

### #HW3. 103201506 數學 4A 邱奕豪

#### Problem1.

4.26

X and Y are independent random variables with  $X \sim \exp(\lambda)$  and  $Y \sim \exp(\mu)$ .

It is impossible to obtain direct observations of X and Y. Instead, we observe the random variables Z and W, where

$$Z = \min\{X, Y\} \quad \text{and} \quad W = \begin{cases} 1 & \text{if } Z = X \\ 0 & \text{if } Z = Y \end{cases}$$

(This is a situation that arises, in particular, in medical experiments. The X and Y variables are censored.)

(a) Find the joint distribution of Z and W

(b) Prove that Z and W are independent. (Hint: show that  $P(Z \leq z | W=i) = P(Z \leq z)$  for  $i=0$  or  $1$ .)

Solution:

$$\begin{aligned} \text{(a) } P(Z \leq z, W=1) &= P(X \leq z, X \leq Y) = \int_0^z \int_x^\infty \frac{1}{\lambda} \frac{1}{\mu} e^{-\frac{y}{\mu}} e^{-\frac{x}{\lambda}} dy dx \\ &= \int_0^z \frac{1}{\lambda} e^{-x(\frac{1}{\mu} + \frac{1}{\lambda})} dx = \frac{\mu}{\lambda + \mu} (1 - e^{-z(\frac{1}{\mu} + \frac{1}{\lambda})}) \end{aligned}$$

$$\begin{aligned} \text{Similarly, } P(Z \leq z, W=0) &= P(Y \leq z, Y \leq X) = \int_0^z \int_y^\infty \frac{1}{\lambda} \frac{1}{\mu} e^{-\frac{y}{\mu}} e^{-\frac{x}{\lambda}} dx dy \\ &= \int_0^z \frac{1}{\mu} e^{-y(\frac{1}{\mu} + \frac{1}{\lambda})} dy = \frac{\lambda}{\lambda + \mu} (1 - e^{-z(\frac{1}{\mu} + \frac{1}{\lambda})}) \end{aligned}$$

$$\text{So, } f(z, w=1) = \frac{d}{dz} P(Z \leq z, W=1) = \frac{1}{\mu} \exp(-z(\frac{1}{\mu} + \frac{1}{\lambda})) \quad , z \geq 0$$

$$f(z, w=0) = \frac{d}{dz} P(Z \leq z, W=0) = \frac{1}{\lambda} \exp(-z(\frac{1}{\mu} + \frac{1}{\lambda})) \quad , z \geq 0$$

$$\text{Hence, } f(z, w) = \left(\frac{1}{\lambda}\right)^{1-w} \left(\frac{1}{\mu}\right)^w \exp(-z(\frac{1}{\mu} + \frac{1}{\lambda})) \quad , z \geq 0, w = 0 \text{ or } 1$$

$$\text{(b) } P(Z \leq z) = P(Z \leq z, W=1) + P(Z \leq z, W=0) = 1 - e^{-z(\frac{1}{\mu} + \frac{1}{\lambda})}$$

$$\begin{aligned} P(Z \leq z | w=1) &= \frac{P(Z \leq z, W=1)}{P(w=1)} = \frac{P(Z \leq z, W=1)}{P(X \leq Y)} \\ &= \frac{\frac{\mu}{\lambda + \mu} (1 - e^{-z(\frac{1}{\mu} + \frac{1}{\lambda})})}{\frac{\mu}{\lambda + \mu}} \quad (P(X \leq Y) = \int_0^z \int_x^\infty \frac{1}{\lambda} \frac{1}{\mu} e^{-\frac{y}{\mu}} e^{-\frac{x}{\lambda}} dy dx = \frac{\mu}{\lambda + \mu}) \\ &= 1 - e^{-z(\frac{1}{\mu} + \frac{1}{\lambda})} = P(Z \leq z) \end{aligned}$$

Similarly,  $P(Z \leq z \mid w=0) = P(Z \leq z)$

So, Z and W are independent.

