Near-consistent robust estimations of moments for unimodal distributions

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Descriptive statistics for parametric models currently rely heavily on the accuracy of distributional assumptions. Here, based on the invariant structures of unimodal distributions, a series of sophisticated yet efficient estimators, robust to both gross errors and departures from parametric assumptions, are proposed for estimating mean and central moments with insignificant asymptotic biases for common continuous unimodal distributions. This article also illuminates the understanding of the common nature of probability distributions and the measures of them.

orderliness | invariant | unimodal | adaptive estimation | U-statistics

The asymptotic inconsistencies between sample mean ($\bar{x}$) and nonparametric robust location estimators in asymmetric distributions on the real line have been noticed for more than two centuries (1) but unsolved. Strictly speaking, it is unsolvable because by trimming, some information about the original distribution is removed, making it impossible to estimate the values of the removed parts without distributional assumptions. Newcomb (1886, 1912) provided the first modern approach to this problem by developing a class of estimators that gives "less weight to the more discordant observations" (2, 3). In 1964, Huber (4) used the minimax procedure to obtain M-estimator for contaminated normal distribution, which has played a pre-eminent role in the later development of robust statistics. As previously demonstrated, under growing asymmetric departures from normality, the bias of the Huber M-estimator increases rapidly. This is a common issue in parametric estimations. For example, He and Fung (1999) constructed (5) a robust M-estimator for the two-parameter Weibull distribution. All moments can be calculated from its estimated parameters. As expected, it is inadequate for the gamma, Perato, lognormal, and the generalized Gaussian distributions (SI Dataset S1). Instead of minimizing the residuals, another old and interesting approach is arithmetically computing the parameters using one or more L-statistics as input values, e.g., the percentile estimators. Examples for the Weibull distribution, the reader is referred to Menon (1963) (6), Dubey (1967) (7), Hassanein (1971) (8), Marks (2005) (9), and Boudt, Caliskan, and Croux (2011) (10)'s works. At the outset of the study of percentile estimators, it was known that percentile estimators arithmetically utilizes the invariant structures of probability distributions (6, 11, 12). Maybe such estimators can be named as I-statistics. Formally, an estimator is classified as an I-statistic if asymptotically it satisfies $\mathrm{I}\left(\mathrm{LE}_1, \cdots, \mathrm{LE}_l\right) = \left(\theta_1, \cdots, \theta_q\right)$ for the distribution it is consistent with, where LEs are estimates including the computation of L-statistics, I is defined mainly with arithmetic operations and θs are the population parameters it estimates. A subclass of I-statistics, arithmetic I-statistics, is defined as LEs are L-statistics, I is solely defined with arithmetic operations. Since some percentile estimators use the logarithmic function to transform all random variables first and then compute the L-statistic, so a percentile estimator might not always be an arithmetic I-statistic (7). In this article, two sub-classes of I-statistics are introduced, arithmetic I-statistics and quantile I-statistics. Examples of quantile I-statistics will be discussed later. In the previous article, it is shown that quantile average is fundamental for all weighted averages. Based on the quantile function, I-statistics are naturally robust. For many parametric distributions, the quantile functions are much more elegant than the pdfs and cdfs. So, I-statistics are often analytically obtainable. However, the performance of the above examples is often worse than that of the robust M-statistics when the distributional assumption is violated (SI Dataset S1). Even when distributions such as the Weibull and gamma belong to the same larger family, the generalized gamma distribution, a misassumption can still result in substantial biases, rendering the approach ill-suited.

