

2022 SUMMER

# 업데이터 통계학 스터디

Chapter 8 – Point Estimation 2

**Sufficiency**

# Sufficiency

$$Y_1 \cdots Y_n \xrightarrow{\text{reduction}} S = \sum Y_i$$

Ex.  $Y_1, \dots, Y_n$ : iid Bernoulli( $p$ )

Inference about  $p$  uses count of successes  $S = \sum_1^n Y_i$   $\sim \text{Bin}(n, p)$

Do we lose information about  $p$  in going from  $n$  observations to 1 sum?

# Sufficiency

Ex.  $Y_1, \dots, Y_n: iid \text{Unif}(0, \theta)$ , Good estimator based on  $W = Y_{(n)}$

Does  $W$  contain all information about  $\theta$  available from data?

Data reduction:  $Y_1, \dots, Y_n \rightarrow S = \sum_{i=1}^n Y_i$  or  $W = Y_{(n)}$

Idea: A sufficient statistic compresses data without losing information about the parameter.

# Sufficient Statistics

## Definition (SS)

$Y_1, \dots, Y_n$ : random sample from a distribution with unknown  $\theta$ .

A statistic  $U = U(Y_1, \dots, Y_n)$  is a sufficient statistic if conditional distribution of  $Y_1, \dots, Y_n$  given  $U$  does not depend on  $\theta$ .

$Y_1 \dots Y_n | U$

Meaning: if you already know  $U = U(Y_1, \dots, Y_n)$  any other statistic does not have any extra information about  $\theta$ .

# Example 8.1

$Y_1, \dots, Y_n$ : iid Bernoulli( $p$ )

Let  $\widehat{S} = \sum_{i=1}^n Y_i \sim \text{Bin}(n, p)$ . Find a distribution of  $Y_1, \dots, Y_n | S$ ?

$$P(Y_1 = y_1, \dots, Y_n = y_n | S = s)$$

$$= \frac{P(Y_1 = y_1, \dots, Y_n = y_n \cap S = s)}{P(S = s)}$$

$$= \left( \frac{P(Y_1 = y_1, \dots, Y_n = y_n)}{P(S = s)} \right) \quad \left( \sum y_i = s \right)$$

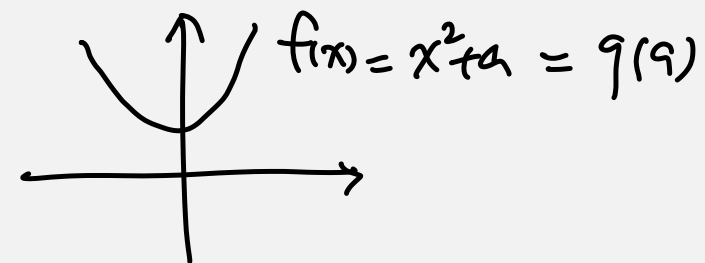
o.w

o

pn! or 2x

(  $\sum y_i = s$  )

# Likelihood Function



## Definition

$y_1, \dots, y_n$ : sample observations taken on corresponding random variables  $Y_1, \dots, Y_n$  whose distributions depend on  $\theta$ . The likelihood function of the sample is *iid*

$$L(\theta|y_1, \dots, y_n) = f(y_1|\theta) \times \dots \times f(y_n|\theta) \stackrel{\text{iid}}{=} (f(y|\theta))^n$$

(Likelihood) = joint probability/density function of  $(Y_1, \dots, Y_n)$

*(Handwritten notes: A red bracket is next to the word "Likelihood". A circle contains the Greek letter sigma with a subscript n,  $\sum_n$ . A red line underlines the phrase "joint probability/density function of". A black circle encloses the random variables  $(Y_1, \dots, Y_n)$  in the definition.)*

## Example 8.2

$$Y_1, \dots, Y_n: \text{Exponential}(\theta) \quad \underline{Y_i \sim \text{Exp}(\theta)} \quad f_{Y_i} : \frac{1}{\theta} e^{-\frac{y_i}{\theta}}$$

$$L(\theta | y_1, \dots, y_n) = ?$$

$$= f(y_1, \dots, y_n | \theta)$$

$$= f(y_1 | \theta) \cdots f(y_n | \theta)$$

$$= \prod_{i=1}^n f(y_i | \theta)$$

$$= \prod_{i=1}^n \frac{1}{\theta} e^{-\frac{y_i}{\theta}} I_{(0, \infty)}(y_i) = \underbrace{\frac{1}{\theta^n} e^{-\frac{\sum y_i}{\theta}}}_{\text{}} \bigg/ \underbrace{\prod_{i=1}^n I_{(0, \infty)}(y_i)}_{\text{}}$$



# Factorization Theorem

## Theorem

$U = U(Y_1, \dots, Y_n)$  is a SS for  $\theta$  iff we can write the likelihood in the form as

$$\underbrace{L(\theta)}_{\theta_0} = g(\underbrace{u(y_1, \dots, y_n)}_{\text{SS}}, \underbrace{\theta}_{\theta x}) \underbrace{h(y_1, \dots, y_n)}_{\theta x} \quad \left( \begin{array}{c} \theta, \gamma \\ \rightarrow \text{SS} \text{ or } \theta x \end{array} \right)$$

# Example 8.3

$Y_1, \dots, Y_n$ : iid Exponential( $\theta$ )

Find a SS for  $\theta$

(red x)

$$L(\theta) = \frac{1}{\theta^n} e^{-\frac{\sum y_i}{\theta}} \prod_{i=1}^n I_{(0, \infty)}(y_i) \quad \left( \frac{1}{\theta^n} e^{-\frac{\sum y_i}{\theta}} \right)$$

$g(y_1, \dots, y_n | \theta)$        $h(y_1, \dots, y_n)$

By Factorization ————— ✓

$\sum y_i$  is a SS for  $\theta$ .