**Problem2.**

7.14

Let X and Y be independent exponential random variables, with

$$f(x|\lambda) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}}, \quad x > 0, \quad f(y|\mu) = \frac{1}{\mu} e^{-\frac{y}{\mu}}, \quad y > 0$$

we observe Z and W

$$Z = \min\{X, Y\} \quad \text{and} \quad W = \begin{cases} 1 & \text{if } Z = X \\ 0 & \text{if } Z = Y \end{cases}$$

In exercise 4.26 the joint distribution of Z and W was obtained. Now assume that  $(Z_i, W_i), i=1, \dots, n$ , are n iid observations. Find the MLEs of  $\lambda$  and  $\mu$

Solution:

$$f(z, w) = \left(\frac{1}{\lambda}\right)^{1-w} \left(\frac{1}{\mu}\right)^w \exp\left(-z\left(\frac{1}{\mu} + \frac{1}{\lambda}\right)\right), \quad z \geq 0, \quad w = 0 \text{ or } 1$$

let  $T = ((Z_1, W_1), (Z_2, W_2), \dots, (Z_n, W_n))$

$$L(\mu, \lambda \mid T) = \left(\frac{1}{\lambda}\right)^{n - \sum_{i=1}^n W_i} \left(\frac{1}{\mu}\right)^{\sum_{i=1}^n W_i} \exp\left(-\sum_{i=1}^n Z_i \left(\frac{1}{\mu} + \frac{1}{\lambda}\right)\right)$$

$$\ln(L(\mu, \lambda \mid T)) = -\left(\sum_{i=1}^n W_i\right) \ln \mu - \left(n - \sum_{i=1}^n W_i\right) \ln \lambda - \sum_{i=1}^n Z_i \left(\frac{1}{\mu} + \frac{1}{\lambda}\right)$$

$$\frac{\partial}{\partial \mu} \ln(L(\mu, \lambda \mid T)) = \frac{-\sum_{i=1}^n W_i}{\mu} + \frac{\sum_{i=1}^n Z_i}{\mu^2} \stackrel{\text{set}}{=} 0$$

$$\Leftrightarrow \hat{\mu} = \frac{\sum_{i=1}^n Z_i}{\sum_{i=1}^n W_i}$$

$$\frac{\partial}{\partial \lambda} \ln(L(\mu, \lambda \mid T)) = \frac{-(n - \sum_{i=1}^n W_i)}{\lambda} + \frac{\sum_{i=1}^n Z_i}{\lambda^2} \stackrel{\text{set}}{=} 0$$

$$\Leftrightarrow \hat{\lambda} = \frac{\sum_{i=1}^n Z_i}{n - \sum_{i=1}^n W_i}$$

$$\frac{\partial^2}{\partial \lambda^2} \ln(L(\mu, \lambda \mid T)) = \frac{n - \sum_{i=1}^n W_i}{\lambda^2} - \frac{2 \sum_{i=1}^n Z_i}{\lambda^3}$$

$$\frac{\partial^2}{\partial \mu^2} \ln(L(\mu, \lambda \mid T)) = \frac{\sum_{i=1}^n W_i}{\mu^2} - \frac{2 \sum_{i=1}^n Z_i}{\mu^3}$$

$$\frac{\partial^2}{\partial \mu \partial \lambda} \ln(L(\mu, \lambda \mid T)) = 0$$

$$H(\mu, \lambda) = \begin{pmatrix} \frac{\sum_{i=1}^n W_i}{\mu^2} - \frac{2 \sum_{i=1}^n Z_i}{\mu^3} & 0 \\ 0 & \frac{n - \sum_{i=1}^n W_i}{\lambda^2} - \frac{2 \sum_{i=1}^n Z_i}{\lambda^3} \end{pmatrix}$$

$$\Rightarrow H(\hat{\mu}, \hat{\lambda}) = \begin{pmatrix} \frac{-\sum_{i=1}^n W_i}{\mu^2} & 0 \\ 0 & \frac{-(n - \sum_{i=1}^n W_i)}{\lambda^2} \end{pmatrix}$$

$$(x, y) H \begin{pmatrix} x \\ y \end{pmatrix} = \frac{-\sum_{i=1}^n W_i}{\mu^2} x^2 - \frac{n - \sum_{i=1}^n W_i}{\lambda^2} y^2 \leq 0$$

So, H is negative semidefinite

Hence,  $\hat{\mu} = \frac{\sum_{i=1}^n Z_i}{\sum_{i=1}^n W_i}$   $\hat{\lambda} = \frac{\sum_{i=1}^n Z_i}{n - \sum_{i=1}^n W_i}$  is the mle estimator

**Problem3.**

Do the same exercise for the Weibull with the common shape parameter  $\gamma$  for X and T.

