

# STAT 5430

## Lecture 04, W, Jan 29

practice  
on  
point  
estimation  
(method  
of  
moments  
& likelihood  
estimation)

- Homework 1 is assigned in Canvas  
(submit/due by next Monday, Feb 3, by midnight)
- Office hours to be announced  
Mine: FM, 12-1 PM & by appointment  
TA (Min-Yi): WR 11-12 in Snedecor 2404

## Point Estimation

### Maximum Likelihood Estimation

*Definition:* Let  $f(x_1, \dots, x_n | \theta)$  be the joint pdf/pmf of  $(X_1, \dots, X_n)$ . Then,

$$L(\theta) = f(x_1, \dots, x_n | \theta), \quad \theta \in \Theta$$

data fixed      ← joint "probability"  
of data values,  
treated  
as a  
function of  $\theta$ .

[as a function of  $\theta$ , given  $(x_1, \dots, x_n)$ ] is called the likelihood function.

Note:

1. If  $X_1, \dots, X_n$  are iid with common pdf/pmf  $f(x | \theta)$ , then

$$L(\theta) = f(x_1, \dots, x_n | \theta) = \prod_{i=1}^n f(x_i | \theta)$$

joint      marginals

2. If  $X_1, \dots, X_n$  are discrete r.v.'s, then

$$L(\theta) = f(x_1, \dots, x_n | \theta) = P(X_1 = x_1, \dots, X_n = x_n | \theta)$$

*Definition:* Let  $(X_1, \dots, X_n)$  have point pdf/pmf  $f(x_1, \dots, x_n | \theta)$ ,  $\theta \in \Theta$ .

Then, for a given set of observations  $(x_1, \dots, x_n)$ , the **maximum likelihood estimate** (MLE) of  $\theta$  is a point  $\hat{\theta}$  in  $\Theta$ , say  $\hat{\theta} = h(x_1, \dots, x_n)$ , such that

$$f(x_1, \dots, x_n | \hat{\theta}) = \max_{\theta \in \Theta} f(x_1, \dots, x_n | \theta) = \max_{\theta \in \Theta} L(\theta)$$

And the maximum likelihood estimator (MLE) of  $\theta$  is defined as  $\hat{\theta} = h(X_1, \dots, X_n)$ .

parameter space      So, MLE  $\hat{\theta} = h(X_1, \dots, X_n)$  &  $L(\hat{\theta}) = \max_{\theta \in \Theta} L(\theta)$

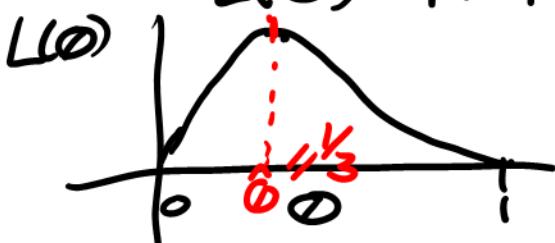
*Example/Discussion:*

$$\text{#} = [0, 1]$$

~~or~~ Observe  $X_1 = 0, X_2 = 1, X_3 = 0$        $X_i = \begin{cases} 1 & \text{w.p. } \theta \\ 0 & \text{w.p. } 1-\theta \end{cases}$

Estimate  $\theta$

$$L(\theta) = P(X_1 = 0, X_2 = 1, X_3 = 0 | \theta) = \prod_{i=1}^3 f(x_i | \theta)$$



$\hat{\theta} = \frac{1}{3}$  (pick  $\theta$  value =  $\theta(1-\theta)^2$ ,  $0 \leq \theta \leq 1$ .  
for which the data " $X_1 = 0, X_2 = 1, X_3 = 0$ "  
seem most plausible  
or have highest likelihood)

# Point Estimation

Finding Maximum Likelihood Estimators (MLEs)

Finding the MLE  $\hat{\theta}$  requires *maximizing* the likelihood  $L(\theta)$  function *over the parameter space*  $\theta \in \Theta$ . There are several potential ways to achieve this.

~~80%~~ 1. If  $L(\theta)$  is smooth (i.e., differentiable) in  $\theta$  (which happens often), consider using calculus to maximize  $L(\theta)$ .

