

lecture 12 ①

Q: Let $x_1, x_2, \dots, x_n \stackrel{iid}{\sim} \text{Bin}(n, p)$ where n is known and p is unknown. Find the MLE for p ?

Solⁿ

Let $X \sim \text{Bin}(n, p)$

$$f_X(x, p) = P_X(x) = \binom{n}{x} p^x q^{n-x}; \quad x = 0, 1, 2, \dots, n$$

$$q = 1 - p$$

Likelihood function

$$L(p) = f(x_1, p) \cdot f(x_2, p) \cdots f(x_n, p)$$

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

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

$$L(p) = p^{\sum_{i=1}^n x_i} (1-p)^{n^2 - \sum_{i=1}^n x_i} \cdot \prod_{i=1}^n \binom{n}{x_i}$$

$$\begin{aligned} &= (1-p)^{(n-x_1) + (n-x_2) + \dots + (n-x_n)} \\ &= (1-p)^{\sum_{i=1}^n (n-x_i)} \\ &= (1-p)^{n^2 - \sum_{i=1}^n x_i} \end{aligned}$$

Taking log

$$l = \ln L(p) = \left(\sum_{i=1}^n x_i \right) \cdot \ln p + \left(n^2 - \sum_{i=1}^n x_i \right) \ln(1-p)$$

$$\frac{\partial l}{\partial p} = \frac{\sum_{i=1}^n x_i}{p} - \frac{\left(n^2 - \sum_{i=1}^n x_i \right)}{(1-p)} + \ln \left(\prod_{i=1}^n \binom{n}{x_i} \right) + 0$$

$$\begin{aligned} \frac{\partial l}{\partial p} = 0 &\Rightarrow \frac{\sum_{i=1}^n x_i}{p} = \frac{n^2 - \sum_{i=1}^n x_i}{1-p} \\ &\Rightarrow \sum_{i=1}^n x_i - p \sum_{i=1}^n x_i = n^2 p - p \sum_{i=1}^n x_i \\ &\Rightarrow p = \frac{\sum_{i=1}^n x_i}{n^2} = \frac{1}{n} \bar{x} \end{aligned}$$

$$\text{Now } \frac{\partial^2 l}{\partial p^2} = - \frac{\sum_{i=1}^n x_i}{p^2} - \frac{\left(n^2 - \sum_{i=1}^n x_i \right)}{(1-p)^2} < 0 \text{ at } p = \frac{\bar{x}}{n}$$

Thus $\hat{p} = \frac{\bar{x}}{n}$ is MLE for p . \neq

Q: Let $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$

- (i) μ is unknown, σ^2 known, find MLE for μ
 (ii) μ is known, σ^2 unknown, find MLE for σ^2
 (iii) μ and σ^2 both unknown; find MLE for μ and σ^2

Solⁿ (i) σ^2 is known (constant)

Put $\sigma^2 = \sigma_0^2$ (constant)

So if $X \sim N(\mu, \sigma_0^2)$ then

$$f_X(\mu) = \frac{1}{\sigma_0 \sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma_0^2}}; \quad \begin{matrix} x \in \mathbb{R} \\ \mu \in \mathbb{R} \end{matrix}$$

The likelihood function for μ

$$L(\mu) = f(x_1, \mu) \cdot f(x_2, \mu) \cdots f(x_n, \mu)$$

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

$$= \prod_{i=1}^n \frac{1}{\sigma_0 \sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma_0^2}}$$

$$= \left(\frac{1}{\sigma_0 \sqrt{2\pi}} \right)^n \cdot e^{-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma_0^2}}$$

$$l = \ln L(\mu) = -n \ln(\sigma_0 \sqrt{2\pi}) - \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma_0^2}$$

$$\frac{\partial l}{\partial \mu} = 0 - \sum_{i=1}^n \frac{2(x_i - \mu)}{2\sigma_0^2} \cdot (-1)$$

$$= \sum_{i=1}^n \frac{(x_i - \mu)}{\sigma_0^2}$$

For maxⁱ, $\frac{\partial l}{\partial \mu} = 0 \Rightarrow \sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma_0^2} \right) = 0$

$$\Rightarrow \sum_{i=1}^n (x_i - \mu) = 0 \Rightarrow \sum_{i=1}^n x_i - n\mu = 0$$

$$\Rightarrow \mu = \frac{\sum_{i=1}^n x_i}{n} = \bar{x}$$

$$\frac{\partial^2 l}{\partial \mu^2} = -\frac{n}{\sigma_0^2} < 0 \text{ at } \mu = \bar{x}$$

Thus $\hat{\mu} = \bar{x}$ is MLE for μ

(ii) μ is known ; σ^2 is unknown (We have to find estimate for σ^2 not for σ)
 Put $\mu = \mu_0$ and $\sigma^2 = v$

