

1. Consider the **Pareto distribution**:

$$f_X(x) = \frac{\alpha \beta^\alpha}{x^{\alpha+1}}, \quad x > \beta.$$

Let  $X_1, X_2, \dots, X_n$  be a random sample from a Pareto distribution where  $\beta = 2$ , and we want to estimate  $\alpha$ . Note that the **method of moments estimator (MOME)** is:

$$\hat{\alpha}_{MOME} = \frac{\bar{Y}}{\bar{Y} - 2}$$

The solution can be found [here](#). However, you do not need to recall how to find the method of moments estimator for this course.

- Install the **extraDistr** package so we can simulate a random sample from the Pareto distribution, where  $\beta = 2$  (`install.packages("extraDistr")`).
- Pick any value for  $\alpha$  to generate a random sample of size  $n$  (also of your choice) from the Pareto distribution. Use  $m = 10^4$  replicates. (Hint: read `??extraDistr::Pareto`).
- Compute a Monte Carlo estimate for  $\hat{\alpha}_{MOME}$ .
- Derive the MLE for  $\alpha$ . (Yes, you need to remember how to compute the MLE for Unit 6.)
- Compute a Monte Carlo estimate for  $\hat{\alpha}_{MLE}$ .
- Determine which estimator is better:  $\hat{\alpha}_{MOME}$  or  $\hat{\alpha}_{MLE}$ ?

(d) ① Likelihood.

$$f_X(x) = \frac{\alpha \beta^\alpha}{x^{\alpha+1}},$$

$$L(\alpha) = \prod_{i=1}^n \frac{\alpha \beta^\alpha}{x_i^{\alpha+1}} = \alpha^n \cdot \beta^{n \cdot \alpha} \cdot \prod_{i=1}^n x_i^{-(\alpha+1)}$$

② Log-likelihood  $\log(\alpha^n \cdot \beta^{n \cdot \alpha} \cdot \prod_{i=1}^n x_i^{-(\alpha+1)})$

$$\ell(\alpha) = n \cdot \log(\alpha) + n \cdot \alpha \log(\beta) - (\alpha+1) \sum_{i=1}^n \log x_i$$

③. Differentiate and set to 0.

$$\frac{\partial \ell(\alpha)}{\partial \alpha} = \frac{n}{\alpha} + n \cdot \log(\beta) - \sum_{i=1}^n \log x_i = 0$$

$$(4) \quad \hat{\alpha}_{MLE} = \frac{n}{\sum_{i=1}^n \log x_i - n \log(\beta)} = \frac{n}{\sum_{i=1}^n \log x_i - n \log 2}$$

$\uparrow \beta=2$

2. Let  $X_1, X_2, \dots, X_{10}$  be a random sample from the  $Exponential(\theta)$  distribution, where  $\theta$  is the scale parameter.

$n=10$

(a) Use the NP Lemma to derive the rejection region (RR) for the uniformly most powerful test (UMP) of:

$$H_0: \theta = 3 \quad \text{v.s.} \quad H_1: \theta > 3$$

Let the significance level be  $\alpha = 0.10$ . Hint: for the final step, you are allowed to use `qexp()` or `qgamma()`. Also, for the exponential distribution,  $\theta > 0$ .

(b) Use the following code to generate samples from the null distribution:

```
n <- 10
alpha <- 0.10
theta <- 3
m <- 10000
x <- matrix(rexp(n*m, rate = 1/theta), nrow = m)
```

Using the rejection region from part (a), compute the type-I error rate.

(c) Assume we instead had the simple alternative hypothesis  $H_1: \theta = 4$ . Using the rejection region from part (a), Compute the type-II error rate. Also, compute the power.

(d) Why do you think the type-II error rate is high, and the power is low? What happens if you increase the value of  $\theta$  for your alternative hypothesis?

Type II error

0.6243

(a). Exponential pdf ( $\theta$ )  $f(x) = \frac{1}{\theta} e^{-\frac{1}{\theta}x}$ ,  $\theta > 0$ ,  $x \in [0, \infty)$

Test?

