Optimal Choices for Trimming in

Trimmed L-moment Method

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Abstract

Trimmed Linear moments (TL-moments) are natural generalization of L-moments that do not require the mean of the underlying distribution to exist. It is known that the sample TL-moments is unbiased estimators to corresponding population TL-moment. Since different choices for the amount of trimming give different variances for the estimators it is important to choose the estimator that has less variance than others. Therefore, we derive an optimal choice for the amount of trimming from known distributions based on the minimum sum of the absolute value of the errors between the quantile probability function and its TL-moments representation. Moreover, we study simulation-based approach to choose an optimal amount of trimming by computing the estimator variance for range of trimming and choose the one which has less variance. Several examples are given to show the benefits of the methods.

Keywords: Estimation, moments, Jacobi polynomial, order statistics, quantile function

1 Introduction

For measuring descriptive features of a univariate distribution, the method of moments is very popular, but their use is confined to sufficiently light-tailed distributions; see, [2]. An appealing alternative is provided by the series of L-moments and TL-moments, which have the form of expectations of selected linear functions of order statistics. The L-moments and TL-moments have an attractive

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properties not shared by the method of moments; see, [8]. For example, L-moments of any order \( k \) exists under merely a finite first moment assumption, making the entire series of L-moments available for heavy-tailed distributions. TL-moments is defined under weaker assumption of L-moments where it does not require a finite first moment assumption. Further, the L-moments and TL-moments completely determine the parent distribution; see, [4].

The need of linear moments has been developed in support of regional frequency analysis in environmental science, which treats the quantile of distributions of variables such as annual maximum precipitation, stream flow, wind speed observed at each site in a given network. Also linear moments approach has special utility in applications where descriptive estimates (location, spread, skewness, and kurtosis) more stable than the usual central moments are critically needed. Such concern arise, for example, in volatility estimation in financial risk management involving market variables such as stock indices, interest rates; see, [6], [13], [11], [10], [1] and [12].

It is known that the sample TL-moments is unbiased estimators to their corresponding population TL-moment. Since different choices for the amount of trimming give different variances it is important to choose the estimators which have less variance than others. Therefore, we introduce and study two approaches for determining the optimal amount of trimming in trimmed L-moments. The first approach is based on the minimum sum of the absolute value of the errors between the quantile probability function and its TL-moments representation. This approach required knowing the probability function and all TL-moments in tractable form. The second one is simulation-based approach where we choose the amount of the trimming by simulating data from the distribution with known parameter and compute the estimator variance for range of trimming and pick the one which has minimum variance.

In Section 2, we review the TL-moments and sample TL-moments. In Section 3 we introduce and study the quantile function and simulation-based approaches for finding the optimal amount of trimming. The estimated optimal amount of trimming from data is given in Section 4.

2 Trimmed L-moments

Let \( X_1, X_2, \ldots, X_n \) be a random sample from a continuous distribution with quantile function \( x(F) \) where \( 0 < F < 1 \), cumulative distribution function \( F(x) = F_x = F \) and let denote the corresponding order statistics by \( X_{1:n}, \ldots, X_{n:n} \). [4] defined the trimmed L-moment (TL-moments) in terms of expected values as

\[
\lambda^{(t_1, t_2)}_r = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r+t_1-k r+t_1+t_2}), \quad r = 1, \ldots, t_1, t_2 = 0, 1, \ldots
\]

As we see TL-moments involves two more values \( t_1 \) and \( t_2 \) (amount of trimming) need to be chosen.

L-moments is special case of TL-moments for \( t_1 = t_2 = 0 \) which can be obtain as
Optimal choices for trimming

\[ \lambda_r = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r-k}) \]

see; [8]. The expected value of order statistics is

\[ E(X_{r;n}) = r \binom{n}{r} \int_0^1 x(F) F^{r-1} (1 - F)^{n-r} dF, \quad r \leq n \]

see; [3]. TL-moments in terms of quantile function can be written as

\[ \lambda_r^{(t_1, t_2)} = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} \frac{(r + t_1 + t_2)!}{(r + t_1 - k - 1)! (t_2 + k)!} \int_0^1 x(F) F^{r+t_1-1} (1 - F)^{t_2+k} dF \]

As shown by [4] TL-moments is defined for heavy tailed distributions and eliminate the influence of the most extreme observations by giving them zero weights. For example, when \( t_1 = t_2 = 1 \), \( E(X_{2;3}) \) is the median of sample of size 3, which give zero weight for first and third value. Since \( E(X_{2;3}) \) exists for Cauchy distribution, the TL-moments is defined for this distribution. While \( E(X_{1;1}) \) does not exist for Cauchy distribution, therefore the L-moments can not be defined for this distribution.

