

# SUGGESTED SOLUTION

Exam TMA4295 Statistical Inference #2015

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## Problem 1

Pareto cdf

$$X \sim f(x|\alpha, \beta) = \text{Par}(\alpha, \beta) = \begin{cases} \alpha^\beta \cdot \beta \cdot x^{-(\beta+1)} & ; \alpha \leq x \\ 0 & ; x < \alpha \end{cases}$$

$$X \Rightarrow F(x|\alpha, \beta) = C\text{Par}(\alpha, \beta) = \begin{cases} 1 - \alpha^\beta x^{-\beta} & ; \alpha \leq x \\ 0 & ; x < \alpha \end{cases}$$

with  $\alpha > 0, \beta > 2$ .

$$E\mu = E\{X\} = [\beta - 1]^{-1} \beta \alpha$$

$$\sigma^2 = \text{Var}\{X\} = [\beta - 1]^{-2} [\beta - 2] \beta \alpha^2$$

Random sample:

$$X_n: \underset{*n}{X_1}, \dots, \underset{*n}{X_n} \text{ iid Par}(\alpha, \beta)$$

Initially in a), b) & c):

$(\alpha, \beta)$ -unknown

a) Factorization Theorem - Theo 6.2.6

Pdf of random sample:

$$\begin{aligned}
 f(x_n | \alpha, \beta) &= \prod_{i=1}^n f(x_i | \alpha, \beta) \\
 &= \alpha^{n\beta} \beta^n \prod_{i=1}^n x_i^{-(\beta+1)} \prod_{i=1}^n I(\alpha \leq x_i) \\
 &= \underbrace{\alpha^{n\beta}}_{h(\alpha, \beta)} \underbrace{\beta^n \left[ \prod_{i=1}^n x_i \right]^{-(\beta+1)}}_{g_1(T_1(x) | \beta)} \underbrace{I(\alpha \leq \min\{x_n\})}_{g_2(T_2(x) | \alpha)}
 \end{aligned}$$

Sufficient statistics:

$$T_1(x) = \prod_{i=1}^n x_i \xrightarrow[\text{transf}]{\text{monotone}} \sum_{i=1}^n \log x_i$$

$$T_2(x) = \min\{x_n\} = x_{(1)} \quad \text{--- order statistic}$$

b) Likelihood:

$$L(\alpha, \beta | x_n) = f(x_n | \alpha, \beta) = \alpha^{n\beta} \beta^n \left[ \prod_{i=1}^n x_i \right]^{-(\beta+1)} I(\alpha \leq x_{(1)})$$

log-likelihood:

$$\log-L(\alpha, \beta | x_n) =$$

$$n\beta \log \alpha + n \log \beta - (\beta+1) \sum_{i=1}^n \log x_i + \log I(\alpha < x_{(1)})$$

Note:

Max:  $\alpha - \beta$  fixed:

$$\log I(\alpha < x_{(1)}) = \begin{cases} 0 & \alpha < x_{(1)} \\ -\infty & x_{(1)} < \alpha \end{cases}$$

$n\beta \log \alpha$  - increase with  $\alpha$

Hence: log-L max at  $x_{(1)}$

$$\text{MLE: } \hat{\alpha} = X_{(1)} = \min\{X_n\}$$

Max:  $\beta - \alpha$  fixed:

$$\frac{\partial}{\partial \beta} \log L(\alpha, \beta | x_n)$$

$$= n \log \alpha + n \frac{1}{\beta} - \sum_i \log x_i = 0$$

$$\hat{\beta} = \left[ \frac{1}{n} \sum_i \log x_i - \log \alpha \right]^{-1}$$

$$\text{MLE: } \hat{\beta} = \left[ \frac{1}{n} \sum_{i=1}^n \log X_i - \log X_{(1)} \right]^{-1}$$

