

# Comparison of Parameter Estimation in the Exponentiated Gumbel Distribution based on Ranked Set Sampling and Simple Random Sampling

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## Abstract

Various parametric families of distribution in lifetime data analysis and failure models are used. In this condition, the gamma distribution, Weibull and log-normal named because of the shape and scale parameters flexible high plasticity analysis of different types of data, especially lifetime data are skew.

Recently, a new distributed Exponential Gumbel distribution by Mudholkar and Srivastava (1993) and Nadarajah (2006) presented and analyzed the characteristics to estimate the parameters of the distributions. In this paper, we estimate the parameters of Gumbel distribution based on Simple Random Sampling, and Ranked Set Sampling, also we will compare these two methods.

*Keywords:* Exponentiated Gumbel distribution, Order Statistics, Simple Random Sampling, Ranked Set Sampling, Maximum Likelihood Estimation.

## Introduction

Ranked set Sampling (**RSS**) method was used to estimate the population mean by McIntyre (1952) for the first time in 1952. Takahasi and Wakimoto (1968) studied unbiased estimators for the population mean based on **RSS** in 1968. The theories and applications of **RSS** has expressed by authors such as Dell and Clutter (1972). Stokes (1980) estimated the population variance using of the data from **RSS** method. In later years, **RSS** was used to estimate the involved parameter in the statistical distribution. Chuvi et al (1994) studied the estimator of the location parameter of the Cauchy distribution, and Lam et al (1994) estimated the parameters of two-parameter exponential distribution with the using of **RSS**.

Lam et al (1996) studied the estimators for location and scale parameters of the logistic distribution, Bhoj and Ahsanullah (1996) estimated the parameters of the Geometric distribution based on RSS. Adatia (2000) achieved estimating the parameters of the Half logistic distribution, and Abu-Dayyeh (2004) studied the estimators of parameters of the two-parameter logistic distribution with data of **RSS**. The method of RSS was used for estimating the parameters of Bivariate Exponential distribution by Chacko and Yageen Thomas (2007) and for the parameters of Bivariate Exponential distribution by AL-Saleh and Diab (2009) and also for the parameter of Weibull Modified distribution by AL- Hadhrami (2010).

In this paper, we will introduce the Exponentiated Gumbel Distribution, and study the maximum likelihood estimate (**MLE**) of the parameters of Exponentiated Gumbel Distribution based on a Simple Random Sample (**SRS**). Then describe the **RSS**, and we will study the estimation of the parameters based on the **RSS**, and finally compare these two sampling methods.

### Definition

If  $X$  is a random variable with the following cumulative distribution function (**cdf**)

$$F(x, \lambda, \alpha) = [G(x, \lambda)]^\alpha = [\exp(-\exp(-\lambda x))]^\alpha \quad \alpha > 0, -\infty < x < \infty, \lambda > 0$$

then  $X$  has the Exponentiated Gumbel Distribution with scale parameter  $\lambda$ , and shape parameter  $\alpha$ . Its density function (**df**) is as follows

$$f(x, \lambda, \alpha) = \lambda \alpha [\exp\{-\exp(-\lambda x)\}]^{\alpha-1} \exp(-\lambda x).$$

We need optimal estimators for the parameters of this distribution. In the beginning, we estimate the parameters of the distribution with the maximum likelihood method based on a **SRS** of size  $n$ .

### Maximum Likelihood Estimators

In this section we consider the maximum likelihood estimators (**MLE's**) of  $GE(\alpha, \lambda)$ . First we consider the case when both  $\alpha$  and  $\lambda$ , are unknown. Let  $X_1, X_2, \dots, X_n$  be a random sample of size  $n$  from  $GE(\alpha, \lambda)$ . Then the log-likelihood function  $L(\alpha, \lambda)$  can be written as

$$l(\alpha, \lambda|x) = (\alpha\lambda)^n \exp\left(-\sum_{i=1}^n \lambda x_i\right) \exp - \left(\exp(-\lambda \sum_{i=1}^n x_i)\right)^\alpha$$

$$L(\alpha, \lambda) = \ln l(\alpha, \lambda | x) = n \ln(\alpha) + n \ln(\lambda) - \lambda \sum_{i=1}^n x_i - \alpha \sum_{i=1}^n e^{-\lambda x_i} \quad (1)$$

