

2) X_1, \dots, X_n iid with density $f(x) = \theta^{-1} e^{-(x-a)/\theta} I(x > a)$; $\theta > 0$

(a) When (a) is known, derive the uniformly most powerful test size α for testing

$H_0: \theta \geq \theta_0$ vs. $\theta < \theta_0$; θ_0 is known constant

Likelihood: $p_\theta(x) = \prod_{i=1}^n \theta^{-1} \exp\left(-\frac{x_i - a}{\theta}\right) I(x_i > a) = \theta^{-n} \exp\left\{-\sum_{i=1}^n \left(\frac{x_i - a}{\theta}\right)\right\} I(x_{(n)} > a)$ known

Let $0 < \theta_0 < \theta_1$

then $\frac{p_{\theta_1}(x)}{p_{\theta_0}(x)} = \frac{\theta_1^{-n} \exp\left\{-\sum_{i=1}^n (x_i - a)/\theta_1\right\} I(x_{(n)} > a)}{\theta_0^{-n} \exp\left\{-\sum_{i=1}^n (x_i - a)/\theta_0\right\} I(x_{(n)} > a)} = \left(\frac{\theta_0}{\theta_1}\right)^n \exp\left\{\underbrace{\left(\frac{1}{\theta_1} - \frac{1}{\theta_0}\right)}_{< 0} \sum_{i=1}^n (x_i - a)\right\} I(x_{(n)} > a)$ if this > 0 then test ↓

So, we can see that this is a non-increasing function of $\sum_{i=1}^n (x_i - a)$ = opposite H_1

Thus, our UMP test of size α is

$$\phi(x) = \begin{cases} 1 & \text{if } \sum_{i=1}^n (a - x_i) > k \\ 0 & \text{if } \sum_{i=1}^n (a - x_i) \leq k \end{cases} = \begin{cases} 1 & \text{if } \sum_{i=1}^n (x_i - a) \leq k \\ 0 & \text{if } \sum_{i=1}^n (x_i - a) > k \end{cases} \quad \text{with } E_{\theta_0}[\phi(x)] = \alpha$$

We know $X_i \sim \text{Exp}(\theta)$ on $(a, \infty) \Rightarrow X_i - a \sim \text{Exp}(\theta)$ on $(0, \infty) \Rightarrow \sum_{i=1}^n (X_i - a) \sim \text{Gamma}(n, \theta)$

Thus, $E_{\theta_0}[\phi(x)] = E_{\theta_0}[I(\sum_{i=1}^n (X_i - a) \leq k)] = P_{\theta_0}\left(\underbrace{\sum_{i=1}^n (X_i - a)}_{\text{Gamma}(n, \theta_0)} \leq k\right) \stackrel{\text{set}}{=} \alpha$

$\Rightarrow k = T_{n, \theta_0}^{-1}(\alpha)$

So, the UMP level- α test for $H_0: \theta \geq \theta_0$ vs. $\theta < \theta_0$ is

$$\phi(x) = \begin{cases} 1 & \text{if } \sum_{i=1}^n (x_i - a) \leq T_{n, \theta_0}^{-1}(\alpha) \\ 0 & \text{if } \sum_{i=1}^n (x_i - a) > T_{n, \theta_0}^{-1}(\alpha) \end{cases} = \begin{cases} 1 & \text{if } \bar{X} = \frac{1}{n} T_{n, \theta_0}^{-1}(\alpha) + a \\ 0 & \text{otherwise} \end{cases}$$

(b) When a is known, derive the asymptotic dist. of the MLE of θ .

$$\text{Likelihood: } \theta^{-n} \exp \left\{ \sum_{i=1}^n (a - x_i) / \theta \right\} \mathbb{I}(x_{(n)} > a) \quad \text{known}$$

$$\Rightarrow \log\text{-Likelihood: } -n \log(\theta) + \frac{1}{\theta} \sum_{i=1}^n (a - x_i) \quad \text{if } x_{(n)} > a$$

$$\text{Then } \frac{\partial l}{\partial \theta} = -\frac{n}{\theta} - \frac{\sum_{i=1}^n (a - x_i)}{\theta^2} \stackrel{\text{set}}{=} 0$$

$$\Rightarrow n\theta = -\sum_{i=1}^n (a - x_i)$$

$$\Rightarrow \hat{\theta} = \frac{1}{n} \sum_{i=1}^n (x_i - a) = \bar{x} - a$$

↑
known.

