

Given $X \sim \text{Exp}(\lambda)$

$$f_X(x) = \lambda e^{-\lambda x} \quad x > 0.$$

$$= g(t, \lambda) h(x)$$

$$g(t, \lambda) = \lambda e^{-\lambda t}$$

$$h(x) = 1$$

$\therefore t = x$ is sufficient for λ .

X is sufficient.

CDF of X : $F_X(x) = 1 - e^{-\lambda x}$

$$\therefore F_X(X) \sim U(0, 1)$$

$$\mathbb{P}(a \leq F_X(x) \leq b) = 1 - \alpha$$

$$\mathbb{P}\left(\frac{\alpha}{2} \leq F_X(x) \leq 1 - \frac{\alpha}{2}\right) = 1 - \alpha$$

$$\mathbb{P}\left(\frac{\alpha}{2} \leq 1 - e^{-\lambda x} \leq 1 - \frac{\alpha}{2}\right) = 1 - \alpha$$

$$\mathbb{P}\left(\frac{\alpha}{2} - 1 \leq -e^{-\lambda x} \leq -\frac{\alpha}{2}\right) = 1 - \alpha$$

$$\mathbb{P}\left(1 - \frac{\alpha}{2} \geq e^{-\lambda x} \geq \frac{\alpha}{2}\right) = 1 - \alpha$$

$$\mathbb{P}\left(\log\left(1 - \frac{\alpha}{2}\right) \geq -\lambda X \geq \log\left(\frac{\alpha}{2}\right)\right) = 1 - \alpha$$

$$\Rightarrow IP\left(-\frac{1}{X} \log\left(1 - \frac{\alpha}{2}\right) \leq \lambda \leq -\frac{1}{X} \log\left(\frac{\alpha}{2}\right)\right) = 1 - \alpha$$

$$IP\left(\left\{-\frac{1}{X} \log\left(1 - \frac{\alpha}{2}\right) \leq \lambda\right\} \cap \left\{-\frac{1}{X} \log\left(\frac{\alpha}{2}\right) \geq \lambda\right\}\right) = 1 - \alpha$$

$$\therefore \left[-\frac{1}{X} \log\left(1 - \frac{\alpha}{2}\right), -\frac{1}{X} \log\left(\frac{\alpha}{2}\right)\right] \text{ is a } 100(1 - \alpha)\%$$

confidence interval for λ .

Let Y = No. of defective components in a sample of 110.

$$Y \sim \text{Bin}(110, \theta).$$

We wish to test

H_0 : Sample came from factory A $\Rightarrow \theta = 0.2$

vs.

H_1 : Sample came from factory B. $\Rightarrow \theta = 0.3$

Set of possible decisions is:

$$\mathcal{D} = \{ \text{Reject } H_0, \text{Retain } H_0 \}$$

\therefore The loss function is

$$L(\theta, \text{Retain } H_0) = \begin{cases} 0 & \theta = 0.2 \\ b & \theta = 0.3 \end{cases}$$

$$L(\theta, \text{Reject } H_0) = \begin{cases} a & \theta = 0.2 \\ 0 & \theta = 0.3 \end{cases}$$

A priori

$$\pi(\theta = 0.2) = 0.5 \quad \text{and} \quad \pi(\theta = 0.3) = 0.5$$

$$P(Y=y|\theta) = \binom{110}{y} \theta^y (1-\theta)^{110-y}$$

$$\pi(\theta|Y=y) = \frac{\pi(\theta) P(Y=y|\theta)}{P(Y=y)} \quad \left. \vphantom{\frac{\pi(\theta) P(Y=y|\theta)}{P(Y=y)}} \right\} \text{BAYES THEOREM}$$

$$\begin{aligned} P(Y=y) &= \cancel{\pi(\theta)} P(Y=y|\theta) \pi(\theta) + P(Y=y|\theta) \pi(\theta) \\ &= \binom{110}{28} 0.2^{28} (0.8)^{82} \times 0.5 \\ &\quad + \binom{110}{28} 0.3^{28} (0.7)^{82} \times 0.5 \\ &= 0.08306. \end{aligned}$$