# Example 8.4

$Y_1, \dots, Y_n$ :  $\text{Geometric}(p)$

Find a SS for  $p$

$$f(y_i | p) = p(1-p)^{y_i-1} \quad (y_i \in \mathbb{N})$$

$$\begin{aligned} L(p) &= \frac{f(y_1 | p) \dots f(y_n | p)}{1} \\ &= p^n (1-p)^{\sum_{i=1}^n y_i - n} \prod_{i=1}^n I_{\mathbb{N}}(y_i) \\ &= \underbrace{\left(\frac{p}{1-p}\right)^n \cdot (1-p)^{\sum y_i}}_{q(\sum y_i, p)} \underbrace{\prod_{i=1}^n I_{\mathbb{N}}(y_i)}_{h(y_1, \dots, y_n)} \end{aligned}$$

$\sum y_i$  is a SS for  $p$ .

By F-T.

# Example 8.5

$Y_1, \dots, Y_n$ : Bernoulli( $p$ )

Find a SS for  $p$

$$f(y_i | p) = p^{y_i} (1-p)^{1-y_i} I_{\{0,1\}}(y_i)$$

$$L(p) = \underbrace{p^{\sum y_i} (1-p)^{n - \sum y_i}}_{\eta(\sum y_i, p)} \underbrace{\prod_{i=1}^n I_{\{0,1\}}(y_i)}_{h(y_1, \dots, y_n)}$$

$$\therefore \sum y_i \quad \text{SS}$$

# Example 8.6

$Y_1, \dots, Y_n$ : Uniform(0,  $\theta$ )

Find a SS for  $\theta$

$$f(y|\theta) = \begin{cases} \frac{1}{\theta} & (0 < y < \theta) \\ 0 & \text{o.w.} \end{cases}$$

$$= \frac{1}{\theta} I_{(0, \theta)}(y)$$

$$L(\theta) = \frac{1}{\theta^n} \prod_{i=1}^n I_{(0, \theta)}(y_i)$$

$\theta \geq y_i$

$$= \frac{1}{\theta^n} I_{(0, \theta)}(\max(y_i)) / I_{(0, \infty)}(\min(y_i))$$

$I(\max(y_i), \theta)$        $\sim$

$\max y_i$  SS

$$\left( \prod_{i=1}^n I_{(0, \theta)}(y_i) \right)$$

$$= I_{(0, \theta)}(\min(y_i)) I_{(0, \theta)}(\max(y_i))$$

$$= I_{(0, \infty)}(\min(y_i)) \cdot I_{(0, \theta)}(\max(y_i))$$

# Example 8.7

$$f(y | \alpha, \beta) = \frac{1}{\Gamma(\alpha) \beta^\alpha} y^{\alpha-1} e^{-\frac{y}{\beta}} I_{(0, \infty)}(y)$$

$Y_1, \dots, Y_n$ : iid  $\text{Gamma}(\alpha, \beta)$

$$L(\alpha, \beta) = \left\{ \frac{1}{\beta^\alpha \Gamma(\alpha)} \right\}^n \left\{ \prod y_i \right\}^{\alpha-1} e^{-\frac{\sum y_i}{\beta}} \prod I_{(0, \infty)}(y_i)$$

1)  $\alpha$  is known, Find a SS for  $\beta$

2)  $\beta$  is known, Find a SS for  $\alpha$

3)  $\alpha$  and  $\beta$  are both unknown, SS for  $(\alpha, \beta)$

$$\textcircled{1} L(\beta) = \underbrace{\frac{1}{\beta^{n\alpha}} e^{-\sum y_i / \beta}}_{g(\sum y_i, \beta)} \times \underbrace{\left\{ \frac{1}{\Gamma(\alpha)} \right\}^n (\prod y_i)^{\alpha-1} \prod I_{(0, \infty)}(y_i)}_h$$

$$\textcircled{2} \quad L(\alpha) = \underbrace{\int \frac{1}{h^\alpha \Gamma(\alpha)} \left\{ \prod_{i=1}^n (\pi y_i) \right\}^{\alpha-1}}_{g(\pi y_i, \alpha)} \cdot \underbrace{e^{-\sum y_i / \beta} \prod_{i=1}^n I_{(0, \infty)}(y_i)}_h$$

$$\textcircled{3} \quad L(\alpha, \beta) = \underbrace{\int \frac{1}{h^\alpha \Gamma(\alpha)} \left\{ \prod_{i=1}^n (\pi y_i) \right\}^{\alpha-1} e^{-\sum y_i / \beta}}_{g(\pi y_i, \sum y_i, \alpha, \beta)} \cdot \underbrace{\prod_{i=1}^n I_{(0, \infty)}(y_i)}_h$$

$(\pi y_i, \sum y_i)$  가  $(\alpha, \beta)$  은 jointly ss.

