

> 확률변수 X_i 들이 이항분포를 따른다고 가정하자.

즉, $X \sim B(n, p)$ 일 때,

최대우도 추정법을 사용하여 최대우도추정량 \hat{p} 을 구하시오.

$$X = \{X_1, X_2, \dots, X_m\}$$

$$X \sim B(n, p)$$

$$\text{pdf: } f_X(x_i; p) = \binom{n}{x_i} p^{x_i} (1-p)^{n-x_i}$$

$$\text{Likelihood: } L = \prod_{i=1}^m f(x_i; p) = \prod_{i=1}^m \frac{n!}{x_i! (n-x_i)!} p^{x_i} (1-p)^{n-x_i}$$

$$\log L = \sum_{i=1}^m \log \frac{n!}{x_i! (n-x_i)!} + \sum_{i=1}^m x_i \log p + \sum_{i=1}^m (n-x_i) \times \log \{1-p\}$$

$$\begin{aligned} \frac{d}{dp} \log L &= \frac{1}{p} \sum_{i=1}^m x_i + \frac{1}{1-p} \times (-1) \times \sum_{i=1}^m (n-x_i) = 0 \\ &= \frac{\sum_{i=1}^m x_i}{p} + \frac{1}{p-1} (mn - \sum_{i=1}^m x_i) = 0 \end{aligned}$$

$$\begin{aligned} (p-1) \sum_{i=1}^m x_i &= -p (mn - \sum_{i=1}^m x_i) \\ p \sum_{i=1}^m x_i - \sum_{i=1}^m x_i &= -mnp + p \sum_{i=1}^m x_i \end{aligned}$$

$$\hat{p} = \frac{\sum_{i=1}^m x_i}{mn}$$

$$\begin{aligned} \hat{p} &= \frac{\sum_{i=1}^m x_i}{m} \times \frac{1}{n} \\ &= \bar{x} \times \frac{1}{n} \end{aligned}$$

$$\therefore \hat{p} = \frac{\bar{x}}{n}$$

➤ 확률변수 X_i 들이 정규분포를 따른다고 가정하자.

즉, $X \sim N(\mu, \sigma^2)$ 일 때,

최대우도 추정법을 사용하여 최대우도추정량 $\hat{\mu}$ 와 σ^2 을 구하시오.

$$X: \{X_1, \dots, X_n\}$$

$$X \sim N(\mu, \sigma^2)$$

$$f(x_i; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$\begin{aligned} \text{Likelihood} &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\ &= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}} \end{aligned}$$

$$\log L = n \log\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}$$

$\langle \mu \rangle$

$$\begin{aligned} \frac{d}{d\mu} \log L &= -\frac{d}{d\mu} \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2} \\ &= -\frac{1}{2\sigma^2} \times \sum_{i=1}^n \frac{d}{d\mu} (x_i^2 - 2\mu x_i + \mu^2) = 0 \end{aligned}$$

$$= -\frac{1}{2\sigma^2} \times \sum_{i=1}^n (-2x_i + 2\mu) = 0$$

$$= 2n\mu = \sum_{i=1}^n 2x_i = 0$$

$$\therefore \hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$$

$\langle \sigma^2 \rangle \quad v = \sigma^2$

$$\log L = n \log \frac{1}{\sigma} + n \log \frac{1}{\sqrt{2\pi}} - \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}$$

$$\frac{d}{d\sigma^2} \log L = \frac{d}{d\sigma^2} n \log \frac{1}{\sigma} - \frac{d}{d\sigma^2} \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2} = 0$$

$$= \frac{d}{dv} n \log \frac{1}{\sqrt{v}} - \frac{d}{dv} \sum_{i=1}^n \frac{(x_i - \mu)^2}{2v} = 0$$

$$= -\frac{1}{2v} n - \frac{d}{dv} \times \frac{1}{v} \sum_{i=1}^n (x_i - \mu)^2 \times \frac{1}{2} = 0$$

$$\frac{1}{2v} n = \frac{1}{v^2} \times \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^2$$

$$nv = \sum_{i=1}^n (x_i - \mu)^2$$

$$v = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

$$\therefore \sigma^2 = \frac{\sum_{i=1}^n (x_i - \mu)^2}{n}$$