

Lecture 16: Asymptotic normality of the MLE

Convergence of the MLE

Suppose that $\gamma_1, \gamma_2, \gamma_3, \dots$ are iid with probability function $f(y_i | \theta)$, $\theta \in \mathbb{R}^d$

Let $\ln(\theta) = \sum_{i=1}^n \log f(\gamma_i | \theta)$, and $\hat{\theta}_n$ be the MLE of θ using first n observations. Let

$$\mathcal{I}_1(\theta) = -\mathbb{E}\left[\frac{\partial^2}{\partial \theta^2} \log f(\gamma_i | \theta)\right]$$

Theorem : Under regularity conditions,

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

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

(asymptotic normality)

Intermediate steps

Using the WLLN and the CLT, argue that:

$$l_n(\theta) = \sum_{i=1}^n \log f(y_i | \theta)$$

CLT: $\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \xrightarrow{d} N(0, 1)$

② • $\frac{1}{n} l_n''(\theta) \xrightarrow{P} -I_1(\theta)$ ✓ (last time)

③ • $\frac{1}{\sqrt{n}} l_n'(\theta) \xrightarrow{d} N(0, I_1(\theta))$

pf ③: $l_n'(\theta) = \sum_{i=1}^n \frac{\partial}{\partial \theta} \log f(y_i | \theta)$ (CLT)

$$\sqrt{n} \left(\frac{1}{n} l_n'(\theta) - \underbrace{\mathbb{E} \left[\frac{\partial}{\partial \theta} \log f(y_i | \theta) \right]}_0 \right) \xrightarrow{d} N(0, \text{Var} \left(\frac{\partial}{\partial \theta} \log f(y_i | \theta) \right))$$

○ (under regularity conditions)

$$\sqrt{n} \cdot \frac{1}{n} l_n'(\theta) \xrightarrow{d} N(0, I_1(\theta))$$

$$\frac{1}{\sqrt{n}} l_n'(\theta) \xrightarrow{d} N(0, I_1(\theta)) \quad //$$

$$\begin{aligned} I_1(\theta) \\ = -\mathbb{E} \left[\frac{\partial^2}{\partial \theta^2} \log f(y_i | \theta) \right] \\ \text{(under regularity conditions)} \end{aligned}$$

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \quad \text{Var}(X_i) = \sigma^2$$

$$\text{Var}(\bar{X}_n) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{\sigma^2}{n}$$

$$\rightarrow 0 \quad \text{as } n \rightarrow \infty$$

(\Rightarrow convergence in probability)

$$\frac{\bar{X}_n - \mu}{\sigma} \xrightarrow{P} 0$$

$$\text{Var}(\sqrt{n} \bar{X}_n) = (\sqrt{n})^2 \text{Var}(\bar{X}_n) = n \cdot \frac{\sigma^2}{n} = \sigma^2$$

$$\sqrt{n} \frac{(\bar{X}_n - \mu)}{\sigma} \xrightarrow{d} N(0, 1)$$

$$\mathbb{E}[\dots] = 0$$

$$\text{Var}(\dots) = 1$$

Putting everything together

Full proof :

① If $\hat{\theta}_n$ is the MLE $\Rightarrow \ell_n(\hat{\theta}_n) = 0$
Also know that $\hat{\theta}_n \xrightarrow{P} \theta$ (by part (c) of the Theorem)
 \Rightarrow for large n , $\hat{\theta}_n \approx \theta$

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

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

$$\Rightarrow \sqrt{n}(\hat{\theta}_n - \theta) \approx \frac{\sqrt{n}\ell_n'(\theta)}{-\ell_n''(\theta)} = \frac{\frac{1}{\sqrt{n}}\ell_n'(\theta)}{-\frac{1}{n}\ell_n''(\theta)}$$

$$\frac{1}{\sqrt{n}}\ell_n'(\theta) \xrightarrow{D} N(0, I_1(\theta))$$

$$-\frac{1}{n}\ell_n''(\theta) \xrightarrow{P} I_1(\theta)$$

(Slutsky's)

$$\Rightarrow \frac{\frac{1}{\sqrt{n}}\ell_n'(\theta)}{-\frac{1}{n}\ell_n''(\theta)} \xrightarrow{D} \frac{1}{I_1(\theta)} N(0, I_1(\theta)) = N(0, I_1^{-1}(\theta))$$

Regularity conditions

Some sufficient regularity conditions:

- The dimension of Θ does not change with n
- $f(y|\theta)$ is a sufficiently smooth function of θ
- we can swap integration and differentiation
- θ is not on the boundary of the parameter space
- θ is identifiable (basically, $f(y|\theta_1) \neq f(y|\theta_2)$ if $\theta_1 \neq \theta_2$)

e.g., for Bernoulli(θ)

θ cannot be 0 or 1

for $N(\mu, \sigma^2)$

σ^2 cannot be 0, etc.

Counterexample : $X_1, X_2, X_3, \dots \stackrel{iid}{\sim} \text{Uniform}(0, \theta)$

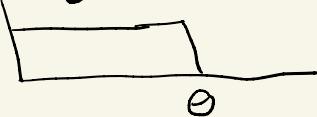
$$\hat{\theta}_n = X_{(n)} \quad \hat{\theta}_n \xrightarrow{P} \theta$$

(previous
class
activity)

$$n(\hat{\theta}_n - \theta) \xrightarrow{d} -\text{Exponential}\left(\frac{1}{\theta}\right)$$

$$\begin{aligned} n\hat{\theta}_n - n\theta &= \underbrace{\frac{1}{\sqrt{n}}}_{\rightarrow 0} \cdot \underbrace{n(\hat{\theta}_n - \theta)}_{\xrightarrow{d} -\text{Exp}\left(\frac{1}{\theta}\right)} & \xrightarrow{P} 0 & (\text{Slutsky's}) \\ & \xrightarrow{d} -\text{Exp}\left(\frac{1}{\theta}\right) & \text{not to} \\ & & \text{a Normal} \end{aligned}$$

Regularity conditions violated:

- θ is on the boundary, so $f(x|\theta)$ is not smooth at θ

 \Rightarrow derivatives are not defined at θ
 $\Rightarrow L(\theta)$ is not even defined

- can't exchange integration $\{$ differentiation
(domain of integration depends on θ)

Counterexample $X_1, X_2, X_3, \dots \stackrel{\text{iid}}{\sim} \text{Bernoulli}(p)$

$$p = 0 \quad \text{or} \quad p = 1$$



$$\hat{p} = \bar{X} \equiv 0$$

$$\hat{p} = \bar{X} \equiv 1$$

$$\sqrt{n}(\bar{X} - p) = 0$$

$$\sqrt{n}(\bar{X} - p) = 0$$

$\xrightarrow{\partial}$ Normal

$\xrightarrow{\partial}$ Normal

regularity condition violated: p is on the boundary of parameter space

More generally: can't converge in dist. if $\text{Var}(\hat{\theta}_n) \equiv 0$