$$\cancel{\pi(\theta)} P(Y=28|\theta=0.2) = 0.03$$

$$\cancel{\pi(\theta)} P(Y=28|\theta=0.3) = 0.049$$

$$P(\theta=0.2|Y=28) = 0.4004$$

$$P(\theta=0.3|Y=28) = 0.5996$$

$$\begin{aligned} E[L(\theta, \text{Retain } H_0)|y] &= 0 \times P(\theta=0.2|y) \\ &\quad + b \times P(\theta=0.3|y) \\ &= 0.5996b \end{aligned}$$

$$\begin{aligned} E[L(\theta, \text{Reject } H_0)] &= a \times P(\theta = 0.2 | y) \\ &\quad + 0 \times P(\theta = 0.3 | y) \\ &= 0.4004a. \end{aligned}$$

We reject H_0 if

$$0.4004a \leq 0.5996b.$$

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Exp}(\theta)$$

Likelihood function:

$$L(\theta | \underline{X}) = \prod_{i=1}^n \theta e^{-\theta x_i}$$

$$= \theta^n e^{-\theta \sum_{i=1}^n x_i}$$

$$= \theta^n e^{-\theta t} \quad \text{where } t = \sum_{i=1}^n x_i$$

Prior distribution:

$$\theta \sim \text{Gamma}(\alpha, \beta)$$

$$\mathbb{E}(\theta) = 2 \quad \text{Var}(\theta) = 1 \quad \text{a priori}$$

$$\Rightarrow \frac{\alpha}{\beta} = 2 \quad \frac{\alpha}{\beta^2} = 1$$

$$\Rightarrow \alpha = 2\beta \quad \alpha = \beta^2$$

$$\Rightarrow \beta^2 = 2\beta$$

$$\beta(\beta - 2) = 0$$

$$\beta = 2$$

$$\alpha = 4$$

Prior pdf:

$$\pi(\theta) = \frac{2^4}{\Gamma(4)} \theta^{4-1} e^{-2\theta}$$

Using Bayes' theorem:

$$\begin{aligned}\pi(\theta | \underline{x}) &\propto \pi(\theta) \times L(\theta | \underline{x}) \\ &= \left\{ \frac{2^4}{\Gamma(4)} \theta^{4-1} e^{-2\theta} \right\} \times \theta^n e^{-\theta t} \\ &\propto \theta^{(n+4)-1} e^{-(t+2)\theta}\end{aligned}$$

Posterior is proportional to a Gamma($n+4$, $t+2$) pdf.

$$\therefore \theta | \underline{x} \sim \text{Gamma}(n+4, t+2)$$

(b) Exact posterior credible interval.

$$P(a < \theta < b | \underline{x}) = 1 - \alpha$$

$$\Rightarrow \int_a^b \pi(\theta | \underline{x}) d\theta = 1 - \alpha$$

$$\int_a^b \frac{(t+2)^{n+4}}{\Gamma(n+4)} \theta^{(n+4)-1} e^{-(t+2)\theta} d\theta = 1 - \alpha$$

In general, since n is large.

$$\theta | t \sim \mathcal{N}(E(\theta | \underline{x}), \text{Var}(\theta | \underline{x})) \text{ approximately.}$$

$$\theta | t \sim \mathcal{N}\left(\frac{n+4}{t+2}, \frac{n+4}{(t+2)^2}\right) = \mathcal{N}\left(\frac{54}{24+2}, \frac{54}{(24+2)^2}\right)$$

$$IP \left(-1.96 < \theta - \frac{54}{24.2} < 1.96 \sqrt{\frac{54}{24.2^2}} \right) = 0.95$$

$$IP \left(\frac{54}{24.2} - 1.96 \sqrt{\frac{54}{24.2^2}} < \theta < \frac{54}{24.2} + 1.96 \sqrt{\frac{54}{24.2^2}} \right) = 0.95$$

$= (1.636, 2.826)$ is a 95% posterior credible interval for θ .