MLE for  $(\mu, \sigma^2)$ :

$$\hat{\mu} = \left[ \hat{\beta} - 1 \right]^{-1} \hat{\beta} \hat{\alpha}$$

$$\hat{\sigma}^2 = \left[ \hat{\beta} - 1 \right]^{-2} \left[ \hat{\beta} - 2 \right]^{-1} \hat{\beta} \hat{\alpha}^2$$

Invariance  
property of MLE  
Theo 7.2.10

c)

Hypothesis:

$$H_0: \beta = \beta_0 \quad \text{versus} \quad H_1: \beta \neq \beta_0 \quad (\beta_0 > 2)$$

Likelihood ratio:

$$\lambda(x_n) = \frac{\sup_{\alpha > 0, \beta \in H_0} L(\alpha, \beta | x_n)}{\sup_{\alpha > 0, \beta \in H_1} L(\alpha, \beta | x_n)}$$

$$\leftarrow \alpha = \hat{\alpha}, \beta = \beta_0$$

$$\leftarrow \alpha = \hat{\alpha}, \beta = \hat{\beta}$$

$$= \frac{\hat{\alpha}^{n\beta_0} \beta_0^n \left[ \prod_i x_i \right]^{-(\beta_0+1)} \mathbb{I}(\hat{\alpha} \leq x_{(1)})}{\hat{\alpha}^{n\hat{\beta}} \hat{\beta}^n \left[ \prod_i x_i \right]^{-(\hat{\beta}+1)} \mathbb{I}(\hat{\alpha} \leq x_{(1)})}$$

$$= \frac{x_{(1)}^{n(\beta_0 - \hat{\beta})} \beta_0^{n-1-n} \left[ \prod_i x_i \right]^{(\hat{\beta} - \beta_0)}}{\hat{\beta}^{n-1-n}}$$

Rejection region  $R_c$ :

$$R_c = \{ \mathbb{X}_n \mid \lambda(\mathbb{X}_n) \leq c \}$$

$$= \left\{ \mathbb{X}_n \mid x_{(1)}^{n(\beta_0 - \hat{\beta})} \beta_0^{n-1} \left[ \prod_{i=1}^n x_i \right]^{-\hat{\beta}} < c \right\}$$

NOTE:  $-2 \ln \lambda(\mathbb{X}_n)$  is NOT asymptotically chi-square distributed, since the regularity conditions in  $f(x \mid \alpha, \beta)$  is not fulfilled.

Assume: fixed  $\alpha_0 > 0$  -  $\beta > 2$  unknown

Sufficient statistic:  $T_1(\mathbb{X}_n) = \sum_{i=1}^n \log X_i$

d) Note:

$$X \mapsto f(x|\beta) = \text{Par}(\beta) = \begin{cases} \alpha_0^\beta \beta x^{-(\beta+1)} & ; \alpha_0 \leq x \\ 0 & ; \text{else} \end{cases}$$

$$f(x|\beta) = \underbrace{\alpha_0^\beta \beta}_{c(\beta)} \cdot \exp\left\{ \underbrace{-(\beta+1)}_{\omega(\beta)} \underbrace{\log x}_{t(x)} \right\}$$

↑ Exponential family  
of pdf

From Theo 6.2.25  $T(\mathbb{X}_n) = \sum_{i=1}^n t(X_i) = \sum_{i=1}^n \log X_i$

is a complete statistic if  $\omega(\beta) = -(\beta+1)$  is an open set -  $\beta > 2 \Rightarrow \omega(\beta) < 3 \Rightarrow$  open.