From [9] the TL-moments can be written in terms of Jacobi polynomial as

\[ \lambda_{r+1}^{(t_1, t_2)} = \frac{r! \Gamma(r + t_1 + t_2 + 2)}{(r + 1) \Gamma(r + t_1 + 1) \Gamma(r + t_2 + 1)} \int_0^1 x(F) F^{t_1} (1 - F)^{t_2} P_r^{(t_1, t_2)}(F) dF \]

where

\[ P_r^{(t_1, t_2)}(F) = \sum_{k=0}^{r} (-1)^{r-k} \binom{r}{k} \binom{r + t_1}{r - k} F^k (1 - F)^{r-k} \]

are the shifted Jacobi polynomials. Also, we could re-write TL-moments as

\[ \lambda_{r+1}^{(t_1, t_2)} = \frac{r! \Gamma(r + t_1 + t_2 + 2)}{(r + 1) \Gamma(r + t_1 + 1) \Gamma(r + t_2 + 1)} \int_0^1 x(F) T_r^{(t_1, t_2)}(F) dF \]

Where

\[ T_r^{(t_1, t_2)}(F) = \sum_{k=0}^{r} (-1)^{r-k} \binom{r}{k} \binom{r + t_1}{r - k} F^k (1 - F)^{r-k+t_2} \]

are the shifted Jacobi system of orthogonal polynomials. Since the weight function \( T_r^{(t_1, t_2)}(F) \) is orthogonal for different values of \( r, t_1 \) and \( t_2 \), the \( \lambda_{r+1}^{(t_1, t_2)} \) captures different types of information about the underlying distribution of \( X \).

2.1 Sample TL-moments

We consider estimators of population TL-moments which are functions of order statistics \( X_{1;n}, \ldots, X_{n;n} \) of a random sample \( X_1, X_2, \ldots, X_n \) of size \( n \). [4] defined an unbiased estimator of population TL-moments as
3 Optimal choosing for amount of trimming

We introduce and study two approaches for obtaining optimal trimming.

3.1 Quantile function Approach

From [9] the representation of the quantile function in terms of TL-moments is given by

\[ x(F) \equiv \sum_{r=0}^{\infty} \frac{(r + 1)(2r + t_1 + t_2 + 1)}{r + t_1 + t_2 + 1} \lambda_r^{(t_1,t_2)} \rho_r^{(t_1,t_2)}(F) \]

This is convergent in the weighted mean square with weight function \( F^{t_1}(1 - F)^{t_2} \).

The error between the quantile function and its TL-moments representation can be written as

\[ e(F) \equiv x(F) - \sum_{r=0}^{\infty} \frac{(r + 1)(2r + t_1 + t_2 + 1)}{r + t_1 + t_2 + 1} \lambda_r^{(t_1,t_2)} \rho_r^{(t_1,t_2)}(F) \]

The optimal values of \( t_1 \) and \( t_2 \) can be chosen as the values which have less sum of the absolute error

\[ \text{Min} \sum |e(F)| \]

For choosing these values among other values we give two methods.

