{T}$. We berekenen de variantiematrix $\mathcal{V}(\mathbf{Y})$ van \mathbf{Y} :

$$\begin{aligned} \mathcal{V}(\mathbf{Y}) &= E[(\mathbf{Y} - E\mathbf{Y})(\mathbf{Y} - E\mathbf{Y})^T] = E[(\mathbf{Y} - E\mathbf{T})(\mathbf{Y} - E\mathbf{T})^T] \\ &= E\left[\left((\mathbf{T} - E\mathbf{T}) - \Phi I_n^{-1} \mathbf{S}_n\right) \left((\mathbf{T} - E\mathbf{T}) - \Phi I_n^{-1} \mathbf{S}_n\right)^T\right] \\ &= \mathcal{V}(\mathbf{T}) + \Phi I_n^{-1} E(\mathbf{S}_n \mathbf{S}_n^T) I_n^{-1} \Phi^T - M - M^T \\ &= \mathcal{V}(\mathbf{T}) + \Phi I_n^{-1} \Phi^T - M - M^T, \end{aligned} \quad (4)$$

waarbij we een vervelende term M hebben genoemd. We berekenen nu M , door eerst gebruik te maken van het feit dat $E\mathbf{S}_n = \mathbf{0}$ en daarna van (3):

$$M = \Phi I_n^{-1} E(\mathbf{S}_n(\mathbf{T} - E\mathbf{T})^T) = \Phi I_n^{-1} E(\mathbf{S}_n \mathbf{T}^T) = \Phi I_n^{-1} \Phi^T. \quad (5)$$

We vinden dus dat

$$\mathcal{V}(\mathbf{Y}) = \mathcal{V}(\mathbf{T}) - \Phi I_n^{-1} \Phi^T, \quad (6)$$

en omdat deze matrix een variantiematrix is, is hij positief semi-definiet. \square

Gevolg 2 (Stelling zoals in de cursus). *Als $m = d$, $\mathbf{g} = Id$ en \mathbf{T} een onvertekende schatter is voor $\boldsymbol{\theta}$, dan is*

$$\mathcal{V}(\mathbf{T}) - I_n^{-1} \quad (7)$$

positief-definiet.

Bewijs. In dit geval is

$$\Phi_{ij} = \frac{\partial \mathbf{E}T_i}{\partial \theta_j} = \frac{\partial \theta_i}{\partial \theta_j} = \delta_{ij}, \quad (8)$$

zodat $\Phi = I$ (de eenheidsmatrix). □

Gevolg 3 (Eén van de opmerkingen). *Als $m = d = 1$ en $g = Id$, dan is*

$$\text{Var}_\theta T \geq \frac{(1 + b'(\theta))^2}{I_n(\theta)}. \quad (9)$$

Bewijs. In dit geval is

$$\Phi = \frac{\partial \mathbf{E}T}{\partial \theta} = \frac{\partial}{\partial \theta}(\theta + b(\theta)) = 1 + b'(\theta). \quad (10)$$

□

Gevolg 4 (Een andere opmerking). *Noteer met Δ de totale afgeleide van \mathbf{g} . Als \mathbf{T} een onvertende schatter is voor $\mathbf{g}(\boldsymbol{\theta})$, dan is*

$$\mathcal{V}(\mathbf{T}) - \Delta I_n^{-1} \Delta^T \quad (11)$$

positief-definiet.

Bewijs. $\Phi = \Delta$. □

2 Theorem of Rao-Blackwell

I don't know how to translate "sufficient" so the rest is in English:

Stelling 5. • *Let $\mathbf{X} = (X_1, \dots, X_n)$ be a sample of X with a distribution $f_{\mathbf{X}}(\mathbf{x}, \theta)$.*

- *Let $T(\mathbf{X})$ be a sufficient statistic for θ .*
 - *Let $U(\mathbf{X})$ be an unbiased estimator for θ that does not depend on \mathbf{X} solely through $T(\mathbf{X})$, i.e. U doesn't factorize as $U = \hat{U} \circ T$.*
- Define $\varphi_\theta : \mathbb{R} \rightarrow \mathbb{R} : t \mapsto E_\theta(U|T = t)$. Then it holds that:*

1. *The function φ_θ does not depend on θ , so we can just write $\varphi_\theta = \varphi$.*
2. *$\varphi(T)$ is an unbiased estimator for θ .¹*
3. *$\forall \theta \in \Theta : \text{Var}_\theta U < \infty \Rightarrow \text{Var}_\theta \varphi(T) < \text{Var}_\theta U$.*

Bewijs. 1. This follows immediately from the definition of a sufficient statistic.

2. $E_\theta \varphi(T) = E_\theta(E_\theta(U|T)) = E_\theta U = \theta$.

3. We will prove that $\text{Var}_\theta U - \text{Var}_\theta \varphi(T) > 0$.

$$\begin{aligned} \text{Var}_\theta U - \text{Var}_\theta \varphi(T) &= E_\theta(U^2) - \theta^2 - E_\theta(\varphi(T)^2) + \theta^2 && \text{because } E_\theta U = E_\theta \varphi(T) = \theta \\ &= E_\theta(U^2 - \varphi(T)^2) = E_\theta(U^2 - E_\theta(U|T)^2) \\ &= E_\theta(E_\theta[U^2 - E_\theta(U|T)^2 | T]) && \text{because } EA = E(E(A|B)) \\ &= E_\theta(E_\theta(U^2|T) - E_\theta(U|T)^2) \\ &\quad \text{because } E_\theta(U|T) \text{ is constant if } T \text{ is known} \\ &= E_\theta(\text{Var}_\theta(U|T)) \geq 0. \end{aligned}$$

Assume that $E_\theta(\text{Var}_\theta(U|T)) = 0$. Then $\text{Var}_\theta(U|T) = 0$ almost surely, and hence $U = E_\theta(U|T)$ almost surely if T is given. But then U only depends on \mathbf{X} through T and this is in contradiction with the assumptions. Hence, $\text{Var}_\theta \varphi(T) < \text{Var}_\theta U$. □

¹Begin NOOIT een zin met een symbool :)