The normal equations become

$$\frac{\partial \ln l}{\partial \alpha} = \frac{n}{\alpha} - \sum_{i=1}^n e^{-\lambda x_i} = 0 \quad (2)$$

$$\frac{\partial \ln l}{\partial \lambda} = \frac{n}{\lambda} - \sum_{i=1}^n x_i + \alpha \sum_{i=1}^n x_i e^{-\lambda x_i} = 0 \quad (3)$$

From (2), we obtain the **MLE** of  $\alpha$  as a function of  $\lambda$ , say  $\hat{\alpha}(\lambda)$ , as

$$\hat{\alpha}(\lambda) = n \left( \sum_{i=1}^n e^{-\lambda x_i} \right)^{-1} \quad (4)$$

Substituting  $\hat{\alpha}(\lambda)$  in (1), we obtain the profile log-likelihood of  $\lambda$  as

$$g(\lambda) = L(\hat{\alpha}(\lambda), \lambda) = c - n \ln \left( \sum_{i=1}^n e^{-\lambda x_i} \right) + n \ln \lambda - \lambda \sum_{i=1}^n x_i = 0 \quad (5)$$

Therefore, the **MLE** of  $\lambda$ , say  $\hat{\lambda}_{MLE}$ , can be obtained by maximizing (5) with respect to  $\lambda$ . It can be shown that the maximum of (5) can be obtained as a fixed point solution  $v(\lambda) = \lambda$ ,

$$v(\lambda) = \left[ \frac{\sum_{i=1}^n x_i (1 - n\lambda)}{n} \right]^{-1} \quad (6)$$

Now consider the **MLE** of  $\alpha$ , when the scale parameter  $\lambda$ , is known. Without loss of generality, we can assume that  $\lambda = 1$ . If  $\lambda$  is known, the **MLE** of  $\alpha$  say  $\hat{\alpha}_{MLE}$  is

$$\hat{\alpha}_{ML} = n \left( \sum_{i=1}^n e^{-x_i} \right)^{-1} \quad (7)$$

Now note that, if  $X_i$ 's are independent and identically distributed  $GE(\alpha, 1)$ , then  $-2\alpha \sum_{i=1}^n e^{x_i}$  follows gamma random variable with shape parameter  $n$  and scale parameter  $\frac{1}{2}$ . Therefore, for  $n > 2$

$$E(\hat{\alpha}_{ML}) = \frac{n}{n-1} \alpha, \quad var(\hat{\alpha}_{ML}) = \frac{n^2}{(n-1)^2(n-2)} \alpha^2$$

Using (7), an unbiased estimate of  $\alpha_u$  can be easily obtained as

$$\hat{\alpha}_u = \frac{n-1}{n} \hat{\alpha}_{ML} = \frac{n-1}{n} \frac{n}{\sum_{i=1}^n e^{x_i}}.$$

### Ranked Set Sampling

In environmental and laboratory studies, small number of units, are selected, and are measured, and are assessed chemical variables that have a negative impact on the environment.

Since the measurement of the chemical units are expensive, using **SRS** is associated with a heavy expenditure. So, it is useful providing a reasonable sampling strategy with fewer units of measurement. In the condition that measurement of the units is difficult or costly, but the units can be ranked simply with the lowest cost, **RSS** offers efficient methods for estimate population parameters than **SRS**.

To selecting a sample of size  $k$  in **RSS** method, we select  $k$  numbers of the samples of size  $k$ . Each of the samples of size  $k$  is ranked the variable of interest, and is selected the smallest unit level from first sample of size  $k$ , second ranked unit from the second sample of size  $k$  and unit has a larger rank from the  $k - th$  sample of size  $k$ . If a larger sample size is required, In this case, these methods can be repeated  $s$  times until be measured a sample of size  $n = sk$ . This  $n$  units are data from **RSS** method.