We know $X_i \sim$ Shifted exponential, shifted by a ,

$$\text{so } X_i - a \sim \text{Exp}(\theta) \mathbb{I}(x > 0)$$

$$\left(\text{Then, } \sum_{i=1}^n (X_i - a) \sim \text{Gamma}(n, \theta) \leftarrow \text{exact, not asymptotic} \right)$$

We want asymptotic dist.

$$\text{By CLT, } \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n (X_i - a) - E(X_i - a) \right) \xrightarrow{d} N(0, \text{Var}(X_i - a))$$

$$\Rightarrow \sqrt{n} (\hat{\theta} - \theta) \xrightarrow{d} N(0, \theta^2)$$

Note: When a is known, this distribution is a member of the exponential family, and hence regularity conditions hold, so we know $\sqrt{n}(\hat{\theta} - \theta) \xrightarrow{d} N(0, I(\theta)^{-1})$

$I(\theta) = -\frac{1}{n} E \left[\frac{\partial^2 \log f_\theta(x)}{\partial \theta^2} \right]$; $\log f_\theta(x) \propto -n \log(\theta) - \frac{\sum_{i=1}^n (x_i - a)}{\theta}$; $\frac{\partial l}{\partial \theta} = -\frac{n}{\theta} + \frac{\sum (x_i - a)}{\theta^2} \stackrel{\text{set}}{=} 0$

$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n (x_i - a)$; $\frac{\partial^2 l}{\partial \theta^2} = \frac{n}{\theta^2} - \frac{2\theta \sum (x_i - a)}{\theta^3}$

$-\frac{1}{n} E \left[\frac{n}{\theta^2} - \frac{2\theta \sum (x_i - a)}{\theta^3} \right] = -\frac{1}{\theta^2} + \frac{2n\theta E(x_i - a)}{n\theta^3} = -\frac{1}{\theta^2} + \frac{2}{\theta^2} = \frac{1}{\theta^2} \rightarrow I(\theta)^{-1} = \theta^2$

(C) Now $a = \theta$; $f(x) = \theta^{-1} e^{-(x-\theta)/\theta} I(x > \theta)$

So X has an exponential dist. shifted by θ
 $\Rightarrow X - \theta \sim \text{Exp}(\theta)$ and $\frac{X - \theta}{\theta} \sim \text{Exp}(1)$

\rightarrow Prove $\frac{\bar{X}}{\theta}$ and $\frac{X_{(1)}}{\theta}$ are pivotal quantities.

Likelihood: $\theta^{-n} \exp\left\{\sum_{i=1}^n (\theta - x_i)/\theta\right\} I(x_{(1)} > \theta)$

We will show the CDFs of the 2 proposed pivots are parameter free:
 Note: $X - \theta \sim \text{Exp}(\theta)$ and $\frac{X - \theta}{\theta} \sim \text{Exp}(1)$

