# Quadratic type minimum risk equivariant estimation of an uniform location-scale using general progressive censored sample

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<u>Abstract</u>

In this paper, by assuming that a general progressive Type II right censored sample, we obtain  $Q_A$ -MRE estimators for the vector parameter of  $(\xi, \tau)'$  based on the general Type II progressive right censored sample. Further MRE estimator of  $(\xi, \tau)'$  is obtained with respect to Linex type loss function. These geralize the results of Chandrasekar et.al. (2002) for progressive Type II right censored sample. The paper is organized as follows: Section 3 deals with the problem of  $Q_A$ -MRE estimators for the vector parameters. In the last Section, we consider the problem of equivariant estimation of the vector parameter under Linex loss function (Varian, 1975).

**Keywords:** Equivariant Estimation, General Progressive Censored sample, Linex Loss function, Q<sub>A</sub>- MRE, Uniform Location- Scale model.

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# **INTRODUCTION**

Progressive Type II right censored sampling is an important method of obtaining data in life-testing studies. As pointed out by Rita Aggarwala and Balakrishnan (1998), the scheme of progressive censoring enables us to use live units, removed early, in other tests. Balakrishnan and Sandhu (1996), by assuming a general progressive Type II right censored sample, derived the BLUE's for the parameters of one-and two-parameter exponential distributions. For the later, they also derived MLE's and shown that they are simply the BLUE's, adjusted for their bias. Let us consider the following general progressive Type II right censoring scheme (Balakrishnan and Sandhu, 1996) : Suppose N randomly selected units were placed on a life test; the failure times of the first r units to fail were not observed ; at the time of the (r+1)<sup>th</sup> failure,  $R_{r+1}$  number of surviving units are withdrawn from the test randomly, and so on; at the time of the (r+i)<sup>th</sup> failure, the remaining  $R_n = N - n - R_{r+1} - R_{r+2} - ... - R_{n-1}$  are withdrawn from the test. Suppose  $X_{r+1:N} \le X_{r+2:N} \le ... \le X_{n:N}$  are the life-times of the completely observed units to fail, and  $R_{r+1}$ ,  $R_{r+2}$ ,...,  $R_n$  are the number of units withdrawn from the test at

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$$N = n + \sum_{i=1}^{n} Ri$$

these failure times, respectively. It follows that i=r+1. If the failure times are from a continuous population with the pdf f and the distribution function F, then the joint pdf of ( $X_{r+1:N}$ ,  $X_{r+2:N}$ ,....,  $X_{n:N}$ ) is given by

$$g_{\theta}(x_{r+1},...,x_{n}) = c[\{F_{\theta}(x_{r+1})\}^{r} X_{i=r+1}^{n} f_{\theta}(x_{i})\{1 - F_{\theta}(x_{i})\}^{R_{i}}]$$

$$g_{\theta}(x_{r+1},...,x_{n}) = c[\{F_{\theta}(x_{r+1})\}^{r} X_{i=r+1}^{n} f_{\theta}(x_{i})\}^{R_{i}}]$$

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$$g_{\theta}(x_{r+1},...,x_{n}) = c[\{F_{\theta}(x_{r+1},...,x_{n})]$$

## **LOCATION- SCALE MODEL**

In this case, the common pdf is taken to be

$$f_{\theta}(x) = \begin{cases} 1/\tau, \xi \leq x \leq \xi + 1; \xi \in \Re, \tau > 0, \\ 0, otherwise \end{cases}$$
  
Note that  $\theta = (\xi, \tau)'$ . Then (1.1) reduces to  
 $g_{\theta}(x_{r+1}, ..., x_n) = c[((x_{r+1} - \xi)/\tau)^r (1/\tau^{n-r-1}) \times \prod_{i=r+1}^n \{1 - (x_i - \xi)/\tau\}^{R_i}], \dots (2.1)$   
 $\xi \leq x_{r+1:N} \leq \dots \leq x_{n:N} \leq \xi + \tau; \xi \in \Re, \tau > 0.$ 

Note that the above pdf belongs to a location – scale model. We are interested in deriving QA-MRE estimator as well as the MRE estimator based on Linex loss function for the vector parameter  $(\xi, \tau)'$ .