In previous work on semiparametric robust mean estimation, although greatly shrinking the asymptotic biases, binomial mean (BM_ϵ) is still inconsistent for any skewed distribution if $\epsilon > 0$ (if $\epsilon \to 0$, since the alternating sum of binomial coefficients is zero, $\mathrm{BM} \to \mu$). All robust location estimators commonly used are symmetric due to the universality of the symmetric distributions. One can construct an asymmetric trimmed mean that is consistent for a semiparametric class of skewed distributions. This approach was investigated previously, but it is not symmetric and therefore only suitable for some special applications (13). From semiparametrics to parametrics, an ideal robust location estimator would have a non-sample-dependent breakdown point (defined in Subsection **??**) and be consistent with any symmetric distribution and a skewed distribution with finite second moments. This is called an invariant mean. Based on the mean-symmetric weighted

Significance Statement

Bias, variance, and contamination are the three main errors in statistics. Consistent robust estimation is unattainable without parametric assumptions. Here, based on a paradigm shift inspired by mean-median-mode inequality, Bickel-Lehmann spread, and adaptive estimation, invariant moments are proposed as a means of achieving near-consistent and robust estimations of moments, even in scenarios where moderate violations of distributional assumptions occur, while the variances are sometimes smaller than those of the sample moments.

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average-median inequality, the recombined mean is defined as

$$rm_{d,\epsilon,n} \coloneqq \lim_{c\to\infty}\left(\frac{(\mathrm{SWA}_{\epsilon,n}+c)^{d+1}}{(median+c)^{d}}-c\right),$$

where d is for bias correction, $\mathrm{SWA}_{\epsilon,n}$ is $\mathrm{BM}_{\epsilon,n}$ in the first three Subsections, while other symmetric weighted averages can also be used in practice as long as the inequalities hold. The next theorem shows the significance of this arithmetic I-statistic.

Theorem .1. *If the second moments are finite, $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ is a consistent mean estimator for the exponential and any symmetric distributions and the Pareto distribution with quantile function $Q(p)=x_m(1-p)^{-\frac{1}{\alpha}}$, $x_m>0$, when $\alpha\to\infty$.*

Proof. Finding d and ϵ that make $rm_{d,\epsilon}$ a consistent mean estimator is equivalent to finding the solution of $E[rm_{d,\epsilon}]=E[X]$. Rearranging the definition, $rm_{d,\epsilon}=\lim_{c\to\infty}\left(\frac{(\mathrm{BM}_\epsilon+c)^{d+1}}{(median+c)^{d}}-c\right)=(d+1)\,\mathrm{BM}_\epsilon-d\mathrm{median}=\mu$. So, $d=\frac{\mu-\mathrm{BM}_\epsilon}{\mathrm{BM}_\epsilon-median}$. The pdf of the exponential distribution is $f(x)=\lambda^{-1}e^{-\lambda^{-1}x}$, $\lambda\geq 0$, $x\geq 0$, the cdf is $F(x)=1-e^{-\lambda^{-1}x}$, $x\geq 0$. The quantile function is $Q(p)=\ln\left(\frac{1}{1-p}\right)\lambda$. $E[x]=\lambda$. $E[median]=Q\left(\frac{1}{2}\right)=\ln 2\lambda$. For the exponential distribution, the expectation of $\mathrm{BM}_{\frac{1}{8}}$ is $E\left[\mathrm{BM}_{\frac{1}{8}}\right]=\lambda\left(1+\ln\left(\frac{46656}{8575\sqrt{35}}\right)\right)$. Obviously, the scale parameter λ can be canceled out, $d\approx 0.375$. The proof of the second assertion follows directly from the coincidence property. For any symmetric distribution with a finite second moment, $E[\mathrm{BM}_\epsilon]=E[median]=E[X]$. Then $E[rm_{d,\epsilon}]=\lim_{c\to\infty}\left(\frac{(E[X]+c)^{d+1}}{(E[X]+c)^{d}}-c\right)=E[X]$. The proof for the Pareto distribution is more general. The mean of the Pareto distribution is given by $\frac{\alpha x_m}{\alpha-1}$. The d value with two unknown percentiles p_1 and p_2 for the Pareto distribution is $d_{Perato}=\frac{\frac{\alpha x_m}{\alpha-1}-x_m(1-p_1)^{-\frac{1}{\alpha}}}{x_m(1-p_1)^{-\frac{1}{\alpha}}-x_m(1-p_2)^{-\frac{1}{\alpha}}}$. Since any weighted average can be expressed as an integral of the quantile function, $\lim_{\alpha\to\infty}\frac{\frac{\alpha}{\alpha-1}-(1-p_1)^{-1/\alpha}}{(1-p_1)^{-1/\alpha}-(1-p_2)^{-1/\alpha}}=-\frac{\ln(1-p_1)+1}{\ln(1-p_1)-\ln(1-p_2)}$, the d value for the Pareto distribution approaches that of the exponential distribution as $\alpha\to\infty$, regardless of the type of weighted average used. This completes the demonstration. ☐

