Semiparametric robust mean estimations based on the orderliness of quantile averages

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As one of the most fundamental problems in statistics, robust location estimation has many prominent solutions, such as the trimmed mean, Winsorized mean, Hodges–Lehmann estimator, Huber M-estimator, and median of means. Recent research findings suggest that their biases concerning the mean can be quite different in asymmetric distributions, but the underlying mechanisms remain largely unclear. In this article, similar to the mean-median-mode inequality, it is proven that in the context of nearly all common unimodal distributions, there exists an orderliness of symmetric quantile averages with different breakdown points. Further deductions explain why the Winsorized mean and median of means generally have smaller biases compared to the trimmed mean. Building on the U-orderliness, the superiority of the median Hodges–Lehmann mean is discussed.

semiparametric | mean-median-mode inequality | asymptotic | unimodal | Hodges–Lehmann estimator

In 1823, Gauss (1) proved that for any unimodal distribution with a finite second moment, $|m - \mu| \leq \sqrt{\frac{3}{4}}\omega$, where μ is the population mean, m is the population median, and ω is the root mean square deviation from the mode, M. This pioneering work revealed that despite potential bias with respect to the mean in robust estimates, the deviation remains bounded in unit of a scale parameter under certain assumptions. Bernard, Kazzi, and Vanduffel (2020) (2) further derived asymptotic bias bounds of any quantile for unimodal distributions by reducing this optimization problem to a parametric one, which can be solved analytically. They showed that the population median, m, has the smallest maximum distance to the population mean, μ, among all symmetric quantile averages (SQA_ϵ). Daniell, in 1920, (3) analyzed a class of estimators, linear combinations of order statistics, and identified that ϵ-symmetric trimmed mean (STM_ϵ) belongs to this class. Another popular choice, the ϵ-symmetric Winsorized mean (SWM_ϵ), named after Winsor and introduced by Tukey (4) and Dixon (5) in 1960, is also an L-estimator. Bieniek (2016) derived exact bias upper bounds of the Winsorized mean based on Danielak and Rychlik's work (2003) on the trimmed mean for any distribution with a finite second moment and confirmed that the former is smaller than the latter (6, 7). In 1963, Hodges and Lehmann (8) proposed a class of nonparametric location estimators based on rank tests and, from the Wilcoxon signed-rank statistic (9), deduced the median of pairwise means as a robust location estimator for a symmetric population. Both L-statistics and R-statistics achieve robustness essentially by removing a certain proportion of extreme values. In 1964, Huber (10) generalized maximum likelihood estimation to the minimization of the sum of a specific loss function, which measures the residuals between the data points and the model's parameters. Some L-statistics are also M-statistics, e.g., the sample mean is an M-estimator with a squared error loss function, while the sample median is an M-estimator with an absolute error loss function (10). The Huber M-estimator is obtained by applying the Huber loss function that combines elements of both squared error and absolute error to achieve robustness against gross errors and high efficiency for contaminated Gaussian distributions (10). Sun, Zhou, and Fan (2020) examined the concentration bounds of Huber M-estimator (11). Mathieu (2022) (12) further derived the concentration bounds of M-statistics and demonstrated that, by selecting the tuning parameter which depends on the variance, Huber M-estimator can also be a sub-Gaussian estimator. The concept of median of means ($\mathrm{MoM}_{k,b=\frac{n}{k}}$, k is the number of size in each block, b is the number of blocks) was implicitly introduced several times in Nemirovsky and Yudin (1983) (13), Jerrum, Valiant, and Vazirani (1986), (14) and Alon, Matias and Szegedy (1996) (15)'s works. Given its good performance even for distributions with infinite second moments, MoM has received increasing attention over the past decade (16–23). Devroye, Lerasle, Lugosi, and Oliveira (2016) showed that MoM nears the optimum of sub-Gaussian mean estimation with regards to concentration bounds when the distribution has a heavy tail (21). For a comparison of concentration bounds of trimmed mean, Huber M-estimator, median of means and other relavent estimators, readers are directed to Gobet, Lerasle, and Métivier's paper (2022) (24). Laforgue, Clemencon, and Bertail (2019) proposed the median of randomized means ($\mathrm{MoRM}_{k,b}$) (23), wherein, rather than partitioning, an arbitrary number, b, of blocks are built independently from the sample, and showed that MoRM has better non-asymptotic sub-Gaussian property compared to MoM. In fact, asymptotically, the Hodges-Lehmann (H-L) estimator is equivalent to $\mathrm{MoM}_{k=2,b=\frac{n}{k}}$ and $\mathrm{MoRM}_{k=2,b}$, and they can be seen as the pairwise mean distribution is approximated by the sampling without replacement and bootstrap, respectively. For the asymptotic validity, readers are referred to the foundational works of Efron (1979) (25), Bickel and Freedman (1981, 1984) (26, 27), and Helmers, Janssen, and Veraverbeke (1990)

Significance Statement

In 1964, van Zwet introduced the convex transformation order for comparing the skewness of two distributions. This paradigm shift played a fundamental role in defining robust measures of distributions, from spread to kurtosis. Here, rather than the stochastic ordering between two distributions, the orderliness of quantile averages within a distribution is investigated. By classifying distributions through the signs of derivatives, a series of sophisticated robust mean estimators are deduced. Nearly all common nonparametric robust location estimators are found to be special cases thereof.

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(28).

Here, the ϵ,b-stratified mean is defined as

$$\mathrm{SM}_{\epsilon,b,n} \coloneqq \frac{b}{n}\left(\sum_{j=1}^{\frac{b-1}{2b\epsilon}} \sum_{i_j=\frac{(2bj-b-1)n\epsilon}{b-1}+1}^{\frac{(2bj-b+1)n\epsilon}{b-1}} X_{i_j}\right),$$

where $X_1 \leq ... \leq X_n$ denote the order statistics of a sample of n independent and identically distributed random variables $X_1, \ldots, X_n$. $b \in \mathbb{N}$, $b \geq 3$. The definition was further refined to guarantee the continuity of the breakdown point by incorporating an additional block in the center when $\lfloor \frac{b-1}{2b\epsilon} \rfloor \bmod 2 = 0$, or by adjusting the central block when $\lfloor \frac{b-1}{2b\epsilon} \rfloor \bmod 2 = 1$ (SI Text). If the subscript n is omitted, only the asymptotic behavior is considered. If b is omitted, $b = 3$ is assumed. $\mathrm{SM}_{\epsilon,b=3}$ is equal to STM_ϵ, when $\epsilon > \frac{1}{6}$. The basic idea of the stratified mean, when $\frac{b-1}{2\epsilon} \in \mathbb{N}$, $b \bmod 2 = 1$ is to distribute the data into $\frac{b-1}{2\epsilon}$ equal-sized non-overlapping blocks according to their order, then further sequentially group these blocks into b equal-sized strata and compute the mean of the middle stratum, which is the median of means of each stratum. In situations where $i \bmod 1 \neq 0$, a potential solution is to generate multiple smaller samples that satisfy the equality by sampling without replacement, and subsequently calculate the mean of all estimations, the details of determining the sample size and sampling times are included in the SI Text. Although the principle is similar to that of the median of means, without the random shift, the result is different from $\mathrm{MoM}_{k=\frac{n}{b},b}$. Additionally, the stratified mean differs from the mean of the sample obtained through stratified sampling methods, introduced by Neymean (1934) (29) or ranked set sampling (30), introduced by McIntyre in 1952, as these sampling methods are designed to obtain more representative samples or improve the efficiency of sample estimates, but the sample mean based on them are not robust. When $b \bmod 2 = 1$, the stratified mean can be regarded as replacing the other equal-sized strata with the middle stratum, which, in principle, is analogous to the Winsorized mean that replaces extreme values with less extreme percentiles. Furthermore, while the bounds confirm that the Winsorized mean and median of means outperform the trimmed mean (6, 7, 21, 24) in worst-case performance, the complexity of bound analysis makes it difficult to achieve a complete and intuitive understanding of these results. Also, a clear explanation for the average performance of them remains elusive. The aim of this paper is to define a series of semiparametric models using the signs of derivatives, reveal their elegant interrelations and connections to parametric models, and show that by exploiting these models, a set of sophisticated robust mean estimators can be deduced, which have strong robustness to departures from assumptions.

