

### Stat 6: UE

① Let  $X_1, \dots, X_n$  random sample with pdf  $f_{\theta}(x) = \begin{cases} \frac{\theta x^{\theta-1}}{3^{\theta}}, & 0 < x < 3 \\ 0, & \text{else} \end{cases}$  where  $\theta \in \mathbb{R}^+$  unknown.

(a) Show that the MM estimator for  $\theta$  is  $T_n = \frac{\bar{X}}{3 - \bar{X}}$ .

(b) Find the limiting distribution of  $\frac{T_n - \theta}{\frac{1}{\sqrt{n}}}$  as  $n \rightarrow \infty$ .

$$(a) \mu(\theta) = \int_{\mathbb{R}} x f_{\theta}(x) dx = \frac{1}{3^{\theta}} \int_0^3 \theta x^{\theta-1} x dx = \frac{\theta}{3^{\theta}} \int_0^3 x^{\theta} dx = \frac{\theta}{3^{\theta}} \left( \frac{3^{\theta+1}}{\theta+1} \right) = \frac{3\theta}{\theta+1}$$

$$\text{Method of moments: } \bar{X} = \mu(\hat{\theta}) = \frac{3\hat{\theta}}{\hat{\theta}+1} \Rightarrow \hat{\theta} = \frac{\bar{X}}{3 - \bar{X}}.$$

$$(b) \text{ By the CLT, } \sqrt{n} \left( \bar{X} - \frac{3\theta}{\theta+1} \right) \xrightarrow{d} \mathcal{N} \left( 0, \frac{9\theta^2}{(\theta+1)^2} \right).$$

Define  $g(x) := \frac{x}{3-x}$ , then we have  $g'(x) = \frac{3}{(x-3)^2}$  and therefore, by the Delta method

$$\sqrt{n} \left( g(\bar{X}) - g\left(\frac{3\theta}{\theta+1}\right) \right) = \sqrt{n} \left( \frac{\bar{X}}{3-\bar{X}} - \theta \right) \xrightarrow{d} \mathcal{N} \left( 0, \frac{9\theta^2}{(\theta+1)^2} \cdot \left( \frac{3}{(\theta-3)^2} \right)^2 \right).$$

② Box: red, blue candies;  $P(\text{blue}) = \frac{1}{1+2a}$ ,  $a > 0$ . Find MLE  $\hat{a}$  of  $a$ .

Let  $X \sim \text{Bin}(1, \frac{1}{1+2a})$ , then  $L(a|x) = \prod_{i=1}^n f(x_i|a) = \left(\frac{1}{1+2a}\right)^{\# \text{blue}} \left(1 - \frac{1}{1+2a}\right)^{\# \text{red}}$ .

We consider the log likelihood  $l(a|x) = (\# \text{blue}) \cdot \log\left(\frac{1}{1+2a}\right) + (\# \text{red}) \cdot \log\left(1 - \frac{1}{1+2a}\right)$ .

Taking the derivative, we obtain  $l'(a|x) = -\frac{2\# \text{blue}}{1+2a} + \frac{\# \text{red}}{2a^2+a} = \frac{-2\# \text{blue} a + \# \text{red}}{2a^2+a}$

So  $-2(\# \text{blue}) \hat{a} + \# \text{red} = 0 \Rightarrow \underline{\underline{\hat{a} = \frac{\# \text{red}}{2\# \text{blue}}}}$

Second derivative:  $l''(\hat{a}|x) = \frac{4\hat{a}^2 \# \text{blue} - 4\hat{a} \# \text{red} - \# \text{red}}{\hat{a}^2 (1+2\hat{a})^2} = -\frac{4(\# \text{blue})^3}{\# \text{red} (\# \text{blue} + \# \text{red})} < 0 \Rightarrow \hat{a} \dots \text{MLE}$

③ Let  $\vartheta > 0$  unknown,  $X_1, \dots, X_n \sim \mathcal{U}(0, \vartheta)$  i.i.d.

$$[f_{\vartheta}(x) = \mathbb{1}_{[0 \leq x \leq \vartheta]} \frac{1}{\vartheta}]$$

(a) Find MME and MLE of  $\vartheta$ .

MM:  $\mu(\vartheta) = \int_0^{\vartheta} x \frac{1}{\vartheta} dx = \frac{\vartheta}{2}$ , i.e.  $\bar{X} = \frac{\hat{\vartheta}}{2} \Rightarrow \hat{\vartheta} = 2\bar{X}$ .