3.1.1 Method 1 (exact method)

For known distributions we can obtain TL-moments analytically for different values of \( t_1 \) and \( t_2 \) in the range \([0,0,\ldots,4,4]\) and evaluate

\[ e(F) \equiv x(F) - \sum_{r=0}^{\infty} \frac{(r + 1)(2r + t_1 + t_2 + 1)}{r + t_1 + t_2 + 1} \lambda_r^{(t_1,t_2)} \rho_r^{(t_1,t_2)}(F) \]

for each pair and pick the values which give less sum of the absolute error. But this method is not tractable in most cases and we suggest instead the following approximation method.
3.1.2 Method 2 (approximation method)

For known distribution we may take \( F \) as one of the following plotting positions

\[
E(F) = \frac{i}{n+1}, \quad \text{Mode}(F) = \frac{i-1}{n-1}, \quad \text{Median}(F) \approx \frac{i-0.33}{n+0.38}
\]

See, [7]. For sufficient \( n \) and \( s \) (quantile function stopping terms) we find

\[
x\left(\frac{i}{n+1}; \theta\right)
\]

This choice will fix \( X \) for different values of the parameter(s) \( \theta \). From this fixed data we compute the error for each pair of the trimming in the range \([(0,0),…,(4,4)] \) and pick the pair which has

\[
\text{Min.} \sum |e_s(F)|
\]

where

\[
e_s(F_i) \equiv x(F_i) - \sum_{r=0}^{s} (r+1)(2r+t_1+t_2+1) \frac{l_{r+1}^{(t_1,t_2)} p_r^{(t_1,t_2)}(F_i)}{r+t_1+t_2+1}
\]

**Example**

In this example we investigate the optimal choice of trimming from logistic, Gumbel and Pareto distributions. The logistic distribution has quantile \( x(F) = \alpha + \beta \log \left[ F/(1-F) \right] \) and without loss of generality we take \( \alpha = 0 \) and \( \beta = 1 \), then

\[
x\left(\frac{i}{n+1}\right) = \log \left( \frac{i}{n+1-i} \right)
\]

The Gumbel distribution has quantile \( x(F) = \alpha - \beta \log[-\log F] \) and without loss of generality we take \( \alpha = 0 \) and \( \beta = 1 \), then

\[
x\left(\frac{i}{n+1}\right) = -\log \left( -\log \left( \frac{i}{n+1} \right) \right)
\]

The Pareto distribution has quantile \( x(F) = \beta [1 - (1-F)^k]/k \) and without loss of generality we take \( \beta = 1 \), then

\[
x\left(\frac{i}{n+1}\right) = \left( 1 - \left( 1 - \log \left( \frac{i}{n+1} \right) \right)^k \right)/k
\]

Table 1 shows the results for the sum of absolute value of the error from the three distributions for different choices of \( t_1 \) and \( t_2 \) using \( n = 200 \) and \( s = 10 \) and 20. For logistic distribution the approximate optimal values at \( t_1 = 1, \ t_2 = 1, \) Gumbel distribution the approximate optimal values at \( t_1 = 0, \ t_2 = 1, \) and Pareto distribution are \( t_1 = 0, \ t_2 = 1 \) for some values of \( k \).
Table 1: values of \( \sum |e_s| \) for different choices of trimming from different distributions using \( n = 200 \) and \( s = 20 \) and 10.