Solution :

$$f(x, \lambda, \gamma) = \frac{\gamma}{\lambda} (x/\lambda)^{\gamma-1} e^{-\left(\frac{x}{\lambda}\right)^\gamma}, \quad x \geq 0$$

$$f(y, \mu, \gamma) = \frac{\gamma}{\mu} (y/\mu)^{\gamma-1} e^{-\left(\frac{y}{\mu}\right)^\gamma}, \quad y \geq 0$$

$$P(Z \leq z, W=0) = P(Z \leq z, Y \leq X) = \int_0^z \int_y^\infty \frac{\gamma}{\lambda} \frac{\gamma}{\mu} (x/\lambda)^{\gamma-1} (y/\mu)^{\gamma-1} e^{-\left(\frac{y}{\mu}\right)^\gamma} e^{-\left(\frac{x}{\lambda}\right)^\gamma} dx dy =$$

$$\frac{\lambda^\gamma}{\mu^{\gamma+\lambda^\gamma}} (1 - \exp(-Z^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})))$$

Similary,  $P(Z \leq z, W=1) = \frac{\mu^\gamma}{\mu^{\gamma+\lambda^\gamma}} (1 - \exp(-Z^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})))$

$$f(z, w=0) = \frac{d}{dz} P(Z \leq z, W=0) = \frac{r z^{r-1}}{\mu^\gamma} \exp(-Z^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})), \quad z \geq 0$$

$$f(z, w=1) = \frac{d}{dz} P(Z \leq z, W=1) = \frac{\gamma z^{r-1}}{\lambda^\gamma} \exp(-Z^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})), \quad z \geq 0$$

$$f(z, w) = \left(\frac{r z^{r-1}}{\lambda^\gamma}\right)^w \left(\frac{r z^{r-1}}{\mu^\gamma}\right)^{1-w} \exp(-Z^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})), \quad z \geq 0, w = 0 \text{ or } 1$$

Then, check Z and W are independent.

Sol:

$$P(Z \leq z) = P(Z \leq z, W=1) + P(Z \leq z, W=0) = 1 - \exp(-Z^r (\frac{1}{\lambda^r} + \frac{1}{\mu^r}))$$

$$P(Z \leq z | w=1) = \frac{P(Z \leq z, W=1)}{P(W=1)} = \frac{P(Z \leq z, W=1)}{P(X \leq Y)}$$

$$= \frac{\frac{\mu^r}{\mu^r + \lambda^r} (1 - \exp(-Z^r (\frac{1}{\lambda^r} + \frac{1}{\mu^r})))}{\frac{\mu^r}{\mu^r + \lambda^r}}$$

$$(\text{because } P(X \leq Y) = \int_0^\infty \int_x^\infty \frac{y}{\lambda} \frac{y}{\mu} (x/\lambda)^{r-1} (y/\lambda)^{r-1} e^{-(\frac{y}{\mu})^r} e^{-(\frac{x}{\lambda})^r} dy dx = \frac{\mu^r}{\mu^r + \lambda^r})$$

$$= 1 - \exp(-Z^r (\frac{1}{\lambda^r} + \frac{1}{\mu^r}))$$

$$= P(Z \leq z)$$

Similarity,  $P(Z \leq z | w=0) = P(Z \leq z)$

So, Z and W are independent.

Then, find the MLEs of  $\lambda$  and  $\mu$  and  $\gamma$ .

Sol :

let  $T = ((Z_1, W_1), (Z_2, W_2), \dots, (Z_n, W_n))$

$$L(\lambda, \mu, \gamma | (Z_n, W_n)) = \prod_{i=1}^n ((\frac{rzi^{r-1}}{\lambda^r})^{wi}) \prod_{i=1}^n ((\frac{rzi^{r-1}}{\mu^r})^{1-wi}) \exp(-\sum_{i=1}^n Zi^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma}))$$

$$\ln(L(\lambda, \mu, \gamma | (Z_n, W_n)))$$

$$= \sum_{i=1}^n (1 - Wi) \ln(\frac{rzi^{r-1}}{\mu^r}) + \sum_{i=1}^n Wi \ln(\frac{rzi^{r-1}}{\lambda^r}) - \sum_{i=1}^n Zi^\gamma (\frac{1}{\lambda^\gamma} + \frac{1}{\mu^\gamma})$$