# Example 8.8

$Y_1, \dots, Y_n: N(\mu, \sigma^2)$

- 1)  $\sigma^2$  is known, Find a SS for  $\mu$
- 2)  $\mu$  is known, Find a SS for  $\sigma^2$
- 3)  $\mu$  and  $\sigma^2$  are both unknown, SS for  $(\mu, \sigma^2)$

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

$$L(\mu, \sigma^2) = \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n \cdot e^{-\frac{\sum (y_i - \mu)^2}{2\sigma^2}}$$

$$\begin{aligned} \textcircled{1} \quad L(\mu) &= \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n e^{-\frac{1}{2\sigma^2} \sum (y_i - \bar{y} + \bar{y} - \mu)^2} \\ &= e^{-\frac{1}{2\sigma^2} \underbrace{\sum (y_i - \bar{y})^2 + n(\bar{y} - \mu)^2 + 2(\bar{y} - \mu) \sum (y_i - \bar{y})}_{=0}} \times \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n e^{-\frac{1}{2\sigma^2} \sum (y_i - \bar{y})^2} \\ &= e^{-\frac{1}{2\sigma^2} \underbrace{\sum (y_i - \bar{y})^2}_n} \times \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n e^{-\frac{1}{2\sigma^2} \sum (y_i - \bar{y})^2} \end{aligned}$$



$$\textcircled{2} \quad L(\sigma^2) = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2}}{\sum \frac{\sum (y_i - \mu)^2}{n}} \times \frac{I_R(y_i)}{h}$$

$$\textcircled{3} \quad L(\mu, \sigma^2) = \left(\frac{1}{\sqrt{2\pi}}\right)^n \frac{1}{\sigma^n} e^{-\frac{1}{2\sigma^2} \sum (y_i - \bar{y})^2 - \frac{n}{2\sigma^2} (\bar{y} - \mu)^2}$$

$$= \frac{1}{\sigma^n} e^{-\frac{1}{2\sigma^2} \sum y_i^2 + \frac{1}{\sigma^2} \sum y_i \bar{y} - \frac{n\bar{y}^2}{2\sigma^2}} \times \left(\frac{1}{\sqrt{2\pi}}\right)^n I_R(y_i)$$

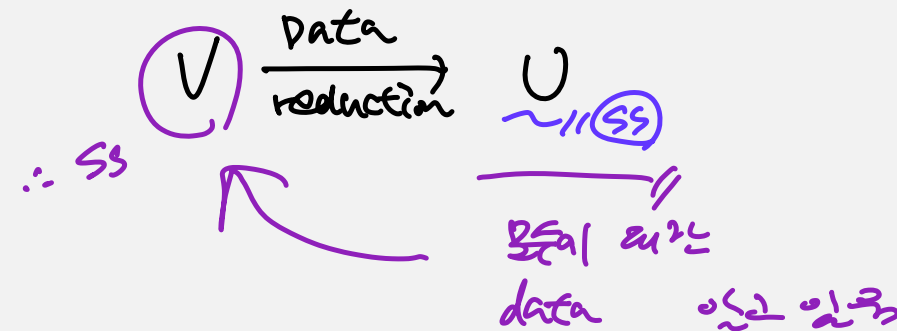
$(\sum y_i^2, \sum y_i)$       Jointly SS for  $(\mu, \sigma^2)$

$$= \frac{1}{\sigma^n} \underbrace{e^{-\frac{1}{2\sigma^2} \sum (y_i - \bar{y})^2}}_{\downarrow (\sum y_i - n\bar{y}), \bar{y}} \underbrace{e^{-\frac{n}{2\sigma^2} (\bar{y} - \mu)^2}}_{\downarrow \text{for linear SS for } \mu}$$

# Sufficient Statistics

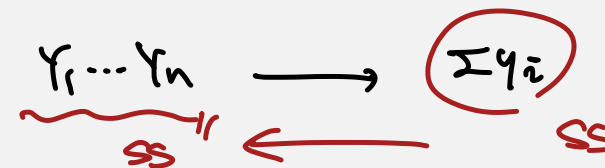
Notes:

$$L(\theta) = \frac{1}{\theta^n} e^{-\frac{\sum y_i}{\theta}} \prod_{i=1}^n I_{(0, \infty)}(y_i)$$



- Any 1-1 function of a sufficient statistic is a sufficient statistic.

Ex.  $Exp(\theta): U = \sum Y_i, V = \frac{1}{n} \sum Y_i$



- Any statistic from which a sufficient statistic is calculated is also a sufficient statistic. Ex) Random sample itself

- Many possible SS's  $\Rightarrow$  MSS (Minimal Sufficient Statistics)

MSS