<table>
<thead>
<tr>
<th>((t_1, t_2))</th>
<th>((0, 0))</th>
<th>((1.1))</th>
<th>((2.2))</th>
<th>((3.3))</th>
<th>((0, 1))</th>
<th>((0, 2))</th>
<th>((1, 2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s = 20 )</td>
<td>2.36</td>
<td>1.07</td>
<td>1.38</td>
<td>1.74</td>
<td>2.36</td>
<td>8.43</td>
<td>1.08</td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>7.49</td>
<td>3.74</td>
<td>4.28</td>
<td>5.37</td>
<td>7.49</td>
<td>21.46</td>
<td>3.75</td>
</tr>
<tr>
<td>((t_1, t_2))</td>
<td>((1, 0))</td>
<td>((0, 0))</td>
<td>((0, 1))</td>
<td>((0, 2))</td>
<td>((1, 1))</td>
<td>((2, 2))</td>
<td>((1, 2))</td>
</tr>
<tr>
<td>( s = 20 )</td>
<td>2.44</td>
<td>1.59</td>
<td>0.76</td>
<td>0.83</td>
<td>1.15</td>
<td>1.03</td>
<td>0.92</td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>8.24</td>
<td>5.21</td>
<td>2.46</td>
<td>2.65</td>
<td>2.73</td>
<td>2.71</td>
<td></td>
</tr>
<tr>
<td>((t_1, t_2))</td>
<td>((0, 1))</td>
<td>((0, 2))</td>
<td>((1, 1))</td>
<td>((2, 2))</td>
<td>((1, 2))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( s = 20 )</td>
<td>10.49</td>
<td>6.53</td>
<td>2.82</td>
<td>3.71</td>
<td>3.63</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>30.53</td>
<td>18.87</td>
<td>8.10</td>
<td>9.77</td>
<td>12.53</td>
<td>8.70</td>
<td>9.2</td>
</tr>
<tr>
<td>( s = 20 )</td>
<td>42.76</td>
<td>26.12</td>
<td>9.29</td>
<td>12.37</td>
<td>15.50</td>
<td>9.94</td>
<td>12.11</td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>105.3</td>
<td>64.69</td>
<td>26.17</td>
<td>30.26</td>
<td>37.55</td>
<td>28.08</td>
<td>28.92</td>
</tr>
<tr>
<td>( s = 20 )</td>
<td>168</td>
<td>101.4</td>
<td>32.68</td>
<td>41.96</td>
<td>52.21</td>
<td>35.15</td>
<td>41.17</td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>355.69</td>
<td>217.70</td>
<td>83.09</td>
<td>93.33</td>
<td>111.37</td>
<td>88.81</td>
<td>89.97</td>
</tr>
<tr>
<td>( s = 20 )</td>
<td>377</td>
<td>226.1</td>
<td>70.27</td>
<td>87.67</td>
<td>108.19</td>
<td>75.46</td>
<td>86.17</td>
</tr>
<tr>
<td>( s = 10 )</td>
<td>734.21</td>
<td>448.65</td>
<td>165.37</td>
<td>182.97</td>
<td>213.67</td>
<td>176.30</td>
<td>177.17</td>
</tr>
</tbody>
</table>

**Logistic distribution**

The distribution has quantile function \( x(F) = \alpha + \beta \log(F/(1 - F)) \) and the first two L-moments are \( \lambda_1^{(0,0)} = \alpha \) and \( \lambda_2^{(0,0)} = \beta \). Their estimators are \( \hat{\alpha} = l_1^{(0,0)} \) and \( \hat{\beta} = l_2^{(0,0)} \) with asymptotic variance \( 3.29/n\beta^2 \) and \( 0.71/n\beta^2 \). While the first two TL-moments are \( \lambda_1^{(1,1)} = \alpha \) and \( \lambda_2^{(1,1)} = 0.5 \beta \). Their estimators are \( \hat{\alpha} = l_1^{(1,1)} \) and \( \hat{\beta} = 2l_2^{(1,1)} \) with asymptotic variance \( 3/n\beta^2 \) and \( 0.79/n\beta^2 \). Asymptotic variances are from [5]. Note that although the choice of \( t_1 = t_2 = 1 \) is reducing the variance of \( \hat{\alpha} \) from \( 3.29/n \) to \( 3/n \), it increases the variance of \( \hat{\beta} \) from \( 0.71/n \) to \( 0.79/n \). Therefore, we have to find method that work with each estimator separately.
3.2 Simulation approach

In this approach we suggest the choice of the optimal values will be based on simulating data from known distribution and compute the estimator variance for different values of trimming and take the one which has minimum variance. We suggest the following steps

1. From known distribution find the estimators as a function in trimming values.
2. Simulate data from the distribution with known parameter using large sample size (at least 100) for different choices of trimming and large number of replication (at least 10000).
3. Take the value which has less variance as an approximate optimal trim.