Then if $X \sim N(\mu_0, v)$

$$f_X(v) = \frac{1}{\sqrt{2\pi \cdot v}} e^{-\frac{(x - \mu_0)^2}{2v}} ; v > 0, x \in \mathbb{R}$$

$$L(v) = f(x_1, v) \cdot f(x_2, v) \cdots f(x_n, v)$$

$$= \prod_{i=1}^n f(x_i, v) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi \cdot v}} e^{-\frac{(x_i - \mu_0)^2}{2v}}$$

$$= \left(\frac{1}{\sqrt{2\pi \cdot v}} \right)^n \cdot e^{-\sum_{i=1}^n \frac{(x_i - \mu_0)^2}{2v}}$$

$$= \left(\frac{1}{\sqrt{2\pi \cdot v}} \right)^n \cdot e^{-\sum_{i=1}^n \frac{(x_i - \mu_0)^2}{2v}}$$

$$l = \ln L(v) = -n \ln(\sqrt{2\pi \cdot v}) - \sum_{i=1}^n \frac{(x_i - \mu_0)^2}{2v}$$

$$l = -\frac{n}{2} \ln(2\pi v) - \sum_{i=1}^n \frac{(x_i - \mu_0)^2}{2v}$$

$$\frac{\partial l}{\partial v} = -\frac{n}{2} \cdot \frac{1}{v} + \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2v^2}$$

$$= -\frac{n}{2v} + \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{2v^2}$$

$$\frac{\partial l}{\partial v} = 0 \Rightarrow v = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_0)^2 \quad (*)$$

$$\text{Now, } \frac{\partial^2 l}{\partial v^2} = -\frac{n}{2v^2} - \frac{\sum_{i=1}^n (x_i - \mu_0)^2}{v^3}$$

$$\frac{\partial^2 l}{\partial v^2} \Big|_{v=(*)} = -\frac{n^2}{2 \sum_{i=1}^n (x_i - \mu_0)^2} - \frac{n^3 \sum_{i=1}^n (x_i - \mu_0)^2}{\left(\sum_{i=1}^n (x_i - \mu_0)^2 \right)^3}$$

\therefore second term is more dominating term so

$$\frac{\partial^2 l}{\partial v^2} < 0 \text{ thus } \hat{v} = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_0)^2 \text{ is MLE}$$

$$\text{Thus } \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_0)^2 \text{ is MLE for } \sigma^2 \quad \#$$

(iii) Both are unknown
 $X \sim N(\mu, \sigma^2)$

$$f_X(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

For our convenience we will take $\sigma^2 = \nu$
 then

$$L(\mu, \nu) = f(x_1, \mu, \nu) \cdot f(x_2, \mu, \nu) \cdots f(x_n, \mu, \nu)$$

$$= \prod_{i=1}^n f(x_i, \mu, \nu)$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\nu}} \cdot e^{-\frac{(x_i-\mu)^2}{2\nu}}$$

$$L(\mu, \nu) = \left(\frac{1}{\sqrt{2\pi\nu}} \right)^n \cdot e^{-\sum_{i=1}^n \frac{(x_i-\mu)^2}{2\nu}}$$

$$l = \ln(L(\mu, \nu)) = -\frac{n}{2} \ln(2\pi\nu) - \sum_{i=1}^n \frac{(x_i-\mu)^2}{2\nu}$$

$$\frac{\partial l}{\partial \mu} = -\frac{n}{2} \cdot 1$$

Now partially diff w.r.t μ and ν respectively

$$\frac{\partial l}{\partial \mu} = 0 - \sum_{i=1}^n \frac{2(x_i-\mu)}{2\nu} \cdot (-1)$$

$$\frac{\partial l}{\partial \mu} = \sum_{i=1}^n \frac{(x_i-\mu)}{\nu} \quad \text{eqn (1)}$$

$$\text{Now; } \frac{\partial l}{\partial \nu} = -\frac{n}{2} \cdot \frac{1}{2\nu} + \sum_{i=1}^n \frac{(x_i-\mu)^2}{2\nu^2}$$

$$\frac{\partial l}{\partial \nu} = -\frac{n}{2\nu} + \sum_{i=1}^n \frac{(x_i-\mu)^2}{2\nu^2} = 0 \quad \text{eqn (2)}$$

$$\text{Now from eqn (1)} \quad \frac{\partial l}{\partial \mu} = 0 \Rightarrow \mu = \bar{x}$$

Now, putting the value of μ in eqn (2)

$$\frac{\partial l}{\partial \nu} = -\frac{n}{2\nu} + \sum_{i=1}^n \frac{(x_i-\bar{x})^2}{2\nu^2}$$

$$\text{Now } \frac{\partial l}{\partial \nu} = 0 \Rightarrow \nu = \frac{1}{n} \sum_{i=1}^n (x_i-\bar{x})^2$$

$$\frac{\partial^2 l}{\partial \mu^2} = -\frac{n}{\sigma^2} = \textcircled{5} = \frac{-n}{\sigma^2} \cdot \sum_{i=1}^n (x_i - \bar{x})^2 < 0$$

Also

$$\frac{\partial^2 l}{\partial \sigma^2} = \frac{n}{2\sigma^2} - \sum_{i=1}^n \frac{(x_i - \bar{x})^2}{2\sigma^3}$$

Again second term will be more dominating at value of σ . So $\frac{\partial^2 l}{\partial \sigma^2} < 0$

Thus $\hat{\mu} = \bar{x}$ and $\hat{\sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$

is MLE for μ and σ and so for μ and σ^2 .

~~Thus~~

Result: Invariance Properties of MLE \rightarrow

Let MLE of θ be $\hat{\theta}$. Consider $g(\theta)$ be one-one function from (H) then

MLE of $g(\theta)$ be $g(\hat{\theta})$.

Ex: If \bar{X} is MLE for θ
then \bar{X}^3 will be MLE for θ^3 #