Quantile average and weighted average

The symmetric trimmed mean, symmetric Winsorized mean, and stratified mean are all L-statistics. More specifically, they are symmetric weighted averages, which are defined as

$$\mathrm{SWA}_{\epsilon,n} \coloneqq \frac{\sum_{i=1}^{\lceil \frac{n}{2} \rceil} \frac{X_i + X_{n-i+1}}{2} w_i}{\sum_{i=1}^{\frac{n}{2}} w_i},$$

where w_is are the weights applied to the symmetric quantile averages according to the definition of the corresponding L-statistic. For example, for the ϵ-symmetric trimmed mean, $w_i = \begin{cases} 0, & i < n\epsilon \\ 1, & i \geq n\epsilon \end{cases}$, provided that $n\epsilon \in \mathbb{N}$. The mean and median are indeed two special cases of the symmetric trimmed mean.

To extend the symmetric quantile average to the asymmetric case, there are two possible definitions for the ϵ,γ-quantile average ($\mathrm{QA}(\epsilon, \gamma, n)$), i.e.,

$$\frac{1}{2}(\hat{Q}_n(\gamma\epsilon) + \hat{Q}_n(1-\epsilon)), \qquad [1]$$

and

$$\frac{1}{2}(\hat{Q}_n(\epsilon) + \hat{Q}_n(1-\gamma\epsilon)), \qquad [2]$$

where $\gamma \geq 0$ and $0 \leq \epsilon \leq \frac{1}{1+\gamma}$, $\hat{Q}_n(p)$ is the empirical quantile function. For trimming from both sides, [1] and [2] are equivalent. [1] is assumed in this article unless otherwise specified, since many common asymmetric distributions are right skewed, and [1] allows trimming only from the right side by setting $\gamma = 0$.

Analogously, the weighted average can be defined as

$$\mathrm{WA}_{\epsilon,\gamma} \coloneqq \frac{\int_{\epsilon_0=0}^{\frac{1}{1+\gamma}} \mathrm{QA}(\epsilon_0, \gamma)\, w_{\epsilon_0}}{\int_{\epsilon_0=0}^{\frac{1}{1+\gamma}} w_{\epsilon_0}}.$$

For instance, the ϵ,γ-trimmed mean ($\mathrm{TM}_{\epsilon,\gamma}$) is a weighted average with a left trim size of $\gamma\epsilon n$ and a right trim size of ϵn, where $w_{\epsilon_0} = \begin{cases} 0, & \epsilon_0 < \epsilon \\ 1, & \epsilon_0 \geq \epsilon \end{cases}$.

Classifying distributions by the signs of derivatives

Let $\mathcal{P}_k$ denote the set of all distributions over $\mathbb{R}$ whose moments, from the first to the kth, are all finite. Without loss of generality, all classes discussed in the following are subclasses of the nonparametric class of distributions $\mathcal{P}_\Upsilon^k \coloneqq \{\text{All continuous distribution } P \in \mathcal{P}_k\}$. Besides fully and smoothly parameterizing by a Euclidean parameter or just assuming regularity conditions, there are many ways to classify distributions. In 1956, Stein initiated the problem of estimating parameters in the presence of an infinite dimensional nuisance shape parameter (31). A notable example discussed in his groundbreaking work was the estimation of the center of symmetry for an unknown symmetric distribution. In 1993, Bickel, Klaassen, Ritov, and Wellner published an influential semiparametrics textbook (32) and systematically classified many common models into three classes: parametric, nonparametric, and semiparametric. However, there is another old and commonly encountered class of distributions that receives little attention in semiparametric literature: the unimodal distribution. It is a very unique semiparametric model because its definition is based on the signs of derivatives, i.e., assuming P is continuous, $(f'(x) > 0 \text{ for } x \leq M) \wedge (f'(x) < 0 \text{ for } x \geq M)$. Let $\mathcal{P}_U$ denote the set of all unimodal distributions. Five parametric distributions in $\mathcal{P}_U$ are detailed as examples here: Weibull, gamma, Pareto, lognormal and generalized Gaussian.

Consider the sign of the derivative of the quantile average with respect to the breakdown point, a right-skewed distribution is called γ-ordered, if and only if

$$\forall 0 \leq \epsilon \leq \frac{1}{1+\gamma}, \frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \leq 0.$$

The left-skewed case can be obtained by reversing the inequality $\frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \leq 0$ to $\frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \geq 0$ and employing the second definition of QA, as given in [2]; for simplicity, it will be omitted in the following discussion. If $\gamma = 1$, the γ-ordered distribution is referred to as ordered. Let $\mathcal{P}_O$ denote the set of all ordered distributions. The Pareto, lognormal, and generalized Gaussian distributions belong to $\mathcal{P}_U \cap \mathcal{P}_O$, as proven in the following discussion and SI Text. When the shape parameters of the Weibull and gamma distributions fall within a certain range, they also belong to $\mathcal{P}_U \cap \mathcal{P}_O$ (SI Text). The minor exceptions occur when the Weibull and gamma distributions are near-symmetric, as shown in the SI Text.

Furthermore, many common right-skewed distributions are partial bounded, indicating a convex behavior of the QA function when $\epsilon \to 0$. If assuming convexity further, the second γ-orderliness can be defined as the following for a right-skewed distribution,

$$\forall 0 \leq \epsilon \leq \frac{1}{1+\gamma}, \frac{\partial^2 \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^2} \geq 0 \wedge \frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \leq 0.$$

Analogously, the νth γ-orderliness of a right-skewed distribution can be defined as $(-1)^{\nu} \frac{\partial^{\nu} \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^{\nu}} \geq 0 \wedge \ldots \wedge -\frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \geq 0$. If $\gamma = 1$, the νth γ-orderliness is referred as νth orderliness. Let $\mathcal{P}_{O_\nu}$ and $\mathcal{P}_{\gamma O_\nu}$ denote the sets of all distributions that are νth ordered and νth γ-ordered, respectively. Many common unimodal distributions are also second and third ordered, as shown in the SI Text. The following theorems can be used to quickly identify parametric distributions in $\mathcal{P}_{O_\nu}$ and $\mathcal{P}_{\gamma O_\nu}$.

Theorem .1. *Any symmetric distribution with a finite second moment is νth ordered.*

Proof. The assertion follows from the fact that for any symmetric distribution with a finite second moment, all symmetric quantile averages coincide. Therefore, the SQA function is always a horizontal line; the νth order derivative is zero. $\square$

As a consequence of Theorem .1 and the fact that generalized Gaussian distribution is symmetric around the median, it is νth ordered.

Theorem .2. *Any continuous right skewed distribution whose Q satisfies $Q^{(\nu)}(p) \geq 0 \wedge \ldots Q^{(i)}(p) \geq 0 \ldots \wedge Q^{(2)}(p) \geq 0$, i mod $2 = 0$, is νth γ-ordered, provided that $0 \leq \gamma \leq 1$.*

Proof. Let $\mathrm{QA}(\epsilon, \gamma) = \frac{1}{2}(Q(\gamma\epsilon) + Q(1-\epsilon))$, where $0 \leq \epsilon \leq \frac{1}{1+\gamma}$ (also assumed in the following discussions for γ-ordered distributions), then $(-1)^j \frac{\partial^j \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^j} = \frac{1}{2}((-\gamma)^j Q^j(\gamma\epsilon) + Q^j(1-\epsilon))$, $\nu \geq j \geq 1$. When j mod $2 = 0$, $(-1)^j \frac{\partial^j \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^j} \geq 0$, when j mod $2 = 1$, the strict positivity is uncertain. If assuming $0 \leq \gamma \leq 1.$, $(-1)^j \frac{\partial^j \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^j} \geq 0$, since $Q^{(j+1)}(\epsilon) \geq 0$. $\square$

It is now trivial to prove that the Pareto distribution follows the νth γ-orderliness, provided that $0 \leq \gamma \leq 1$, since the quantile function of the Pareto distribution is $Q(p) = x_m(1-p)^{-\frac{1}{\alpha}}$, $x_m > 0$, $\alpha > 0$, $Q^{(\nu)}(p) \geq 0$ according to the chain rule.

