

## CH5115 QUIZ-3.

(2) i)

$$f(y) = \frac{\lambda^y e^{-\lambda}}{y!} \quad y > 0, \quad y \in \mathbb{Z}^+ \text{ (positive integers)}$$

$$l = \prod_{k=1}^N \frac{\lambda^{y[k]} e^{-\lambda}}{(y[k])!}$$

$$\Rightarrow h = \ln l(\theta | y)$$

$$= \ln \left( \prod_{k=1}^N \frac{\lambda^{y[k]} e^{-\lambda}}{y[k]!} \right)$$

$$= \sum_{k=1}^N y[k] \ln \lambda - N\lambda - \sum_{k=1}^N \ln(y[k]!)$$

$$\Rightarrow L = \sum_{k=1}^N y[k] \ln \lambda - N\lambda - \sum_{k=1}^N \ln(y[k]!)$$

$$\Rightarrow \frac{\partial L}{\partial \lambda} = \frac{\sum y[k]}{\lambda} - N$$

$$\text{Maximise } L \Rightarrow \frac{\partial L}{\partial \lambda} = 0$$

$$\Rightarrow \lambda = \frac{\sum y[k]}{N} \text{ is the maximum of } f.$$

$$\frac{\partial^2 L}{\partial \lambda^2} = - \frac{\sum y[k]}{\lambda^2}$$

Since  $\lambda^2 > 0 \quad \forall \lambda \in \mathbb{R}^+$  and  $y[k] \in \mathbb{Z}^+$   
for all  $k$ , we have  $\frac{\partial^2 L}{\partial \lambda^2} < 0$  at  $\lambda = \frac{\sum y[k]}{N}$

$\therefore$  The point is indeed a maxima.

Also,  $\forall \lambda > \frac{\sum y[k]}{N}$  the function is decreasing

Given constraint :  $\lambda \geq b$

$$\Rightarrow \hat{\lambda} = \begin{cases} \frac{\sum y[k]}{N} & \frac{\sum y[k]}{N} \geq b \\ b & \frac{\sum y[k]}{N} < b \end{cases}$$

this can be simplified to

$$\boxed{\hat{\lambda}_{MLE} = \max\left(\frac{\sum y[k]}{N}, b\right)}$$

ii)  $Y \sim \Gamma(1, \theta) \Rightarrow f(y) = \frac{1}{\Gamma(1)\theta^1} y^{1-1} e^{-y/\theta}$

$$\Rightarrow f(y) = \frac{e^{-y/\theta}}{\theta} \quad (\text{exponential PDF})$$

$\theta > 0$

where  $\theta > 0$

$$\Rightarrow f(y) = \frac{e^{-y/\theta}}{\theta} \quad \text{--- (1)}$$

$$l = \prod_{k=1}^N \frac{e^{-y[k]/\theta}}{\theta} = \prod_{k=1}^N \frac{e^{-y[k]/\theta}}{\theta} \quad \text{--- (2)}$$

$$\Rightarrow \mathcal{L} = -\frac{\sum y[k]}{\theta} - N \ln \theta$$

$$\Rightarrow \frac{\partial L}{\partial \theta} = \frac{\sum_{k=1}^N y[k]}{\theta^2} - \frac{N}{\theta}$$

$$\Rightarrow \frac{\partial^2 L}{\partial \theta^2} = - \frac{2 \sum_{k=1}^N y[k]}{\theta^3} + \frac{N}{\theta^2} \quad \text{--- (3)}$$

$$I(\theta) = - \mathbb{E} \left( \frac{\partial^2 L}{\partial \theta^2} \right) = \frac{2 \sum \mathbb{E}(y[k])}{\theta^3} + \frac{N}{\theta^2}$$

[Fisher - Information] --- (4)

Mean of exponential distribution  $\lambda e^{-\lambda} = \frac{1}{\lambda}$

$$\Rightarrow \mathbb{E}(y[k]) = \frac{1}{\theta} = \theta \quad \text{--- (5)}$$

