

Assignment

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Q1. mean = θ_1 (Normal Distribution)
variance = θ_2

max likelihood estimate?

The likelihood function is:

$$L(\theta_1, \theta_2 | x_1, x_2, \dots, x_n) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x_i - \theta_1)^2}{2\theta_2}}$$

Take log on both sides

$$\ln L(\theta_1, \theta_2 | x_1, x_2, \dots, x_n) = -\frac{n}{2} \ln(2\pi\theta_2) - \frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2$$

Differentiate w.r.t θ_1 & θ_2 & then equate to 0

for θ_1 :

$$\frac{\partial}{\partial \theta_1} \ln L(\theta_1, \theta_2 | x_1, x_2, \dots, x_n) = \frac{1}{\theta_2} \sum_{i=1}^n (x_i - \theta_1)$$

equate to 0

$$\frac{1}{\theta_2} \sum_{i=1}^n (x_i - \hat{\theta}_1) = 0$$

$$\sum_{i=1}^n (x_i - \hat{\theta}_1) = 0$$

$$\hat{\theta}_1 = \frac{1}{n} \sum_{i=1}^n x_i$$

So MLE for θ_1 is sample mean.

for θ_2 :

$$\frac{\partial}{\partial \theta_2} \ln L(\theta_1, \theta_2 | x_1, x_2, \dots, x_n) = \frac{-n}{2\theta_2} + \frac{1}{2\theta_2^3} \sum_{i=1}^n (x_i - \theta_1)^2$$

equate to 0

$$\frac{-n}{2\hat{\theta}_2} + \frac{1}{2\hat{\theta}_2^3} \sum_{i=1}^n (x_i - \hat{\theta}_1)^2 = 0$$

$$\frac{n}{2\hat{\theta}_2} = \frac{1}{2\hat{\theta}_2^3} \sum_{i=1}^n (x_i - \hat{\theta}_1)^2$$

$$\hat{\sigma}_1^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\sigma}_1)^2$$

So MLE for σ is sample variance

Q2.

Bernoulli distribution

parameter $\rightarrow \theta \in \Theta = (0,1)$ unknown

$\rightarrow m$ (known +ve \mathbb{Z})

The likelihood function is \rightarrow

$$L(\theta | x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i = x_i | \theta)$$

Since X_i follows Bernoulli distribution,

$$P(X_i = x_i | \theta) = \theta^{x_i} (1-\theta)^{m-x_i} \text{ for each } i$$

Making log on both sides

$$\begin{aligned} \ln L(\theta | x_1, x_2, \dots, x_n) &= \sum_{x_i=1}^n \ln(\theta^{x_i} (1-\theta)^{m-x_i}) \\ &= \sum_{i=1}^n (x_i \ln \theta + (m-x_i) \ln(1-\theta)) \end{aligned}$$

Differentiate wrt θ

$$\frac{d}{d\theta} (\ln L(\theta | x_1, x_2, \dots, x_n)) = 0$$

$$\sum_{i=1}^n \left(\frac{x_i}{\theta} - \frac{n-x_i}{1-\theta} \right) = 0$$

$$\sum_{i=1}^n \frac{x_i}{\theta} = mn - \sum_{i=1}^n \frac{x_i}{1-\theta}$$

$$\therefore \theta = \frac{\sum_{i=1}^n x_i}{n \cdot m}$$

So max likelihood estimate of θ is :

$$\hat{\theta}_{MLE} = \frac{\sum_{i=1}^n x_i}{n \cdot m}$$