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1. (a) $\theta > 0$, $f(x) = \begin{cases} \frac{1}{\theta} & \text{if } 0 < x < 2\theta \\ 0 & \text{otherwise} \end{cases}$

$$E(X) = \int_0^{2\theta} \frac{1}{\theta} \cdot x \, dx = \frac{2}{2} \theta$$

$$\hat{\theta}_{MLE} = \bar{x}, \quad \hat{\theta}_{MME} = \frac{2}{3} \bar{x}.$$

② $\log L(\theta; x_1, \dots, x_n) = \begin{cases} \sum_{i=1}^n -\log \theta & \text{if } \forall x_i, \text{ s.t. } 0 < x_i < 2\theta \Leftrightarrow \frac{x_i}{2} < \theta < x_i \\ 0 & \text{otherwise} \end{cases}$

$$\frac{\partial \log L(\theta)}{\partial \theta} = \frac{-n}{\theta} < 0,$$

$$\hat{\theta}_{MLE} = \arg \max_{\theta} \frac{\partial \log L(\theta)}{\partial \theta} = \frac{1}{2} \max\{x_1, \dots, x_n\}$$

(b) $f(x) = \begin{cases} -\frac{1}{\theta} & \text{if } x \in (\theta, 0) \\ 0 & \text{otherwise} \end{cases}$

① $E(X) = \int_0^0 -\frac{1}{\theta} x \, dx = \frac{1}{2}\theta$

$$\hat{\theta}_{MLE} = 2\bar{x},$$

② $\log L(\theta; x_1, \dots, x_n) = \begin{cases} \sum_{i=1}^n -\log(-\theta) & \text{if } 0 < x_i < \theta, \\ 0 & \text{otherwise} \end{cases}$

$$\frac{\partial \log L(\theta)}{\partial \theta} = -\frac{n}{\theta} > 0 \text{ is monotonically ascending.}$$

$$\hat{\theta}_{MLE} = \min(x_1, \dots, x_n)$$

(c) $\hat{\theta}_{MME} = \begin{cases} \frac{2}{3}\bar{x} & \text{if } \theta > 0 \\ 2\bar{x} & \text{if } \theta < 0 \end{cases}$

$$\hat{\theta}_{MLE} = \begin{cases} \frac{1}{n} \max\{x_1, \dots, x_n\} & \text{if } \theta > 0 \\ \min\{x_1, \dots, x_n\} & \text{if } \theta < 0 \end{cases} ?$$

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2. (a) $P_{X_k}(k) = \theta(1-\theta)^k, k=0, 1, \dots$
 $= \exp \{ \log \theta + k \cdot \log(1-\theta) \}$

it is exponential class

$\sum_{i=1}^n X_i$ is sufficient complete statistic

(b) Mgf: $M_X(t) = E(e^{tX}) = \sum_{x=0}^{+\infty} e^{tx} \cdot \theta(1-\theta)^x = \sum_{x=0}^{+\infty} [e^t \cdot (1-\theta)]^x \cdot \theta$
 $= \frac{\theta}{1 - e^t(1-\theta)}, 0 < e^t(1-\theta) < 1$

$X_i=k$ stands for k successive true and 1 false.

$\sum X_i=n$ stands for n times true in first n trials, next is false

$P(\sum_{i=1}^n X_i = n) = \binom{n+n-1}{n} \theta^n (1-\theta)^n, n=0, 1, \dots$

(c) $\sum X_i$ is sufficient complete statistic,

$E(\sum X_i) = nE(X) = n \cdot (\frac{1-\theta}{\theta})$

$E(X_i) = \frac{1-\theta}{\theta}$? unbiased estimator?

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3. (a) $H_0: \theta = 1/2$ null hypothesis, simple hypothesis
 $H_1: \theta < 1/2$ alternative hypothesis, composite hypothesis

		Ground Truth	
		H_0	H_1
Reject H_0	type I error	true	
	true	type II error	

(b) set $\theta' = \frac{1}{2}$, $\theta'' < \frac{1}{2}$

$$\frac{L(\theta'); x_1 - x_n)}{L(\theta''; x_1 - x_n)} = \frac{\prod_{i=1}^n \theta'^{x_i} (1-\theta')^{1-x_i}}{\prod_{i=1}^n \theta''^{x_i} (1-\theta'')^{1-x_i}} = \prod_{i=1}^n \left(\frac{\theta'}{\theta''} \cdot \frac{1-\theta''}{1-\theta'} \right)^{x_i} \cdot \left(\frac{1-\theta'}{1-\theta''} \right) \leq k$$

$$\Leftrightarrow \text{since } \frac{1-\theta'}{1-\theta''} < 1, \sum_{i=1}^n x_i \cdot \log \left(\frac{\theta'}{\theta''} \cdot \frac{1-\theta''}{1-\theta'} \right) \leq k$$

$$\Leftrightarrow \frac{\theta'}{\theta''} > 1, \sum_{i=1}^n x_i \leq c.$$

$C = \{x_1 | \sum_{i=1}^n x_i \leq c\}$ is critical region, when $\alpha = P(\sum_{i=1}^n x_i \leq c | \theta = 1/2)$