Theorem .3. *A right-skewed continuous distribution with a monotonic decreasing pdf is γ-ordered, if $0 \leq \gamma \leq 1$.*

Proof. A monotonic decreasing pdf means $f'(x) = F^{(2)}(x) \leq 0$. Since $Q'(p) \geq 0$, let $x = Q(F(x))$, then by differentiating both sides of the equation twice, one can obtain $0 = Q^{(2)}(F(x))(F'(x))^2 + Q'(F(x))F^{(2)}(x) \Leftrightarrow Q^{(2)}(F(x)) = -\frac{Q'(F(x))F^{(2)}(x)}{(F'(x))^2} \geq 0$. The desired result is derived from Theorem .2. $\square$

Theorem .3 gives a valuable insight into the relation between modality and γ-orderliness. The conventional definition states that a distribution with a monotonic pdf is still considered unimodal. However, within its supported interval, its mode number is zero. The number of modes and their magnitudes are closely related to the possibility of orderliness being valid, although counterexamples can always be constructed. A proof of γ-orderliness, if $0 \leq \gamma \leq 1$, can be easily established for the gamma distributions when $\alpha \leq 1$ as the pdf of the gamma distribution is $f(x) = \frac{\lambda^{-\alpha} x^{\alpha-1} e^{-\frac{x}{\lambda}}}{\Gamma(\alpha)}$, $x \geq 0$, $\lambda > 0$, $\alpha > 0$, which is a product of two monotonic decreasing functions under constraints. For $\alpha > 1$, the proof is challenging, numerical results show that the orderliness is valid until $\alpha > 140$ (SI Text), but it is instructive to consider that when $\alpha \to \infty$ the gamma distribution converges to a Gaussian distribution with mean $\mu = \alpha\lambda$ and variance $\sigma = \alpha\lambda^2$.

Theorem .4. *If transforming a symmetric unimodal random variable X with a function $\phi(x)$ such that $\frac{d^2\phi}{dx^2} \geq 0 \wedge \frac{d\phi}{dx} \geq 0$ over the interval supported, then the convex transformed distribution is ordered. If the quantile function of X satifies $Q^{(2)}(\epsilon) \leq 0$, the convex transformed distribution is second ordered.*

Proof. Let $\phi\mathrm{SQA}(\epsilon) = \frac{1}{2}(\phi(Q(\epsilon)) + \phi(Q(1-\epsilon)))$, then, $\frac{d\phi\mathrm{SQA}}{d\epsilon} = \frac{1}{2}(\phi'(Q(\epsilon))Q'(\epsilon) - \phi'(Q(1-\epsilon))Q'(1-\epsilon)) = \frac{1}{2}Q'(\epsilon)(\phi'(Q(\epsilon)) - \phi'(Q(1-\epsilon))) \leq 0$, since for a symmetric distribution, $m - Q(\epsilon) = Q(1-\epsilon) - m$, differentiating both sides, $-Q'(\epsilon) = -Q'(1-\epsilon)$, $Q'(\epsilon) \geq 0, \phi^{(2)} \geq 0$. Notably, differentiating twice, $Q^{(2)}(\epsilon) = -Q^{(2)}(1-\epsilon)$, $\frac{d^{(2)}\phi\mathrm{SQA}}{d\epsilon^{(2)}} = \frac{1}{2}\left(\left(\phi^{(2)}(Q(\epsilon)) + \phi^{(2)}(Q(1-\epsilon))\right)(Q'(\epsilon))^2\right) + \frac{1}{2}\left((\phi'(Q(\epsilon)) - \phi'(Q(1-\epsilon)))Q^{(2)}(\epsilon)\right)$. The sign of $\frac{d^{(2)}\phi\mathrm{SQA}}{d\epsilon^{(2)}}$ depends on $Q^{(2)}(\epsilon)$. $\square$

The mean-median-mode inequality for distributions of the powers and roots of the variates of a given distribution was investigated by Henry Rietz in 1927 (33), but the most trivial solution is the exponential transformation since the derivatives are always positive. An application of Theorem .4 is that the lognormal distribution is ordered as it is exponentially transformed from the Gaussian distribution whose $Q^{(2)}(\epsilon) = -2\sqrt{2}\pi\sigma e^{2\mathrm{erfc}^{-1}(2\epsilon)^2}\mathrm{erfc}^{-1}(2\epsilon) \leq 0$ (so, it is also second ordered).

Theorem .4 also reveals a relation between convex transformation and orderliness, since ϕ is the non-decreasing convex function in van Zwet's trailblazing work *Convex transformations of random variables* (34). Consider a near-symmetric distribution S, such that SQA_ϵ as a function of ϵ fluctuates from 0 to $\frac{1}{2}$, with $\mu = m$. By definition, S is not ordered. Let s be the pdf of S. Applying the transformation $\phi(x)$ to S decreases $s(Q_S(\epsilon))$, and the decrease rate, due to the order, is much smaller for $s(Q_S(1-\epsilon))$. As a consequence, as the second derivative of $\phi(x)$ increases, eventually, after a point, $s(Q_S(\epsilon))$ becomes greater than $s(Q_S(1-\epsilon))$ even if it was not previously. Thus, the SQA_ϵ function becomes monotonically decreasing, and S becomes ordered. Accordingly, in a family of distributions that differ by a skewness-increasing transformation in van Zwet's sense, violations of orderliness typically occur only when the distribution is near-symmetric.

In 1895, Pearson proposed using the mean-median difference $\mu - m$ as a measure of skewness after standardization (35). Bowley (1926) proposed a measure of skewness based on the SQA-median difference $\mathrm{SQA}_\epsilon - m$ (36). Groeneveld and Meeden (1984) (37) generalized these measures of skewness based on van Zwet's convex transformation (34) and investigated their properties. Similar to the orderliness, a distribution is called monotonically right skewed if and only if $\forall 0 \leq \epsilon_1 \leq \epsilon_2 \leq \frac{1}{2}, \mathrm{SQA}_{\epsilon_1} - m \geq \mathrm{SQA}_{\epsilon_2} - m$. Since m is a constant, the monotonic skewness is equivalent to the orderliness. The validity of robust measures of skewness based on the SQA-median difference is closely related to the orderliness of the distribution, because for a non-ordered distribution, the results from $\mathrm{SQA}_\epsilon - m$ with different breakdown points might be very different especially if the inequality $\mathrm{SQA}_\epsilon \geq m$ is not valid for some ϵ.

There was a widespread misbelief that the median of an arbitrary unimodal distribution always lies between its mean and mode until Runnenburg (1978) and van Zwet (1979) (38, 39) endeavored to determine sufficient conditions for the inequality to hold, thereby implying the possibility of its violation (counterexamples can be found in the papers by Dharmadhikari and Joag-Dev (1988), Basu and DasGupta (1997), and Abadir (2005)) (40–42). The class of distributions that satisfy the mean-median-mode inequality constitutes a subclass of $\mathcal{P}_U$. Analogously, the above definition of γ-orderliness can also be expressed as

$$\forall 0 \leq \epsilon_1 \leq \epsilon_2 \leq \frac{1}{1+\gamma}, \mathrm{QA}_{\epsilon_1,\gamma} \geq \mathrm{QA}_{\epsilon_2,\gamma}.$$

The following necessary and sufficient condition hints at the relation between the mean-median-mode inequality and the orderliness.

Theorem .5. *Let P_Υ^k denote an arbitrary distribution in the set $\mathcal{P}_\Upsilon^k$. $P_\Upsilon^k \in \mathcal{P}_{\gamma O}$ if and only if the pdf satisfies the inequality $f(Q(\gamma\epsilon)) \geq f(Q(1-\epsilon))$ for all $0 \leq \epsilon \leq \frac{1}{1+\gamma}$ or $f(Q(\gamma\epsilon)) \leq f(Q(1-\epsilon))$ for all $0 \leq \epsilon \leq \frac{1}{1+\gamma}$, $Q(\epsilon)$ is the quantile function.*

Proof. Without loss of generality, just consider the right-skewed continuous case. From the definition of γ-ordered distribution, deducing $\frac{Q(\gamma\epsilon-\delta)+Q(1-\epsilon+\delta)}{2} \geq \frac{Q(\gamma\epsilon)+Q(1-\epsilon)}{2} \Leftrightarrow Q(\gamma\epsilon-\delta)-Q(\gamma\epsilon) \geq Q(1-\epsilon)-Q(1-\epsilon+\delta) \Leftrightarrow Q'(1-\epsilon) \geq Q'(\gamma\epsilon)$, where δ is an infinitesimal quantity. Since the quantile function is the inverse function of the cumulative distribution function (cdf), $Q'(1-\epsilon) \geq Q'(\gamma\epsilon) \Leftrightarrow F'(Q(\gamma\epsilon)) \geq F'(Q(1-\epsilon))$, the proof is complete by noticing that the derivative of cdf is the probability density function (pdf). □

According to Theorem .5, if a probability distribution is right skewed and monotonic, it will always be γ-ordered. While the same conclusion can be drawn from Theorem .3, Theorem .5 can be easily extended to the discrete case and the $\gamma > 1$ case. For a right skewed continuous unimodal distribution, if $Q(\gamma\epsilon) > M$, the inequality $f(Q(\gamma\epsilon)) \geq f(Q(1-\epsilon))$ holds. The principle can be extended to unimodal-like distributions as well. Suppose there is a right skewed continuous multimodal distribution following the mean-γ-median-first mode inequality with many small modes on the right side, with the first mode, M, having the greatest probability density and the γ-median, $Q(\frac{\gamma}{1+\gamma})$, falling within the first dominant mode, i.e., if $x > Q(\frac{\gamma}{1+\gamma})$, $f(Q(\frac{\gamma}{1+\gamma})) \geq f(x)$, then, if $Q(\gamma\epsilon) > M$, the inequality $f(Q(\gamma\epsilon)) \geq f(Q(1-\epsilon))$ also holds. In other words, while a distribution following the mean-γ-median-mode inequality may not be strictly γ-ordered, the inequality that defines γ-orderliness remains valid for most quantile averages. The mean-γ-median-mode inequality can also indicate possible bounds for γ in practice, e.g., for any distributions, when $\gamma \to \infty$, the γ-median will be greater than the mean and the mode, when $\gamma \to 0$, the γ-median will be smaller than the mean and the mode.

