

Exercise - 1 / Question - 4

① Single data point: $p(x_n | \theta)$

② Likelihood: $L(\theta) = p(X | \theta) = \prod_{n=1}^N p(x_n | \theta)$

③ Log-likelihood:

$$\ell(\theta) = \ln(L(\theta)) = \ln\left(\prod_{n=1}^N p(x_n | \theta)\right)$$

$$= \ln(p(x_1 | \theta) \cdot p(x_2 | \theta) \cdot \dots \cdot p(x_N | \theta))$$

← Apply

Get

Rule of log:

$$\log(a \cdot b) = \log a + \log b$$

$$= \ln(p(x_1 | \theta)) + \ln(p(x_2 | \theta)) + \dots + \ln(p(x_N | \theta))$$

$$= \sum_{n=1}^N \ln(p(x_n | \theta))$$

$$\ell(\theta) = \ln(L(\theta)) = \ln\left(\prod_{n=1}^N p(x_n | \theta)\right) = \sum_{n=1}^N \ln(p(x_n | \theta))$$

④ Maximize Log-likelihood, i.e. take derivative and set to zero:

$$\frac{\partial \ell(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta} \sum_{n=1}^N \ln(p(x_n | \theta))$$

$$= \frac{\partial}{\partial \theta} [\ln(p(x_1 | \theta)) + \ln(p(x_2 | \theta)) + \dots + \ln(p(x_N | \theta))]$$

$$= \frac{2}{2\theta} \ln(p(x_1|\theta)) + \frac{2}{2\theta} \ln(p(x_2|\theta)) + \dots + \frac{2}{2\theta} \ln(p(x_N|\theta))$$

Rule of derivative:

$$\frac{d}{dx} \ln[f(x)] = \frac{1}{f(x)} f'(x)$$

Apply

↑

Get

$$= \frac{1}{p(x_1|\theta)} \cdot \frac{2}{2\theta} p(x_1|\theta) + \dots + \frac{1}{p(x_N|\theta)} \frac{2}{2\theta} p(x_N|\theta)$$

$$= \sum_{n=1}^N \frac{\frac{2}{2\theta} p(x_n|\theta)}{p(x_n|\theta)} \stackrel{!}{=} 0$$

① $p(x|\theta) = \theta^2 \cdot x \cdot \exp(-\theta x) \cdot \underbrace{g(x)}_{\substack{1 \text{ if } x > 0 \\ 0 \text{ otherwise}}}$ where $g(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$

!! As we know all data points

$x_1, \dots, x_N > 0$, $g(x)$ will take value 1 for all data points x_1, \dots, x_N .

$$= \theta^2 \cdot x \cdot \exp(-\theta x) \cdot 1$$

③ $E(\theta) = \ln(L(\theta)) = \ln\left(\prod_{n=1}^N p(x_n|\theta)\right) = \sum_{n=1}^N \ln(\underbrace{p(x_n|\theta)})$

!! As we know $p(x|\theta)$ from ①, let's put it there.

$$= \sum_{n=1}^N \ln(\theta^2 \cdot x_n \cdot \exp(-\theta x_n))$$

$$(4) \frac{\partial E(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta} \left[\sum_{n=1}^N \ln(\theta^2 \cdot x_n \cdot \exp(-\theta x_n)) \right]$$

Apply

?

Get

Rule of log:

$$\log(a \cdot b) = \log a + \log b$$

$$= \frac{\partial}{\partial \theta} \left[\sum_{n=1}^N \ln \theta^2 + \ln x_n + \ln(\exp(-\theta x_n)) \right]$$

$$= \frac{\partial}{\partial \theta} \left[\sum_{n=1}^N \ln \theta^2 + \sum_{n=1}^N \ln x_n + \sum_{n=1}^N \ln(\exp(-\theta x_n)) \right]$$

Rule of log:

$$\log_b M^k = k \log_b M$$

Apply

Rule of log:

$$\log_b b^k = k$$

$$= \frac{\partial}{\partial \theta} \left[\sum_{n=1}^N 2 \ln \theta + \sum_{n=1}^N \ln x_n + \sum_{n=1}^N -\theta x_n \right]$$

$$= \frac{\partial}{\partial \theta} \left[2N \ln \theta + \sum_{n=1}^N \ln x_n + \left(\sum_{n=1}^N -x_n \right) \cdot \theta \right]$$

$$= \frac{2(2N \ln \theta)}{\partial \theta} + \frac{\partial}{\partial \theta} \sum_{n=1}^N \ln x_n - \sum_{n=1}^N x_n \cdot \frac{\partial (\theta)}{\partial \theta}$$

$$= 2N \cdot \frac{1}{\theta} + 0 - \sum_{n=1}^N x_n \cdot 1$$

$$= \frac{2N}{\theta} + 0 - \sum_{n=1}^N x_n \stackrel{!}{=} 0$$

$$\frac{2N}{\theta} \rightarrow \sum_{n=1}^N x_n$$

$$\Rightarrow \theta = \frac{2N}{\sum_{n=1}^N x_n}$$