Also Note that $\sum_{i=1}^n (x_i - \theta) \sim \text{Gamma}(n, \theta)$

$$\sum_{i=1}^n \left(\frac{x_i - \theta}{\theta}\right) \sim \text{Gamma}(n, 1) \Rightarrow \frac{1}{n} \sum_{i=1}^n \left(\frac{x_i - \theta}{\theta}\right) \sim \text{Gamma}(n, \frac{1}{n}) \equiv \text{Exp}(1)$$

$$P\left(\frac{\bar{X}}{\theta} \leq t\right) = P\left(\frac{\frac{1}{n} \sum_{i=1}^n x_i}{\theta} \leq t\right) = P\left(\frac{\frac{1}{n} \sum_{i=1}^n x_i}{\theta} - \frac{\theta}{\theta} \leq t - 1\right) = P\left(\frac{\frac{1}{n} \sum_{i=1}^n (x_i - \theta)}{\theta} \leq t - 1\right)$$

OR $P\left(\frac{x_i}{\theta} \leq t\right) = P\left(\underbrace{\frac{x_i - \theta}{\theta}}_{\text{Exp}(1)} \leq t - 1\right) = 1 - \exp(-(t-1))$, which is clearly $\perp \theta$

So $\frac{x_i}{\theta}$ is a pivotal quantity, and hence $\frac{\bar{X}}{\theta}$ is a pivotal quantity

$$\text{We know } P\left(\frac{X_{(1)}}{\theta} \leq t\right) = 1 - P\left(\frac{X_{(1)}}{\theta} \geq t\right) = 1 - P\left(\frac{x_1}{\theta}, \dots, \frac{x_n}{\theta} \geq t\right) = 1 - P\left(\frac{x_1}{\theta} \geq t\right)^n$$

$$= 1 - \left[1 - P\left(\frac{x_1}{\theta} \leq t\right)\right]^n = 1 - \left[1 - P\left(\underbrace{\frac{x_1 - \theta}{\theta}}_{\text{Exp}(1)} \leq t - 1\right)\right]^n$$

$$= 1 - \left[1 - (1 - e^{-(t-1)})\right]^n = 1 - \left[e^{-(t-1)}\right]^n = 1 - e^{-n(t-1)}$$

which is also parameter free, and hence $\frac{X_{(1)}}{\theta}$ is a pivot

(d) Obtain two confidence intervals w/ $1-\alpha$ level for θ based on two pivots in (c):

In (c), we found $P\left(\frac{\bar{X}}{\theta} \leq t\right) = 1 - e^{-(t-1)}$

$$\text{So, } \frac{\bar{X}}{\theta}$$

$$\Rightarrow \frac{\bar{X}}{\theta} - 1 \sim \text{Gamma}(n, \frac{1}{n})$$

To obtain a $1-\alpha$ confidence interval for θ , we must have

$$P\left(a \leq \frac{\bar{X}}{\theta} - 1 \leq b\right) = 1-\alpha$$

where a and b are quantiles of $\text{Gamma}(n, \frac{1}{n})$

So, we need a to be the $\frac{\alpha}{2}$ percentile of $T(n, \frac{1}{n}) \Rightarrow a = T_{n, \frac{1}{n}}^{-1}(\frac{\alpha}{2})$

b to be $(1-\frac{\alpha}{2})$ percentile of $T(n, \frac{1}{n}) \Rightarrow b = T_{n, \frac{1}{n}}^{-1}(1-\frac{\alpha}{2})$

So, a $1-\alpha$ CI for θ based on pivot $\frac{\bar{X}}{\theta}$ is:

$$a \leq \frac{\bar{X}}{\theta} - 1 \leq b \Leftrightarrow \frac{\bar{X}}{b+1} \leq \theta \leq \frac{\bar{X}}{a+1}$$

$$\Leftrightarrow \left[\frac{\bar{X}}{1 + T_{n, \frac{1}{n}}^{-1}(1-\frac{\alpha}{2})} \leq \theta \leq \frac{\bar{X}}{1 + T_{n, \frac{1}{n}}^{-1}(\frac{\alpha}{2})} \right]$$

Now, in (c) we also found $P\left(\frac{X_{(1)}}{\theta} \leq t\right) = 1 - e^{-n(t-1)}$