Remarkably, Bernard et al. (2020) (2) proved the bias bounds of the ϵ-quantile for $\mathcal{P}_U$. From that, they derived the bias bound of the symmetric quantile average. Here, let $\mathcal{P}_{\mu,\sigma}$ denotes the set of distributions whose mean is μ and standard deviation is σ, the bias upper bound of the quantile average, $0 \leq \gamma < 5$, is given as

$$\sup_{P \in \mathcal{P}_U \cap \mathcal{P}_{\mu=0,\sigma=1}} \mathrm{QA}(\epsilon,\gamma) = \begin{cases} \frac{1}{2}\left(\sqrt{\frac{4}{9\epsilon}-1} + \sqrt{\frac{3\gamma\epsilon}{4-3\gamma\epsilon}}\right) & \frac{1}{6} \geq \epsilon \geq 0 \\ \frac{1}{2}\left(\sqrt{\frac{3(1-\epsilon)}{4-3(1-\epsilon)}} + \sqrt{\frac{3\gamma\epsilon}{4-3\gamma\epsilon}}\right) & \frac{1}{1+\gamma} \geq \epsilon > \frac{1}{6}. \end{cases}$$

The proof and the $\gamma \geq 5$ case is given in the SI Text. The next theorem highlights its safeguarding role in defining estimators based on orderliness.

Theorem .6. *The above bias upper bound function, $\sup_{P \in \mathcal{P}_U \cap \mathcal{P}_{\mu=0,\sigma=1}} QA(\epsilon,\gamma)$, is monotonic decreasing with respect to ϵ over the interval $[0, \frac{1}{1+\gamma}]$ when $0 \leq \gamma \leq 1$.*

Proof. When $\frac{1}{6} \geq \epsilon \geq 0$, $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial\epsilon} = \frac{\gamma}{\sqrt{\frac{\epsilon\gamma}{12-9\epsilon\gamma}}(4-3\epsilon\gamma)^2} - \frac{1}{3\sqrt{\frac{4}{\epsilon}-9}\epsilon^2}$. To prove $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial\epsilon} \leq 0$, it is equivalent to showing $\frac{\sqrt{\frac{\epsilon\gamma}{12-9\epsilon\gamma}}(4-3\epsilon\gamma)^2}{\gamma} \geq 3\sqrt{\frac{4}{\epsilon}-9}\epsilon^2$. Define $L(\epsilon,\gamma) = \frac{\sqrt{\frac{\epsilon\gamma}{12-9\epsilon\gamma}}(4-3\epsilon\gamma)^2}{\gamma}$, $R(\epsilon,\gamma) = 3\sqrt{\frac{4}{\epsilon}-9}\epsilon^2$, then $\frac{L(\epsilon,\gamma)}{\epsilon^2} = \frac{\sqrt{\frac{\epsilon\gamma}{12-9\epsilon\gamma}}(4-3\epsilon\gamma)^2}{\gamma\epsilon^2} = \frac{1}{\gamma}\left(\frac{4}{\epsilon}-3\gamma\right)^2\sqrt{\frac{1}{\frac{12}{\epsilon\gamma}-9}}$, $\frac{R(\epsilon,\gamma)}{\epsilon^2} = 3\sqrt{\frac{4}{\epsilon}-9}$. When $\gamma = 0$, $\frac{L(\epsilon,\gamma)}{\epsilon^2} = \infty$, $\frac{L(\epsilon,\gamma)}{\epsilon^2} > \frac{R(\epsilon,\gamma)}{\epsilon^2}$. When $\epsilon = 0$, both terms are infinity and thus equal. For other cases, $\frac{L(\epsilon,\gamma)}{\epsilon^2} > \frac{R(\epsilon,\gamma)}{\epsilon^2} \iff \frac{1}{\gamma}\sqrt{\frac{1}{\frac{12}{\epsilon\gamma}-9}}\left(\frac{4}{\epsilon}-3\gamma\right)^2 > 3\sqrt{\frac{4}{\epsilon}-9} \iff \frac{1}{\gamma}\left(\frac{4}{\epsilon}-3\gamma\right)^2 > 3\sqrt{\frac{12}{\epsilon\gamma}-9}\sqrt{\frac{4}{\epsilon}-9}$. Let $LmR\left(\frac{1}{\epsilon}\right) = \frac{1}{\gamma^2}\left(\frac{4}{\epsilon}-3\gamma\right)^4 - 9\left(\frac{12}{\epsilon\gamma}-9\right)\left(\frac{4}{\epsilon}-9\right)$. $\frac{\partial LmR(1/\epsilon)}{\partial(1/\epsilon)} = \frac{16\left(\frac{4}{\epsilon}-3\gamma\right)^3}{\gamma^2} - 36\left(\frac{12}{\epsilon\gamma}-9\right) - \frac{108\left(4\frac{4}{\epsilon}-9\right)}{\gamma} = \frac{4\left(4(\frac{4}{\epsilon}-3\gamma)^3-27\gamma(\frac{4}{\epsilon}-3\gamma)+27(9-\frac{4}{\epsilon})\gamma\right)}{\gamma^2} = \frac{4\left(256\frac{1}{\epsilon}^3-576\frac{1}{\epsilon}^2\gamma+432\frac{1}{\epsilon}\gamma^2-216\frac{1}{\epsilon}\gamma-108\gamma^3+81\gamma^2+243\gamma\right)}{\gamma^2}$. Since $256\frac{1}{\epsilon}^3 - 576\frac{1}{\epsilon}^2\gamma + 432\frac{1}{\epsilon}\gamma^2 - 216\frac{1}{\epsilon}\gamma - 108\gamma^3 + 81\gamma^2 + 243\gamma \geq 1536\frac{1}{\epsilon}^2 - 576\frac{1}{\epsilon}^2 + 432\frac{1}{\epsilon}\gamma^2 - 216\frac{1}{\epsilon}\gamma - 108\gamma^3 + 81\gamma^2 + 243\gamma \geq 924\frac{1}{\epsilon}^2 + 36\frac{1}{\epsilon}^2 - 216\frac{1}{\epsilon} + 432\frac{1}{\epsilon}\gamma^2 - 108\gamma^3 + 81\gamma^2 + 243\gamma \geq 924\frac{1}{\epsilon}^2 + 36\frac{1}{\epsilon}^2 - 216\frac{1}{\epsilon} + 513\gamma^2 - 108\gamma^3 + 243\gamma > 0$, $\frac{\partial LmR(1/\epsilon)}{\partial(1/\epsilon)} > 0$. Also, $LmR(6) = \frac{81(\gamma-8)\left((\gamma-8)^3+15\gamma\right)}{\gamma^2} > 0 \iff \gamma^4 - 32\gamma^3 + 399\gamma^2 - 2168\gamma + 4096 > 0$. Since $\gamma^4 > 0$, if $0 \leq \gamma \leq 1$, then $32\gamma^3 < 256$, and it suffices to prove that $399\gamma^2 - 2168\gamma + 4096 > 256$. Applying the quadratic formula demonstrates the validity of this inequality. Hence, $LmR\left(\frac{1}{\epsilon}\right) \geq 0$ for $\epsilon \in [0, \frac{1}{6}]$, provided that $0 \leq \gamma \leq 1$. The first part is finished.