$$\frac{\partial}{\partial \lambda} \ln(L(\lambda, \mu, \gamma | (Z_n, W_n))) = \frac{-\gamma}{\lambda} \sum_{i=1}^n Wi + \frac{\gamma}{\lambda^{\gamma+1}} \sum_{i=1}^n Zi^\gamma = \text{set } 0$$

$$\Rightarrow \hat{\lambda} = \sqrt[\gamma]{\frac{\sum_{i=1}^n Zi^\gamma}{\sum_{i=1}^n Wi}}$$

$$\frac{\partial}{\partial \mu} \ln(L(\lambda, \mu, \gamma | (Z_n, W_n))) = \frac{-\gamma}{\mu} \sum_{i=1}^n (1 - Wi) + \frac{\gamma}{\mu^{\gamma+1}} \sum_{i=1}^n Zi^\gamma = \text{set } 0$$

$$\Rightarrow \hat{\mu} = \sqrt[\gamma]{\frac{\sum_{i=1}^n Zi^\gamma}{\sum_{i=1}^n (1 - Wi)}}$$

$$\frac{\partial}{\partial \gamma} \ln(L(\lambda, \mu, \gamma | (Z_n, W_n))) = \ln \lambda \sum_{i=1}^n Wi + \frac{n}{\gamma} + \sum_{i=1}^n \ln Zi - n \ln \mu - \ln \mu \sum_{i=1}^n Wi = \text{set } 0$$

$$\Rightarrow \hat{\psi} = \frac{n}{n \ln \hat{\mu} - \sum_{i=1}^n \ln Z_i - \ln \frac{\hat{\mu}}{\lambda} \sum_{i=1}^n W_i}$$

**Problem4.**

exercise 7.50 (a) Details including the calculation of  $E(S)=$  , (b) Details including the calculation of  $a$  , (c) Detailed formulas to apply the Factorization thm and verify the completeness

Solution :

(a)

Note:  $\frac{(n-1)S^2}{\theta^2} \sim \chi^2(n-1)$

Let  $T = \frac{(n-1)S^2}{\theta^2}$

$$\begin{aligned} E(\sqrt{T}) &= \int_0^\infty t^{\frac{1}{2}} \frac{\left(\frac{1}{2}\right)^{\frac{n-1}{2}} t^{\frac{n-1}{2}-1} e^{-\frac{t}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} dt \\ &= \frac{\left(\frac{1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} \int_0^\infty t^{\frac{n}{2}-1} e^{-\frac{t}{2}} dt \\ &= \frac{\left(\frac{1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} \times \frac{\Gamma\left(\frac{n}{2}\right)}{\left(\frac{1}{2}\right)^{\frac{n}{2}}} \\ &= \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)\sqrt{2}} \end{aligned}$$

$$\Rightarrow E\left(\frac{\sqrt{n-1}S}{\theta}\right) = \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)\sqrt{2}}$$

$$\Rightarrow E(s) = \frac{\theta}{\sqrt{n-1}} \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)\sqrt{2}}$$

Then,  $E(ax + (1-a)CS) = aE(x) + (1-a)CE(S)$

$$\begin{aligned} &= a\theta + (1-a)\theta \\ &= \theta \end{aligned}$$

(b)

$$\text{Var}(ax + (1-a)CS) = a^2 \text{var}(x) + (1-a)^2 C^2 \text{var}(S) + \text{cov}(ax, (1-a)CS)$$

$$= a^2 \frac{\theta^2}{n} + (1-a)^2 C^2 (E(S^2) - (E(S))^2)$$

$$= \frac{a\theta^2}{n} + (1-a)^2 C^2 \left(\theta^2 - \frac{\theta^2}{c^2}\right)$$

$$= \left(\frac{a^2}{n} + (1-a)^2 c^2 - (1-a)^2\right) \theta^2$$

$$\Rightarrow \min\left\{\frac{a^2}{n} + (1-a)^2 c^2 - (1-a)^2\right\}$$

$$\Rightarrow \frac{d}{da}\left(\frac{a^2}{n} + (1-a)^2 c^2 - (1-a)^2\right) \stackrel{set}{=} 0$$

$$\Rightarrow \hat{a} = \frac{nc^2 - n}{1 + nc^2 - n}$$

$$\frac{d^2}{da^2}\left(\frac{a^2}{n} + (1-a)^2 c^2 - (1-a)^2\right) = \frac{2}{n} + 2c^2 - 2 > 0 \quad (\text{because } c^2 > 1 \text{ for all } n \geq 2)$$

$$\Rightarrow \text{So, } \hat{a} = \frac{nc^2 - n}{1 + nc^2 - n} \text{ produces the estimator with minimum variance}$$

