

REAL DATA APPLICATIONS OF TOPP-LEONE GENERATED FAMILY OF DISTRIBUTIONS

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Abstract

In this article, we compare the fits of three members of Topp-Leone generated family of distributions, namely, the Topp-Leone generated log-logistic distribution, the Topp-Leone generated Lomax distribution, and the Topp-Leone generated Weibull distribution with the help of two real data sets. All the computational studies are performed using R-software.

Keywords: Topp-Leone generated family; AIC; BIC; AICC; KS statistic.

1. Introduction

The Topp-Leone generated (TL-G) family of distributions was proposed by [1]. This distribution has the property to model bathtub shaped hazard rate functions for all $\nu \in (0, 1)$. It is also used for modeling the lifetime phenomena. Let us consider the probability density function (p.d.f.) of the TL-G family of distributions with parameters ν and θ given by

$$f(u; \nu, \theta, \varepsilon) = 2\nu\theta z(u; \varepsilon) Z(u; \varepsilon)^{\theta\nu-1} (1 - Z(u; \varepsilon)^\theta) (2 - Z(u; \varepsilon)^\theta)^{\nu-1}, \quad u \in \mathbb{R}; \theta, \nu > 0, \quad (1.1)$$

and the cumulative distribution function (c.d.f.) given by

$$F(u; \nu, \theta, \varepsilon) = \left(Z(u; \varepsilon)^\theta (2 - Z(u; \varepsilon)^\theta) \right)^\nu, \quad u \in \mathbb{R}; \theta, \nu > 0.$$

Where $Z(u; \varepsilon)$ and $z(u; \varepsilon)$ denote the c.d.f. and the p.d.f. of the base-line distribution, respectively. Also, ε includes the parameters which specify the base-line distribution.

For convenience, a random variable U with p.d.f. given in Equation (1.1), we use $U \sim \text{TL-G}(\nu, \theta, \varepsilon)$. In particular, various cases of $\text{TL-G}(\nu, \theta, \varepsilon)$ can be obtained by using $Z(u; \varepsilon)$ as a parent distribution function such as exponential, normal, gamma, and we get TL-exponential, TL-normal, and TL-gamma distributions, respectively. In recent years, some authors introduced and studied several such distributions by considering different $Z(u; \varepsilon)$, see, for example, [2], [3], and [4].

In this article, we choose log-logistic and Lomax (see, [5]) distributions as base-line distributions with

$$Z(u; \beta, \lambda) = \frac{(\lambda u)^\beta}{1 + (\lambda u)^\beta} \text{ and } Z^*(u; \beta, \lambda) = 1 - (1 + \lambda u)^{-\beta}, \text{ respectively, and get Topp-Leone generated log-}$$

logistic (TL-log logistic) and Topp-Leone generated Lomax (TLGLo) distributions, respectively. The p.d.f. of the TL-loglogistic distribution and the TLGLo distribution are given by

$$f_U(u) = 2\nu\theta\beta\lambda^{\beta\nu} \frac{u^{\beta\theta\nu-1}}{\left[1 + (\lambda u)^\beta\right]^{1+\theta\nu}} \left[1 - \left(\frac{(\lambda u)^\beta}{1 + (\lambda u)^\beta}\right)^\theta\right] \left[2 - \left(\frac{(\lambda u)^\beta}{1 + (\lambda u)^\beta}\right)^\theta\right]^{\nu-1},$$

$$u > 0, \nu > 0, \theta > 0, \beta > 0, \lambda > 0,$$

and

$$f_U^*(u) = 2\nu\theta\beta\lambda(1 + \lambda u)^{-(\beta+1)} \left[1 - (1 + \lambda u)^{-\beta}\right]^{\theta\nu-1} \left[1 - \left(1 - (1 + \lambda u)^{-\beta}\right)^\theta\right] \left[2 - \left(1 - (1 + \lambda u)^{-\beta}\right)^\theta\right]^{\nu-1},$$

$u > 0, \nu > 0, \theta > 0, \beta > 0, \lambda > 0,$

respectively, and their corresponding c.d.f.'s are

$$F_U(u) = \left[\frac{(\lambda u)^\beta}{1 + (\lambda u)^\beta}\right]^{\theta\nu} \left[2 - \left(\frac{(\lambda u)^\beta}{1 + (\lambda u)^\beta}\right)^\theta\right]^\nu, \quad u > 0, \nu > 0, \theta > 0, \beta > 0, \lambda > 0,$$

and

$$F_U^{**}(u) = \left(1 - e^{-(\lambda u)^\beta}\right)^{\nu\theta} \left[2 - \left(1 - e^{-(\lambda u)^\beta}\right)^\theta\right]^\nu, \quad u > 0, \nu > 0, \theta > 0, \beta > 0, \lambda > 0.$$

To discuss the importance of the TL-G family of distributions, we compare the fitting of the above mentioned distributions under some criteria. For this comparison, we consider two real data sets defined in Section 2. Also, we estimate the unknown parameters of each model by using the method of maximum likelihood (ML) and evaluate the log-likelihood function for each model.

