# On the equivariant estimation of an uniform location model under general progressive type II right censored sample

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Abstract We consider the problem of obtaining Minimum Risk Equivariant (MRE) estimator for the parameter of the uniform model in three situations by assuming that a general progressive Type II right censored sample, these generalize the results of Chandrasekar *et al.* (2002) for progressive Type II right censored sample. The paper is organized as follows: Section 2 deals with the problem of equivariant estimation under Squared error loss function. In Section 3, the problem of equivariant estimation under Absolute error loss function discussed. Finally, we dealt with the problem of equivariant estimation (Varian, 1975) in Section 4. Keywords: Equivariant Estimation, General Progressive Censored Sample, Linex Loss function, MRE, Uniform

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Location Model.

# INTRODUCTION

Progressive Type II right censored sampling is an important method of acquiring data in life-testing studies. Aggarwala and Balakrishnan (1998) points out that 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<sub>r+1</sub> number of surviving units are withdrawn from the test randomly, and so on; at the time of the (r+i)<sup>th</sup> failure, R<sub>r+1</sub> number of surviving units are randomly withdrawn from the test. Suppose  $X_{r+1:N} \leq X_{r+2:N} \leq .... \leq X_{n:N}$  are the life-times of the completely observed units to fail, and R<sub>r+1</sub>, R<sub>r+2</sub>, ..., R<sub>n</sub> are the number of units withdrawn from the test at these failure

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

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

$$= \mathbf{c} \{F_{\theta}(\mathbf{x}_{r+1})\}^{r} \stackrel{\text{i}}{=} r+1}{\mathbf{f}_{\theta}(\mathbf{x}_{i})\{1 - F_{\theta}(\mathbf{x}_{i})\}^{R_{i}}},$$

$$\mathbf{c} = \binom{N}{r} (N-r) \prod_{j=r+2}^{n} \left(N - \sum_{i=r+1}^{j-1} R_{i} - j + 1\right),$$
(1.1)
where

**Location Model** The pdf is taken to be

 $f_{\xi}(x) = \begin{cases} 1 \ , & \xi \leq x \leq \xi + 1 \ ; \ \xi \in R \\ 0 \ , & \text{otherwise} \end{cases}$ 

and from (1.1) we get

$$g_{\xi}(x_{r+1},...,x_n) = c(x_{x+1} - \xi) \prod_{i=1}^n (1 - x_i + \xi)^{R_i}, \quad \xi \le x_{r+1} \le x_n \le \xi + 1; \xi \in \mathbb{R}$$
(1.2)

Thus the distribution of  $(X_{r+1:N},...,X_{n:N})$  belongs to a location family with the location parameter  $\xi$ . We are interested in deriving MRE estimator of  $\xi$  by considering three loss functions. Following Lehmann and Casella (1998), the MRE estimator of  $\xi$  is given by  $\delta^*(\mathbf{X}) = \delta_0(\mathbf{X}) - v^*(\mathbf{Y})$ , where  $\delta_0$  is a location equivariant estimator,  $v(\mathbf{y}) = v^*(\mathbf{y})$ minimizes  $E_0[\rho\{\delta_0(\mathbf{x})-v(\mathbf{y})\}|\mathbf{y}]$  and  $E_0$  denotes  $E_{\xi}$  when  $\xi = 0$ . Here  $Y_i = X_{i:N} - X_{r+1:N}, i = r+2,...,n$ ,  $\mathbf{Y} = (Y_{r+2},...,Y_n)_{\text{and }} \rho$  is an invariant loss function.

#### SQUARED ERROR LOSS

If the loss is squared error, then

$$v^* = E_0 \left( \delta_0 \mid \mathbf{y} \right)_{\text{Take}} \delta_0(\mathbf{X}) = \frac{X_{r+1:N} + X_{n:N}}{2}. \text{ Clearly } \delta_0 \text{ is an equivarian}$$

estimator but not complete sufficient. Since we are interested in the evaluation of conditional distribution under  $\xi = 0$ , we take  $\xi = 0$  in (1.2). In order to find  $v^*$ , consider the transformation  $Y_{r+1} = (X_{r+1:N} + X_{n:N})/2$  and  $Y_i = X_{i:N} - X_{r+1:N}, i = r + 2,..., n$ . Then  $X_{r+1:N} = Y_{r+1} - Y_n/2$  and  $X_{i:N} = Y_i + Y_{r+1} - Y_n/2, i = r + 2,..., n$  and the lacebian of the transformation is I=1. Thus the ising of  $\xi \in \{Y_{r+1}, Y_{r+2}, ..., Y_n\}$ .