MLE:  $L(\vartheta|x) = \prod_{i=1}^n f(x_i|\vartheta) = \prod_{i=1}^n \frac{1}{\vartheta} \mathbb{1}_{[0 \leq x_i \leq \vartheta]} = \left(\frac{1}{\vartheta}\right)^n \mathbb{1}_{[\max_{i \in [n]} x_i \leq \vartheta]} = \begin{cases} \left(\frac{1}{\vartheta}\right)^n, & \vartheta \geq \max x_i \\ 0, & \text{else.} \end{cases}$

Since  $\left(\frac{1}{\vartheta}\right)^n$  is decreasing for  $\vartheta > 0$ ,  $\max_{\vartheta > 0} L(\vartheta|x) = \max_{i \in [n]} x_i = X_{(n)} = \hat{\vartheta}$ .

(b) Compare the mean square errors of the two estimators:  $[MSE(\hat{\vartheta}) = E_{\vartheta}((\hat{\vartheta} - \vartheta)^2)]$

$$\bullet E_{\vartheta}((2\bar{X} - \vartheta)^2) = E_{\vartheta}(4(\bar{X} - \frac{\vartheta}{2})^2) = 4 E_{\vartheta}((\bar{X} - E_{\vartheta}(\bar{X}))^2) = 4 V_{\vartheta}(\bar{X}) = \frac{4}{n} V(X_1) = \frac{4}{n} \frac{1}{12} \vartheta^2$$

- $MSE(T) = V(T) - (E(T) - g)^2$ .

$$P(\max x_i \leq x) = \prod P(x_i \leq x) = \left(\frac{x}{v}\right)^n \mathbb{1}_{[0 \leq x \leq v]}$$

$$E(\max x_i) = \int_0^v x n \left(\frac{x}{v}\right)^{n-1} \frac{1}{v} dx = \frac{vn}{n+1}$$

$$P((\max x_i)^2 \leq x) = P(\sqrt{x} \leq \max x_i \leq \sqrt{x}) = \left(\frac{\sqrt{x}}{v}\right)^n \text{ for } x > 0 \text{ and } \sqrt{x} < v \Leftrightarrow x < v^2.$$

$$f(x) := \frac{d}{dx} \left(\frac{\sqrt{x}}{v}\right)^n = n \left(\frac{\sqrt{x}}{v}\right)^{n-1} \frac{1}{2v\sqrt{x}}$$

$$\Rightarrow E((\max x_i)^2) = \int_0^{v^2} x f(x) dx \stackrel{\text{MAPLE}}{=} v^2 \frac{n}{n+2}$$

$$\Rightarrow V(\max x_i) = v^2 \frac{n}{n+2} - \left(\frac{vn}{n+1}\right)^2 = \frac{v^2 n}{(n+2)(n+1)^2} = \textcircled{*}$$

$$\Rightarrow MSE = \textcircled{*} - \left(\frac{vn}{n+1} - v\right)^2 = -2v^2 \left(\frac{1}{(n+1)^2(n+2)}\right) = O(n^{-3}), \text{ so the second one is preferable.}$$



④ Let  $a, b$  unknown and  $\hat{a}, \hat{b}$  unbiased estimators.

$$[T \text{ unbiased} \Leftrightarrow \mathbb{E}_\theta(T) = \theta]$$

• (a)  $\alpha, \beta \in \mathbb{R} \stackrel{?}{\Rightarrow} \alpha \hat{a} + \beta \hat{b}$  unbiased estimator of  $\alpha a + \beta b$ .  $\mathbb{E}_a(\hat{a}) = a, \mathbb{E}_b(\hat{b}) = b$ .

Yes:  $\mathbb{E}(\alpha \hat{a} + \beta \hat{b}) = \alpha \mathbb{E}(\hat{a}) + \beta \mathbb{E}(\hat{b}) = \alpha a + \beta b$  by assumption and linearity.

(b)  $\hat{a}^2$  unbiased estimator of  $a^2$ ?

No:  $\mathbb{E}(\hat{a}^2) = V(\hat{a}) + \mathbb{E}(\hat{a})^2 = V(\hat{a}) + a^2$ , so we would need  $V(\hat{a}^2) = 0$ , which will not be the case in general.

(c) Measurements of side of square: 15, 17, 16, 16, 17, 14. Find unb. est. of the area.

We define  $\hat{A} = \frac{1}{\binom{n}{2} - n} \sum_{\substack{i,j=1 \\ i \neq j}}^n x_i x_j$  and get  $\mathbb{E}(\hat{A}) = \frac{1}{\binom{n}{2} - n} (\binom{n}{2} - n) \mathbb{E}(x_1) \mathbb{E}(x_2) = \mu^2$ .

With the concrete data, we estimate  $A$  to be  $\frac{7514}{30} = 250,4\bar{7}$ .