Hence  $T_1(\mathbb{X}_n)$  is a complete sufficient statistics

The MLE for  $\beta$  is

$$\beta^* = \left[ \frac{1}{n} \sum_{i=1}^n \log X_i - \log \alpha_0 \right]^{-1}$$

Can be seen from:

$$\beta^* = \arg \max_{\beta} \{ \log -L(\alpha_0, \beta | \mathbb{X}_n) \} \text{ in point b)}$$

e) The estimator  $\beta^*$  is consistent for  $\beta$   
- since all MLE are consistent for exponential family pdfs - Theo 10.1.6

Consider:

$$\sqrt{n} [\beta^* - \beta] \xrightarrow[n \rightarrow \infty]{\text{dist}} N(0, v(\beta))$$

with  $v(\beta)$  being Cramér-Rao Lower Bound

$$v(\beta) = \left[ - \frac{d^2}{d\beta^2} \log L(\beta|x) \right]^{-1} \quad \text{Theo 10.1.12}$$

$$= \left[ \frac{1}{\beta^2} \right]^{-1} = \beta^2$$

The estimator  $\beta^*$  is asymptotically efficient for  $\beta$  - since  $\beta^*$  is MLE for  $\beta$  -  
Theo 10.1.12.

Parameter inference in Bayesian setting.

Prior model:

$$\beta \rightsquigarrow f(\beta | \lambda, k) = \text{Gam}(\lambda, k)$$

$$= \begin{cases} \lambda^k [k!]^{-1} \beta^{k-1} \exp\{-\lambda\beta\} & ; \beta \geq 0 \\ 0 & ; \beta < 0 \end{cases}$$

for known  $\lambda \in \mathbb{R}_+$  and  $k \in \mathbb{N}_+$ .

$$f(\beta | \alpha_0, \lambda, k, \#_n)$$

$$= \text{const}_1 \times f(\#_n | \beta, \alpha_0) \times f(\beta | \lambda, k)$$

$$= \text{const}_1 \times \alpha_0^{n\beta} \cdot \beta^n \prod_i x_i^{-(\beta+1)} \cdot \beta^{k-1} \exp\{-\lambda\beta\}$$

$$= \text{const}_1 \beta^{k+n-1} \cdot \exp\{n\beta \ln \alpha_0\} \exp\{-(\beta+1) \sum_i \ln x_i\} \exp\{-\lambda\beta\}$$

$$= \text{const}_2 \times \beta^{k+n-1} \times \exp\left\{-\left(\lambda + \sum_i \ln x_i - n \ln \alpha_0\right)\beta\right\}$$

$$= \text{Gam}\left(\underbrace{\lambda + \sum_i \ln x_i - n \ln \alpha_0}_{\lambda | \#_n}, \underbrace{k+n}_{k | \#_n}\right)$$

Hence the Gamma pdf is a conjugate prior model for iid samples from the Pareto pdf with given  $\alpha_0$ .

$$E(\beta | \alpha_0, \lambda, k, \#_n) = \frac{k | \#_n}{\lambda | \#_n} = \frac{k+n}{\lambda + \sum_i \ln x_i - n \ln \alpha_0}$$

from the Gamma pdf.

Assume: fixed  $\beta_0 > 2$  -  $\alpha > 0$  unknown

Sufficient statistic:  $T_2(\mathbf{X}_n) = \min\{X_n\} = X_{(1)}$

g)  $X_1 \sim \text{Par}(\alpha, \beta_0)$       $E\{X_1\} = [\beta_0 - 1]^{-1} \beta_0 \alpha$

$\text{Var}\{X_1\} = [\beta_0 - 1]^{-2} [\beta_0 - 2]^{-1} \beta_0 \alpha^2$

$\alpha^+ = \beta_0^{-1} [\beta_0 - 1] X_1$

$E\{\alpha^+\} = \beta_0^{-1} [\beta_0 - 1] E\{X_1\} = \alpha$

Use Rao-Blackwell construction Theo 7.3.17:

$\tilde{\alpha} = E\{ \beta_0^{-1} [\beta_0 - 1] X_1 \mid X_{(1)} = t \}$

$= \beta_0^{-1} [\beta_0 - 1] E\{ X_1 \mid X_{(1)} = t \}$

$= \beta_0^{-1} [\beta_0 - 1] \left[ E\{ X_1 \mid X_{(1)} = t, (1) = 1 \} p((1) = 1 \mid X_{(1)} = t) \right.$

