

Methods of Point estimation

[2] The Method of Maximum Likelihood

First, let's Recall that

Lecture (5)

Summation

$$\sum_{i=1}^n c = nc$$

$$\begin{aligned}\sum_{i=1}^n c f(x_i) &= c f(x_1) + c f(x_2) + \dots + c f(x_n) \\ &= c \sum_{i=1}^n f(x_i)\end{aligned}$$

$$\sum_{i=1}^n (f(x_i) \pm g(x_i)) = \sum_{i=1}^n f(x_i) \pm \sum_{i=1}^n g(x_i)$$

Product

$$\prod_{i=1}^n f(x_i) = f(x_1) \cdot f(x_2) \cdot f(x_3) \cdot \dots \cdot f(x_n)$$

$$\prod_{i=1}^n c = c^n$$

$$\begin{aligned}\prod_{i=1}^n c g(x_i) &= c g(x_1) \cdot c g(x_2) \cdot c g(x_3) \cdot \dots \cdot c g(x_n) \\ &= c^n \prod_{i=1}^n g(x_i)\end{aligned}$$

$$\prod_{i=1}^n g_1(x_i) g_2(x_i) = \prod_{i=1}^n g_1(x_i) \cdot \prod_{i=1}^n g_2(x_i)$$

Ln

$$\ln e = 1$$

$$\ln(ab) = \ln a + \ln b$$

$$\ln\left(\frac{a}{b}\right) = \ln a - \ln b$$

$$\ln(1) = 0 \quad \ln(\infty) = \infty \quad \ln(0) = -\infty$$

$$\ln a^n = n \ln a$$

$$\ln e^m = m$$

$$\ln(a+b) \neq \text{Can't be simplified}$$

Differentiation

$$\frac{d}{dx}(c) = 0$$

$$\frac{d}{dx} e^{f(x)} = e^{f(x)} \cdot f'(x)$$

$$\frac{d}{dx} x^n = n x^{n-1}$$

$$\frac{d}{dx} (f(x))^n = n (f(x))^{n-1} \cdot f'(x)$$

$$\frac{d}{dx} \ln f(x) = \frac{1}{f(x)} \cdot f'(x)$$

$$\frac{d}{dx} \left(\frac{1}{x} \right) = -\frac{1}{x^2}$$

Method of MaxLikelihood MLE

Let X_1, X_2, \dots, X_n random sample of size n
 X_1, X_2, \dots, X_n are i.i.d

the likelihood function is the joint pdf (or pmf) of random sample

$$L(\theta) = f_{\text{joint}}(x_1, x_2, \dots, x_n; \theta)$$

$$L(\theta) = \prod_{i=1}^n f(x_i; \theta)$$

$$L(\theta) = \prod_{i=1}^n f(x_i; \theta)$$

f^n of unknown parameter θ only

MLE (maximum likelihood estimator) of θ is the value of θ that maximize the likelihood $f^n L(\theta)$

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$$\text{MLE} \quad \left. \frac{dL(\theta)}{d\theta} \right|_{\theta=\hat{\theta}} = 0$$

Search for $\hat{\theta}$ that maximize the value of $L(\theta)$

Recall
Max point of $f(x)$ at $f'(x) = 0$

Note that any value of θ that maximize $L(\theta)$ will also maximize the $\ln L(\theta)$ log-likelihood

loglikelihood $L^*(\theta) = \ln L(\theta)$ product

$$\text{MLE} \quad \left. \frac{dL^*}{d\theta} = \frac{d}{d\theta} (\ln L(\theta)) \right|_{\theta=\hat{\theta}} = 0$$

Steps

1- write $L(\theta) = f(x_1; \theta) \cdot f(x_2; \theta) \cdots f(x_n; \theta)$
joint pdf, use properties of π

2- take \ln of both sides

$$L^*(\theta) = \ln f(x_1; \theta) + \ln f(x_2; \theta) \cdots + \ln f(x_n; \theta)$$

3- differentiate w.r.t θ

equate the equation to zero to get $\hat{\theta}$

Ex ① If X_1, X_2, \dots, X_n are the value of a random sample from a Bernoulli Population.

Find the MLE of its parameter θ

if $X \sim \text{Bernoulli}(\theta)$

$$f(x; \theta) = \theta^x (1-\theta)^{1-x} \quad x=0,1$$

pdf

$$\begin{aligned} L(\theta) &= \prod_{i=1}^n f(x_i; \theta) \\ &= \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i} \\ &= \prod_{i=1}^n \theta^{x_i} \cdot \prod_{i=1}^n (1-\theta)^{1-x_i} \\ &= \theta^{\sum_{i=1}^n x_i} \cdot (1-\theta)^{n-\sum_{i=1}^n x_i} \end{aligned}$$

take ln for both sides

$$L^*(\theta) = \ln \left(\theta^{\sum x_i} (1-\theta)^{n-\sum x_i} \right)$$

$$L^*(\theta) = \sum x_i \ln \theta + (n - \sum x_i) \ln(1-\theta)$$

Differentiate w.r.t θ to get MLE

$$\frac{dL^*(\theta)}{d\theta} = 0$$

$$\sum x_i \left(\frac{1}{\theta} \right) + (n - \sum x_i) \frac{-1}{1-\theta} = 0$$

$$\frac{\sum x_i}{\theta} = \frac{n - \sum x_i}{1-\theta}$$

Recall

In Bernoulli trial one trial with prob of success = p

, prob of fail = $1-p$

X : No of success

$$f(x) = p^x (1-p)^{1-x}$$

$x=0,1$

$X \sim \text{Bernoulli}(p)$

Bernoulli is binomial ($n=1, p$)

