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## Problem 1

$$\begin{aligned} \text{a) Likelihood is } L(\lambda) &= \prod_{i=1}^n \left( \frac{1}{\lambda} e^{-\frac{x_i}{\lambda}} \right) \\ &= \left( \frac{1}{\lambda} \right)^n e^{-\frac{1}{\lambda} \sum_{i=1}^n x_i} \end{aligned}$$

The Log of the likelihood is

$$\log(L(\lambda)) = -n \log(\lambda) - \frac{1}{\lambda} \sum_{i=1}^n x_i$$

The maximum likelihood estimator maximizes

$\log(L(\lambda))$ . To obtain it, we solve  $\frac{d \log(L(\lambda))}{d\lambda} = 0$

and check if  $\frac{d^2 \log(L(\lambda))}{d^2 \lambda} \Big|_{\lambda = \hat{\lambda}_{MLE}} < 0$ .

$$\frac{d \log(L(\lambda))}{d\lambda} = -\frac{n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^n x_i; \text{ setting it to zero}$$

$$\text{we solve } \hat{\lambda}_{MLE} = \frac{\sum_{i=1}^n x_i}{n}$$

$$\frac{d^2 \log(L(\lambda))}{d\lambda^2} = \frac{n}{\lambda^2} - \frac{2}{\lambda^3} \sum_{i=1}^n x_i = \frac{1}{\lambda^2} \left( n - \frac{2}{\lambda} \sum_{i=1}^n x_i \right)$$

$$\frac{d^2 \log(L(\lambda))}{d\lambda^2} \Big|_{\hat{\lambda}_{MLE}} = \frac{1}{\hat{\lambda}_{MLE}^2} \left( n - \frac{2n}{\sum_{i=1}^n x_i} \cdot \sum_{i=1}^n x_i \right) = \frac{1}{\hat{\lambda}_{MLE}^2} \cdot (-n) < 0$$

Hence  $\frac{\sum_{i=1}^n x_i}{n}$  is indeed the maximum likelihood estimator

$$b) \quad E(\hat{\lambda}_{MLE}) = E\left(\frac{\sum_{i=1}^n x_i}{n}\right) = \frac{1}{n} \sum_{i=1}^n E(x_i)$$

$$E(x_i) = M'(0)$$

$$M(t) = \int_0^{\infty} e^{tx} \cdot \frac{1}{\lambda} e^{-\frac{x}{\lambda}} dx$$

$$= \frac{1}{\lambda} \int_0^{\infty} e^{x(t-\frac{1}{\lambda})} dx \quad \text{for } t < \frac{1}{\lambda}$$

$$= \frac{1}{\lambda} \cdot \frac{1}{t-\frac{1}{\lambda}} e^{x(t-\frac{1}{\lambda})} \Big|_{x=0}^{\infty}$$

$$= -\frac{1}{\lambda} \cdot \frac{1}{t-\frac{1}{\lambda}} = \frac{-1}{\lambda t - 1} = \frac{1}{1-\lambda t}$$

$$M'(t) = -\frac{1}{(1-\lambda t)^2} \cdot (-\lambda) = \frac{\lambda}{(1-\lambda t)^2}$$

Hence  $M'(0) = \lambda$

Hence  $E(x_i) = \lambda$  and  $E(\hat{\lambda}_{MLE}) = \lambda$ . Therefore  $\hat{\lambda}_{MLE}$  is unbiased.

$$c) \quad MSE = E\left(\hat{\lambda}_{MLE} - \lambda\right)^2 = \text{Var}(\hat{\lambda}_{MLE}) = \text{Var}\left(\frac{\sum_{i=1}^n x_i}{n}\right)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i)$$

$$\text{Var}(x_i) = M''(0) - M'(0)^2$$

$$M''(t) = \left( \frac{\lambda}{(1-\lambda t)^2} \right)' = -2\lambda \cdot \frac{1}{(1-\lambda t)^3} \cdot (-\lambda)$$

$$= \frac{2\lambda^2}{(1-\lambda t)^3}$$

$$\text{Hence } M''(0) = 2\lambda^2, \quad \text{Var}(x_i) = 2\lambda^2 - \lambda^2 = \lambda^2$$

$$\text{Hence } \text{MSE} = \text{Var}(\hat{\lambda}_{\text{MLE}}) = \frac{1}{n^2} (\underbrace{\lambda^2 + \lambda^2 + \dots + \lambda^2}_n)$$

$$= \frac{\lambda^2}{n}$$

Problem 2.

a) 
$$\left[ \bar{x} - Z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + Z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} \right]$$

$\downarrow$  sample mean       $\downarrow$  standard deviation of the population  
 $\downarrow$  sample size

100(1- $\frac{\alpha}{2}$ ) percentile of standard Normal distribution

b) The 95% CI is 
$$\left[ \bar{x} - 1.96 \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + 1.96 \cdot \frac{\sigma}{\sqrt{n}} \right]$$

$$= \left[ 98 - 1.96 \cdot \frac{2}{\sqrt{9}}, 98 + 1.96 \cdot \frac{2}{\sqrt{9}} \right]$$



b) 95% CI is

$$\left[ 0.823 - 1.96 \sqrt{\frac{0.823 \cdot 0.177}{1000}}, 0.823 + 1.96 \sqrt{\frac{0.823 \cdot 0.177}{1000}} \right]$$
$$= [0.499, 0.547]$$

c)  $p$  from this sample is 0.823

$$n \geq \left( \frac{Z_{\frac{\alpha}{2}}}{E} \right)^2 p(1-p) = \left( \frac{1.96}{0.03} \right)^2 \cdot 0.823 \cdot 0.177$$
$$= 621.8$$

Hence the smallest sample size is 622

d) using  $p = 0.5$

$$n \geq \left( \frac{1.96}{0.03} \right)^2 \cdot 0.5 \cdot 0.5 = 1067.11$$

Hence the smallest sample size is 1068.