

# Assignment

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Q1 mean =  $\theta_1$  (Normal distribution)  
variance =  $\theta_2$

max likelihood estimate  
function

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

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

for  $\theta_1$

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

$$R.H.S = 0$$

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

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

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

so MLE of  $\theta_1 \rightarrow$  sample mean



for  $\theta_2$

$$\frac{d}{d\theta_2} \ln L(\cdot) = \frac{-n}{2\theta_2} + \frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \theta_1)^2$$

R.H.S = 0

$$\frac{-n}{2\theta_2} = \frac{1}{2\theta_2} \sum_{i=1}^n (x_i - \hat{\theta}_1)^2$$

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

so MLE for  $\theta_2 \rightarrow$  sample variance

Q2 Bernoulli distribution

parameter  $\rightarrow \theta \in \theta = (0,1)$  unknown  
 $\rightarrow n$  (known + ve  $z$ )

MLE

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

$$P(x_i = x_i | \theta) = \theta^{x_i} (1-\theta)^{n-x_i}$$

taking log

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

$$= \sum_{i=1}^n (x_i \ln \theta + (n-x_i) \ln(1-\theta))$$



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

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

so max likelihood estimate of  $\theta$  is :

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