

$$(x \geq (\theta - \delta)) \hat{P} = (x \geq (\theta - \delta) n -) \hat{P} \quad (2)$$

1.

$$(a) f(x|\theta) = \frac{1}{2\theta - \theta} I_{[\theta, 2\theta]}(x) = \frac{1}{\theta} I_{[\theta, 2\theta]}(x)$$

$$\Rightarrow f(x|\theta) = \theta^{-n} I_{[\theta, +\infty)}(x_{(1)}) I_{[0, 2\theta]}(x_{(n)}) \\ = \theta^{-n} I_{[x_{(n)}/2; x_{(1)}]}(\theta)$$

$$x_{(1)} \geq \theta, x_{(n)} \leq 2\theta \Leftrightarrow \frac{x_{(n)}}{2} \leq \theta \leq x_{(1)}$$

$$\therefore L(\theta|x) \propto \theta^{-n} I_{[x_{(n)}/2; x_{(1)}]}(\theta)$$

θ^{-n} is a decreasing function of θ ; hence the mle is $x_{(n)}/2$

$$(b) P(|\hat{\theta} - \theta| > \epsilon) = P(\hat{\theta} - \theta > \epsilon) + P(\hat{\theta} - \theta < -\epsilon) \\ = P(\hat{\theta} > \theta + \epsilon) + P(\hat{\theta} < \theta - \epsilon) \\ = P(x_{(n)} > 2(\theta + \epsilon)) + P(x_{(1)} < 2(\theta - \epsilon)) \\ = 0 + [F(2(\theta - \epsilon))]^n$$

$$F(x) = \frac{x - \theta}{\theta}, \theta < x < 2\theta$$

$$= \left(\frac{2(\theta - \epsilon)}{\theta} \right)^n \quad \theta \leq 2(\theta - \epsilon) \leq 2\theta$$

$$= \left(\frac{2\theta - 2\epsilon - \theta}{\theta} \right)^n = \left(\frac{\theta - 2\epsilon}{\theta} \right)^n$$

$$= \left(\frac{\theta - 2\epsilon}{\theta} \right)^n \rightarrow 0$$

$$\therefore \hat{\theta} \xrightarrow{P} \theta$$

$$(c) P(-m(\hat{\theta} - \theta) \leq x) = P(\hat{\theta} - \theta \geq -x/m)$$

$$= 1 - P(X_m \leq 2(\theta - x/m))$$

$$= 1 - [F(2(\theta - x/m))]^m$$

$$= 1 - \left[\frac{2(\theta - x/m) - \theta}{\sigma} \right]^m \quad \theta < 2(\theta - x/m) < 2\theta$$

$$= 1 - \left(\frac{\theta - 2x/m}{\sigma} \right)^m$$

$$= 1 - \left(1 - \frac{2x/\theta}{m} \right)^m \quad \frac{\theta}{2} < \theta - x/m < \theta \Rightarrow 0 < x < m\theta$$

-0.783737310

$$-2x/\theta$$

$$\rightarrow 1 - e^{-2x/\theta}, x > 0$$

$$= F_{\epsilon_{2x/\theta}}^{(x)} \quad x \in \mathbb{R}$$

$$(d) \sqrt{n}(\hat{\theta} - \theta) = n(\hat{\theta} - \theta) \frac{1}{\sqrt{n}} \xrightarrow{d} 0 \text{ by Slutsky etc...}$$

the result that states that $\sqrt{n}(\hat{\theta} - \theta) \xrightarrow{d} N(0, [I_{X(\theta)}]^{-1})$
 is valid only under regularity conditions. This model
 is not regular as the support depends on θ .

3.

(e) $\frac{f(\underline{x}|\theta)}{f(\underline{x}'|\theta)} = \frac{I_{[\underline{x}_{(m)/2}; \underline{x}_{(n)}]}^{(\theta)}}{I_{[\underline{x}_{(m)/2}; \underline{x}_{(n)}]}^{(\theta)}}$ which does not depend on θ iff

$$\begin{cases} \underline{x}_{(m)/2} = \underline{y}_{(n)/2} \\ \underline{x}_{(1)} = \underline{y}_{(1)} \end{cases}$$

and we can hence conclude that a minimal sufficient statistic is $(\underline{x}_{(1)}, \underline{x}_{(m)})$

there are no estimators of θ which are sufficient.