Theorem .1 implies that for the Weibull, gamma, Pareto, lognormal and generalized Gaussian distribution, $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ is consistent for at least one particular case of these two-parameter distributions. The biases of $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ for distributions with skewness between those of the exponential and symmetric distributions are tiny (SI Dataset S1). $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ has excellent performance for all these common unimodal distributions (SI Dataset S1).

Besides introducing the concept of invariant mean, the purpose of this paper is to demonstrate that, in light of previous works, the estimation of central moments can be transformed into a location estimation problem by using U-statistics, the central moment kernel distributions have nice properties, and a series of sophisticated yet efficient robust estimators can be constructed whose biases are typically smaller than the variances ($n=5400$, Table **??**) for unimodal distributions.

Background and Main Results

A. Invariant mean. It has long been known that a theoretical model can be adjusted to fit the first two moments of the observed data. A continuous distribution belonging to a location–scale family has the form $F(x)=F_0\left(\frac{x-\mu}{\lambda}\right)$, where F_0 is a "standard" distribution. Then, $F(x)=Q^{-1}(x)\to x=Q(p)=\lambda Q_0(p)+\mu$. So, any weighted average can be expressed as $\lambda\mathrm{WA}_0(\epsilon)+\mu$, where $\mathrm{WA}_0(\epsilon)$ is an integral of $Q_0(p)$ according to the definition of the weighted average. The simultaneous cancellation of μ and λ in $\frac{(\lambda\mu_0+\mu)-(\lambda\mathrm{BM}_0(\epsilon)+\mu)}{(\lambda\mathrm{BM}_0(\epsilon))+\mu-(\lambda median_0+\mu)}$ ensures that d is a constant. Consequently, the roles of BM_ϵ and median in $rm_{d,\epsilon}$ can be replaced by any weighted averages, although for the definition of invariant mean, only symmetric weighted averages are considered here.

The performance in heavy-tailed distributions can be improved further by constructing the quantile mean as

$$qm_{d,\epsilon,n}\coloneqq\hat{Q}_n\left(\left(\hat{F}_n(\mathrm{SWA}_{\epsilon,n})-\frac{1}{2}\right)d+\hat{F}_n(\mathrm{SWA}_{\epsilon,n})\right),$$

provided that $\hat{F}_n(\mathrm{SWA}_{\epsilon,n})\geq\frac{1}{2}$, where $\hat{F}_n(x)$ is the empirical cumulative distribution function of the sample, $\hat{Q}_n$ is the sample quantile function. The most popular method for computing the sample quantile function was proposed by Hyndman and Fan in 1996 (14). To minimize the finite sample bias, here, $\hat{F}_n(x)\coloneqq\frac{1}{n}\left(\frac{x-\hat{Q}_n\left(\frac{sp}{n}\right)}{\hat{Q}_n\left(\frac{1}{n}(sp+1)\right)-\hat{Q}_n\left(\frac{sp}{n}\right)}+sp\right)$, where $sp=\sum_{i=1}^{n}\mathbf{1}_{X_i\leq x}$, $\mathbf{1}_A$ is the indicator of event A. The solution of $\hat{F}_n(\mathrm{SWA}_{\epsilon,n})<\frac{1}{2}$ is reversing the percentile by $1-\hat{F}_n(\mathrm{SWA}_{\epsilon,n})$, the obtained percentile is also reversed. Without loss of generality, in the following discussion, only the $\hat{F}_n(\mathrm{SWA}_{\epsilon,n})\geq\frac{1}{2}$ case will be considered. Moreover, in extreme heavy-tailed distributions, the calculated percentile can exceed the breakdown point of SWA_ϵ, so the percentile will be modified to $1-\epsilon$ if this happens. The quantile mean uses the location-scale invariant in a different way as shown in the following proof.

