

Chapter – 6.4

Find the maximum likelihood estimator for the Bernoulli distribution

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

Solution: Let us consider

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

$$\ln(L(p)) = \left(\sum x_i \right) \ln(p) + \left(n - \sum x_i \right) \ln(1 - p)$$

$$\frac{d}{dp} \ln(L(p)) = \frac{\sum x_i}{p} + \frac{n - \sum x_i}{1 - p}$$

$$\frac{d}{dp} \ln(L(p)) = 0$$

$$\Rightarrow \frac{\sum x_i}{p} = \frac{n - \sum x_i}{1 - p}$$

$$\Rightarrow \sum x_i - p \sum x_i = np - p \sum x_i$$

$$\Rightarrow np = \sum x_i$$

$$\Rightarrow p = \frac{\sum x_i}{n}$$

$$\frac{d^2}{dp^2} \ln(L(p)) = -\frac{\sum x_i}{p^2} - \frac{n - \sum x_i}{(1 - p)^2} < 0 \quad \text{for } p = \frac{\sum x_i}{n}$$

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

Example 1: Find the maximum likelihood estimator for the Exponential distribution $f(x; \theta) = \frac{1}{\theta} e^{\frac{-x}{\theta}}$.

Solution: Let us consider

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

$$\begin{aligned} \ln(L(\theta)) &= -n \ln(\theta) - \frac{\sum x_i}{\theta} \\ \frac{d}{d\theta} \ln(L(\theta)) &= -\frac{n}{\theta} + \frac{\sum x_i}{\theta^2} \end{aligned}$$

$$\begin{aligned} \frac{d}{d\theta} \ln(L(\theta)) &= 0 \\ \Rightarrow -\frac{n}{\theta} + \frac{\sum x_i}{\theta^2} &= 0 \\ \Rightarrow \frac{\sum x_i}{\theta^2} &= \frac{n}{\theta} \\ \Rightarrow n\theta &= \sum x_i \\ \Rightarrow \theta &= \frac{\sum x_i}{n} \end{aligned}$$

$$\frac{d^2}{d\theta^2} \ln(L(\theta)) = -\frac{n}{\theta^2} - \frac{2\sum x_i}{\theta^3} < 0 \text{ for } \theta = \frac{\sum x_i}{n}$$

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

Example 2: Find the maximum likelihood estimator for the Geometric distribution $f(x; p) = p(1 - p)^{x-1}$.

Solution: Let us consider

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

$$\ln(L(p)) = n \ln(p) + \left(\sum x_i - n \right) \ln(1 - p)$$

$$\frac{d}{dp} \ln(L(p)) = \frac{n}{p} - \frac{\sum x_i - n}{1 - p}$$

$$\frac{d}{dp} \ln(L(p)) = 0$$

$$\Rightarrow \frac{n}{p} = \frac{\sum x_i - n}{1 - p}$$

$$\Rightarrow n - np = p \sum x_i - np$$

$$\Rightarrow p \sum x_i = n$$

$$\Rightarrow p = \frac{n}{\sum x_i}$$

$$\frac{d^2}{dp^2} \ln(L(p)) = -\frac{n}{p^2} - \frac{\sum x_i - n}{(1 - p)^2} < 0 \text{ for } p = \frac{n}{\sum x_i}$$

$$\therefore \hat{p} = \frac{n}{\sum x_i} = \frac{1}{\bar{x}}$$

Example 3: Find the maximum likelihood estimator for the Binomial

distribution $f(x; \theta_1, \theta_2) = \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x-\theta_1)^2}{2\theta_2}}$.