$\left. + E\{ X_1 \mid X_{(1)} = t, (1) \neq 1 \} p((1) \neq 1 \mid X_{(1)} = t) \right]$

Ⓐ:  $E\{X_1 \mid X_1 = t\} \frac{1}{2} = \frac{1}{2} t$

Ⓑ:  $E\{X_1 \mid X_1 > t\} \frac{n-1}{n} = [1 - F(t)]^{-1} \int_t^\infty u f(u) du \cdot \frac{n-1}{n}$

$= \frac{n-1}{n} \cdot \alpha^{-\beta_0} t^{\beta_0} \int_t^\infty u \beta_0 \alpha^{\beta_0} u^{-(\beta_0+1)} du$

$= \frac{n-1}{n} \alpha^{-\beta_0} t^{\beta_0} \beta_0 \alpha^{\beta_0} \int_t^\infty u^{-\beta_0} du$

$= \frac{n-1}{n} t^{\beta_0} (\beta_0 [\beta_0 - 1]^{-1}) t^{-(\beta_0+1)}$

$= \frac{n-1}{n} \beta_0 [\beta_0 - 1]^{-1} t$

$\left[ \frac{1}{-(\beta_0+1)} u^{-(\beta_0+1)} \right]_t^\infty$

$\left[ \frac{1}{(\beta_0-1)} t^{-(\beta_0-1)} \right]$



$$\begin{aligned}\tilde{\alpha} &= \beta_0^{-1} [\beta_0 - 1] \left[ \frac{1}{n} \sum + \frac{n-1}{n} \beta_0 [\beta_0 - 1]^{-1} \sum \right] \\ &= \left[ 1 - [n\beta_0]^{-1} \right] \sum\end{aligned}$$

Hence the estimator is:

$$\tilde{\alpha} = \left[ 1 - [n\beta_0]^{-1} \right] \sum_{(1)}$$

h) Consider:

$$\alpha^* = \sum_{(1)}$$

Order stat cdf:

$$\sum_{(1)} \rightsquigarrow F_{\sum_{(1)}}(x | \alpha, \beta_0) = [1 - F(x)]^n \Rightarrow$$

$$\sum_{(1)} \rightsquigarrow f_{\sum_{(1)}}(x | \alpha, \beta_0) = n f(x) [1 - F(x)]^{n-1}$$

$$= n \beta_0 \alpha^{\beta_0} x^{-(\beta_0+1)} [\alpha^{\beta_0} x^{-\beta_0}]^{n-1} I(\alpha \geq x)$$

$$= n \beta_0 \alpha^{n\beta_0} x^{-(n\beta_0+1)} I(\alpha \geq x)$$

$$= \text{Par}(\alpha, n\beta_0) \rightarrow \begin{cases} E\{\sum_{(1)}\} = [n\beta_0 - 1]^{-1} n\beta_0 \alpha \\ \text{Var}\{\sum_{(1)}\} = [n\beta_0 - 1]^{-2} [n\beta_0 - 2]^{-1} n\beta_0 \alpha^2 \end{cases}$$

$$E\{\sum_{(1)}\} = \left[ 1 - [n\beta_0]^{-1} \right]^{-1} \alpha \xrightarrow{n \rightarrow \infty} \alpha \quad \text{NOTE: } \tilde{\alpha} !!$$

$$\text{Var}\{\sum_{(1)}\} = [n\beta_0 - 1]^{-2} [1 - 2[n\beta_0]^{-1}]^{-1} \alpha \xrightarrow{n \rightarrow \infty} 0$$

$\alpha^*$  is consistent since:

$$E\{\alpha^*\} \xrightarrow{n \rightarrow \infty} \alpha, \quad \text{Var}\{\alpha^*\} \xrightarrow{n \rightarrow \infty} 0 \quad \text{Theo 10.1.3}$$