3.2.1 Applications

Laplace distribution

The Laplace distribution is heavy tail distribution and it is known that the L-moments estimators are not efficient with respect to maximum likelihood estimators. The Laplace distribution has the following quantile function

\[ x(F) = \begin{cases} \alpha + \beta \log(2F) & F \leq 0.5 \\ \alpha - \beta \log(2(1 - F)) & F > 0.5 \end{cases} \]

The first TL-moments is \( \lambda_{11}^{(t_{1},t_{2})} = \alpha \) and second TL-moments for some pre-chosen values of trimming are

\[ \lambda_{2}^{(0,0)} = 0.75\beta, \lambda_{2}^{(1,1)} = 0.343\beta, \lambda_{2}^{(2,2)} = 0.218\beta, \lambda_{2}^{(3,3)} = 0.159\beta, \text{ and } \lambda_{2}^{(4,4)} = 0.124\beta. \]

We simulate data from Laplace distribution with \( \alpha = 0 \) and \( \beta = 1 \) and find the variance for the estimators \( \hat{\alpha} \) and \( \hat{\beta} \). Table 2 shows the results where the less variance for \( \hat{\alpha} \) at \( t_1 = 4, t_2 = 4 \) and for \( \hat{\beta} \) at \( t_1 = 0, t_2 = 0 \). Hence,

\[ \lambda_{1}^{(4,4)} = \alpha, \hat{\alpha} = l_{1}^{(4,4)} \text{ with asymptotic variance } 1.23\beta^2/n \]

and

\[ \lambda_{2}^{(0,0)} = 0.75\beta, \hat{\beta} = \frac{4}{3} l_{2}^{(0,0)} \text{ with asymptotic variance } 1.037\beta^2/n \]

The asymptotic variances are obtained from [5]. Their efficiency to L-moments estimators are

\[ 2/1.23 = 1.62 \quad \text{and} \quad 1.037/1.0237 = 1 \]

Their efficient to maximum likelihood estimators are

\[ 1.17/1.23 = 0.95 \quad \text{and} \quad 1/1.037 = 0.96 \]
Table 2: The simulated mean and variance of $\hat{\alpha}$ and $\hat{\beta}$ for various values of trimming from Laplace distribution using $n = 100$ and the number of replications is 10000.

<table>
<thead>
<tr>
<th>$(t_1, t_2)$</th>
<th>(0,0)</th>
<th>(1,1)</th>
<th>(2,2)</th>
<th>(3,3)</th>
<th>(4,4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\alpha}$ Mean</td>
<td>0.0018</td>
<td>0.0017</td>
<td>0.0015</td>
<td>0.0014</td>
<td>0.0013</td>
</tr>
<tr>
<td>Variance</td>
<td>0.0199</td>
<td>0.0144</td>
<td>0.0132</td>
<td>0.0127</td>
<td><strong>0.0124</strong></td>
</tr>
<tr>
<td>$\hat{\beta}$ Mean</td>
<td>1.0002</td>
<td>1.002</td>
<td>1.003</td>
<td>1.001</td>
<td>1.0049</td>
</tr>
<tr>
<td>Variance</td>
<td><strong>0.0104</strong></td>
<td>0.0114</td>
<td>0.01367</td>
<td>0.0157</td>
<td>0.0178</td>
</tr>
</tbody>
</table>

Gumbel distribution

The Gumbel distribution has the following quantile function

$$x(F) = \alpha - \beta \log(-\log F)$$

The first TL-moments and second TL-moments for some pre-chosen values are

$$\lambda_1^{(0,0)} = \alpha + 0.577 \beta, \lambda_1^{(1,1)} = \alpha + 0.459 \beta, \lambda_1^{(1,0)} = \alpha + 1.269 \beta, \lambda_1^{(0,1)} = \alpha - 0.116 \beta$$

and

$$\lambda_2^{(0,0)} = 0.692 \beta, \lambda_2^{(1,1)} = 0.353 \beta, \lambda_2^{(1,0)} = 0.607 \beta, \text{and} \lambda_2^{(0,1)} = 0.431 \beta.$$  

We simulate data from Gumbel distribution with $\alpha = 0$ and $\beta = 1$ and find the variance for the estimators $\hat{\alpha}$ and $\hat{\beta}$. Table 3 shows the results where the less variance for $\hat{\alpha}$ at $t_1 = 0, t_2 = 1$ and for $\hat{\beta}$ at $t_1 = 0, t_2 = 2$. Hence,

$$\lambda_2^{(0,1)} = 0.431 \beta, \hat{\beta} = l_2^{(0,1)}/0.431 \text{ with asymptotic variance } 0.67 \beta^2/n$$

and

$$\lambda_1^{(0,1)} = \alpha - 0.1158 \beta, \hat{\alpha} = l_1^{(0,1)} + 0.268 l_2^{(0,1)} \text{ with asymptotic variance } 1.11 \beta^2/n.$$  