Jacobian of the transformation is J=1. Thus the joint pdf of 
$$(x_{r+1}, y_{r+2}, ..., y_n)$$
 is given by  

$$h(y_{r+1}, ..., y_n) = c(y_{r+1} - y_n/2)^r \{1 - (y_{r+1} - y_n/2)\}^{R_{r+1}}$$

$$\prod_{i=r+2}^n \{1 - (y_i + y_{r+1} - y_n/2)\}^{R_i}, \qquad 0 < y_{r+2} < y_{r+3} < ... < y_n, \ y_n/2 < y_{r+1} < 1 - y_n/2, \ 0 < y_n < 1.$$

Also, the joint pdf of  $(Y_{r+2},...,Y_n)$  is given by

$$\begin{split} h_{i}(y_{r+2},...,y_{n}) &= c \int_{y_{i}/2}^{1-y_{i}/2} (1 - (y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ h_{2}(y_{r+1} | y_{r+2},...,y_{n}) &= [(y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= [(y_{r+1} - y_{n}/2)^{2} (1 - (y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{r+1} - y_{n}/2))^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} + y_{i} - (x_{i} - x_{i+1} + x_{i}))^{2})^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - (y_{i} - y_{i} - (x_{i} - x_{i} - x_{i+1} + x_{i}))^{2})^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - 2R_{i} - y_{i-1} + (X_{i+1} + x_{i} - x_{i}))^{2})^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - 2R_{i} - y_{i-1} + (X_{i+1} + x_{i} - x_{i})^{2})^{R_{i-1}} \times \\ &= \frac{\pi}{2r+2} (1 - 2R_{i} - \frac{\pi}{2r+2} (1 - 2R_{i} - y_{i-1} + (X_{i+1} + x_{i} - x_{i})^{2})^{R_{i-1}}$$

$$\delta^*(\mathbf{X}) = \delta_0(\mathbf{X}) - E_0(\delta_0 | \mathbf{y}) = \frac{X_{r+1:N} + X_{n:N}}{2} - v^*,$$

where  $v^*$  is as given in (2.2).

**Remark 2.1:** when the loss is squared error, the Pittman estimator of  $\xi$  is  $\delta^*(\mathbf{X}) = \frac{X_{r+1:N} + X_{n:N}}{2} - v^*$ , which coincides with (2.3).

(2.3)

**Remark2.2:** If r=0 and  $R_i = r_i$  then the above estimator in (2.3) reduces to the one in Uniform Location model under

# **ABSOLUTE ERROR LOSS FUNCTION**

If the loss is absolute error, then the MRE estimator of  $\xi$  is  $\delta^*(\mathbf{X}) = \frac{X_{r+1:N} + X_{n:N}}{2} - v_0$ ,

where  $v_0$  is the median of the distribution with pdf given in (2.1).

Progressive Type-II censored sample case (Leo Alexander, 2000).

#### LINEX LOSS FUNCTION

Consider the location invariant Linex loss function (Varian, 1975),

L(
$$\xi$$
;  $\delta$ )=  $e^{a(\delta-\xi)} - a(\delta-\xi) - 1, a \in \mathbf{R} - \{0\}$ . Take  $\delta_0(\mathbf{X}) = (X_{r+1:N} + X_{n:N})/2$ .  
In order to find  $\mathbf{v}^* = E_0 [\rho\{\delta_0(\mathbf{x}) - \mathbf{v}\} | \mathbf{y}]$ , consider  
 $R(\delta|\mathbf{y}) = E_0\{(e^{a(\delta_0-\mathbf{v})}) - a(\delta_0 - \mathbf{v}) - 1)|\mathbf{y}\} = e^{-av}E_0(e^{a\delta_0}|\mathbf{y}) - aE_0(\delta_0|\mathbf{y}) + av - 1$   
 $= e^{-av}E_0(e^{a\delta_0}|\mathbf{y}) - av^* + av - 1$ ,  
where  $\mathbf{v}^*$  is given by (2.2). Define  $M(a;\mathbf{y}) = E_0(e^{a\delta_0}|\mathbf{y})$ .  
Now,  $\frac{dR}{dv} = e^{-av}(-a)M(a;\mathbf{y}) + a \qquad \frac{d^2R}{dv^2} = e^{-av}a^2M(a;\mathbf{y})$ .

Note that  $\frac{d^2 R}{dv^2} \ge 0 \quad \forall v.$ 

$$\frac{dR}{dv} = 0 \Longrightarrow e^{-av} M(a; \mathbf{y}) = 1$$

Thus av

$$\Rightarrow v^* = \log M(a; \mathbf{y}) / a$$
  
= 1/a{cgf\_of}  $(\delta_0 | \mathbf{y})_{\text{at a}}$ 

Therefore the MRE estimator of  $\xi$  is given by

$$\delta^*(\mathbf{X}) = \frac{X_{r+1:N} + X_{n:N}}{2} - \frac{1}{a} \{ cgf_{\text{of}} (\delta_0 \mid \mathbf{y})_{\text{at a}} \}$$

**Remark4.1:** If r = 0 then the above estimator reduces to

$$\delta^*(\mathbf{X}) = \frac{X_{1:N} + X_{n:N}}{2} - \frac{1}{a} \{ cgf_{\text{of}} (\delta_0 | \mathbf{y}) \text{ at a} \}, \text{ which is the one obtained under Linex Loss function of}$$

Progressive Type-II Right censored sample case. (Leo Alexander, 2000)

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