2. Applications based on real data sets

In this section, we evaluate two real data sets to compare the fits of TL-log logistic, TLGLo, and TLGW distributions. We choose some criteria to decide best fitted distribution which are Akaike information criterion (AIC), Bayesian information criterion (BIC), Akaike information criterion corrected (AICC), Kolmogorov-Smirnov (KS) statistic with its *p*-value.

The first data set contains observed number of hours spent repairing an airborne communications transceiver by [6], which was previously provided by [7]. The data are described below:

0.2, 0.3, 0.5, 0.5, 0.5, 0.6, 0.6, 0.7, 0.7, 0.8, 0.8, 1.0, 1.0, 1.0, 1.0, 1.1, 1.3, 1.5, 1.5, 1.5, 1.5, 2.0, 2.0, 2.2, 2.5, 2.7, 3.0, 3.0, 3.3, 3.3, 4.0, 4.0, 4.5, 4.7, 5.0, 5.4, 5.4, 7.0, 7.5, 8.8, 9.0, 10.3, 22.0, 24.5.

The second data set contains 63 observations of the gauge lengths of each of the 10 mm recorded by [8]. The data are described below:

1.901, 2.132, 2.203, 2.228, 2.257, 2.350, 2.361, 2.396, 2.397, 2.445, 2.454, 2.474, 2.518, 2.522, 2.525, 2.532, 2.575, 2.614, 2.616, 2.618, 2.624, 2.659, 2.675, 2.738, 2.740, 2.856, 2.917, 2.928, 2.937, 2.937, 2.977, 2.996, 3.030, 3.125, 3.139, 3.145, 3.220, 3.223, 3.235, 3.243, 3.264, 3.272, 3.294, 3.332, 3.346, 3.377, 3.408, 3.435, 3.493, 3.501, 3.537, 3.554, 3.562, 3.628, 3.852, 3.871, 3.886, 3.971, 4.024, 4.027, 4.225, 4.395, 5.020.

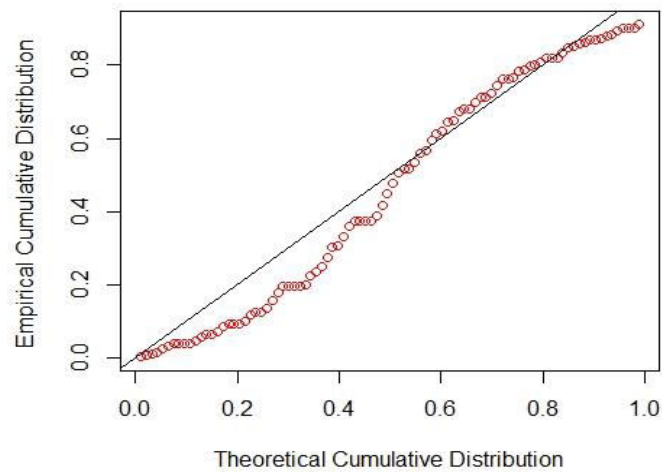
A few descriptive statistics for both data sets are shown in Table 1.

Table 1: Descriptive statistics for the Data Sets 1 and 2

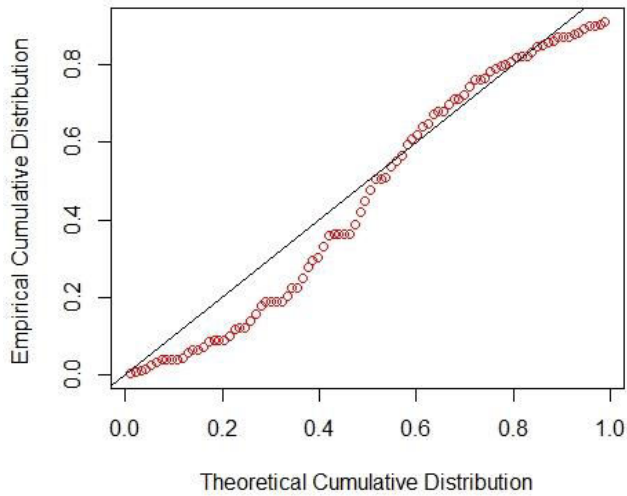
Descriptive statistics	Data Set 1	Data Set 2
Minimum	0.200	1.901
Median	1.750	2.996
Mean	3.607	3.059
Maximum	24.500	5.020
Standard deviation	4.944195	0.6209216

