PH 712 Probability and Statistical Inference

Part VIII: Point Estimation II (Aympototic Properties)

Zhiyang Zhou (zhou67@uwm.edu, zhiyanggeezhou.github.io)

Consistency of MM and ML estimators

- For an iid sample, under certain conditions:
 - $-\hat{\theta}_{\mathrm{MM}} \approx \theta \text{ as } n \to \infty$
 - $-\hat{\theta}_{\mathrm{ML}} \approx \theta \text{ as } n \to \infty$

Asymptotic efficiency of MLE (CB Thm 10.1.12 & Ex. 10.7)

- For an iid sample, under certain conditions:
 - $-\sqrt{n}(\hat{\theta}_{\mathrm{ML}} \theta) \approx \mathcal{N}(0, I_1^{-1}(\theta)) \text{ as } n \to \infty$
 - * For an iid sample, $I_1(\theta) = n^{-1}I_n(\theta)$, no longer a function of n
 - · In practice, unknown $\theta \Rightarrow$ unknown $I_n(\theta)$
 - * $I_n(\theta) \approx I_n(\hat{\theta}_{\mathrm{ML}}) \approx \hat{I}_n(\hat{\theta}_{\mathrm{ML}})$
 - · Fisher information (evaluated at θ) $I_n(\theta) = -\mathbb{E}\{H(\theta)\}$
 - · Observed Fisher information $\hat{I}_n(\hat{\theta}_{\mathrm{ML}}) = -H(\hat{\theta}_{\mathrm{ML}})$
 - Application (approximating the distribution of $\hat{\theta}_{\mathrm{ML}}$): $\hat{\theta}_{\mathrm{ML}} \approx \mathcal{N}(\theta, \hat{I}_{n}^{-1}(\hat{\theta}_{\mathrm{ML}}))$, i.e., approximately, $\hat{\theta}_{\mathrm{ML}}$ is normally distributed with mean θ and variance $\hat{I}_{n}^{-1}(\hat{\theta}_{\mathrm{ML}})$.

Delta method

- Approximating the distribution of $h(T_n)$ when T_n is normally distributed as $n \to \infty$
- (CB Thm 5.5.24, delta method) Suppose T_n is an estimator of θ . If $\sqrt{n}(T_n \theta) \approx \mathcal{N}(0, \sigma^2)$, h is NOT a function of n, AND $h'(\theta) \neq 0$, then

$$\sqrt{n}\{h(T_n) - h(\theta)\} \approx \mathcal{N}(0, \{h'(\theta)\}^2 \sigma^2).$$

- $-\Rightarrow \mathrm{E}\{h(T_n)\}\approx h(\theta) \text{ AND } \mathrm{var}\{h(T_n)\}\approx \{h'(T_n)\}^2\sigma^2/n \text{ if } h'(\theta)\neq 0.$
- (CB Thm 5.5.26, second-order delta method) Suppose T_n is an estimator of θ . If $\sqrt{n}(T_n \theta) \approx \mathcal{N}(0, \sigma^2)$, h is NOT a function of n, $h'(\theta) = 0$, AND $h''(\theta) \neq 0$, then

$$\frac{2n\{h(T_n) - h(\theta)\}}{h''(\theta)\sigma^2} \approx \chi^2(1).$$

 $-\Rightarrow \mathbb{E}\{h(T_n)\}\approx h(\theta)+h''(\theta)\sigma^2/(2n) \text{ AND } \operatorname{var}\{h(T_n)\}\approx \{h''(T_n)\}^2\sigma^4/(2n^2) \text{ if } h'(\theta)=0 \text{ but } h''(\theta)\neq 0.$

CB Example 10.1.17 & Ex. 10.9

• $X_1, \ldots, X_n \stackrel{\text{iid}}{\sim} p(x \mid \lambda) = \lambda^x \exp(-\lambda)/x!, x \in \mathbb{Z}^+ \cup \{0\}, \lambda > 0$. To estimate $h(\lambda) = \Pr(X_i = 0)$.

- 1. What is the MLE for $\Pr(X_i = 0)$, say W_n ? 2. Approximate the variance of W_n . 3. Suppose $T_n = n^{-1} \sum_i \mathbf{1}_{\{0\}}(X_i)$. Approximate the variance of T_n . 4. Compute $\operatorname{ARE}(T_n, W_n)$, the ARE of T_n with respect to W_n .