(c)

$$f(x|\theta) = \frac{1}{\theta^2 \sqrt{2\pi}} \exp\left(\frac{-1}{2\theta^2} (xi - \theta)^2\right)$$

$$\begin{aligned} L(\theta|X) &= \left(\frac{1}{2\pi\theta^2}\right)^{\frac{n}{2}} \exp\left(\frac{-1}{2\theta^2} \sum_{i=1}^n (xi - \theta)^2\right) \\ &= \left(\frac{1}{2\pi}\right)^{\frac{n}{2}} \left(\frac{1}{\theta}\right)^n \exp\left(\frac{-1}{2\theta^2} (\sum_{i=1}^n (xi - \bar{x})^2 - n(\theta - \bar{x})^2)\right) \\ &= \left(\frac{1}{2\pi}\right)^{\frac{n}{2}} \left(\frac{1}{\theta}\right)^n \exp\left(\frac{-(n-1)S^2}{2\theta^2} + \frac{n(\theta - \bar{x})^2}{2\theta^2}\right) \end{aligned}$$

$$\text{Let } h(x) = \left(\frac{1}{2\pi}\right)^{\frac{n}{2}} \quad \text{and} \quad g(T(x), \theta) = \left(\frac{1}{\theta}\right)^n \exp\left(\frac{-(n-1)S^2}{2\theta^2} + \frac{n(\theta - \bar{x})^2}{2\theta^2}\right)$$

By factorization thm,  $(\bar{x}, S^2)$  is sufficient statistics

$$E(\bar{X}) = \theta \quad \text{and} \quad E(S) = \frac{\theta}{c}$$

$$\text{Let } g(x) = \bar{X} - CS$$

$$\Rightarrow E(g(x)) = E(\bar{x}) - E(CS) = \theta - \theta = 0$$

$$\text{But } g(x) = \bar{X} - CS \neq 0$$

So,  $(\bar{x}, S^2)$  is not a complete sufficient statistics.

**Problem5.**

exercise 7.51(a)-(d). Prove your answer by formulas (not just words).

Solution :

(a)

$$\begin{aligned} E(\theta - a_1\bar{x} - a_2(CS))^2 &= \text{var}(\theta - a_1\bar{x} - a_2(CS)) + (E(\theta - a_1\bar{x} - a_2(CS)))^2 \\ &= (a_1)^2 \text{var}(\bar{x}) + (a_2)^2 c^2 \text{var}(S) + \theta^2 (a_1 + a_2 - 1)^2 \\ &= \frac{a_1^2}{n} \theta^2 + (a_2 c)^2 - a_2^2 \theta^2 + \theta^2 (a_1 + a_2 - 1)^2 \\ &= \left(\frac{a_1^2}{n} + (a_2 c)^2 - a_2^2 \theta^2 + (a_1 + a_2 - 1)^2\right) \theta^2 \end{aligned}$$

$$\Rightarrow \min\left(\frac{a_1^2}{n} + (a_2 c)^2 - a_2^2 \theta^2 + (a_1 + a_2 - 1)^2\right)$$

$$\Rightarrow \frac{\partial}{\partial a_1} \left(\frac{a_1^2}{n} + (a_2 c)^2 - a_2^2 \theta^2 + (a_1 + a_2 - 1)^2\right) = \frac{2a_1}{n} + 2(a_1 + a_2 - 1) \stackrel{set}{=} 0$$

$$\Rightarrow \frac{\partial}{\partial a_2} \left(\frac{a_1^2}{n} + (a_2 c)^2 - a_2^2 \theta^2 + (a_1 + a_2 - 1)^2\right) = 2a_2 c^2 + 2(a_1 + a_2 - 1) - 2a_2 \stackrel{set}{=} 0$$

$$\Rightarrow \begin{cases} a_1 + a_1 n + a_2 n - n = 0 \\ a_2 c^2 + a_1 - 1 = 0 \end{cases}$$

$$\Rightarrow \hat{a}_1 = 1 - \frac{c^2}{(n+1)c^2 - n} \quad \hat{a}_2 = \frac{1}{(n+1)c^2 - n}$$