Solution: Let us consider

$$\begin{aligned} L(\theta_1, \theta_2) &= \prod_{i=1}^n f(x_i; \theta_1, \theta_2) \\ &= \prod_{i=1}^n 2\pi\theta_2^{-\frac{1}{2}} e^{-\frac{(x_i-\theta_1)^2}{2\theta_2}} \\ &= (2\pi\theta_2)^{-\frac{n}{2}} e^{-\frac{\sum(x_i-\theta_1)^2}{2\theta_2}} \end{aligned}$$

$$\ln(L(\theta_1, \theta_2)) = -\frac{n}{2} \ln(2\pi\theta_2) - \frac{\sum(x_i - \theta_1)^2}{2\theta_2}$$

$$\frac{d}{d\theta_1} \ln(L(\theta_1, \theta_2)) = -\frac{2\sum(x_i - \theta_1)^2}{2\theta_2} (-1)$$

$$\frac{d}{d\theta_1} \ln(L(\theta_1, \theta_2)) = 0$$

$$\Rightarrow -\frac{\sum(x_i - \theta_1)^2}{\theta_2} = 0$$

$$\Rightarrow \sum x_i - n\theta_1 = 0$$

$$\Rightarrow n\theta_1 = \sum x_i$$

$$\Rightarrow \theta_1 = \frac{\sum x_i}{n}$$

$$\frac{d^2}{d\theta_1^2} \ln(L(\theta_1, \theta_2)) = -\frac{n}{\theta_2} < 0 \quad \text{for } \theta_1 = \frac{\sum x_i}{n}$$

$$\therefore \widehat{\theta_1} = \frac{\sum x_i}{n} = \mu$$

$$\ln (L(\theta_1, \theta_2)) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\theta_2) - \frac{\sum(x_i - \mu)^2}{2\theta_2}$$

$$\frac{d}{d\theta_2} \ln (L(\theta_1, \theta_2)) = -\frac{n}{2\theta_2} + \frac{\sum(x_i - \mu)^2}{2\theta_2^2}$$

$$\begin{aligned}\frac{d}{d\theta_2} \ln(L(\theta_1, \theta_2)) &= 0 \\ \Rightarrow \frac{n}{2\theta_2} &= \frac{\sum(x_i - \mu)^2}{2\theta_2^2} \\ \Rightarrow \theta_2 &= \frac{\sum(x_i - \mu)^2}{n}\end{aligned}$$

$$\frac{d^2}{d\theta_2^2} \ln (L(\theta_1, \theta_2)) = \frac{n}{2\theta_2^2} - \frac{\sum(x_i - \mu)^2}{\theta_2^3} < 0 \text{ for } \theta_2 = \frac{\sum(x_i - \mu)^2}{n}$$

$$\therefore \widehat{\theta_2} = \frac{\sum(x_i - \mu)^2}{n} = \sigma^2$$

Exercise 3: Find the maximum likelihood estimator for the Poisson distribution $f(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!}$.

Solution: Let us consider

$$\begin{aligned} L(\lambda) &= \prod_{i=1}^n f(x_i; \lambda) \\ &= \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \\ &= \frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod_{i=1}^n (x_i!)} \\ &= \frac{e^{-n\lambda} \lambda^{\sum x_i}}{k} \end{aligned}$$

$$\ln(L(\lambda)) = -n\lambda + \left(\ln(\lambda) \sum x_i \right) - \ln(k)$$

$$\frac{d}{d\lambda} \ln(L(\lambda)) = -n + \frac{\sum x_i}{\lambda}$$

$$\frac{d}{d\lambda} \ln(L(\lambda)) = 0$$

$$\Rightarrow -n + \frac{\sum x_i}{\lambda} = 0$$

$$\Rightarrow \frac{\sum x_i}{\lambda} = n$$

$$\Rightarrow \lambda = \frac{\sum x_i}{n}$$

$$\frac{d^2}{d\lambda^2} \ln(L(\lambda)) = -\frac{\sum x_i}{\lambda^2} < 0 \text{ for } \lambda = \frac{\sum x_i}{n}$$

$$\therefore \hat{\lambda} = \frac{\sum x_i}{n} = \bar{x}$$