Note

$$\begin{aligned} \theta^{x_1} \cdot \theta^{x_2} \cdot \theta^{x_3} \cdots \theta^{x_1+x_2+\dots} &= \theta \\ (1-\theta)^{1-x_1} (1-\theta)^{1-x_2} (1-\theta)^{1-x_3} \cdots &= \\ (1-\theta)^{n-\sum x_i} &= \end{aligned}$$

$$(1-\hat{\theta}) \sum x_i = \hat{\theta} (n - \sum x_i) \quad \div n$$

$$(1-\hat{\theta}) \frac{\sum x_i}{n} = \hat{\theta} \left(\frac{n}{n} - \frac{\sum x_i}{n} \right)$$

$$(1-\hat{\theta}) \bar{x} = \hat{\theta} (1-\bar{x})$$

$$\bar{x} - \bar{x} \hat{\theta} = \hat{\theta} - \hat{\theta} \bar{x}$$

$$\boxed{\hat{\theta} = \bar{x}}$$

estimator of θ (probability of success)

Ex(2) let X_1, X_2, \dots, X_n be a random sample from exponential population
Find MLE for the parameter θ

$$X \sim \exp(\lambda)$$

$$f(x) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}} \quad \lambda > 0, x > 0$$

pdf

$$f(x_i; \theta) = \frac{1}{\theta} e^{-\frac{x_i}{\theta}}$$

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

$$= \prod_{i=1}^n \frac{1}{\theta} e^{-\frac{x_i}{\theta}}$$

const

$$= \frac{1}{\theta^n} \prod_{i=1}^n e^{-\frac{x_i}{\theta}}$$

$$L(\theta) = \frac{1}{\theta^n} e^{-\frac{\sum x_i}{\theta}} = \theta^{-n} e^{-\frac{\sum x_i}{\theta}}$$

$$e^{-\frac{x_1}{\theta}} + e^{-\frac{x_2}{\theta}} + e^{-\frac{x_3}{\theta}} \dots$$

$$= e^{-\frac{\sum x_i}{\theta}}$$

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$$L^*(\theta) = \ln L(\theta) = \ln \theta^{-n} e^{-\frac{\sum x_i}{\theta}}$$

$$L^*(\theta) = -n \ln \theta - \frac{\sum x_i}{\theta}$$

$$\frac{d}{d\theta} L^*(\theta) = 0 \Rightarrow -n\left(\frac{1}{\theta}\right) - \sum x_i \left(-\frac{1}{\theta^2}\right) = 0$$

$$\sum x_i \left(\frac{1}{\theta^2}\right) = \frac{n}{\theta}$$

$$\hat{\theta} = \frac{\sum x_i}{n} = \bar{X}$$

If Several Unknown Parameters
 $\theta_1, \theta_2, \dots, \theta_k$

$$\frac{\partial}{\partial \theta_1} L(\theta_1, \theta_2, \dots, \theta_k) = 0$$

$$\frac{\partial}{\partial \theta_2} L(\theta_1, \theta_2, \dots, \theta_k) = 0$$

⋮

$$\frac{\partial}{\partial \theta_k} L(\theta_1, \theta_2, \dots, \theta_k) = 0$$

then solve k equation in k Unknowns

Ex ③ If X_1, X_2, \dots, X_n constitute a random sample from normal population with the mean μ , variance σ^2
Find joint MLE of μ, σ^2

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

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

$$L(\mu, \sigma^2) = \prod_{i=1}^n \left(\frac{1}{2\pi}\right)^{\frac{1}{2}} \left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}$$