(b)

$$B^2(T^*) = (E(T^* - \theta))^2 = (a_1 + a_2 - 1)^2 \theta^2$$

$$\text{Var}(T^*) = \left(\frac{a_1^2}{n} + a_2^2 (c^2 - 1)\right) \theta^2$$

$$\text{MSE}(T^*) = \left((a_1 + a_2 - 1)^2 + \left(\frac{a_1^2}{n} + a_2^2 (c^2 - 1)\right)\right) \theta^2$$

$$= \left(\frac{(c^2 - 1)^2 + (c^2 - 1) + n(c^2 - 1)^2}{((n+1)c^2 - n)^2}\right) \theta^2$$

$$= \left(\frac{(c^2 - 1)(c^2(n+1) - n)}{((n+1)c^2 - n)^2}\right) \theta^2$$

$$E(T) = \theta \quad B^2(T) = 0$$

$$\text{Var}(T) = \left(\frac{a^2}{n} + (1 - a)^2 c^2 - (1 - a)^2\right) \theta^2$$

$$\begin{aligned}
\text{MSE}(T) &= \left(\frac{a^2}{n} + (1-a)^2 c^2 - (1-a)^2\right) \theta^2 \\
&= \left\{ \frac{n(c^2-1)^2}{(1+nc^2-n)^2} + (1-a)^2(c^2-1) \right\} \theta^2 \\
&= \frac{n(c^2-1)^2 + c^2 - 1}{(1+nc^2-n)^2} \theta^2 \\
&= \frac{(c^2-1)(n(c^2-1)+1)}{(1+nc^2-n)^2} \theta^2 \\
\frac{\text{MSE}(T^*)}{\text{MSE}(T)} &= \frac{\frac{(c^2-1)(c^2(n+1)-n)}{((n+1)c^2-n)^2} \theta^2}{\frac{(c^2-1)(n(c^2-1)+1)}{(1+nc^2-n)^2} \theta^2} = \frac{(c^2(n+1)-n)(1+n(c^2-1))^2}{((n+1)c^2-n)^2 (n(c^2-1)+1)} \\
&= \frac{n(c^2-1)+1}{(n+1)c^2-n} \\
&= \frac{n(c^2-1)+1}{n(c^2-1)+c^2} < 1 \quad (\text{because } c^2 > 1 \text{ for all } n > 2)
\end{aligned}$$

So, the MSE of  $T^*$  is smaller than the MSE of the  $T$ .

(c)

$$\begin{aligned}
F_{T^{*+}}(t) &= P(T^{*+} \leq t) \\
&= P(\max\{0, T^*\} \leq t) \\
&= \begin{cases} 0 & t < 0 \\ P(T^* \leq 0) & t = 0 \\ P(T^* \leq t) & t > 0 \end{cases}
\end{aligned}$$

$$\begin{aligned}
E(\theta - T^{*+})^2 &= (\theta - 0)^2 P(T^{*+} = 0) + \int_0^\infty (\theta - t)^2 f_{T^*}(t) dt \\
&= \theta^2 P(T^* \leq 0) + \int_0^\infty (\theta - t)^2 f_{T^*}(t) dt \\
&= \int_{-\infty}^0 \theta^2 f_{T^*}(t) dt + \int_0^\infty (\theta - t)^2 f_{T^*}(t) dt \\
&\leq \int_{-\infty}^0 (\theta - t)^2 f_{T^*}(t) dt + \int_0^\infty (\theta - t)^2 f_{T^*}(t) dt \\
&= \int_{-\infty}^\infty (\theta - t)^2 f_{T^*}(t) dt \\
&= E(\theta - T^*)^2
\end{aligned}$$

So, MSE of  $T^{*+}$  is smaller than the mse of  $T^*$

(d)

$$f(X|\theta) = \frac{1}{\theta\sqrt{2\pi}} \exp\left(\frac{-1}{2\theta^2}(x - \theta)^2\right)$$

because this pdf does not fit the definition of a location parameter or scale



parameter.

So,  $\theta$  can't be classified as a location parameter or scale parameter.