Theorem A.1. *$qm_{d\approx 0.321,\epsilon=\frac{1}{8}}$ is a consistent mean estimator for the exponential, Pareto ($\alpha\to\infty$) and any symmetric distributions provided that the second moments are finite.*

Proof. Similarly, rearranging the definition, $d=\frac{F(\mu)-F(\mathrm{BM}_\epsilon)}{F(\mathrm{BM}_\epsilon)-\frac{1}{2}}$. Recall the cdf is $F(x)=1-e^{-\lambda^{-1}x}$, $x\geq 0$, the expectation of BM_ϵ can be expressed as $\lambda\mathrm{BM}_0(\epsilon)$, so $F(\mathrm{BM}_\epsilon)$ is free of λ. When $\epsilon=\frac{1}{8}$, $d=\frac{-e^{-1}+e^{-\left(1+\ln\left(\frac{46656}{8575\sqrt{35}}\right)\right)}}{\frac{1}{2}-e^{-\left(1+\ln\left(\frac{46656}{8575\sqrt{35}}\right)\right)}}\approx 0.321$.

The proof of the symmetric case is similar. Since for any symmetric distribution with a finite second moment, $F(E[\mathrm{BM}_\epsilon])=F(\mu)=\frac{1}{2}$. Then, the expectation of the quantile mean is $qm_{d,\epsilon}=F^{-1}\left(\left(F(\mu)-\frac{1}{2}\right)d+F(\mu)\right)=F^{-1}(0+F(\mu))=\mu$.

For the assertion related to the Pareto distribution, the cdf of it is $1-\left(\frac{x_m}{x}\right)^{\alpha}$. So, the d value with two unknown percentile p_1 and p_2 is $d_{Pareto}=\frac{1-\left(\frac{x_m}{\frac{\alpha x_m}{\alpha-1}}\right)^{\alpha}-\left(1-\left(\frac{x_m}{x_m(1-p_1)^{-\frac{1}{\alpha}}}\right)^{\alpha}\right)}{\left(1-\left(\frac{x_m}{x_m(1-p_1)^{-\frac{1}{\alpha}}}\right)^{\alpha}\right)-\left(1-\left(\frac{x_m}{x_m(1-p_2)^{-\frac{1}{\alpha}}}\right)^{\alpha}\right)}=\frac{1-\left(\frac{\alpha-1}{\alpha}\right)^{\alpha}-p_1}{p_1-p_2}$. When $\alpha\to\infty$, $\left(\frac{\alpha-1}{\alpha}\right)^{\alpha}=\frac{1}{e}$. The d value for the exponential distribution is identical, since $d_{exp} = \frac{\left(1-e^{-1}\right)-\left(1-e^{-\ln\left(\frac{1}{1-p_1}\right)}\right)}{\left(1-e^{-\ln\left(\frac{1}{1-p_1}\right)}\right)-\left(1-e^{-\ln\left(\frac{1}{1-p_2}\right)}\right)} = \frac{1-\frac{1}{e}-p_1}{p_1-p_2}$. All results are now proven. □