#### **OUADRATIC TYPE LOSS FUNCTION**

If the loss function is of the quadratic type, then by the simultaneous equivariant estimation approach of Edwin Prabakaran and Chandrasekar (1994), let us consider the problem of estimation of  $(\xi, \tau)'$ . Consider  $\delta_0(X) = (\delta_{01}(X), \delta_{02}(X))',$ where  $\delta_{01}(X) = X_{r+1:N}$  and  $\delta_{02}(X) = X_{n:N} - X_{r+1:N}$ . Here  $\delta_0(X)$  is an equivariant estimator and  $(X_{r+1:N}, X_{n:N})'$  is a

sufficient statistic but not complete. In order to find  $(w_1^*, w_2^*)$  as given by the following

$$w_1^* = \frac{E(\delta_{01}\delta_{02} | \mathbf{z})}{E(\delta_{02}^2 | \mathbf{z})} \text{ and } 1/w_2^* = \frac{E(\delta_{02} | \mathbf{z})}{E(\delta_{02}^2 | \mathbf{z})},$$

consider the transformation

$$Z_{r+1} = X_{r+1:N}, \quad Z_{r+2} = X_{n:N} - X_{r+1:N}$$

$$Z_{i} = \frac{X_{i-1:N} - X_{r+1:N}}{X_{n:N} - X_{r+1:N}}, \quad i = r+3, \dots, n ,$$

and

so that  $X_{r+1:N} = Z_{r+1} X_{n:N} = Z_{r+1} + Z_{r+2}$ and  $X_{i-1:N} = Z_{r+1} + Z_{r+2}Z_i, i = r+3,...,n.$ 

The Jacobian of the transformation is given by

$$J = Z_{r+2}^{n-r-2}.$$
  
Thus the joint pdf of  $(Z_{r+1},...,Z_n)$  is given by

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$$\begin{split} h(Z_{r+1},...,Z_n) &= c[z_{r+1}^r z_{r+2}^{n-r-2} (1 - z_{r+1}^r)^{N_{r-1}} \times \\ &\{1 - (z_{r+1} + z_{r+2})\}^{R_n} \times \\ &\frac{n^{-1}}{t_{n-r+2}} \{1 - (z_{r+1} + z_{r+2}z_1)\}^{R_n} \} ...(3.1) \\ &0 < z_{r+1} + z_{r+2} < 1. \\ \end{split}$$
Also the joint pdf of  $(Z_{r+3},...,Z_n)$  is given by  $h_1(z_{r+3},...,z_n)$  is given by  $h_1(z_{r+3},...,z_n)$   $= c[\int_{0}^{1} \int_{0}^{1-z_{r+2}} z_{r+1}^{n-r-2} (1 - z_{r+1})^{R_{r+1}} \times \\ &\{1 - (z_{r+1} + z_{r+2})\}^{R_n} \times \\ &\frac{n^{-1}}{t_{n-r+2}} \{1 - (z_{r+1} + z_{r+2}z_1)\}^{R_n} dz_{r+2} \} \\ &0 < z_{r+3} < ... < z_n < 1.... (3.2) \\ \end{aligned}$ 
Thus the conditional pdf of  $(Z_{r+1}, Z_{r+2})$  given  $(Z_{r+3}, ..., Z_n)$  is given by  $h_2((z_{r+1}, z_{r+2})) |z_{r+3}, ..., z_n) = \frac{h(z_{r+1}, ..., z_n)}{h_1(z_{r+3}, ..., z_n)}, \quad 0 < z_{r+1} + z_{r+2} < 1. \\ \end{aligned}$ 
Where  $h(z_{r+1}, ..., z_n) = \frac{h(z_{r+1}, ..., z_n)}{h_1(z_{r+3}, ..., z_n)}$  are given in equations (3.1) and (3.2) respectively. Similarly  $h_3((z_{r+2})) |z_{r+3}, ..., z_n) = \frac{\int_{0}^{1-z_{r+2}} h(z_{r+1}, ..., z_n) dz_{r+1}}{h_1(z_{r+3}, ..., z_n)}, \quad (3.4)$ 
In view of (3.3).  $\sum_{Now} E(\delta_{01}\delta_{02} |z|) = E(Z_{r+1}Z_{r+2} |z)$ 

In view of (3.3). Also  $E\left(\delta_{02}^{2} \mid \mathbf{z}\right) = E\left(Z_{r+2}^{2} \mid \mathbf{z}\right)$ 

$$=\frac{\int_{0}^{1}\int_{0}^{1-z_{r+2}} z_{r+2}^{2} h(z_{r+1},...,z_{n}) dz_{r+1} dz_{r+2}}{h_{1}(z_{r+3},...,z_{n})},$$
(3.6)

In view of (3.4).

