

## Predictive Analysis Assignment

### Parameter Estimation

Q.1 Let  $(X_1, X_2, \dots)$  be a random sample of size  $n$  taken from a normal population with parameters: mean  $= \theta_1$  & variance  $= \theta_2$ . Find the maximum likelihood Estimates of these two parameters.

Sol. PMF  $(x_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x_i - \mu)^2 / 2\sigma^2}$  for normal dist.

here  $\mu = \theta_1$   
 $\sigma^2 = \theta_2$

$$f(x_i | \theta_1, \theta_2) = \frac{1}{\sqrt{2\pi\theta_2}} e^{-(x_i - \theta_1)^2 / 2\theta_2}$$

Now likelihood function

$$L(\theta_1, \theta_2) = \prod_{i=1}^n f(x_i | \theta_1, \theta_2)$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\theta_2}} e^{-(x_i - \theta_1)^2 / 2\theta_2}$$

$$L(\theta_1, \theta_2) = \prod_{i=1}^n (\theta_1)^{-1/2} \prod_{i=1}^n (2\pi)^{-1/2} \prod_{i=1}^n e^{-(x_i - \theta_1)^2 / 2\theta_2}$$

$$L(\theta_1, \theta_2) = \left(\frac{\theta_2}{2}\right)^{-n/2} (2\pi)^{-n/2} e^{-\left(\sum_{i=1}^n (x_i - \theta_1)^2 / 2\theta_2\right)}$$

$$L(\theta_1, \theta_2) = \frac{\theta_2^{-n/2}}{2} (2\pi)^{-n/2} e^{-\frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2}$$

taking log on both sides.

$$\ln L(\theta_1, \theta_2) = \ln \left[ \frac{\theta_2^{-n/2}}{2} (2\pi)^{-n/2} e^{-\frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2} \right]$$

$$= \ln(\theta_2)^{-n/2} + \ln(2\pi)^{-n/2} + \ln\left(e^{-\frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2}\right)$$

$$\ln L(\theta_1, \theta_2) = -\frac{n}{2} \ln \theta_2 - \frac{n}{2} \ln 2\pi - \frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2 \quad \text{--- (1)}$$

now, differentiating both sides w.r.t  $\theta_1$

$$\frac{\partial L(\theta_1, \theta_2)}{\partial \theta_1} = \frac{1}{\theta_2} \sum_{i=1}^n (x_i - \theta_1)$$

$$\text{now, } \frac{\partial L(\theta_1, \theta_2)}{\partial \theta_1} = 0$$

$$\text{hence, } \frac{1}{\theta_2} \sum_{i=1}^n (x_i - \theta_1) = 0$$

$$(1/\theta_2) \left( \sum_{i=1}^n x_i - n\theta_1 \right) = 0$$

$$\sum_{i=1}^n x_i - n\theta_1 = 0.$$



$$\theta_1 = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\theta_1 = \bar{x}_n$$

$$\boxed{\theta_{1, \text{MLE}} = \bar{x}_n} \quad - (2)$$

Differentiating ① w.r.t ②

$$\frac{\partial L(\theta_1, \theta_2)}{\partial \theta_2} = -\frac{n}{2\theta_2} - \frac{1}{2(\theta_2)^2} \sum_{i=1}^n (x_i - \theta_1)^2$$

$$\text{Since } \frac{\partial L(\theta_1, \theta_2)}{\partial \theta_2} = 0$$

$$-\frac{n}{2\theta_2} - \frac{1}{2\theta_2^2} \sum_{i=1}^n (x_i - \theta_1)^2 = 0$$

$$\frac{1}{2\theta_2^2} \sum_{i=1}^n (x_i - \theta_1)^2 = -\frac{n}{2\theta_2}$$

$$\theta_2 = \frac{1}{n} \sum_{i=1}^n (x_i - \theta_1)^2$$

from ②:

$$\boxed{\theta_{2, \text{MLE}} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2}$$

Q.2 Let  $X_1, X_2, \dots, X_n$  be a random sample from  $B(m, \theta)$  distribution, where  $\theta \in (0, 1)$  is unknown and 'm' is a known positive integer. Compute value of  $\theta$  using MLE.

Sol.  $PMF(x_i) = {}^m C_{x_i} p^{x_i} (1-p)^{n-x_i}$

here  $n = m, p = \theta$

$$P(x_i | m, \theta) = {}^m C_{x_i} \theta^{x_i} (1-\theta)^{m-x_i}$$

for likelihood function,

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

$$= \prod_{i=1}^n ({}^m C_{x_i} \theta^{x_i} (1-\theta)^{m-x_i})$$

$$= \prod_{i=1}^n {}^m C_{x_i} \prod_{i=1}^n \theta^{x_i} \prod_{i=1}^n (1-\theta)^{m-x_i}$$

$$= \prod_{i=1}^n {}^m C_{x_i} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{\sum_{i=1}^n (m-x_i)}$$

$$= \prod_{i=1}^n {}^m C_{x_i} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{nm - \sum_{i=1}^n x_i}$$



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Taking  $\ln$  on both sides,

$$\ln L(p) = \ln \left( \prod_{i=1}^n {}^m C_{x_i} \prod_{i=1}^n \theta^{x_i} (1-\theta)^{nm - \sum_{i=1}^n x_i} \right)$$

$$= \ln \left( \prod_{i=1}^n {}^m C_{x_i} \right) + \ln \left( \theta^{\sum_{i=1}^n x_i} \right) + \ln \left( (1-\theta)^{nm - \sum_{i=1}^n x_i} \right),$$

$$= \ln \left( \prod_{i=1}^n {}^m C_{x_i} \right) + \ln(\theta) \cdot \sum_{i=1}^n x_i + \ln(1-\theta) \cdot (nm - \sum_{i=1}^n x_i)$$

Differentiating w.r.t.  $\theta$

$$\frac{\partial L(p)}{\partial \theta} = \frac{1}{\theta} \sum_{i=1}^n x_i + \left( \frac{-1}{1-\theta} \right) (nm - \sum_{i=1}^n x_i)$$

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

Now  $\frac{\partial L(p)}{\partial \theta} = 0$ .

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

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

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

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

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

$$\theta = \frac{\bar{x}_n}{n}$$

$$\theta_{MLE} \in (0,1) = \frac{\bar{x}_n}{n}$$