The definitions of location and scale parameters are such that they must satisfy $F(x;\lambda,\mu) = F(\frac{x-\mu}{\lambda};1,0)$. Recall that $x = \lambda Q_0(p) + \mu$, so the percentile of any weighted average is free of λ and μ, guaranteeing the validity of the quantile mean. quantile mean is a quantile I-statistic. Formally, an estimator is classified as a quantile I-statistic, if LEs are percentiles of a distribution obtained by plugging L-statistics into a cumulative distribution function and I is defined with arithmetic operations and quantile functions. $qm_{d\approx 0.321,\epsilon=\frac{1}{8}}$ works better in the fat-tail scenarios (SI Dataset S1). Theorem .1 and A.1 show that $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ and $qm_{d\approx 0.321,\epsilon=\frac{1}{8}}$ are both consistent mean estimators for any symmetric distribution and a skewed distribution with finite second moments. It's obvious that the breakdown points of $rm_{d\approx 0.375,\epsilon=\frac{1}{8}}$ and $qm_{d\approx 0.321,\epsilon=\frac{1}{8}}$ are both $\frac{1}{8}$. Therefore they are all invariant means.

To study the impact of the choice of SWAs in rm and qm, it is constructive to consider a symmetric weighted average as a mixture of symmetric quantile averages. Although using a less-biased symmetric weighted average can generally improve performance (SI Dataset S1), there is a higher risk of violation in the semiparametric framework. However, the mean-SWA-median inequality is robust to small fluctuations of the SQA function of the underlying distribution. Suppose the SQA function is generally decreasing in $[0, u]$, but increasing in $[u, \frac{1}{2}]$, since $1-2\epsilon$ of the symmetric quantile averages will be included in the computation of SWA_ϵ, as long as $|u - \frac{1}{2}| \ll 1 - 2\epsilon$, and other parts of the SQA function satisfy the inequality constraints which define the νth orderliness, the mean-SWA_ϵ-median inequality will still be valid (as an example, the SQA function is non-monotonic when the shape parameter of the Weibull distribution $\alpha > \frac{1}{1-\ln(2)} \approx 3.259$ as shown in the previous article, yet the mean-$\text{BM}_{\frac{1}{8}}$-median inequality is still valid when $\alpha \leq 3.322$). Another key factor determining the risk of violation is the skewness of the distribution. In the previous article, it is shown that in a family of distributions that differ by a skewness-increasing transformation in van Zwet's sense, the violation of orderliness, if it happens, often only occurs when the distribution is near-symmetric (15). The over-corrections in rm and qm are dependent on the SWA_ϵ-median difference, which is correlated to the skewness (16, 17), so the over-correction is often tiny with a moderate d. This qualitative analysis provides another perspective, in addition to the bias bounds (18), that rm and qm based on the mean-SWA_ϵ-median inequality are generally safe.

B. Robust estimations of the central moments. In 1976, Bickel and Lehmann, in their third paper of the landmark series *Descriptive Statistics for Nonparametric Models* (19), generalized a class of estimators called "measures of disperse," which is now often named as Bickel-Lehmann dispersion. As an example, they proposed a first version of the trimmed standard deviation, $\hat{\tau}^2(F;\epsilon) \equiv \tau^2(F;\epsilon)$, for independent and identically distributed random variables X with a distribution F, where $\tau^2(F;\epsilon) = \frac{1}{1-2\epsilon}\int_{Q(\epsilon)}^{Q(1-\epsilon)} y dG(y)$, Q is the quantile function of G, G is the distribution of $Y = X^2$. Obviously, when $\epsilon = 0$, the result is equivalent to the second raw moment. In 1979, in the same series (20), they explored another class of estimators called "measures of spread," which "does not require the assumption of symmetry." From that, a popular efficient scale estimator, the Rousseeuw-Croux scale estimator (21), was derived in 1993, but the importance of tackling the symmetry assumption has been greatly underestimated. In the final section of the paper, they considered another two possible versions of the trimmed standard deviations, which were modified here for comparison,