Similarly,  $E(\delta_{02} | \mathbf{z}) = E(Z_{r+2} | \mathbf{z})$ 

$$=\frac{\int_{0}^{1-z_{r+2}} \int_{0}^{1-z_{r+2}} z_{r+2}h(z_{r+1},...,z_n)dz_{r+1}dz_{r+2}}{h_1(z_{r+3},...,z_n)},$$
(3.7)

In view of (3.4). Thus

where

$$w_1^* = \frac{E(\delta_{01}\delta_{02} | \mathbf{z})}{E(\delta_{02}^2 | \mathbf{z})},$$

$$E(\delta_{01}\delta_{02} | \mathbf{z})_{\text{and}} E(\delta_{02}^2 | \mathbf{z})_{\text{are given in (3.6) and (3.7) respectively and}$$

$$1/w_2^* = \frac{E(\delta_{02} | \mathbf{z})}{E(\delta_{02}^2 | \mathbf{z})},$$

$$E(\delta_{02} | \mathbf{z})_{\text{and}} E(\delta_{02}^2 | \mathbf{z})_{\text{are given in (3.6) and (3.7) respectively}}$$

where  $E(\delta_{02} | \mathbf{Z})$  and  $E(\delta_{02} | \mathbf{Z})$  are given in (3.6) and (3.7) respectively. Therefore the MRE estimator  $\delta^* = (\delta_1^*, \delta_2^*)_{\text{of}} \theta = (\xi, \tau)'_{\text{is given by}}$   $\delta_1^* = X_{r+1:N} - (X_{n:N} - X_{r+1:N})w_1^*$ and  $\delta_2^* = (X_{n:N} - X_{r+1:N})/w_2^*$ .

**Remark3.1:** if r=0 and  $R_i=r_i$  then the above estimator reduces to the one in simultaneous Equivariant estimation of the parameters of a Uniform Location- Scale model based on progressive Type-II right censored sample case (Leo Alexander, 2000).

## LINEX LOSS FUNCTION

Following Varian (1975), the MRE estimator of  $(\xi, \tau)^{t}$  under Linex loss function, is provided. We have  $R(\delta | \mathbf{z}) = E[\{e^{a(\delta_{01}-gw_{1})} - a(\delta_{01} - gw_{1}) - 1 + e^{b(\delta_{02}/w_{2}-1)} - b(\delta_{02}/w_{2} - 1) - 1\} | \mathbf{z}],$ where  $\delta_{01} = X_{r+1:N}$  and  $\delta_{02} = X_{n::N} - X_{r+1:N}$ . Consider  $R(\delta | \mathbf{z}) = E[\{e^{a(\delta_{01}-aw_{1}\delta_{02})} | \mathbf{z}] - aE(\delta_{01} | \mathbf{z}) + aw_{1}E(\delta_{02} | \mathbf{z}) - 1 + e^{-b}E(e^{b/w_{2}\delta_{02}} | \mathbf{z}] + b - b/w_{2}E(\delta_{02} | \mathbf{z}) - 1$   $+ e^{-b}E(e^{b/w_{2}\delta_{02}} | \mathbf{z}] + b - b/w_{2}E(\delta_{02} | \mathbf{z}) - 1$   $= \frac{\int_{0}^{1-z_{r+2}} e^{a(z_{r+1}-w_{1}z_{r+2})}h(z_{r+1},...,z_{n})dz_{r+1}dz_{r+2}}{h_{1}(z_{r+3},...,z_{n})} - a\frac{\int_{0}^{1-z_{r+2}} \int_{0}^{1-z_{r+2}} b(z_{r+1},...,z_{n})dz_{r+1}dz_{r+2}}{h_{1}(z_{r+3},...,z_{n})} + b$  $-b/w_{2}\frac{\int_{0}^{1-z_{r+2}} f(z_{r+1},...,z_{n})dz_{r+1}dz_{r+2}}{h(z_{r+1},...,z_{n})dz_{r+1}dz_{r+2}} - 1$ .

Thus  $(w_1^*, w_2^*)'$  is to be obtained as the value of  $(w_1, w_2)'$  by minimizing  $R(\delta | \mathbf{z})$ .

Therefore the MRE estimator of  $(\xi, \tau)'$  is given by

$$\delta_1^* = X_{r+1:N} - (X_{n:N} - X_{r+1:N}) w_1^* \text{ and } \delta_2^* = (X_{n:N} - X_{r+1:N}) / w_2^*.$$

**Remark 4.1:** If r=0 and  $R_i = r_i$ , i = 1, 2, ..., n, then the above estimators reduce to those obtained in (Leo Alexander, T, 2000).

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