Further, we have drawn the probability-probability plots (PP-plots) for both data sets in Figures 1 and 2, from which we can easily observe that the models TL-log logistic, TLGW, and TLGLo provide a suitable fit to the data sets.

TL-log logistic



TLGW



TLGLo

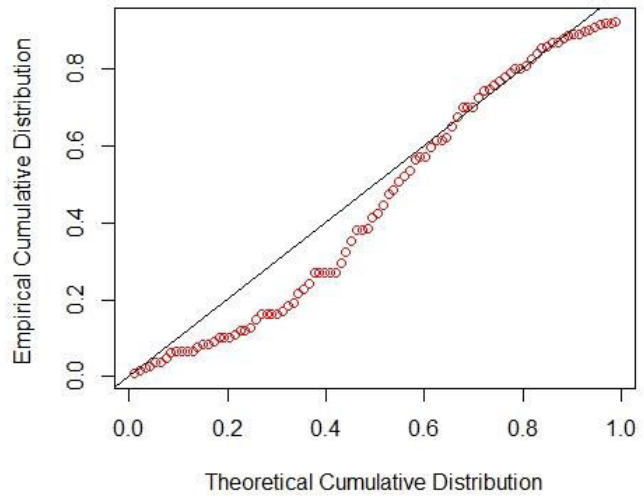


Figure 1: The PP-plots of the repairing time of airborne communications transceiver data for the TL-log logistic, TLGW, and TLGLo distributions

