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Question 1:-

Let $(x_1, x_2, x_3, \dots, x_n)$ be a random sample of size n taken from a normal population with parameters, mean $= \theta_1$ and variance $= \theta_2$. Find the maximum likelihood estimates of these parameters.

Given that x_1, x_2, \dots, x_n is a random sample from a normal distribution with mean $= \theta_1$ and variance θ_2 the likelihood function is

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

Taking log on both sides

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

To find MLE, we will differentiate the log-likelihood with respect to θ_1 and θ_2 , set derivative equal to zero.

For θ_1

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

Setting this equal to zero

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

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

So MLE for θ_1 is the sample mean,

For θ_2

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

Setting this equal to zero.

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

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

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

So, MLE for θ_2 is the sample variance

Question a!

Let X_1, X_2, \dots, X_n be random sample from $B(m, \theta)$ distribution, where $\theta \in \Theta = (0, 1)$ is unknown and m is known the integer, compute values of θ using the MLE.

Answer:-

To find the MLE of θ for random sample X_1, X_2, \dots, X_n from a Bernoulli Distribution with parameter θ and m known. The likelihood for this scenario is -

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

Since X_i follows a Bernoulli distribution

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

Taking log on both sides.

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

now differentiate with respect to θ and set to zero.

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

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

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

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

So max likelihood estimate for θ .

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