When $\frac{1}{1+\gamma} \geq \epsilon > \frac{1}{6}$, $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial \epsilon} = \sqrt{3}\left(\frac{\gamma}{\sqrt{\gamma\epsilon}(4-3\gamma\epsilon)^{\frac{3}{2}}} - \frac{1}{\sqrt{1-\epsilon}(3\epsilon+1)^{\frac{3}{2}}}\right)$. When $\gamma = 0$, $\frac{\gamma}{\sqrt{\gamma\epsilon}(4-3\gamma\epsilon)^{\frac{3}{2}}} = \frac{\sqrt{\gamma}}{\sqrt{\epsilon}(4-3\gamma\epsilon)^{\frac{3}{2}}} = 0$, $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial \epsilon} < 0$. For other cases, to determine whether $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial \epsilon} < 0$, showing $\frac{\sqrt{\gamma\epsilon}(4-3\gamma\epsilon)^{\frac{3}{2}}}{\gamma} > \sqrt{1-\epsilon}\,(3\epsilon+1)^{\frac{3}{2}} \iff \frac{\gamma\epsilon(4-3\gamma\epsilon)^{3}}{\gamma^2} > (1-\epsilon)(3\epsilon+1)^3 \iff -27\gamma^2\epsilon^4 + 108\gamma\epsilon^3 + \frac{64\epsilon}{\gamma} + 27\epsilon^4 - 162\epsilon^2 - 8\epsilon - 1 > 0$ is sufficient. When $\gamma \leq 1$, the inequality can be further simplified to $108\gamma\epsilon^3 + \frac{64\epsilon}{\gamma} - 162\epsilon^2 - 8\epsilon - 1 > 0$. Since $\epsilon \leq \frac{1}{1+\gamma}$, $\gamma \leq \frac{1}{\epsilon} - 1$ and $0 \leq \gamma \leq 1$, $0 \leq \gamma \leq \min(1, \frac{1}{\epsilon} - 1)$. When $\frac{1}{6} \leq \epsilon \leq \frac{1}{2}$, $\frac{1}{\epsilon} - 1 > 1$, so $0 \leq \gamma \leq 1$. When $\frac{1}{2} \leq \epsilon < 1$, $0 \leq \gamma \leq \frac{1}{\epsilon} - 1$. Let $h(\gamma) = 108\gamma\epsilon^3 + \frac{64\epsilon}{\gamma}$, $\frac{\partial h(\gamma)}{\partial \gamma} = 108\epsilon^3 - \frac{64\epsilon}{\gamma^2}$. When $\gamma \leq \sqrt{\frac{64\epsilon}{18\epsilon^3}}$, $\frac{\partial h(\gamma)}{\partial \gamma} \geq 0$, when $\gamma \geq \sqrt{\frac{64\epsilon}{18\epsilon^3}}$, $\frac{\partial h(\gamma)}{\partial \gamma} \leq 0$, therefore, the minimum of $h(\gamma)$ must be when γ is equal to the boundary point of the domain. When $\frac{1}{6} \leq \epsilon \leq \frac{1}{2}$, $0 \leq \gamma \leq 1$, since $h(0) \to \infty$, $h(1) = 108\epsilon^3 + 64\epsilon$, the minimum occurs at the boundary point $\gamma = 1$, $108\gamma\epsilon^3 + \frac{64\epsilon}{\gamma} - 162\epsilon^2 - 8\epsilon - 1 > 108\epsilon^3 + 56\epsilon - 162\epsilon^2 - 1$. Let $g(\epsilon) = 108\epsilon^3 + 56\epsilon - 162\epsilon^2 - 1$. $g'(\epsilon) = 324\epsilon^2 - 324\epsilon + 56$, when $\epsilon \leq \frac{2}{9}$, $g'(\epsilon) \geq 0$, when $\epsilon \geq \frac{2}{9}$, $g'(\epsilon) \leq 0$, since $g(\frac{1}{6}) = \frac{13}{3}$, $g(\frac{1}{2}) = 0$, so $g(\epsilon) \geq 0$, the inequality is satisfied. When $\frac{1}{2} \leq \epsilon < 1$, $0 \leq \gamma \leq \frac{1}{\epsilon} - 1$. Since $h(\frac{1}{\epsilon} - 1) = 108(\frac{1}{\epsilon} - 1)\epsilon^3 + \frac{64\epsilon}{\frac{1}{\epsilon} - 1}$, $108\gamma\epsilon^3 + \frac{64\epsilon}{\gamma} - 162\epsilon^2 - 8\epsilon - 1 > 108\left(\frac{1}{\epsilon} - 1\right)\epsilon^3 + \frac{64\epsilon}{\frac{1}{\epsilon} - 1} - 162\epsilon^2 - 8\epsilon - 1 = \frac{-108\epsilon^4 + 54\epsilon^3 - 18\epsilon^2 + 7\epsilon + 1}{\epsilon - 1}$. Let $nu(\epsilon) = -108\epsilon^4 + 54\epsilon^3 - 18\epsilon^2 + 7\epsilon + 1$, $nu'(\epsilon) = -432\epsilon^3 + 162\epsilon^2 - 36\epsilon + 7$, $nu''(\epsilon) = -1296\epsilon^2 + 324\epsilon - 36 < 0$, since $nu'(\epsilon = \frac{1}{2}) = -\frac{49}{2} < 0$, so $nu'(\epsilon) < 0$. since $nu'(\epsilon = \frac{1}{2}) = -\frac{49}{2} < 0$, so $nu'(\epsilon) < 0$, since $nu(\epsilon = \frac{1}{2}) = 0$, so $nu(\epsilon) \leq 0$. So, the inequality is also valid within the range of $\frac{1}{1+\gamma} \geq \epsilon > \frac{1}{6}$, therefore, $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial \epsilon} \leq 0$ for $\frac{1}{1+\gamma} \geq \epsilon > \frac{1}{6}$. The first and second formula, when $\epsilon = \frac{1}{6}$, are all equal to $\frac{1}{2}\left(\frac{\sqrt{\frac{\gamma}{4-\frac{\gamma}{2}}}}{\sqrt{2}} + \sqrt{\frac{5}{3}}\right)$. It follows that $\sup_{\mathrm{QA}}(\epsilon,\gamma)$ is continuous over $[0, \frac{1}{1+\gamma}]$. Hence, $\frac{\partial \sup_{\mathrm{QA}}(\epsilon,\gamma)}{\partial \epsilon} \leq 0$ holds for the entire range $0 \leq \epsilon \leq \frac{1}{1+\gamma}$, when $0 \leq \gamma \leq 1$, which leads to the assertion of this theorem. □

For a right-skewed distribution, considering the upper bound is enough. This monotonicity implies that the extent of any violations of the γ-orderliness, $0 \leq \gamma \leq 1$, is bounded for a unimodal distribution, e.g., for a right-skewed unimodal distribution, if $\exists 0 \leq \epsilon_1 \leq \epsilon_2 \leq \epsilon_3 \leq \frac{1}{1+\gamma}$, $\mathrm{QA}_{\epsilon_2} \geq \mathrm{QA}_{\epsilon_3} \geq \mathrm{QA}_{\epsilon_1}$, QA_{ϵ_2} will not be too far away from QA_{ϵ_1}, since $\sup_{P \in \mathcal{P}_U \cap \mathcal{P}_\Upsilon^2} \mathrm{QA}_{\epsilon_1} > \sup_{P \in \mathcal{P}_U \cap \mathcal{P}_\Upsilon^2} \mathrm{QA}_{\epsilon_2} > \sup_{P \in \mathcal{P}_U \cap \mathcal{P}_\Upsilon^2} \mathrm{QA}_{\epsilon_3}$.

Inequalities related to weighted averages

The bias bound of the ϵ-symmetric trimmed mean is also monotonic for $\mathcal{P}_U \cap \mathcal{P}_2$, as proven in the SI Text using the formulae provided in Bernard et al.'s paper (2). So far, it appears clear that the bias of an estimator is closely related to its degree of robustness. For a right-skewed unimodal distribution, often, $\mu \geq \mathrm{STM}_\epsilon \geq m$. Then analogous to the γ-orderliness, the γ-trimming inequality is defined as $\forall 0 \leq \epsilon_1 \leq \epsilon_2 \leq \frac{1}{1+\gamma}, \mathrm{TM}_{\epsilon_1,\gamma} \geq \mathrm{TM}_{\epsilon_2,\gamma}$. A necessary and sufficient condition for the γ-trimming inequality is the monotonic decrease of the bias of the ϵ,γ-trimmed mean as a function of the breakdown point ϵ for a right skewed distribution, proven in the SI Text. γ-orderliness is a sufficient condition for the γ-trimming inequality, as proven in the SI Text, but it is not necessary.