$X_{i(tc)}$ ,  $i = 1, 2, \dots, k$   $c = 1, 2, \dots, s$  are sample sets of ranked from Exponentiated Gumbel Distribution of size  $n = sk$ , that  $k$  is the size of the collection, and  $s$  is the number of iterations (without loss of generality, in order to compare with **SRS**, we get zero for the location parameter). For simplicity  $Y_{ic} = X_{i(tc)}$  is considered, and  $c$  is fixed.  $Y_{ic}$ 's are independent random variables with density function of  $i - th$  order statistic

$$g(y_{ic}) = \frac{k!}{(i-1)!(k-i)!} [F(y_{ic})]^{i-1} [1 - F(y_{ic})]^{k-i} f(y_{ic})$$

Likelihood function of sample  $Y_{1c}, Y_{2c}, \dots, Y_{kc}$ , and the log-likelihood function are derived as follows

$$L(\underline{y} | \underline{a}, \lambda) = \prod_{c=1}^s \prod_{i=1}^k \frac{k! a \lambda e^{-\lambda y_{ic}} [\exp(-e^{-\lambda y_{ic}})]^{ai} [1 - (\exp(-e^{-\lambda y_{ic}}))^{a}]^{k-i}}{(i-1)!(k-i)!}$$

$$\begin{aligned} \text{Log}L &= C + ks(\ln a + \ln \lambda) + \sum_{c=1}^s \sum_{i=1}^k (ai)e^{-\lambda y_{ic}} \\ &+ \sum_{c=1}^s \sum_{i=1}^k (k-i) \ln [1 - (\exp(-e^{-\lambda y_{ic}}))^a] - \lambda \sum_{c=1}^s \sum_{i=1}^k y_{ic} \end{aligned}$$

where  $\mathbf{c}$  is fixed. We derivative of the log-likelihood function ratio to  $\mathbf{a}$  and  $\lambda$ , and we put them equal to zero

$$\begin{aligned} \frac{\partial \text{Log}L}{\partial \lambda} &= \frac{ks}{\lambda} - \sum_{c=1}^s \sum_{i=1}^k y_{ic} + \sum_{c=1}^s \sum_{i=1}^k (ai)y_{ic} e^{-\lambda y_{ic}} \\ &- a \sum_{c=1}^s \sum_{i=1}^k \frac{(k-i)(e^{-\lambda y_{ic}})(1 - e^{-\lambda y_{ic}})^a y_{ic}}{1 - (\exp(-e^{-\lambda y_{ic}}))^a} \end{aligned} \quad (8)$$

$$\frac{\partial \text{Log}L}{\partial a} = \frac{ks}{a} + \sum_{c=1}^s \sum_{i=1}^k (i) e^{-\lambda y_{ic}} - \sum_{c=1}^s \sum_{i=1}^k \frac{(k-i)(\exp(-e^{-\lambda y_{ic}}))^a \ln(\exp(-e^{-\lambda y_{ic}}))}{1 - (\exp(-e^{-\lambda y_{ic}}))^a} \quad (9)$$

Estimators  $\mathbf{a}$  and  $\lambda$  are obtained of nonlinear equations (8) and (9). These equations are solved by using numerical methods.

## Simulation

In this section, simulation results based on maximum likelihood estimation of parameters of two simple random sampling and sampling size sets and repetitions per set to rank different (for  $\lambda = 1$ ,  $\alpha = 1, 1.5$  based on 1000 replications of software Maple) have been done.

Maximum likelihood estimation  $\mathbf{a}$  and  $\lambda$  in simple random sampling of equations (2) and (3) and set the sampling rate from equation (8) and (9) is obtained. In order to compare more accurately estimate the parameters using both Newton-Raphson done.