X_1, \dots, X_n iid $\mathcal{N}(\mu, \sigma^2)$ σ^2 known.

(a) $\bar{X} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$ distribution of mle \bar{X} .

\therefore 95% confidence interval for μ is

$$\left[\bar{X} - 1.96 \frac{\sigma}{\sqrt{n}}, \bar{X} + 1.96 \frac{\sigma}{\sqrt{n}} \right].$$

(b) In a Bayesian setting, prior for μ is

$$\mu \sim \mathcal{N}(\psi, \phi^2)$$

$$\pi(\mu) = \frac{1}{\sqrt{2\pi}\phi^2} \exp \left\{ -\frac{1}{2\phi^2} (\mu - \psi)^2 \right\}$$

Likelihood function

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

Posterior:

$$\pi(\mu | \underline{x}) \propto \pi(\mu) L(\mu | \underline{x}) \quad \text{BAYES THEOREM}$$

$$= (2\pi\phi^2)^{-\frac{1}{2}} (2\pi\sigma^2)^{-\frac{n}{2}}$$

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

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

$$\begin{aligned}
\pi(\mu | \underline{x}) &\propto \exp \left\{ -\frac{1}{2\phi^2} (\mu^2 - 2\psi\mu + \psi^2) \right. \\
&\quad \left. - \frac{1}{2\sigma^2} \left(\sum_{i=1}^n x_i^2 - 2\mu \sum_{i=1}^n x_i + n\mu^2 \right) \right\} \\
&\propto \exp \left\{ -\frac{1}{2\phi^2} (\mu^2 - 2\psi\mu) - \frac{1}{2\sigma^2} (n\mu^2 - 2\mu \sum x_i) \right\} \\
&= \exp \left\{ -\left(\frac{1}{2\phi^2} + \frac{n}{2\sigma^2} \right) \left(\mu^2 - 2 \left(\frac{\psi}{2\phi^2} + \frac{\sum x_i}{2\sigma^2} \right) \mu \right) \right\} \\
&= \exp \left\{ -\frac{(\sigma^2 + n\phi^2)}{2\phi^2\sigma^2} \left(\mu^2 - 2 \left(\frac{\psi\sigma^2 + \phi^2 \sum x_i}{\sigma^2 + n\phi^2} \right) \mu \right) \right\}
\end{aligned}$$

Is proportional to a normal pdf
with mean

$$\frac{\psi\sigma^2 + \phi^2 \sum x_i}{\sigma^2 + n\phi^2} = \mu_1$$

and

$$\text{variance } \frac{\phi^2\sigma^2}{\sigma^2 + n\phi^2} = \sigma_1^2$$

$$\text{Posterior } \mu | \underline{x} \sim \mathcal{N}(\mu_1, \sigma_1^2)$$

Credible interval :

$$IP\left(-1.96 < \frac{\mu - \mu_1}{\sigma_1} < 1.96\right) = 0.95$$

\therefore 95%^{central} credible interval is:

$$(\mu_1 - 1.96\sigma_1, \mu_1 + 1.96\sigma_1)$$

$$\frac{\psi\sigma^2 + \phi^2 \sum x_i}{\sigma^2 + n\phi^2} = \frac{\psi\frac{\sigma^2}{n} + \phi^2 \bar{x}}{\frac{\sigma^2}{n} + \phi^2} = \mu_1$$

Variance

$$\frac{\phi^2\sigma^2}{\sigma^2 + n\phi^2} = \frac{\phi^2\frac{\sigma^2}{n}}{\frac{\sigma^2}{n} + \phi^2} = \sigma_1^2$$

$$\lim_{n \rightarrow \infty} \mu_1 = \bar{x}$$

$$\lim_{n \rightarrow \infty} \sigma_1^2 = \frac{\sigma^2}{n}$$

$$\text{as } n \rightarrow \infty \quad \mu | \underline{x} \sim \mathcal{N}\left(\bar{x}, \frac{\sigma^2}{n}\right)$$