So, to get a $1-\alpha$ CI for θ , we will find a and b st $P(a \leq \frac{X_{(1)}}{\theta} \leq b) = 1-\alpha$

$$\text{We need } 1 - e^{-n(a-1)} = \frac{\alpha}{2} \text{ and } 1 - e^{-n(b-1)} = 1 - \frac{\alpha}{2}$$

$$e^{-n(a-1)} = 1 - \frac{\alpha}{2}$$

$$-n(b-1) = \log\left(\frac{\alpha}{2}\right)$$

$$a-1 = -\frac{1}{n} \log\left(1 - \frac{\alpha}{2}\right)$$

$$b = 1 - \frac{1}{n} \log\left(\frac{\alpha}{2}\right)$$

$$a = 1 - \frac{1}{n} \log\left(1 - \frac{\alpha}{2}\right)$$

$$\text{So, a } 1-\alpha \text{ CI for } \theta \text{ based on pivot } \frac{X_{(1)}}{\theta} \text{ is: } \left[\frac{X_{(1)}}{1 - \frac{1}{n} \log\left(\frac{\alpha}{2}\right)} \leq \theta \leq \frac{X_{(1)}}{1 - \frac{1}{n} \log\left(1 - \frac{\alpha}{2}\right)} \right]$$

(e) When n is sufficiently large, which CI has shorter length?

The interval based on $\frac{X_{(1)}}{\theta}$ is $\frac{X_{(1)}}{1 - \frac{1}{n} \log(\frac{\alpha}{2})} \leq \theta \leq \frac{X_{(1)}}{1 - \frac{1}{n} \log(1 - \frac{\alpha}{2})}$

As $n \rightarrow \infty$ $\frac{1}{n} \log(\frac{\alpha}{2}) \rightarrow 0$ and $\frac{1}{n} \log(1 - \frac{\alpha}{2}) \rightarrow 0$

and so the length of this interval is

$$\frac{X_{(1)}}{1-0} - \frac{X_{(1)}}{1-0} = 0$$

The interval based on $\frac{\bar{X}}{\theta}$ is $\frac{\bar{X}}{1 + \Gamma_{n,h}^{-1}(\frac{\alpha}{2})} \leq \theta \leq \frac{\bar{X}}{1 + \Gamma_{n,h}^{-1}(\frac{\alpha}{2})}$

As $n \rightarrow \infty$, $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \rightarrow E(X_i)$

$$E(X_i) = \int_0^{\infty} \frac{x_i}{\theta} \exp\left(-\frac{x_i}{\theta} + 1\right) dx$$

$$= \exp(1) \int_0^{\infty} \frac{x_i}{\theta} \exp\left(-\frac{x_i}{\theta}\right) dx = \theta e' \int u e^u du = \theta e [u e^u - \int e^u du]$$

$$u = -\frac{x_i}{\theta} \quad du = -\frac{1}{\theta} dx$$

$$c = u \quad v = e^u \\ dc = du \quad dv = e^u du$$

$$= \theta e [u e^u - e^u] = \theta e \left[-\frac{x_i}{\theta} e^{-x_i/\theta} - e^{-x_i/\theta} \right]_{\theta}^{\infty}$$

$$= \theta e [1e^{-1} + e^{-1}] = \theta e [2e^{-1}] = +2\theta$$

So, the length of the CI is

$$2\theta \left[\frac{1}{1 + \Gamma_{n,h}^{-1}(\frac{\alpha}{2})} - \frac{1}{1 + \Gamma_{n,h}^{-1}(\frac{\alpha}{2})} \right]$$

For a given n , this has length 0 if $\alpha=1$, but that would give a 0% CI! Hahaha!

However, as $n \rightarrow \infty$, $\text{Gamma}(n, \frac{1}{n}) \rightarrow N(1, \frac{1}{n}) \rightarrow N(1, 0)$

So would have length 0?

So, CI based on $\frac{X_{(1)}}{\theta}$ is shorter as $n \rightarrow \infty$?