Bias, mean squared error and sampling efficiency ratings set to a random sample per  $n = 9, 12, 15, 20, 24, 30, 32, 40$ . The size of sample (3, 4) and repetition rate (3, 5, 8, 10) that ( $n = ks$ ).  $\lambda = 1$ ,  $\alpha = 1, 1.5$ . Using the calculations presented in Table 1 and 2, given the following tables can be seen. The values of the mean squared error and bias estimators in simple random sampling,

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the sampling rate is greater than the set. Set the sampling rate for a fixed set size by increasing the repetition rate of the mean square error and bias can be reduced.

**Table1.** Bias and (*MSE*) of the exponentiated Gumbel distribution parameters for  $\lambda = 1, \alpha = 1$  with *RSS* and *SRS*

$(m, k)$	<i>RSS</i>		$n$	<i>SRS</i>		$Efficiency = \frac{MSE(SRS)}{MSE(RSS)}$	
	$\alpha$	$\lambda$		$\alpha$	$\lambda$	$\alpha$	$\lambda$
(3,3)	1.3940(1.9433)	0.8984(0.8091)	9	2.4746(6.9351)	1.9586(1.5869)	3.5687	1.9613
(4,3)	0.0999(0.0470)	0.2415(0.0647)	12	1.5049(2.3249)	1.7865(1.8744)	49.4695	28.9706
(3,5)	1.3303(0.7030)	0.8995(0.8071)	15	1.3961(2.1103)	1.7965(0.9562)	3.0018	1.1847
(4,5)	0.0873(0.0450)	0.1781(0.0373)	20	1.3773(2.0505)	1.3179(1.7388)	45.5613	46.6162
(3,8)	0.3397(0.3018)	0.3399(0.1163)	24	1.2074(1.4733)	0.5804(0.9454)	4.8817	8.1289
(3,10)	0.3225(0.0510)	0.3216(0.0103)	30	1.0759(1.3379)	0.5577(0.9453)	26.2333	91.776
(4,8)	0.0775(0.0440)	0.1851(0.0348)	32	1.3305(1.8936)	0.7910(1.0077)	4.3036	28.9458
(4,10)	0.0740(0.0410)	0.2453(0.0336)	40	1.2819(1.6790)	0.2911(0.9438)	28.0892	14.8396

**Table2.** Bias and (*MSE*) of the exponentiated Gumbel distribution parameters for  $\lambda = 1, \alpha = 1.5$  with *RSS* and *SRS*

$(m, k)$	<i>RSS</i>		$n$	<i>SRS</i>		$Efficiency = \frac{MSE(SRS)}{MSE(RSS)}$	
	$\alpha$	$\lambda$		$\alpha$	$\lambda$	$\alpha$	$\lambda$
(3,3)	0.5771(0.3335)	0.5679(0.4207)	9	1.6164(2.6438)	1.6484(2.2666)	7.9274	5.3876
(4,3)	0.5942(0.3534)	0.6816(0.4697)	12	0.9699(0.9675)	0.9338(1.2461)	2.7376	2.6529
(3,5)	0.5578(0.3113)	0.4878(0.1704)	15	0.8974(0.8970)	1.5045(2.1076)	2.8814	12.3658
(4,5)	0.5752(0.3323)	0.5099(0.2602)	20	0.8851(0.8512)	0.9032(1.1420)	2.5615	4.3889

(3,8)	0.5543(0.3079)	0.4373(0.1659)	24	0.7716(0.6022)	1.4651(2.0935)	1.9558	12.6190
(3,10)	0.5428(0.2983)	0.4292(0.1565)	30	0.1506(0.5957)	0.8511(1.5217)	1.9969	9.7233
(4,8)	0.5641(0.3183)	0.4853(0.2429)	32	0.8536(0.7835)	0.8876(1.1884)	2.4615	2.4615
(4,10)	0.5619(0.3159)	0.3943(0.2404)	40	0.8212(0.6903)	0.7957(1.1460)	2.1851	3.1798

## Results

The bias and the **MSE** of the estimators of the parameter of the exponentiated Gumbel distribution based on **RSS** are smaller than **SRS** by comparing simulation results. Thus the **RSS** gives more efficient estimators than **SRS**.

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