(c) power function: $\gamma_c(\theta) = P(\sum_{i=1}^n x_i \leq c | \theta) = P(x_1 - x_n \in C | \theta)$
 $= \binom{n}{c} \theta^c (1-\theta)^{n-c}, \text{ if } c = 0, 1, \dots, n$
 $= \binom{n}{c} \theta^c (1-\theta)^{n-c}, \text{ if } 0 < c < n$

(d) $\alpha = P(\{x_1 - x_n\} \in C | \theta = 1/2) = P(\sum_{i=1}^n x_i \leq c | \theta = 1/2)$
 $= \binom{n}{c} (\frac{1}{2})^n \quad \text{if } c = 0, 1, \dots, n$
 $= \binom{n}{c} (\frac{1}{2})^n \quad \text{if } 0 < c < n.$

(e) likelihood ratio test: $\hat{\theta} = \arg \max_{\theta} L(\theta; x_1 - x_n) = 1/2$

$$\hat{\theta} = \arg \max_{\theta \in \frac{1}{2}} L(\theta; x_1 - x_n)$$

$$= \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i}$$

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$$\log L(\theta; x_1 - x_n) = \left(\frac{n}{\theta} x_1 \right) \log \theta + \left(\frac{n}{\theta} 1 - x_1 \right) \log(1-\theta)$$

$$\frac{\partial \log L}{\partial \theta} = \frac{\sum x_i}{\theta} + \frac{n - \sum x_i}{\theta(1-\theta)} = \frac{n\theta - \sum x_i}{\theta(1-\theta)} = 0$$

$$\Rightarrow \theta = \bar{x},$$

$$\frac{\partial^2 \log L}{\partial \theta^2} = -\frac{\sum x_i}{\theta^2} - \frac{n - \sum x_i}{(\theta-1)^2} \leq 0,$$

$$\text{so } \hat{\theta} = \arg\max_{\theta \in [0, 1]} L(\theta; x_1 - x_n) = \min(\bar{x}, 1/\bar{x}) \leq 1/2$$

critical region $\bar{C} = \left\{ \frac{L(\hat{\theta})}{L(\bar{\theta})} \leq k \right\}$

$$= \left\{ \frac{\prod (\frac{1}{\bar{\theta}})^{x_i} (\frac{1}{1-\bar{\theta}})^{1-x_i}}{\prod (\frac{1}{\hat{\theta}})^{x_i} (\frac{1}{1-\hat{\theta}})^{1-x_i}} \leq k \right\}$$

$$= \left\{ \sum_{i=1}^n x_i \leq c \right\} \text{ is the same as UMP test.}$$

4. UMP def: $\forall \mu'' \neq \mu, \mu' = 0$

$$\Delta = P(\{x_1 - x_n \in C | \mu'\})$$

$$\forall A, \text{ s.t. } P(\{x_1 - x_n \in A | \mu'\}) = \Delta$$

$$P(\{x_1 - x_n \in C | \mu'') \geq P(\{x_1 - x_n \in A | \mu'')$$

$$\forall \mu'' \neq \mu, \mu' = 0$$

$$\Delta = P(\sqrt{n} |\bar{x}| > z(2\alpha/2) | \mu' = 0)$$

$$\forall A, \text{ s.t. } P(\{x_1 - x_n \in A | \mu'\}) = \Delta$$

$$P(\sqrt{n} |\bar{x}| > z(2\alpha/2) | \mu'') \geq P(\{x_1 - x_n \in A | \mu'') ?$$

$$\sqrt{n}(\bar{x} - \mu) \sim N(0, 1)$$

$$P(\sqrt{n} |\bar{x}| > z(2\alpha/2) | \mu = 0) = P(\sqrt{n} \bar{x} > z(2\alpha/2)) + P(\sqrt{n} \bar{x} < -z(2\alpha/2)) = 2\alpha.$$

$$P(\sqrt{n} |\bar{x}| > z(2\alpha/2) | \mu \neq 0) = P(\sqrt{n}(\bar{x} - \mu) > z(2\alpha/2) - \mu\sqrt{n} | \mu \neq 0) + P(\sqrt{n}(\bar{x} - \mu) < -z(2\alpha/2) - \mu\sqrt{n} | \mu \neq 0)$$

we need to find A. A = ?

Find a UMP test.