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

take \ln of both sides

$$\begin{aligned} L^*(\mu, \sigma^2) &= \text{Const} + \frac{n}{2} \ln\left(\frac{1}{\sigma^2}\right) - \frac{\sum (x_i-\mu)^2}{2\sigma^2} \\ &= \text{Const.} - \frac{n}{2} \ln \sigma^2 - \frac{\sum (x_i-\mu)^2}{2\sigma^2} \end{aligned}$$

$$\frac{\partial L^*(\mu, \sigma^2)}{\partial \mu} = \frac{-1}{2\sigma^3} 2 \sum (x_i - \hat{\mu}) (-1) = 0$$

$$\sum (x_i - \hat{\mu}) = 0$$

$$\sum x_i - n\hat{\mu} = 0$$

$$\boxed{\hat{\mu} = \frac{\sum x_i}{n} = \bar{x}}$$

$$L^*(M, \sigma^2) = \text{Const} - \frac{n}{2} \ln \sigma^2 - \frac{\sum (x_i - \mu)^2}{2} \frac{1}{\sigma^2}$$

$$\frac{\partial L^*(M, \sigma^2)}{\partial \sigma^2} = 0 \Rightarrow -\frac{n}{2} \frac{1}{\sigma^2} - \frac{\sum (x_i - \mu)^2}{2} \left(\frac{1}{\sigma^2}\right)^2$$

take care treat σ^2
as one symbol θ

$$\cancel{\frac{-n}{2 \hat{\sigma}^2}} - \cancel{\frac{1}{2} \sum (x_i - \mu)^2} \left(\frac{-1}{(\hat{\sigma}^2)^2}\right) = 0$$

$$\frac{\sum (x_i - \mu)^2}{\hat{\sigma}^2} = n$$

$$\frac{1}{\sigma} \rightarrow \frac{-1}{\sigma^2}$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \mu)^2$$

$$\hat{\mu} = \bar{x}$$

$$\boxed{\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2}$$

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Problem 4 : sheet (2)

[4] let X_1, X_2, \dots, X_n be a random sample from a geometric distribution

$$f(x; \theta) = \theta(1-\theta)^{x-1}$$

$X = 1, 2, 3, \dots$

θ : prob of success

X : No. of trials

Find a formula for estimating θ by

Using (a) Method of Moments

(b) Method of ML

(a) Method of Moments
Population

$$\begin{aligned} \mu_1 &= E(X) \\ &= \sum_{X=1}^{\infty} X f(x) \\ &= \frac{1}{\theta} \end{aligned}$$

Sample

$$m_1 = \frac{1}{n} \sum_{i=1}^n X_i = \bar{X}$$

$$\begin{aligned} \mu_1 &= m_1 \\ \frac{1}{\theta} &= \bar{X} \end{aligned}$$

$$\Rightarrow \boxed{\hat{\theta} = \frac{1}{\bar{X}}}$$

(b) Method of MLE

$$L(\theta) = \prod_{i=1}^n \theta(1-\theta)^{X_i-1}$$

تمت

$$= \theta^n \prod_{i=1}^n (1-\theta)^{X_i-1}$$

$$= \theta^n (1-\theta)^{\sum X_i - n}$$

$$\begin{aligned} &(1-\theta)^{X_1-1} (1-\theta)^{X_2-1} (1-\theta)^{X_3-1} \dots \\ &\quad \quad \quad \sum X_i - n \\ &= (1-\theta)^{\sum X_i - n} \end{aligned}$$

$$L(\theta) = \theta^n (1-\theta)^{\sum x_i - n}$$

$$L^*(\theta) = \ln \theta^n (1-\theta)^{\sum x_i - n}$$

$$L^*(\theta) = n \ln \theta + (\sum x_i - n) \ln (1-\theta)$$

$$\frac{dL^*(\theta)}{d\theta} = 0$$

$$n \frac{1}{\theta} + (\sum x_i - n) \frac{-1}{1-\hat{\theta}} = 0$$

$$\frac{\sum x_i - n}{1-\hat{\theta}} = \frac{n}{\hat{\theta}}$$

$$\hat{\theta} \sum x_i - n \hat{\theta} = n - n \hat{\theta}$$

$$\hat{\theta} \sum x_i = n$$

$$\boxed{\hat{\theta} = \frac{n}{\sum x_i} = \frac{1}{\bar{x}}}$$

Invariance Property of MLE's

let $\hat{\theta}$ be the MLE of θ

then $g(\hat{\theta})$ is a MLE for $g(\theta)$

where g is one-to-one

e.g if $\hat{\theta}$ is MLE for variance θ

then $\sqrt{\hat{\theta}}$ is the MLE for standard deviation $\sqrt{\theta}$

Ex Problem (4), (5) Ch. 2

for Geometric(P)

4) $MLE_P \text{ of } \hat{P} = \frac{1}{\bar{X}}$

5) $\therefore \hat{P} = \frac{1}{\bar{X}}$

Find the MLE of the following quantities

a) $E(X) = \frac{1}{P}$

MLE of $E(X) = \frac{1}{\hat{P}} = \frac{1}{\frac{1}{\bar{X}}} = \bar{X}$

b) $V(X) = \frac{1-P}{P^2}$

MLE $V(X) = \frac{1-\hat{P}}{\hat{P}^2} = \frac{1-\frac{1}{\bar{X}}}{\frac{1}{\bar{X}^2}} = \bar{X}^2 - \bar{X}$

c) $P(X > K) = (1-P)^K$ MLE of $P(X > K) = (1-\frac{1}{\bar{X}})^K$
 $K=1, 2, \dots$