$$\left[n\left(\frac{1}{2}-\epsilon\right)\right]^{-\frac{1}{2}}\left[\sum_{i=\frac{n}{2}}^{n(1-\epsilon)}\left[X_i - X_{n-i+1}\right]^2\right]^{\frac{1}{2}}, \qquad [1]$$

and

$$\left[\binom{n}{2}\left(1-\epsilon-\gamma\epsilon\right)\right]^{-\frac{1}{2}}\left[\sum_{i=\binom{n}{2}\epsilon}^{\binom{n}{2}(1-\gamma\epsilon)}\left(X-X'\right)_i^{2}\right]^{\frac{1}{2}}, \qquad [2]$$

where $(X-X')_1 \leq \ldots \leq (X-X')_{\binom{n}{2}}$ are the order statistics of the "pseudo-sample". The paper ended with, "We do not know a fortiori which of the measures [1] or [2] is preferable and leave these interesting questions open."

Observe that the kernel of the unbiased estimation of the second central moment by using U-statistic is $\psi_2(x_1, x_2) = \frac{1}{2}(x_1 - x_2)^2$. If adding the $\frac{1}{2}$ term in [2], as $\epsilon \to 0$, the result is equivalent to the standard deviation estimated by using U-statistic (also noted by Janssen, Serfling, and Veraverbeke in 1987) (22). In fact, they also showed that, when ϵ is 0, [2] is $\sqrt{2}$ times the standard deviation.

To address their open questions, the nomenclature used in this paper is introduced as follows:

Nomenclature. Given a robust estimator $\hat{\theta}$. The first part of the name of the robust statistic defined in this paper is a prefix that indicates the type of estimator, and the second part is the name of the population parameter θ that the estimator is consistent with as $\epsilon \to 0$. The abbreviation of the estimator is the initial letter(s) of the first part plus the common abbreviation of the consistent estimator that measures the population parameter. If the estimator is symmetric and not a U-statistic, ϵ is indicated in the subscript of the abbreviation of the estimator. If the estimator is asymmetric, the corresponding γ is also indicated after ϵ. If the estimator is a weighted U-statistic, the breakdown point of the location estimator is indicated (except the median).

In the previous semiparametric robust mean article, it is shown that the bias of a reasonable robust estimator should be monotonic with respect to the breakdown point in a semiparametric distribution and, naturally, its name should align with the consistent estimator. The trimmed standard deviation following this nomenclature is $\text{T}sd_{\epsilon,\gamma,n} := \left[\text{TM}_{\epsilon,\gamma}\left(\left(\psi_2\left(X_{N_1}, X_{N_2}\right)\right)_{N=1}^{\binom{n}{2}}\right)\right]^{-\frac{1}{2}}$, where $\text{TM}_{\epsilon,\gamma}(Y)$ denotes the ϵ,γ-trimmed mean with the sequence $\left(\psi_2\left(X_{N_1}, X_{N_2}\right)\right)_{N=1}^{\binom{n}{2}}$ as an input. If the square root is removed, it is named as the trimmed variance ($\mathrm{T}var_{\epsilon,\gamma,n}$). It is now very clear that this definition, essentially the same as [2], should be preferable. Not only because it is essentially a trimmed U-statistic for the standard deviation but also because the γ-orderliness of the second central moment kernel distribution is ensured by the next exciting theorem.

Theorem B.1. *The second central moment kernel distribution generated from any continuous unimodal distribution is γ-ordered, if $\gamma \geq 1$.*