Substituting (5) in (4),

$$I(\theta) = \frac{2 N \theta}{\theta^3} - \frac{N}{\theta^2} \Rightarrow I(\theta) = \frac{N}{\theta^2}$$

$$\Rightarrow \text{Jeffrey's prior } \pi(\theta) \propto (I(\theta))^{1/2}$$

$$\Rightarrow \pi(\theta) \propto \sqrt{\frac{1}{\theta^2}}$$

$$\Rightarrow \pi(\theta) \propto \frac{1}{\theta}$$

No. Paragunya's choice is not in the list

of Jeffrey's prior

Correct prior:  $\boxed{\pi(\theta) \propto \frac{1}{\theta}}$

$$\begin{aligned}
 b) \quad f(\theta|y_N) &= \frac{f(y_N|\theta)f(\theta)}{f(y_N)} = \frac{\pi(\theta)f(y_N|\theta)}{f(y_N)} \quad \downarrow \text{likelihood, } l. \\
 &= \frac{C}{\theta} \cdot \frac{e^{\sum_{k=1}^N y[k]}}{\theta^N} \\
 &= \frac{C}{\theta} \cdot \frac{\exp\left(-\sum_{k=1}^N \frac{y[k]}{\theta}\right)}{\theta^N}
 \end{aligned}$$

$$f(\theta|y_N) = \frac{C}{\theta^{N+1}} \times \exp\left(-\sum_{k=1}^N \frac{y[k]}{\theta}\right) \quad \text{--- (6)}$$

where  $C$  is the proportionality constant which should be adjusted to make  $f(\theta|y_N)$  a valid pdf.

c) Consider 2 RVs  $X \in Y$  and  $Y = \frac{1}{X}$ .

$$\Rightarrow F(Y \leq y) = F\left(\frac{1}{X} \leq y\right) \\ = F\left(X \geq \frac{1}{y}\right)$$

$$\Rightarrow F(Y \leq y) = 1 - F\left(X \leq \frac{1}{y}\right)$$

differentiate both sides w.r.t  $y$ .

$$\Rightarrow f_Y(y) = \frac{1}{y^2} f_X\left(\frac{1}{y}\right)$$

$y \rightarrow T$ ,  $x \rightarrow \theta$  ( $\because$  In this problem  $T = \frac{1}{\theta}$ )

$$\Rightarrow f_T(T | y_N) = \frac{1}{T^2} f_X\left(\frac{1}{T}\right)$$

$$= -C \frac{T^{N+1}}{T^2} \exp\left(-T \sum_{k=1}^N y[k]\right)$$

$$\Rightarrow f(T | y_N) = -C T^{N-1} \exp\left(-T \sum y[k]\right) \quad \text{--- (7)}$$



The MMSE is the mean of the above PDF.

$$\hat{T} = \int_0^{\infty} T f(T|y_N) dT \quad \text{--- (8)}$$

$$1 = \int_0^{\infty} f(T|y_N) dT \quad \text{--- (9)}$$

$$\frac{(8)}{(9)} \Rightarrow \int_0^{\infty} T^N \exp(-T \sum y[k]) (-c) dT = \hat{T} \quad \text{--- (10)}$$

$$\int_0^{\infty} T^{N-1} \exp(-T \sum y[k]) (-c) dT$$

Since  $c$  is a constant we can simply cancel it.

it. We also recognise that.

$$\int_0^{\infty} x^N e^{-ax} dx = \frac{\Gamma(n+1)}{a^{n+1}}$$

(replace variable  $x$  as  $u$  to get the result)

$$\Rightarrow \int_0^{\infty} x^N e^{-ax} dx = \frac{N!}{a^{N+1}} \quad \text{--- (11)}$$

$a = \sum y[k]$  ; Substituting (11) in (10)

$$\frac{N!}{(\sum y(k))^{N+1}} \times \frac{(\sum y(k))^N}{(N-1)!} = \hat{T}$$

$$\Rightarrow \hat{T} = \frac{N}{\sum_{k=1}^N y[k]}$$

estimator

Thus the  $MSE_x$  of  $T$  is

$$\hat{T} = \frac{N}{\sum_{k=1}^N y[k]}$$