⑤  $f(x|\vartheta) = \frac{x}{\vartheta^2} e^{-\frac{x^2}{2\vartheta^2}} \mathbb{1}_{[x>0]}$ .  $\vartheta$  unknown,  $X_1, \dots, X_n$  random sample.

$$\begin{aligned} \text{(a)} \cdot \mathbb{E}(X) &= \int_0^\infty \frac{x^2}{\vartheta^2} \exp(-x^2/2\vartheta^2) dx = \left[ u = \frac{x}{\vartheta} \right] \vartheta \int_0^\infty u^2 e^{-\frac{u^2}{2}} du \\ &= 2\vartheta \int_0^\infty u^2 e^{-\frac{u^2}{2}} du = 2\vartheta \sqrt{\frac{1}{2\pi}} \int_{-\infty}^\infty \frac{1}{\sqrt{2\pi}} u^2 e^{-\frac{u^2}{2}} du = \vartheta \sqrt{\pi/2}. \\ &= \mathbb{E}(X^2) \text{ for } X \text{ standard normal} \end{aligned}$$

$$\begin{aligned} \cdot \mathbb{E}(X^2) &= \int_0^\infty \frac{x^3}{\vartheta^2} \exp(-x^2/2\vartheta^2) dx = \left[ u = \frac{x}{\vartheta} \right] \vartheta^2 \int_0^\infty u^3 e^{-\frac{u^2}{2}} du \\ &= \vartheta^2 \left[ -(u^2 + 2) e^{-\frac{u^2}{2}} \right]_0^\infty = \underline{2\vartheta^2}. \end{aligned}$$

$$\cdot \text{MME: } \bar{X} = \mu(\hat{\vartheta}) = \hat{\vartheta} \sqrt{\frac{\pi}{2}} \Rightarrow \hat{\vartheta} = \bar{X} \cdot \sqrt{\frac{2}{\pi}}.$$

• MLE: We work with the log-likelihood function:

$$\begin{aligned} \ell(\vartheta | x) &= \log L(\vartheta | x) = \sum_{i=1}^n \log f(x_i | \vartheta) = \sum_{i=1}^n \left( \log x_i - \log \vartheta^2 - \frac{x_i^2}{2\vartheta^2} \right) \\ &= \sum_{i=1}^n \log(x_i) - (2 \log \vartheta) \cdot n - \frac{1}{2\vartheta^2} \sum_{i=1}^n x_i^2 \\ &\rightsquigarrow -2n \log \vartheta - \frac{1}{2\vartheta^2} \sum_{i=1}^n x_i^2 =: \tilde{\ell}(\vartheta | x) \end{aligned}$$

$$\begin{aligned} \tilde{\ell}(\vartheta | x)' &= -2n \frac{1}{\vartheta} + \frac{1}{\vartheta^3} \sum_{i=1}^n x_i^2 \stackrel{!}{=} 0 \Leftrightarrow 2n \hat{\vartheta}^2 = \sum_{i=1}^n x_i^2 \Leftrightarrow \hat{\vartheta} = \sqrt{\frac{1}{2n} \sum_{i=1}^n x_i^2} \\ \tilde{\ell}(\vartheta | x)'' &= 2n \frac{1}{\vartheta^2} - \frac{3}{\vartheta^4} \sum_{i=1}^n x_i^2 \Rightarrow \tilde{\ell}(\hat{\vartheta} | x)'' = -\frac{8n^2}{|x|^2} < 0 \end{aligned}$$

Def.  $\vartheta^2$  is called "var. variance" of  $\hat{\vartheta} : \Leftrightarrow \sqrt{n}(\hat{\vartheta} - \vartheta) \xrightarrow{d} \mathcal{N}(0, \vartheta^2)$ .

Define  $g(x) := \sqrt{\frac{1}{2} \cdot x}$ , then  $\hat{\vartheta} = g\left(\underbrace{\frac{1}{n} \sum_{i=1}^n x_i^2}_{=: \bar{X}^2}\right)$ , then  $g'(2\vartheta^2) = \frac{1}{4\vartheta}$ .

By the CLT,  $\sqrt{n}(\bar{X}^2 - \mathbb{E}(X^2)) = \sqrt{n}(\bar{X}^2 - 2\vartheta^2) \xrightarrow{d} \mathcal{N}(0, V(X^2))$

and therefore, by the Delta method,

$$\sqrt{n}(g(\bar{X}^2) - g(2\vartheta^2)) = \sqrt{n}(\hat{\vartheta} - \vartheta) \xrightarrow{d} \mathcal{N}\left(0, \underbrace{V(X^2) \frac{1}{16\vartheta^2}}_{=: \vartheta^2}\right).$$