Proof. Let $Q(p)$, $0 \leq p \leq 1$, denote the quantile of the continuous unimodal distribution $f_X(x)$. The corresponding probability density is $f(Q(p))$. Generating the distribution of the pair $(Q(p_i), Q(p_j))$, $i < j$, $p_i < p_j$, the corresponding probability density is $f_{X,X}(Q(p_i), Q(p_j)) = 2f(Q(p_i))f(Q(p_j))$. Transforming the pair $(Q(p_i), Q(p_j))$, $i < j$, by the function $\Phi(x_1, x_2) = x_1 - x_2$, the pairwise difference distribution has a mode that is arbitrary close to $M - M = 0$. The monotonic increasing of the pairwise difference distribution was first implied in its unimodality proof done by Hodges and Lehmann in 1954 (23). Whereas they used induction to get the result, Dharmadhikari and Jogdeo in 1982 (24) gave a modern proof of the unimodality using Khintchine's representation (25). Assuming absolute continuity, Purkayastha (26) introduced a much simpler proof in 1998. Transforming the pairwise difference distribution by squaring and multiplying $\frac{1}{2}$ does not change the monotonicity, making the pdf become monotonically decreasing with mode at zero. In the previous semiparametric robust mean estimation article, it is proven that a right skewed distribution with a monotonic decreasing pdf is always γ-ordered, which gives the desired result. □

Remark. The assumption of continuity of distributions is important for monotonicity because, unlike in the continuous case, it is possible to get pairs with the same value for a discrete distribution. For example, let the probabilities of the singletons $\{1\}$, $\{2\}$, $\{3\}$, $\{4\}$ and $\{5\}$ of a probability mass function of a discrete probability distribution be $\frac{1}{11}$, $\frac{4}{11}$, $\frac{3}{11}$, $\frac{2}{11}$, and $\frac{1}{11}$, respectively. This is a unimodal distribution, but the corresponding ψ_2 distribution is non-monotonic, whose singletons $\{0\}$, $\{0.5\}$, $\{2\}$, $\{4.5\}$ and $\{8\}$ have probabilities $\frac{21}{66}$, $\frac{24}{66}$, $\frac{2}{14}$, $\frac{6}{66}$, and $\frac{1}{66}$, respectively.

Previously, it was shown that any symmetric distribution with a finite second moment is νth ordered. That means the orderliness does not require unimodality, e.g., for a symmetric bimodal distribution, it is also ordered. Examples from the Weibull distribution show that unimodality does not guarantee orderliness. Theorem B.1 reveals another profound relationship between unimodality and orderliness, which is sufficient for trimming inequality.

In 1928, Fisher constructed k-statistics as unbiased estimators of cumulants (27). Halmos (1946) proved that the functional θ admits an unbiased estimator if and only if it is a regular statistical functional of degree k and showed a relation of symmetry, unbiasness and minimum variance (28). In 1948, Hoeffding generalized U-statistics (29) which enable the derivation of a minimum-variance unbiased estimator from each unbiased estimator of an estimable parameter. Heffernan (1997) (30) obtained an unbiased estimator of the kth central moment by using U-statistics and demonstrated that it is the minimum variance unbiased estimator for distributions with finite moments (31, 32). In 1976, Saleh generalized the Hodges-Lehmenn estimator (33) to the trimmed H-L mean (he named "Wilcoxon one-sample statistic") (34). In 1984, Serfling pointed out the speciality of Hodges-Lehmann estimator, which is neither a simple L-statistics nor U-statistic, and considered the generalized L-statistics and U-statistic structure (35). Also in 1984, Janssen and Serfling and Veraverbeke (36) showed that the Bickel-Lehmann spread also belongs to the same class. It was gradually clear that the Hodges-Lehmenn estimator, trimmed H-L mean and trimmed standard deviation are all trimmed U-statistics (37–39). Due to the combinatorial explosion, the bootstrap (40), introduced by Efron in 1979, is indispensable in large sample studies. In 1981, Bickel and Freedman (41) showed that the bootstrap is asymptotically valid to approximate the original distribution in a wide range of situations, including U-statistics. The limit laws of bootstrapped trimmed U-statistics was proven by Helmers, Janssen, and Veraverbeke (1990) (42).

Data Availability. Data for Table **??** are given in SI Dataset S1. All codes have been deposited in GitHub.

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