

Rhythm 102103241

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3009

Q1. Maximum likelihood estimator for Normal distribution

mean = $\theta_1 = \mu$
variance = $\theta_2 = \sigma^2$

given:-

pdf for Normal distribution

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

$$-\infty \leq x \leq \infty$$

$$-\infty \leq \theta_1 \leq \infty$$

$$\theta_2 > 0$$

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

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

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

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

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

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

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

$\Rightarrow \Rightarrow$

$$\frac{d \log L(x; \theta_1, \theta_2)}{d\theta_1} = 0 - 0 - 2 \sum_{i=1}^n \frac{(x_i - \theta_1)}{2\theta_2}$$

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

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

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

Divide b.s. by n.

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

$$\Rightarrow \hat{\theta}_1 = \bar{x}$$

$$ii) \quad \frac{d \log L(\lambda; \theta_1, \theta_2)}{d \theta_2} = 0$$

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

$$\Rightarrow \hat{\theta}_2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})$$

9) Suppose $x_1, x_2, \dots, x_n \sim B(m, \theta)$

proof

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

$$x_i \in (0, 1, 2, \dots, m)$$

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

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

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

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

$$\Rightarrow L(\theta) = \prod_{i=1}^n \binom{m}{x_i} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{mn - \sum_{i=1}^n x_i}$$

$$\Rightarrow \log L(\theta) = \log \left[\prod_{i=1}^n \binom{m}{x_i} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{mn - \sum_{i=1}^n x_i} \right]$$

$$= \log \left(\prod_{i=1}^n \binom{m}{x_i} \right) + \log \left[\theta^{\sum_{i=1}^n x_i} \right] + \log \left[(1-\theta)^{mn - \sum_{i=1}^n x_i} \right]$$

$$\log L(\theta) = \log \left[\prod_{i=1}^n m(x_i) \right] + \left(\sum_{i=1}^n x_i \right) \log \theta + \left(mn - \sum_{i=1}^n x_i \right) \log (1-\theta)$$

Diff w.r.t θ B.S.

$$\frac{d \log L(\theta)}{d\theta} = \frac{1}{\theta} \sum_{i=1}^n x_i - \frac{1}{1-\theta} \left(mn - \sum_{i=1}^n x_i \right)$$

\Downarrow
0

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

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

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

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

$$\hat{\theta} = \frac{\sum_{i=1}^n x_i}{mn} = \frac{\bar{x}}{m}$$