Theorem .7. *For a right-skewed distribution following the γ-trimming inequality, the quantile average is always greater or equal to the corresponding trimmed mean with the same ϵ and γ, provided that $0 \leq \epsilon \leq \frac{1}{1+\gamma}$ and $\gamma \geq 0$.*

Proof. Without loss of generality, assuming the distribution is continuous. According to the definition of the γ-trimming inequality: $\frac{1}{1-\epsilon-\gamma\epsilon+2\delta}\int_{\gamma\epsilon-\delta}^{1-\epsilon+\delta} Q(u)\,du \geq \frac{1}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du$, if $0 \leq \epsilon \leq \frac{1}{1+\gamma}$ and $\gamma \geq 0$, where δ is an infinitesimal positive quantity. Then, rewriting the inequality as $\int_{\gamma\epsilon-\delta}^{1-\epsilon+\delta} Q(u)\,du - \frac{1-\epsilon-\gamma\epsilon+2\delta}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du \geq 0 \Leftrightarrow \int_{1-\epsilon}^{1-\epsilon+\delta} Q(u)\,du + \int_{\gamma\epsilon-\delta}^{\gamma\epsilon} Q(u)\,du - \frac{2\delta}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du \geq 0$. Since $\delta \to 0^+$, $\frac{1}{2\delta}\left(\int_{1-\epsilon}^{1-\epsilon+\delta} Q(u)\,du + \int_{\gamma\epsilon-\delta}^{\gamma\epsilon} Q(u)\,du\right) = \frac{Q(\gamma\epsilon)+Q(1-\epsilon)}{2} \geq \frac{1}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du$, the proof is complete. □

An analogous result can be obtained in the following theorem.

Theorem .8. *For a right-skewed continuous distribution following the γ-trimming inequality, the Winsorized mean is always greater or equal to the corresponding trimmed mean with the same ϵ and γ, provided that $0 \leq \epsilon \leq \frac{1}{1+\gamma}$ and $0 \leq \gamma \leq 1$.*

Proof. According to Theorem .7, $\frac{Q(\gamma\epsilon)+Q(1-\epsilon)}{2} \geq \frac{1}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du \Leftrightarrow \gamma\epsilon\left(Q(\gamma\epsilon)+Q(1-\epsilon)\right) \geq \left(\frac{2\gamma\epsilon}{1-\epsilon-\gamma\epsilon}\right)\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du$. Then, if $0 \leq \gamma \leq 1$, $\left(1 - \frac{1}{1-\epsilon-\gamma\epsilon}\right)\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du + \gamma\epsilon\left(Q(\gamma\epsilon)+Q(1-\epsilon)\right) \geq 0 \Rightarrow \int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du + \gamma\epsilon Q(\gamma\epsilon) + \epsilon Q(1-\epsilon) \geq \int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du + \gamma\epsilon\left(Q(\gamma\epsilon)+Q(1-\epsilon)\right) \geq \frac{1}{1-\epsilon-\gamma\epsilon}\int_{\gamma\epsilon}^{1-\epsilon} Q(u)\,du$, the proof is complete. □

If assuming γ-orderliness, the result in Theorem .8 can be extended to the $\gamma > 1$ case, as proven in the SI Text. Replacing the trimmed mean in the γ-trimming inequality with Winsorized mean forms the definition of γ-Winsorization inequality. γ-orderliness also implies the γ-Winsorization inequality, if $0 \leq \gamma \leq 1$, as proven in the SI Text.

To construct weighted averages based on the γ-orderliness, let $\mathcal{B}_i = \int_{i\epsilon}^{(i+1)\epsilon} \mathrm{QA}(u,\gamma)\,du$, $ka = k\epsilon + c$, from the γ-orderliness, $-\frac{\partial \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon} \geq 0 \Rightarrow \forall 0 \leq a \leq 2a \leq \frac{1}{1+\gamma}, -\frac{(\mathrm{QA}(2a,\gamma)-\mathrm{QA}(a,\gamma))}{a} \geq 0 \Rightarrow \mathcal{B}_i - \mathcal{B}_{i+1} \geq 0$. Let $\mathcal{B}_i = \mathcal{B}_0$, then, based on the γ-orderliness, ϵ,γ-block Winsorized mean, is defined here for comparison in the SI Dataset S1 as

$$\mathrm{BWM}_{\epsilon,\gamma,n} := \frac{1}{n}\left(\sum_{i=n\gamma\epsilon+1}^{(1-\epsilon)n} X_i + \sum_{i=n\gamma\epsilon+1}^{2n\gamma\epsilon+1} X_i + \sum_{i=(1-2\epsilon)n}^{(1-\epsilon)n} X_i\right),$$

which is double weighting the leftest and rightest blocks having the size $\gamma\epsilon n$ and ϵn. Since their sizes are different, the $0 \leq \gamma \leq 1$ is still necessary for the γ-block Winsorization inequality. If γ is omitted, $\gamma = 1$ is assumed. This terminology is the same for other weighted averages. The solutions for $i \bmod 1 \neq 0$ are the same as that in SM. From the second γ-orderliness $\frac{\partial^2 \mathrm{QA}_{\epsilon,\gamma}}{\partial^2 \epsilon} \geq 0 \Rightarrow \forall 0 \leq a \leq 2a \leq 3a \leq \frac{1}{1+\gamma}, \frac{1}{a}\left(\frac{(\mathrm{QA}(3a)-\mathrm{QA}(2a))}{a} - \frac{(\mathrm{QA}(2a)-\mathrm{QA}(a))}{a}\right) \geq 0 \Rightarrow \mathcal{B}_i - 2\mathcal{B}_{i+1} + \mathcal{B}_{i+2} \geq 0$. So, based on the second orderliness, SM_ϵ can be seen as assuming $\gamma = 1$, replacing the two blocks, $\mathcal{B}_i + \mathcal{B}_{i+2}$ with one block $2\mathcal{B}_{i+1}$. From the νth γ-orderliness, the recurrence relation of the derivatives naturally produces the alternating binomial coefficients,

$$(-1)^\nu \frac{\partial^\nu \mathrm{QA}_{\epsilon,\gamma}}{\partial \epsilon^\nu} \geq 0 \Rightarrow \forall 0 \leq a \leq \ldots \leq (\nu+1)a \leq \frac{1}{2},$$

$$\frac{(-1)^\nu}{a}\left(\frac{\frac{\mathrm{QA}(\nu a+a)^{\cdot^{\cdot^{\cdot}}}}{a} - \frac{\cdot^{\cdot^{\cdot}}\mathrm{QA}(2a)}{a}}{a} - \frac{\frac{\mathrm{QA}(\nu a)^{\cdot^{\cdot^{\cdot}}}}{a} - \frac{\cdot^{\cdot^{\cdot}}\mathrm{QA}(a)}{a}}{a}\right)$$

$$\geq 0 \Leftrightarrow \frac{(-1)^\nu}{a^\nu}\left(\sum_{j=0}^{\nu}(-1)^j \binom{\nu}{j} \mathrm{QA}\left((\nu - j + 1)\,a\right)\right) \geq 0$$

$$\Rightarrow \sum_{j=0}^{\nu}(-1)^j \binom{\nu}{j} \mathcal{B}_{i+j} \geq 0.$$

Based on the νth orderliness, the ϵ-binomial mean is introduced as

$$\mathrm{BM}_{\nu,\epsilon,n} := \frac{1}{n}\left(\sum_{i=1}^{\frac{1}{2}\epsilon^{-1}(\nu+1)^{-1}} \sum_{j=0}^{\nu}\left(1 - (-1)^j \binom{\nu}{j}\right) \mathfrak{B}_{i_j}\right),$$

where $\mathfrak{B}_{i_j} = \sum_{l=n\epsilon(j+(i-1)(\nu+1))+1}^{n\epsilon(j+(i-1)(\nu+1)+1)} (X_l + X_{n-l+1})$. If ν is not indicated, it is default as $\nu = 3$. Since the alternating sum of binomial coefficients is zero, when $\nu \lll \epsilon^{-1}$, $\epsilon \to 0$, $\mathrm{BM} \to \mu$. If $\frac{1}{2}\epsilon^{-1}(\nu+1)^{-1} \in \mathbb{N}$, the asymmetry case is dividing the sample into ϵ^{-1} blocks in the same way as BWM and then further weighting each block using binomial coefficients ($0 \leq \gamma \leq 1$ is needed). The solutions for the continuity of the breakdown point and $l \bmod 1 \neq 0$ are the same as that in SM and not repeated here. The equality $\mathrm{BM}_{\nu=1,\epsilon} = \mathrm{BWM}_\epsilon$ holds, and similarly, $\mathrm{BM}_{\nu=2,\epsilon} = \mathrm{SM}_{\epsilon,b=3}$, when their respective ϵs are identical and $\gamma = 1$. The reason that $\mathrm{SM}_{\epsilon=\frac{1}{9}}$ has similar biases as $\mathrm{WM}_{\epsilon=\frac{1}{9}}$ (SI Text) is that the Winsorized mean is using two single quantiles to replace the trimmed parts, not two blocks. The following theorems explain this difference.

