

Convergence of the MLE

Some more theorems about convergence

Continuous mapping theorem:

Let X_1, X_2, \dots be a sequence of random variables
Let g be a continuous function.

- ① If $X_n \xrightarrow{d} X$ then $g(X_n) \xrightarrow{d} g(X)$
- ② If $X_n \xrightarrow{P} X$ then $g(X_n) \xrightarrow{P} g(X) \leftarrow \text{HW}$
- ③ If $X_n \xrightarrow{\text{a.s.}} X$ then $g(X_n) \xrightarrow{\text{a.s.}} g(X)$

Slutsky's theorem:

Let $\{X_n\}, \{Y_n\}$ be sequences of random variables,
and suppose $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{P} c$. Then
 \uparrow constant

$$\cdot X_n + Y_n \xrightarrow{d} X + c$$

$$\cdot X_n Y_n \xrightarrow{d} Xc$$

$$\cdot \frac{X_n}{Y_n} \xrightarrow{d} \frac{X}{c}, \text{ provided } c \text{ is invertible}$$

Convergence of the MLE

Suppose that Y_1, Y_2, Y_3, \dots are iid with probability function $f(y|\theta)$, $\theta \in \mathbb{R}^d$

Let $l_n(\theta) = \sum_{i=1}^n \log f(Y_i|\theta)$, and $\hat{\theta}_n$ the MLE using first n observations. Let $\mathcal{I}_1(\theta) = -\mathbb{E}\left[\frac{\partial^2}{\partial \theta^2} \log f(Y_1|\theta)\right]$
(Fisher information for a single observation)

Theorem: Under regularity conditions,

(a) $\hat{\theta}_n \xrightarrow{P} \theta$ as $n \rightarrow \infty$ (consistency)

(b) $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} N(0, \mathcal{I}_1^{-1}(\theta))$ as $n \rightarrow \infty$
(asymptotic normality)

we will prove (b) when $d=1$

Proof sketch of (b): (when $d=1$)

$$\textcircled{1} \quad \sqrt{n} (\hat{\theta}_n - \theta) \approx \frac{\frac{1}{\sqrt{n}} l'_n(\theta)}{-\frac{1}{n} l''_n(\theta)} \quad (\text{Taylor expansion})$$

$$\textcircled{2} \quad \frac{1}{n} l''_n(\theta) \xrightarrow{P} -\mathcal{I}_1(\theta)$$

$$\textcircled{3} \quad \frac{1}{\sqrt{n}} l'_n(\theta) \xrightarrow{d} N(0, \mathcal{I}_1(\theta))$$

$$\textcircled{4} \quad \text{Apply Slutsky's: } \sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} \frac{1}{\mathcal{I}_1(\theta)} N(0, \mathcal{I}_1(\theta)) \\ = N(0, \mathcal{I}_1^{-1}(\theta))$$

$$X \sim N(\mu, \sigma^2) \Rightarrow aX \sim N(a\mu, a^2\sigma^2) \\ a = \frac{1}{\mathcal{I}_1(\theta)} \quad \sigma^2 = \mathcal{I}_1(\theta) \quad a^2\sigma^2 = \frac{1}{\mathcal{I}_1(\theta)}$$

Intermediate steps

Using results we have previously derived, argue that:

$$\begin{aligned} \textcircled{2} \quad & + \quad \frac{1}{n} \ell''(\theta | \mathbf{Y}) \xrightarrow{p} -\mathcal{I}_1(\theta) & \frac{1}{n} \ell''(\theta) \xrightarrow{p} -\mathcal{I}_1(\theta) \\ \textcircled{3} \quad & + \quad \frac{1}{\sqrt{n}} \ell'(\theta | \mathbf{Y}) \xrightarrow{d} N(0, \mathcal{I}_1(\theta)) & \frac{1}{\sqrt{n}} \ell'(\theta) \xrightarrow{d} N(0, \mathcal{I}_1(\theta)) \end{aligned}$$

Pf of ② : $\ell_n''(\theta) = \sum_{i=1}^n \frac{\partial^2}{\partial \theta^2} \log f(\gamma_i | \theta)$

$$\underbrace{\frac{1}{n} \ell_n''(\theta)}_{\frac{\partial^2}{\partial \theta^2} \log f(\gamma | \theta)} \xrightarrow{p} \mathbb{E} \left[\frac{\partial^2}{\partial \theta^2} \log f(\gamma_i | \theta) \right] \quad \text{by WLLN}$$
$$= -\mathcal{I}_1(\theta) \quad //$$

Pf of ③ : $\ell_n'(\theta) = \sum_{i=1}^n \frac{\partial}{\partial \theta} \log f(\gamma_i | \theta)$

By CLT, $\sqrt{n} \left(\frac{1}{n} \ell_n'(\theta) - \mathbb{E} \left[\frac{\partial}{\partial \theta} \log f(\gamma_i | \theta) \right] \right) \xrightarrow{d} N(0, \text{var} \left(\frac{\partial}{\partial \theta} \log f(\gamma_i | \theta) \right))$

$$\mathbb{E} \left[\frac{\partial}{\partial \theta} \log f(\gamma_i | \theta) \right] = 0$$

$$\text{var} \left(\frac{\partial}{\partial \theta} \log f(\gamma_i | \theta) \right) = \mathcal{I}_1(\theta)$$

$$\Rightarrow \sqrt{n} \left(\frac{1}{n} \ell_n'(\theta) - 0 \right) \xrightarrow{d} N(0, \mathcal{I}_1(\theta))$$

$$\Rightarrow \frac{1}{\sqrt{n}} \ell_n'(\theta) \xrightarrow{d} N(0, \mathcal{I}_1(\theta))$$

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Full proof :

① If $\hat{\theta}_n$ is MLE, then $l_n'(\hat{\theta}_n) = 0$

If $\hat{\theta}_n \approx \theta$ (which holds because $\hat{\theta}_n \xrightarrow{P} \theta$), then

$$0 = l_n'(\hat{\theta}_n) \approx l_n'(\theta) + (\hat{\theta}_n - \theta) l_n''(\theta)$$

$$\Rightarrow \hat{\theta}_n - \theta \approx \frac{l_n'(\theta)}{-l_n''(\theta)}$$

$$\Rightarrow \sqrt{n}(\hat{\theta}_n - \theta) \approx \frac{\sqrt{n}(l_n'(\theta))}{-l_n''(\theta)}$$

$$= \frac{\frac{1}{\sqrt{n}} l_n'(\theta)}{-\frac{1}{n} l_n''(\theta)} \xrightarrow{d} N(0, \mathcal{I}_1^{-1}(\theta))$$

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Regularity conditions