(f) $g_m(x) = \frac{d}{dx} \left[\frac{x-\theta}{\theta} \right]^n = n \theta^{-n} (x-\theta)^{n-1}, \theta < x < 2\theta$

$$g_1(x) = \frac{d}{dx} \left[1 - \left(1 - \frac{x-\theta}{\theta} \right)^n \right] = \frac{d}{dx} \left[1 - \left(2 \frac{\theta-x}{\theta} \right)^n \right]$$

$$= n \theta^{-n} (2\theta-x)^{n-1}, \theta < x < 2\theta$$

$$E[\underline{x}_{(m)}] = \int_{\theta}^{2\theta} n \theta^{-n} x (2\theta-x)^{\frac{n-1}{2}} dx =$$

$$= n \theta^{-n} \int_{\theta}^{2\theta} x (2\theta-x)^{n-1} dx$$

$$a=1, b=-\theta, m=n-1$$

$$= n \theta^{-n} \left. \frac{n}{n+1} \frac{x+\theta}{\theta} (x-\theta)^{\frac{n-1}{2}} \right|_{\theta}^{2\theta}$$

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

$\therefore \frac{n+1}{2n+1} \underline{x}_{(n)}$ is unbiased

$$E[X_{(1)}] = \int_0^{2\theta} x \cdot n\theta^{-n} (2\theta-x)^{n-1} dx$$

$$= n\theta^{-n} \int_0^{2\theta} x (-x+2\theta)^{n-1} dx$$

~~term under and~~

$$\alpha = 1; b = 2\theta; m = n-1$$

$$= n\theta^{-n} \left[-\frac{x}{m(n+1)} (-x+2\theta)^n \right] \Big|_0^{2\theta}$$

$$= n\theta^{-n} - \frac{-n\theta - 2\theta}{m(n+1)} \theta^n$$

$$\left[\frac{n+2}{n+1} \theta \right] = \left[\frac{n+1}{n+2} (\theta - 1) - 1 \right] \frac{\theta}{2\theta} = \left[\frac{\theta-1}{2} \right] \frac{\theta}{2\theta} = \frac{\theta-1}{4}$$

$\therefore \frac{n+1}{n+2} X_{(1)}$ is unbiased for θ

(g) $T_1 - T_2$ is a function of the minimal sufficient statistic which has zero expectation but is clearly not zero. Hence, $(X_1; X_m)$ is not complete. Since the m.s. statistic is bi-dimensional, there are no 1-dimensional sufficient statistics; hence, there are no estimators of θ which are sufficient.

Ans: $\hat{\theta}_1 = \frac{1+2X_1}{1+2X_2}$

2.

$$\begin{aligned}
 (a) \quad f(x, y | \lambda) &= f(y|x, \lambda) f(x|\lambda) \\
 &= \frac{\sqrt{\pi}x}{\sqrt{2\pi}} \cdot \frac{1}{y} \cdot \exp\left\{-\frac{(\ln y)^2}{2}\lambda x\right\} \lambda e^{-\lambda x}, \\
 &\quad y > 0, x > 0 \\
 &= \frac{\sqrt{x}}{\sqrt{2\pi}y} \lambda^{3/2} \exp\left\{-\lambda\left(\frac{(\ln y)^2}{2}x + x\right)\right\}
 \end{aligned}$$

~~ln L~~

$$\Rightarrow \ln L = c + \frac{3}{2} \ln \lambda - \lambda \left(\frac{(\ln y)^2}{2} x + x \right)$$

$$\frac{d \ln L}{d \lambda} = \frac{3}{2} \frac{1}{\lambda} - \left[\frac{(\ln y)^2}{2} x + x \right] = S(\lambda | x, y)$$

$$\Rightarrow S(\lambda | x, y) = \frac{3}{2} \frac{n}{\lambda} - \sum_{i=1}^n \left[\frac{(\ln y_i)^2}{2} x_i + x_i \right]$$

$$= -\frac{3}{2} n \left(\frac{3}{2} \frac{1}{\lambda} \sum_{i=1}^n \left(\frac{(\ln y_i)^2}{2} x_i + x_i \right) - \frac{1}{\lambda} \right)$$

$$= -\frac{3}{2} n \left(\frac{1}{n} \sum_{i=1}^n \left[\frac{(\ln y_i)^2}{3} x_i + \frac{2}{3} x_i \right] - \frac{1}{\lambda} \right)$$

∴ the most efficient estimator of $\frac{1}{\lambda}$ is

$$T = \frac{1}{n} \sum_{i=1}^n \left[\frac{(\ln y_i)^2}{3} x_i + \frac{2}{3} x_i \right]$$

$$= \frac{1}{n} \sum_{i=1}^n z_i$$