Theorem .9. *For a right-skewed γ-ordered continuous distribution, the Winsorized mean is always greater or equal to the corresponding block Winsorized mean with the same ϵ and γ, provided that $0 \leq \gamma \leq 1$.*

Proof. From the definitions of BWM and WM, removing the trimmed mean part, the statement requires $\lim_{n\to\infty}\left((n\gamma\epsilon)\, X_{n\gamma\epsilon+1} + (n\epsilon)\, X_{n-n\epsilon}\right) \geq \lim_{n\to\infty}\left(\sum_{i=n\gamma\epsilon+1}^{2n\gamma\epsilon} X_i + \sum_{i=n\epsilon}^{2n\epsilon-1} X_{n-i}\right)$. If $0 \leq \gamma \leq 1$, every X_i can pair with a X_{n-i} to formed a quantile average, and the remaining X_{n-i}s are all smaller than $X_{n-n\epsilon}$, so the inequality is valid. □

If using single quantiles, based on the second γ-orderliness, the stratified quantile mean can be defined as

$$\mathrm{SQM}_{\epsilon,\gamma,n} := 4\epsilon \sum_{i=1}^{\frac{1}{4\epsilon}} \frac{1}{2}(\hat{Q}_n\left((2i-1)\gamma\epsilon\right) + \hat{Q}_n\left(1 - (2i-1)\epsilon\right)),$$

$\mathrm{SQM}_{\epsilon=\frac{1}{4}}$ is the Tukey's midhinge (43). In fact, SQM is a subcase of SM when $b \to \infty$, so the solution for $\frac{1}{\epsilon} \bmod 4 \neq 0$ is the same.

Theorem .10. *For a right-skewed second γ-ordered continuous distribution, $\mathrm{SQM}_{\epsilon,\gamma}$ is always greater or equal to the corresponding $\mathrm{BM}_{\nu=2,\epsilon,\gamma}$ with the same ϵ and γ, provided that $0 \leq \gamma \leq 1$.*

Proof. The computation of $\mathrm{BM}_{\nu=2}$ involves alternating between weighting and non-weighting, let 0 means the block is assigned with a weight of zero, 1 means the block is assigned with a weighted of one, the sequence of denoting whether the block is weighted or not weighted is: $0, 1, 0, 0, 1, 0, \ldots$. Let the sequence be denoted by $a_{\mathrm{BM}_{\nu=2}}(j)$, the formula for this sequence is $a_{\mathrm{BM}_{\nu=2}}(j) = \left\lfloor \frac{j \bmod 3}{2} \right\rfloor$. Similarly, the computation of SQM can be seen as placing quantiles at the beginning of all blocks if $\epsilon < \frac{1}{1+\gamma}$, and at the end of all blocks if $\epsilon > \frac{1}{1+\gamma}$, the sequence of denoting whether the quantile in each block is weighted or not weighted is: $0, 1, 0, 1, 0, 1, \ldots$. Let the sequence be denoted by $a_{\mathrm{SM}}(j)$, the formula for this sequence is $a_{\mathrm{SM}}(j) = j \bmod 2$. These sequences are also suitable if pairing all blocks and quantiles into block average, $\mathfrak{B}$, and quantile average, QA. There are two possible pairing of $a_{\mathrm{BM}_{\nu=2}}(j)$ and $a_{\mathrm{SM}}(j)$, one is $a_{\mathrm{BM}_{\nu=2}}(j) = a_{\mathrm{SM}}(j) = 1$, another is $0, 1, 0$ in $a_{\mathrm{BM}_{\nu=2}}(j)$ pairing with $1, 0, 1$ in $a_{\mathrm{SM}}(j)$. By leveraging the same principle as Theorem .9 and the second γ-orderliness (replacing the two quantile averages with one quantile average in the middle), the desired result follows. □

The biases of $\mathrm{SQM}_{\epsilon=\frac{1}{8}}$, which is based on the second orderliness with quantile approach, are also very close to those of $\mathrm{BM}_{\nu=3,\epsilon=\frac{1}{8}}$ (Figure 1), which is based on the third orderliness with block approach.

Hodges–Lehmann inequality and U-orderliness

The Hodges–Lehmann estimator is a very unique robust location estimator due to its definition being substantially dissimilar from conventional symmetric weighted averages. Hodges and Lehmann (8) in their landmark paper *Estimates of location based on rank tests* proposed two methods to compute the H-L estimator, Wilcoxon score and median of pairwise means, whose time complexities are $O(nlog(n))$ and $O(n^2)$, respectively. The Wilcoxon score is an estimator based on signed-rank test, or R-statistic (8), and was later independently discovered by Sen (44, 45). However, the median of pairwise means is a generalized L-statistic (classified by Serfling in 1984) (46) and a trimmed U-statistic (classified by Janssen, Serfling, and Veraverbeke in 1987) (47). By modifying the hl_k kernel pointed by Janssen, Serfling and Veraverbeke in 1987 (47) and weighted average generalized here, it is clear now that the H-L estimator is a weighted H-L mean, the definition of which is provided as follows,

$$\mathrm{WeHLM}_{k,\epsilon,\gamma,n} := \mathrm{WA}_{\epsilon_0,\gamma,n}\left(\left(hl_k\left(X_{N_1}, \cdots, X_{N_k}\right)\right)_{N=1}^{\binom{n}{k}}\right),$$

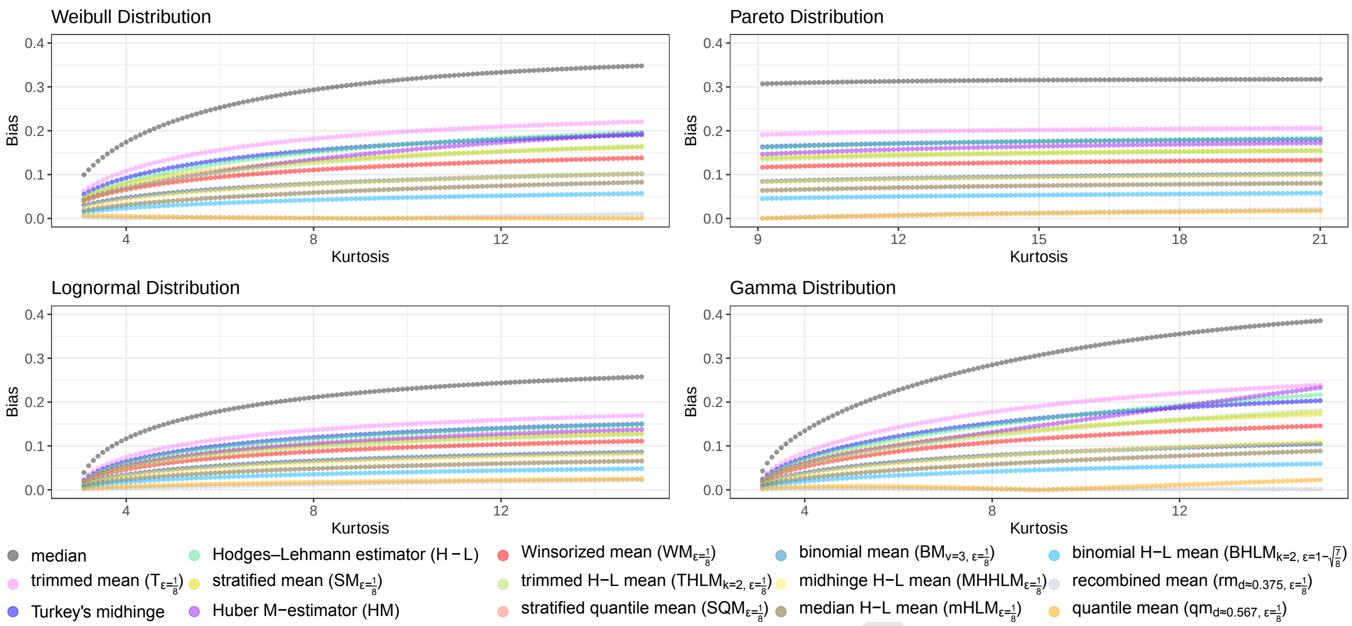

Fig. 1. Standardized asymptotic biases (with respect to μ) of fifteen robust location estimators (including two parametric estimators from a relevant paper for better comparison) in four two-parameter right skewed unimodal distributions as a function of the kurtosis. The methods were described in the SI Text.