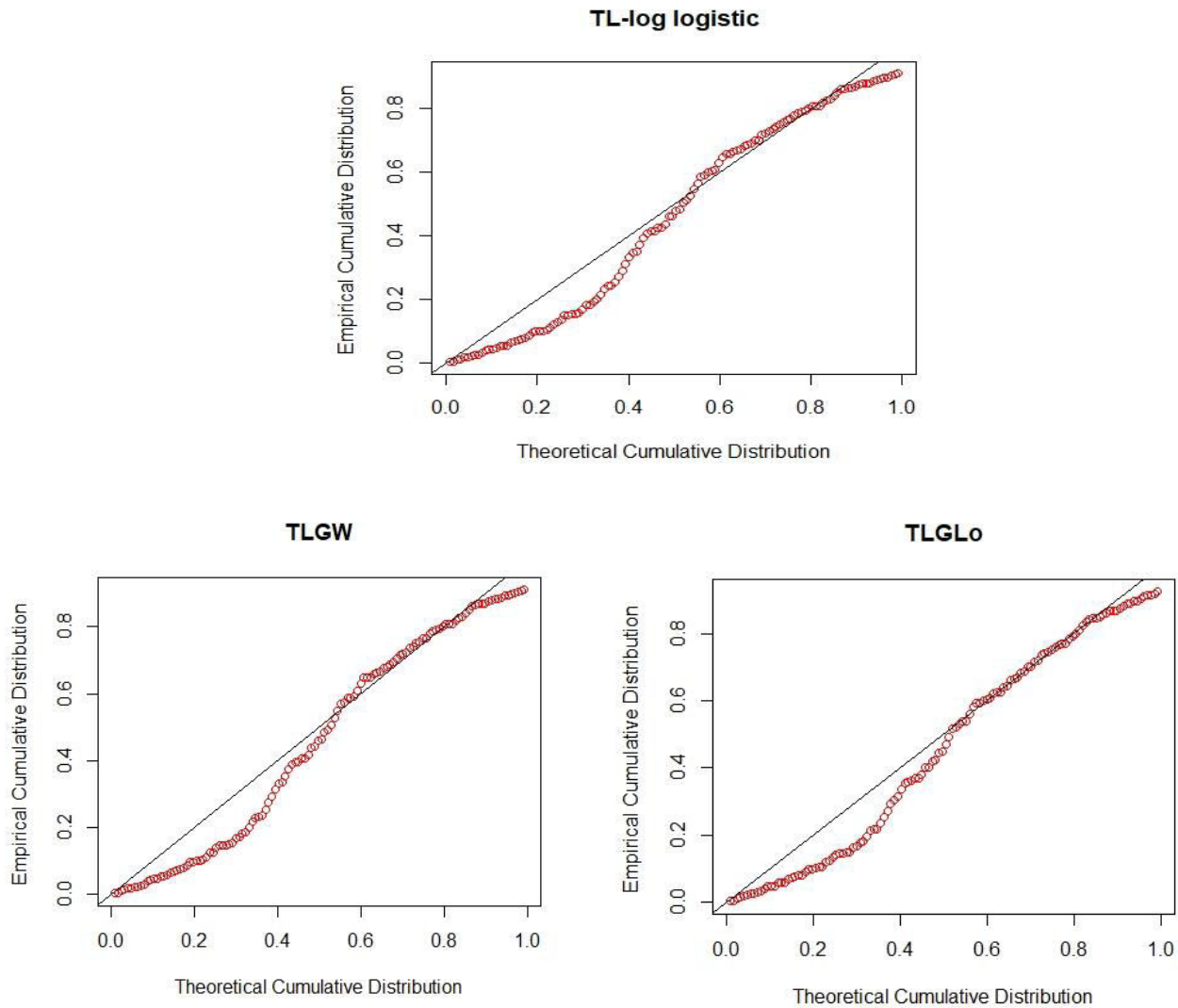


Figure 2: The PP-plots for the data of the gauge lengths for the TL-loglogistic, TLGW, and TLGLo distributions

In order to estimate the unknown parameters in each model, we use the method of ML estimation, and then to compare the results of the models, we use AIC, AICC, BIC, KS, and p -value. Also, we determine $-\log l$ (log-likelihood function) for each models (see, Tables 2 and 3). The strongest model meets the smallest AIC, BIC, AICC, and KS-statistic, and the highest p -value.

Table 2: ML-estimates and loglikelihood functions for the TL-log logistic, TLGW, and TLGLo models, and the statistics AIC, AICC, BIC, and KS statistics with its p -values for repairing time of airborne communication transceiver

Models	ML-estimates	$-\log l$	AIC	BIC	AICC	KS statistic	p -values
TL-log logistic		-99.55465	207.1093	214.4239	208.0849	0.086957	0.995

	$\hat{\nu} = 0.1048540$ $\hat{\theta} = 92.3674740$ $\hat{\beta} = 0.9768692$ $\hat{\lambda} = 7.4358103$						
TLGW	$\hat{\nu} = 3.013868$ $\hat{\theta} = 20.536544$ $\hat{\beta} = 0.181533$ $\hat{\lambda} = 571.376529$	-99.81147	207.6229	214.9375	208.5985	0.1087	0.9487
TLGLo	$\hat{\nu} = 3.539238e - 04$ $\hat{\theta} = 2.670313e + 03$ $\hat{\beta} = 1.079512e + 03$ $\hat{\lambda} = 2.455555e - 04$	-104.972	217.944	225.2586	218.9196	0.15217	0.6612

Table 3: ML-estimates and log-likelihood functions for the TL-log logistic, TLGW, and TLGLo models, and the statistics AIC, AICC, BIC, and KS statistics with its *p* -values for the gauge lengths data

Models	ML-estimates	$-\log l$	AIC	BIC	AICC	KS statistic	<i>p</i> - values
TL-log logistic	$\hat{\nu} = 0.1324324$ $\hat{\theta} = 30.9651194$ $\hat{\beta} = 5.6684962$ $\hat{\lambda} = 0.4442241$	-56.44526	120.8905	129.4631	121.5802	0.079365	0.9888
TLGW	$\hat{\nu} = 13.49923566$ $\hat{\theta} = 0.02088991$ $\hat{\beta} = 28.27730026$ $\hat{\lambda} = 0.20264199$	-66.73314	141.4663	150.0388	142.1559	0.19048	0.2032

TLGLo	$\hat{\nu} = 7.271080e - 02$ $\hat{\theta} = 1.395350e+ 03$ $\hat{\beta} = 1.942276e+ 02$ $\hat{\lambda} = 8.457492e - 03$	-59.38903	126.7781	135.3506	127.4677	0.12698	0.69
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In this analysis, it is easy to see that the TL-log logistic model is the best model among TLGW and TLGLo distributions for both data sets because TL-log logistic has the smallest values of AIC, AICC, BIC, KS statistic, and the highest p -value.

3. Conflicts of Interest

All the authors have equally participated towards the article and there is no potential conflicts of interest.

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