~~20%~~ 2. If  $L(\theta)$  is *not* smooth, need to think more carefully about how to maximize  $L(\theta)$  over  $\Theta$  for the specific model at hand. (~~don't use calculus~~)

3. Often times in practice,  $L(\theta)$  is maximized numerically using some computing.

\* 4. Maximizing  $\log L(\theta)$  is equivalent to maximizing  $L(\theta)$  & can be easier.

5. In particular, if  $X_1, \dots, X_n$  are iid with common pdf/pmf  $f(x|\theta)$  where the "support"  $\{x : f(x|\theta) > 0\}$  changes with  $\theta$ , then using *indicator functions* to write  $f(x|\theta)$  and  $L(\theta)$  can help in maximization.

*range or what's possible for data* e.g. indicator  $I(A)$  is  $I(A) = \begin{cases} 1 & \text{if } A \text{ occurs} \\ 0 & \text{otherwise} \end{cases}$

## Using Calculus to Determine the MLE

If the likelihood function  $L(\theta) = f(x_1, \dots, x_n|\theta)$  is differentiable, it can often be maximized over  $\Theta$  using calculus.

Assume  $\Theta \subset \mathbb{R}$  is open and that  $L(\theta)$  is twice differentiable on  $\Theta$ . Then,

$$\hat{\theta} \text{ maximizes } L(\theta) \iff \frac{dL(\theta)}{d\theta}\Big|_{\hat{\theta}} = 0 \quad \text{and} \quad \frac{d^2L(\theta)}{d\theta^2}\Big|_{\hat{\theta}} < 0.$$

Since  $\log(\cdot)$  is an increasing function,  $\hat{\theta}$  maximizes  $L(\theta) \iff \hat{\theta}$  maximizes  $\log L(\theta)$ . Hence,

$$\hat{\theta} \text{ is an MLE if } \frac{d \log L(\theta)}{d\theta}\Big|_{\hat{\theta}} = 0 \quad \text{and} \quad \frac{d^2 \log L(\theta)}{d\theta^2}\Big|_{\hat{\theta}} < 0.$$

## Point Estimation

Finding Maximum Likelihood Estimators (MLEs)/Example using Calculus

*Example:* Let  $X_1, \dots, X_n$  be a random sample from a Geometric( $p$ ) distribution,  $0 < p < 1$ . Find the MLE of  $p$ .

Solution:  $L(p) \equiv f(x_1, \dots, x_n | p) = \prod_{i=1}^n f(x_i | p) = \prod_{i=1}^n [p(1-p)^{x_i-1}]$

$$= p^n (1-p)^{\sum_{i=1}^n x_i - n}$$

as long  
 as each  
 $x_i \in \{1, 2, 3, 4, \dots\}$

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

(Note: We will assume that it NOT true " $x_1 = \dots = x_n = 1$ "; that is,  $\sum_{i=1}^n x_i > n$ )

$$\frac{d \log L(p)}{dp} \Big|_{p=\hat{p}} = \frac{n}{\hat{p}} + \frac{(\sum_{i=1}^n x_i - n)}{(1-\hat{p})} (-1) = 0$$

i.e.  $n(1-\hat{p}) = \hat{p} (\sum_{i=1}^n x_i - n)$

i.e.  $\hat{p} = \frac{n}{\sum_{i=1}^n x_i} = \frac{1}{\bar{x}_n} \in (0, 1)$  ( $\hat{p}$  is in parameter  $(0, 1)$  if  $\sum_{i=1}^n x_i > n$ )

check:  $\frac{d^2 \log L(p)}{dp^2} = -\frac{n}{p^2} - \frac{(\sum_{i=1}^n x_i - n)}{(1-p)^2} < 0$  ( $\frac{d \hat{p}^{-1}}{dp} = -1 \cdot \hat{p}^{-2}$ )

for all  $p \in (0, 1)$  including  $\hat{p} = \frac{1}{\bar{x}_n}$

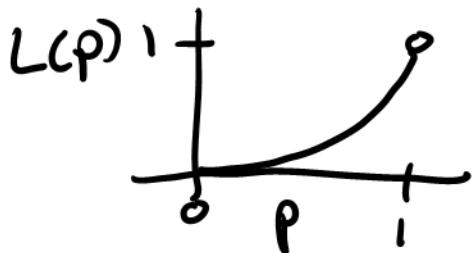
$\Rightarrow$  MLE of  $p$  is  $\hat{p} = \frac{1}{\bar{x}_n}$  (if  $\sum_{i=1}^n x_i > n$ )