where $k \in \mathbb{N}$, $hl_k = \frac{1}{k}\sum_{i=1}^{k} x_i$, $\mathrm{WA}_{\epsilon_0,\gamma,n}(Y)$ denotes the ϵ_0,γ-weighted average with the sequence $\left(hl_k\left(X_{N_1},\cdots,X_{N_k}\right)\right)_{N=1}^{\binom{n}{k}}$ as an input. The asymptotic breakdown point of $\mathrm{WeHLM}_{k,\epsilon,\gamma}$ is $\epsilon = 1-(1-\epsilon_0)^{\frac{1}{k}}$ (proven in another relavant paper). Bootstrap can be used to ensure the continuity of k and therefore the breakdown point, i.e., let the bootstrap size be b, then sampling $(1-k+\lfloor k\rfloor)b$ times with the size of each sampling, $\lfloor k\rfloor$, then sampling $(1-\lceil k\rceil+k)b$ times with the size of each sampling, $\lceil k\rceil$, then computing the pooled kernel distributions. The $k=1$ case is the weighted average. Set the WA as TM_{ϵ_0}, it was named as trimmed H-L mean here (Figure 1, $\epsilon_0 = \frac{15}{64}$). $\mathrm{THLM}_{k=2}$ is close to the Wilcoxon's one-sample statistic investigated by Saleh in 1976 (48), which is first censoring the sample, and then computing the pairwise means. The hl_2 kernel distribution has a probability density function $f_{hl_2}(x) = \int_0^{2x} 2f(t)\, f(2x-t)\, dt$ (a result after the transformation of variables), the support of the original distribution is assumed to be $[0,\infty)$ for simplicity. The expected value of the H-L estimator is the positive solution of $\int_0^{\text{H-L}} \left(f_{hl_2}(s)\right) ds = \frac{1}{2}$. Due to the complexity of this equation, analytically proving the validity of the mean-H-L-median inequality for a distribution is hard. As an example, for the exponential distribution, $f_{hl_2}(x) = 4\lambda^{-2}xe^{-2\lambda^{-1}x}$, $E[\text{H-L}] = \frac{-W_{-1}\left(-\frac{1}{2e}\right)-1}{2}\lambda \approx 0.839\lambda$, where W is the Lambert W function.

Analogous to the trimming inequality, the Hodges-Lehmann inequality can be defined as $\forall k_2 \geq k_1 \geq 1, m\mathrm{HLM}_{k_2} \geq m\mathrm{HLM}_{k_1}$, where $m\mathrm{HLM}_k$ is setting the WA as median. Since $m\mathrm{HLM}_{k=1} = m$, $m\mathrm{HLM}_{k=2} =$H-L, $m\mathrm{HLM}_{k=\infty} = \mu$, if a distribution follows the H-L inequality, it also follows the mean-H-L-median inequality. Furthermore, the Hodges-Lehmann inequality is a special case of the γ-U-orderliness, i.e.,

$$(\forall k_2 \geq k_1 \geq 1, \mathrm{QHLM}_{k_2,\epsilon,\gamma} \geq \mathrm{QHLM}_{k_1,\epsilon,\gamma}) \vee$$
$$(\forall k_2 \geq k_1 \geq 1, \mathrm{QHLM}_{k_2,\epsilon,\gamma} \leq \mathrm{QHLM}_{k_1,\epsilon,\gamma}),$$

where QHLM_k is setting the WA as QA. The direction of the inequality depends on the relative magnitudes of $\mathrm{QA}_{\epsilon,\gamma}$ and μ, since $\mathrm{QHLM}_{k=1,\epsilon,\gamma} = \mathrm{QA}_{\epsilon,\gamma}$ and $\mathrm{QHLM}_{k=\infty,\epsilon,\gamma} = \mu$. U-orderliness is defined as setting $\gamma = 1$.

Theorem .11. *U-orderliness implies orderliness.*

Proof. Suppose $n \bmod 2 = 0$, $n \to \infty$, $\frac{1}{2}(X_1+X_n) \geq \ldots \geq \frac{1}{2}(X_i+X_{n-i+1}) \geq \ldots \geq \frac{1}{2}\left(X_{\frac{n}{2}}+X_{\frac{n}{2}+1}\right)$ is valid for a sample from a right-skewed ordered distribution. Let $\tilde{\epsilon} = \frac{i}{n}$, when $\tilde{\epsilon} \to 0$, $\mathrm{SmQHLM}_{k_2,\tilde{\epsilon}} \leq \mathrm{SmQHLM}_{k_1,\tilde{\epsilon}}$ is equivalent to the orderliness, since $\mathrm{SmQHLM}_{k=j,\tilde{\epsilon}\to 0,n} = \frac{1}{2j}\left(\sum_{i=1}^{j}(X_i+X_{n-i+1})\right)$ and Theorem .7 implies that $\mu \leq \mathrm{SQA}_{\epsilon}$. ◻

Be aware that the U-orderliness itself does not assume any orderliness within the hl_k kernel distribution. The $hl_{k=n-1}$ kernel distribution has n elements, and their order is the same as the original distribution, so it is ordered if and only if the original distribution is ordered. If assuming symmetry, the result is trivial since the k-fold convolutions of a symmetric distribution is also symmetric (proved by Laha in 1961)(49). However, proving other cases is challenging. For example, $f'_{hl_2}(x) = 4f(2x)\, f(0) + \int_0^{2x} 4f(t)\, f'(2x-t)\, dt$, the strict negative of $f'_{hl_2}(x)$ is not guaranteed if just assuming $f'(x) < 0$, so, even if the original distribution is monotonic, the hl_2 kernel distribution might be non-monotonic. Also, unlike the pairwise difference distribution, if the original distribution is unimodal, the pairwise mean distribution might be non-unimodal, as demonstrated by a counterexample given by Chung in 1953 and mentioned by Hodges and Lehmann in 1954 (50, 51). If all hl_k kernel distributions, $k \geq 1$, are νth ordered, then the distribution is νth U-ordered. From that, the binomial H-L mean (set the WA as BM) can be constructed (Figure 1), while its maximum breakdown point is ≈ 0.065 if $\nu = 3$. A comparison of the biases of $\mathrm{BM}_{\nu=3,\epsilon=\frac{1}{8}}$, $\mathrm{SQM}_{\epsilon=\frac{1}{8}}$, $\mathrm{THLM}_{k=2,\epsilon=\frac{1}{8}}$, $\mathrm{WHLM}_{k=2,\epsilon=\frac{1}{8}}$, $\mathrm{MHHLM}_{k=\frac{2\ln(2)-\ln(3)}{3\ln(2)-\ln(7)},\epsilon=\frac{1}{8}}$ (midhinge H-

L mean), $m\mathrm{HLM}_{k=\frac{\ln(2)}{3\ln(2)-\ln(7)},\epsilon=\frac{1}{8}}$, $\mathrm{THLM}_{k=5,\epsilon=\frac{1}{8}}$, and $\mathrm{WHLM}_{k=5,\epsilon=\frac{1}{8}}$ is appropriate (Figure 1, SI Dataset S1), given their same breakdown points, with $m\mathrm{HLM}_{k=\frac{\ln(2)}{3\ln(2)-\ln(7)},\epsilon=\frac{1}{8}}$ exhibiting the smallest biases. This result and Theorem .11 align with Devroye et al. (2016)'s seminal work that MoM is nearly optimal with regards to concentration bounds for heavy-tailed distributions (21), since when k is much smaller than n, the difference between sampling with replacement and without replacement is negligible, $m\mathrm{HLM}_{k,n}$ is asymptotically equivalent to $\mathrm{MoM}_{k,b=\frac{n}{k}}$ if assuming k is a constant. Hence, $\mathrm{MoM}_{k,b=\frac{n}{k}}$ is also based on U-orderliness.

In 1958, Richtmyer introduced the concept of quasi-Monte Carlo simulation that utilizes low-discrepancy sequences, resulting in a significant reduction in computational expenses for large sample simulation (52). Among various numerical sets, Sobol sequences are often favored in quasi-Monte Carlo methods (53). Building upon this principle, in 1991, Do and Hall extended it to bootstrap and found that the quasi-random approach resulted in lower variance compared to other bootstrap Monte Carlo procedures (54). By using a deterministic approach, the variance of $m\mathrm{HLM}_{k,n}$ is much lower than that of $\mathrm{MoM}_{k,b=\frac{n}{k}}$ (SI Dataset S1), when k is small. This highlights the superiority of the median Hodges-Lehmann mean over the median of means, as it not only can provide an accurate estimate for moderate sample sizes, but also allows the use of quasi-bootstrap, where the bootstrap size can be adjusted as needed.

Data Availability. Data for Figure 1 are given in SI Dataset S1. All codes are attached.

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