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

$$\frac{L(\mu'; x_1, \dots, x_n)}{L(\mu''); x_1, \dots, x_n} = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n \cdot \exp\left\{-\sum_{i=1}^n \frac{(x_i - \mu')^2}{2}\right\}}{\left(\frac{1}{\sqrt{2\pi}}\right)^n \cdot \exp\left\{-\sum_{i=1}^n \frac{(x_i - \mu'')^2}{2}\right\}}$$

$$= \exp\left\{\sum_{i=1}^n \frac{(x_i - \mu'')^2}{2} - \frac{(x_i - \mu')^2}{2}\right\}$$

$$= \exp\left\{\sum_{i=1}^n (\mu' - \mu'') (x_i - \frac{\mu' + \mu''}{2})\right\} \leq k$$

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$$\Leftrightarrow \text{if } \mu' > \mu'', \quad \sum_{i=1}^n x_i \leq c$$

$$\text{so that } A := \left\{ \sum_{i=1}^n x_i \leq c \right\}, \quad \alpha = P\left(\sum_{i=1}^n x_i \leq c \mid \mu = 0\right) = P\left(\sum_{i=1}^n x_i \leq -z(2)\right)$$

$$P(\sum_{i=1}^n x_i > z(2/2) \mid \mu'') \neq P(\sum_{i=1}^n x_i \leq -z(2) \mid \mu''), \quad \text{RHS is best test when } \mu'' < 0$$

$$\text{hence } P(\sum_{i=1}^n x_i > z(2/2) \mid \mu'') < P(\sum_{i=1}^n x_i \leq -z(2) \mid \mu'').$$

NOT UMP. \square

$$5. (a) \quad \text{if } 6^{1/2} = 1, \quad 6''^{1/2} > 1 \quad f_{X|X}(x) = \frac{1}{\sqrt{2\pi} 6} \cdot \exp\left\{-\frac{(x-\mu)^2}{2 \cdot 6^2}\right\}$$

$$\frac{L(6^{1/2})}{L(6''^{1/2})} = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n \cdot \left(\frac{1}{6}\right)^n \cdot \exp\left\{-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2 \cdot 6^2}\right\}}{\left(\frac{1}{\sqrt{2\pi}}\right)^n \cdot \left(\frac{1}{6''}\right)^n \cdot \exp\left\{-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2 \cdot 6''^2}\right\}}$$

$$= \left(\frac{6''}{6}\right)^n \cdot \exp\left\{\sum_{i=1}^n \frac{(x_i - \mu)^2}{2 \cdot 6''^2} - \frac{(x_i - \mu)^2}{2 \cdot 6^2}\right\} \leq k$$

$$\Leftrightarrow \sum_{i=1}^n (x_i - \mu)^2 \left(\frac{1}{2 \cdot 6''^2} - \frac{1}{2 \cdot 6^2} \right) \leq k,$$

$$\Leftrightarrow \sum_{i=1}^n (x_i - \mu)^2 \geq c$$

$$\alpha = P\left(\sum_{i=1}^n (x_i - \mu)^2 \geq c \mid 6^2 = 1\right),$$

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$$(b) \bar{\mu} \triangleq \underset{\mu}{\operatorname{argmax}} L(\mu, \sigma^2=1)$$

$$\hat{\mu}, \hat{\sigma}^2 \triangleq \underset{\mu, \sigma^2}{\operatorname{argmax}} L(\mu, \sigma^2)$$

$$L(\mu, \sigma^2=1) = \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n \cdot \exp \left\{ -\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2} \right\}$$

$$\frac{\partial L}{\partial \mu} \left(-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2} \right) = \sum_{i=1}^n (x_i - \mu), \quad \frac{\partial^2 L}{\partial \mu^2} \left(-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2} \right) = -n < 0$$

$$\bar{\mu} = \bar{x},$$

$$\log L(\mu, \sigma^2) = n \log \frac{1}{\sqrt{2\pi}\sigma} - n \log \sigma + \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}.$$

$$\frac{\partial L}{\partial \mu} = \sum_{i=1}^n \frac{(x_i - \mu)}{\sigma^2}, \quad \frac{\partial^2 L}{\partial \mu^2} = -\frac{n}{\sigma^2} + \frac{\sum (x_i - \mu)^2}{\sigma^4}$$

$$\Rightarrow \hat{\mu} = \bar{x}, \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$$

$$\text{since } \hat{\sigma} \geq 1, \quad \hat{\sigma} = \max \left\{ 1, \frac{\sum (x_i - \bar{x})^2}{n} \right\}$$

$$\begin{aligned} \frac{L(\bar{\mu}, \sigma^2=1)}{L(\hat{\mu}, \hat{\sigma}^2)} &= \frac{\left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n \cdot \exp \left\{ -\sum_{i=1}^n \frac{(x_i - \bar{\mu})^2}{2\sigma^2} \right\}}{\left(\frac{1}{\sqrt{2\pi}\hat{\sigma}}\right)^n \exp \left\{ -\sum_{i=1}^n \frac{(x_i - \hat{\mu})^2}{2\hat{\sigma}^2} \right\}} \\ &= \left(\frac{\hat{\sigma}}{\sigma}\right)^n \cdot \exp \left\{ \sum_{i=1}^n \frac{(x_i - \hat{\mu})^2}{2\hat{\sigma}^2} - \frac{(x_i - \bar{\mu})^2}{2\sigma^2} \right\} \leq k \end{aligned}$$

$$\Leftrightarrow \sum_{i=1}^n (x_i - \bar{x})^2 \geq k$$

$$2 = \max_{\mu} P \left(\sum_{i=1}^n (x_i - \bar{x})^2 \geq k \mid \sigma^2=1, \mu \right) \rightarrow$$

6. (a)

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