Semiparametric robust mean estimations based on the orderliness of quantile averages

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As arguably 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 with respect to mean can be quite different in asymmetric distributions, but the underlying mechanisms remain largely unclear. Here, 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 supremacy of weighted 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. Bernard, Kazzi, and Vanduffel (2020) (2) derived bias bounds for the ϵ-symmetric quantile average (SQA_ϵ) for unimodal distributions, building on the works of Karlin and Novikoff (1963) and Li, Shao, Wang, and Yang (2018) (3, 4). They showed that the population median, m, has the smallest maximum distance to the population mean, μ, among all symmetric quantile averages. Daniell, in 1920, (5) analyzed a class of estimators, linear combinations of order statistics, and identified that ϵ-symmetric trimmed mean (TM_ϵ) belongs to this class. Another popular choice, the ϵ-symmetric Winsorized mean (WM_ϵ), which was named after Winsor and introduced by Tukey (6) and Dixon (7) in 1960, is also an L-statistic. Without assuming unimodality, Bieniek (2016) derived exact bias upper bounds of the Winsorized mean based on Danielak and Rychlik's work (2003) on the trimmed mean and confirmed that the former is smaller than the latter (8, 9). In 1964, Huber (10) introduced an M-estimator that can minimize the impact of outliers on parameter estimation by combining the squared error loss and absolute error loss in its objective function. While some L-statistics are also M-statistics, e.g., median, M-statistics are generally very different. Minsker (2018) (11) and Mathieu (2022) (12) studied the concentration bounds of M-statistics. Comparing these bounds to those of nonparametric L-statistics (13), it is obvious that that the worse-case performance of M-statistics is generally inferior. In 1963, Hodges and Lehmann (14) proposed a class of nonparametric location estimators based on rank tests and, from the Wilcoxon signed-rank statistic (15), deduced the median of pairwise means as a robust location estimator for a symmetric population. The concept of median of means ($\mathrm{MoM}_{k,b}$, k is the number of size in each block, b is the number of blocks) was implicit several times in Nemirovsky and Yudin (1983) (16), Jerrum, Valiant, and Vazirani (1986), (17) and Alon, Matias and Szegedy (1996) (18)'s works. Having good performance even for distributions with infinite second moments, the advantages of MoM have received increasing attention over the past decade (13, 19–25). Devroye, Lerasle, Lugosi, and Oliveira (2016) showed that MoM nears the optimum of nonparametric mean estimation with regards to concentration bounds when the distribution has a heavy tail (13). Asymptotically, the Hodges-Lehmann (H-L) estimator is equivalent to $\mathrm{MoM}_{k=2,b=\frac{n}{k}}$, and it can be seen as the pairwise mean distribution is approximated by the bootstrap and sampling without replacement, respectively (for the asymptotic validity, the reader is referred to the foundational works of Efron (1979) (26), Bickel and Freedman (1981, 1984) (27, 28), and Helmers, Janssen, and Veraverbeke (1990) (29)).

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

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

where $X_1 \leq \ldots \leq X_n$ denote the order statistics of a sample of n independent and identically distributed random variables $X_1, \ldots, X_n$, $\epsilon \bmod \frac{2}{b-1} = 0$, $\frac{1}{\epsilon} \geq 9$, $b \in \mathbb{N}$. $n \geq \frac{b-1}{2\epsilon}$. If the subscript n is omitted, only the asymptotic behavior is considered. If b is omitted, $b=3$ is assumed. In situations where $n \bmod \frac{b-1}{2\epsilon} \neq 0$, a possible solution is to generate several smaller samples that satisfy the equality by sampling without replacement, and then computing the mean of all estimations. This procedure can be viewed as sampling smaller samples from the population several times, thereby preserves the original distribution. The basic idea of the stratified mean is to

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 inequalities, 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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distribute the random variables into $\frac{b-1}{2\epsilon}$ blocks according to their order, then further sequentially group these blocks into b strata and compute the mean of the middle stratum, which is the median of means of each stratum. Therefore, the stratified mean is a type of stratum mean in stratified sampling introduced by Neyman in 1934 (30). Although the principle is similar to that of the median of means, without the random shift, the result is different from $\mathrm{MoM}_{k=\frac{n}{b},b}$. The median of means and stratified mean are consistent mean estimators if their asymptotic breakdown points are zero. However, if $\epsilon = \frac{1}{9}$, the biases of the $\mathrm{SM}_{\frac{1}{9}}$ and the $\mathrm{WM}_{\frac{1}{9}}$ are almost indistinguishable in common asymmetric distributions (Figure **??**, if no other subscripts, ϵ is omitted for simplicity), meaning that their robustness to departures from the symmetry assumption is practically similar. More importantly, the bounds confirm that the worst-case performance of Winsorized mean are better than those of the trimmed mean in terms of bias (8, 9), the complexity of bound analysis makes it difficult to achieve a complete and intuitive understanding. The aim of this paper is to define a series of semiparametric models using inequalities, 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 typically have strong robustness to departures from assumptions.

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

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