Note: For discrete r.v.s (Geometric, binomial, etc), pathological cases for MLE can occur if  $x_1 = \dots = x_n = M$ , where  $M$  is either minimum or maximum value of  $X_i$

e.g. (Geometric  $x_1 = \dots = x_n = 1$ )

$$\Rightarrow L(p) = p^n$$

$\Rightarrow$  on  $p \in (0, 1)$ ,  $L(p)$  has no maximum here  
in the parameter space  $(0, 1)$



$\Rightarrow$  No MLE for  $p$  when  
 $x_1 = \dots = x_n = 1$  here

But, if  $(\alpha, \beta)$  is parameter space,

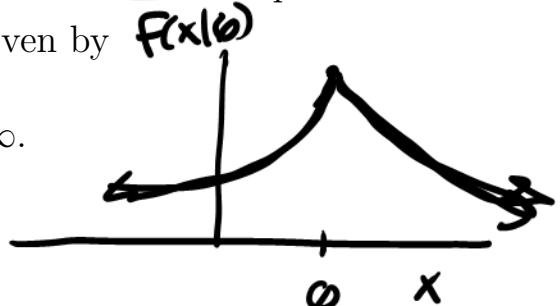
then  $L(p) = p^n$  has a max at  $\hat{p} = 1$ .  
(MLE exists)

## Point Estimation

Finding Maximum Likelihood Estimators (MLEs)/Examples without Calculus

*Example:* (Non-differentiable likelihood) Let  $X_1, \dots, X_n$  be a random sample from a Double Exponential( $\theta$ ) distribution,  $\theta \in \mathbb{R}$ , with pdf given by

*continuous*  $f(x|\theta) = \frac{1}{2}e^{-|x-\theta|}, \quad -\infty < x < \infty.$



Find the MLE of  $\theta$ .

$$\begin{aligned} L(\theta) &= f(x_1, \dots, x_n | \theta) = \prod_{i=1}^n f(x_i | \theta) \\ &= \left(\frac{1}{2}\right)^n e^{-\sum_{i=1}^n |x_i - \theta|} \end{aligned}$$

$\hat{\theta}$  maximizes  $L(\theta) \Leftrightarrow \hat{\theta}$  minimizes  $\sum_{i=1}^n |x_i - \theta|$   
 $\Leftrightarrow \hat{\theta} = \text{median}(x_1, \dots, x_n)$

(In contrast,  $\sum_{i=1}^n (x_i - \theta)^2$  is minimized at  $\theta = \bar{x}_n$ )

*Example:* Let  $\theta \geq 1$  be an integer. Let  $\underline{X}$  be a r.v. with a discrete uniform distribution on  $\{1, \dots, \theta\}$ ; that is,

*distribution has support or range depending on  $\theta$*   $P(X = x|\theta) = \begin{cases} \frac{1}{\theta} & \text{for } x = 1, \dots, \theta \\ 0 & \text{otherwise.} \end{cases} = \frac{1}{\theta} I(\text{pos intgr } x \leq \text{intgr } \theta)$

If  $\underline{X} = 2$  is observed, what is the maximum likelihood estimate of  $\theta$ ?

$$\underline{L}(\theta) = P(X=2|\theta) = f(2|\theta) \text{ for } \theta = 1, 2, 3, \dots$$

$$= \frac{1}{\theta} I(2 \leq \text{intgr } \theta) = \begin{cases} 0 & \text{if } \theta = 1 \\ \frac{1}{2} & \text{if } \theta = 2 \\ \frac{1}{3} & \text{if } \theta = 3 \\ \vdots & \vdots \\ \frac{1}{m} & \text{if } \theta = m \end{cases}$$

$\Rightarrow$  MLE of  $\theta$   
is  $\hat{\theta} = 2$

$$\text{or } L(2) = \max_{\theta \in \{1, 2, 3, \dots\}} L(\theta)$$

$$\text{if } \theta = m$$