Likelihood Ratio Test.

Review. NP Lemma. the RR is determined by  $\frac{L(\theta_0)}{L(\theta_a)} < k$

$$\begin{aligned} (1) L(\theta) &= \frac{1}{\theta} e^{-\frac{1}{\theta}x_1} * \frac{1}{\theta} e^{-\frac{1}{\theta}x_2} \dots * \frac{1}{\theta} e^{-\frac{1}{\theta}x_{10}} \\ &= \frac{1}{\theta^{10}} * e^{-\frac{1}{\theta} \sum_{i=1}^{10} x_i} \end{aligned}$$

$$e^a \cdot e^b = e^{a+b}$$

$$\frac{L(\theta_0)}{L(\theta_a)} = \frac{\frac{1}{\theta_0^{10}} \cdot e^{-\frac{1}{\theta_0} \sum_{i=1}^{10} x_i}}{\frac{1}{\theta_a^{10}} \cdot e^{-\frac{1}{\theta_a} \sum_{i=1}^{10} x_i}}$$

$$= \left( \frac{\theta_a}{\theta_0} \right)^{10} e^{-\frac{1}{\theta_0} - (-\frac{1}{\theta_a}) \sum_{i=1}^{10} x_i} = \left( \frac{\theta_a}{\theta_0} \right)^{10} e^{(\frac{1}{\theta_a} - \frac{1}{\theta_0}) \sum_{i=1}^{10} x_i} < k$$

$$k_1 = k / \left( \frac{\theta_a}{\theta_0} \right)^{10}$$

$$\Rightarrow e^{(\frac{1}{\theta_\alpha} - \frac{1}{\theta_0}) \sum_{i=1}^n x_i} < k_1 \quad \log(e^{(\frac{1}{\theta_\alpha} - \frac{1}{\theta_0}) \sum_{i=1}^n x_i}) < \log(k_1)$$

$$\Rightarrow \underline{(\frac{1}{\theta_\alpha} - \frac{1}{\theta_0}) \sum_{i=1}^n x_i} < k_2$$

$$\Rightarrow \sum_{i=1}^n x_i > k^* \quad \left( \text{RR} \mid H_0 \right)$$

$\theta_\alpha > \theta_0$   
 $\frac{1}{\theta_\alpha} < \frac{1}{\theta_0}$   
 $\frac{1}{\theta_\alpha} - \frac{1}{\theta_0} < 0$

$$0.1 = \alpha = P \left( \sum_{i=1}^{10} x_i > k^* \mid \theta_0 = 3 \right)$$

Review. if the  $x_1, \dots, x_n$  iid Exponential ( $\theta$ ).

$$\Rightarrow T = \sum_{i=1}^n x_i \sim \text{Gamma}(n, \theta)$$

$$\Rightarrow \sum_{i=1}^{10} x_i \sim \text{Gamma}(10, \theta_{\uparrow})$$

$\theta_0 = 3.$

$$k \Rightarrow \text{pgamma}(\underline{0.1}, \text{shap}=10, \text{scale}=3, \text{lower.tail} = \text{FALSE}).$$

$$k \Rightarrow 42.61797.$$

$$k^* \approx 42.61797.$$

$$\text{RR} = \left\{ \sum_{i=1}^n x_i > 42.61797 \right\}$$

(c). Type II error =  $P(\text{fail to reject} \mid \theta_a = 4)$

RR  $\Rightarrow \sum_{i=1}^{10} x_i > k^*$   $H_a$  is true

$\Rightarrow \sum_{i=1}^{10} x_i \leq k^*$

Type II error =  $P(\sum_{i=1}^{10} x_i \leq k^* \mid \theta_a = 4)$

(d)  $T \sim \text{Gamma}(10, \theta) \Rightarrow E[T] = 10 \cdot \theta$

$H_0$   $E_{H_0}[T] = 30$

$H_a$   $E_{H_a}[T] = 40$

$H_a = 6 \Rightarrow E_{H_a}[T] = 60$

$k^* \approx 42 \dots$