Their efficiency to L-moments estimators are

$$0.80/0.67 = 1.19 \quad \text{and} \quad 1.11/1.11 = 1$$

Their efficiency to maximum likelihood estimators are

$$0.61/0.67 = 0.91 \quad \text{and} \quad 1.08/1.11 = 0.97$$
Table 3: The simulated mean and variance of $\alpha$ and $\beta$ for various values of trimming from Gumbel distribution using $n = 100$ and the number of replications is 10000.

<table>
<thead>
<tr>
<th>$(t_1, t_2)$</th>
<th>$\beta$</th>
<th>$(0,0)$</th>
<th>$(1,1)$</th>
<th>$(1,0)$</th>
<th>$(0,1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.0003</td>
<td>0.999</td>
<td>1.0007</td>
<td>0.9999</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.0079</td>
<td>0.0087</td>
<td>0.0129</td>
<td>0.0068</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.0008</td>
<td>-0.0027</td>
<td>-0.0014</td>
<td>-0.0001</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.0111</td>
<td>0.0121</td>
<td>0.0145</td>
<td>0.0111</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: simulated data from Gumbel distribution, $n = 50$.

<p>| | | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
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<tbody>
<tr>
<td>34.3</td>
<td>50.4</td>
<td>55.3</td>
<td>69.8</td>
<td>39.0</td>
<td>18.5</td>
<td>15.9</td>
<td>34.5</td>
<td>27.3</td>
</tr>
<tr>
<td>52.7</td>
<td>24.33</td>
<td>18.66</td>
<td>72.37</td>
<td>46.78</td>
<td>29.4</td>
<td>79.82</td>
<td>21.51</td>
<td>62.12</td>
</tr>
<tr>
<td>14.6</td>
<td>17.88</td>
<td>42.17</td>
<td>36.15</td>
<td>32.17</td>
<td>33.98</td>
<td>31.73</td>
<td>23.08</td>
<td>33.78</td>
</tr>
<tr>
<td>47.01</td>
<td>64.8</td>
<td>26.7</td>
<td>32.3</td>
<td>22.10</td>
<td>23.66</td>
<td>19.09</td>
<td>26.5</td>
<td>42.16</td>
</tr>
<tr>
<td>26.8</td>
<td>6.77</td>
<td>33.3</td>
<td>60.2</td>
<td>12.19</td>
<td>24.25</td>
<td>64.38</td>
<td>31.23</td>
<td>48.68</td>
</tr>
</tbody>
</table>

The values of $\sum |\hat{e}_x|$ for different trimming are given in Table 5 for $s = 6$ and $s = 8$. The values which have less error are $(t_1 = 0, t_2 = 1)$. Therefore, the quantile function approach is working well for given data.

Table 5: The values of $\sum |\hat{e}_x|$ for different trimming for $s = 6$ and $s = 8$.

<table>
<thead>
<tr>
<th>$(t_1, t_2)$</th>
<th>$(0,0)$</th>
<th>$(1,1)$</th>
<th>$(0,1)$</th>
<th>$(1,0)$</th>
<th>$(1,2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s = 6$</td>
<td>61.9</td>
<td>54.21</td>
<td>52.7</td>
<td>60.7</td>
<td>66</td>
</tr>
<tr>
<td>$s = 8$</td>
<td>48.11</td>
<td>44.88</td>
<td>42.13</td>
<td>44.43</td>
<td>56.67</td>
</tr>
</tbody>
</table>
5 Conclusion

In this work we introduced and studied two approaches for obtaining the optimal amount of trimming in TL-moment method. The quantile approach depends on the less error between the theoretical quantile function and its TL-moment representation. Since this approach works with the distribution as a whole, it will be insensitive for optimal amount of trimming for each parameter separately while the simulation-based approach could be used with each parameter rather than the whole model. In the same time the quantile approach can be used for estimating the optimal amount of trimming from given data and this can be considered as an advantage for this approach.

References


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