

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 symmetric trimmed mean, symmetric Winsorized mean, Hodges–Lehmann estimator, Huber M -estimator, and median of means. Recent studies suggest that their maximum biases concerning the mean can be quite different in asymmetric distributions, but the underlying mechanisms and average performance remain largely unclear. In this article, similar to the mean-median-mode inequality, it is proven that within the context of nearly all common unimodal distributions, there is an orderliness of symmetric quantile averages with varying breakdown points. Further deductions explain why the Winsorized mean and median of means typically 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 with finite second moments 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 $_{\epsilon}$). Daniell, in 1920, (3) analyzed a class of estimators, linear combinations of order statistics, and identified that ϵ -symmetric trimmed mean (STM $_{\epsilon}$) belongs to this class. Another popular choice, the ϵ -symmetric Winsorized mean (SWM $_{\epsilon}$), 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 -estimators are also M -estimators, e.g., the sample mean is an M -estimator with a squared error loss function, 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 -estimators 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 (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 (16–18). 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 (17). For a comparison of concentration bounds of trimmed mean, Huber M -estimator, median of means and other relevant estimators, readers are directed to Gobet, Lerasle, and Métivier's paper (2022) (19). Laforgue, Clemencon, and Bertail (2019) proposed the median of randomized means (MoRM $_{k,b}$) (18), wherein, rather than partitioning, an arbitrary number, b , of blocks are built independently from the sample, and showed that MoRM has a better non-asymptotic sub-Gaussian property compared to MoM. In fact, asymptotically, the Hodges–Lehmann (H-L) estimator is equivalent to MoM $_{k=2,b=\frac{n}{k}}$ and 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) (20), Bickel and

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, instead of examining 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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71 Freedman (1981, 1984) (21, 22), and Helmers, Janssen, and
72 Veraverbeke (1990) (23).

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

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

73 where $X_1 \leq \dots \leq X_n$ denote the order statistics of a sample
74 of n independent and identically distributed random variables
75 X_1, \dots, X_n . $b \in \mathbb{N}$, $b \geq 3$. The definition was further refined to
76 guarantee the continuity of the breakdown point by incorporat-
77 ing an additional block in the center when $\lfloor \frac{b-1}{2b\epsilon} \rfloor \bmod 2 = 0$,
78 or by adjusting the central block when $\lfloor \frac{b-1}{2b\epsilon} \rfloor \bmod 2 = 1$ (SI
79 Text). If the subscript n is omitted, only the asymptotic
80 behavior is considered. If b is omitted, $b = 3$ is assumed.
81 $SM_{\epsilon, b=3}$ is equivalent to STM_{ϵ} , when $\epsilon > \frac{1}{6}$. The basic idea
82 of the stratified mean, when $\frac{b-1}{2\epsilon} \in \mathbb{N}$, $b \bmod 2 = 1$, is to dis-
83 tribute the data into $\frac{b-1}{2\epsilon}$ equal-sized non-overlapping blocks
84 according to their order, then further sequentially group these
85 blocks into b equal-sized strata and compute the mean of the
86 middle stratum, which is the median of means of each stratum.
87 In situations where $i \bmod 1 \neq 0$, a potential solution is to
88 generate multiple smaller samples that satisfy the equality
89 by sampling without replacement, and subsequently calculate
90 the mean of all estimations. The details of determining the
91 sample size and sampling times are provided in the SI Text.
92 Although the principle resembles that of the median of means,
93 without the random shift, $SM_{\epsilon, b, n}$ is different from $MoM_{k=\frac{n}{b}, b}$.
94 Additionally, the stratified mean differs from the mean of the
95 sample obtained through stratified sampling methods, intro-
96 duced by Neyman (1934) (24) or ranked set sampling (25),
97 introduced by McIntyre in 1952, as these sampling methods
98 aim to obtain more representative samples or improve the
99 efficiency of sample estimates, but the sample means based
100 on them are not robust. When $b \bmod 2 = 1$, the stratified
101 mean can be regarded as replacing the other equal-sized strata
102 with the middle stratum, which, in principle, is analogous to
103 the Winsorized mean that replaces extreme values with less
104 extreme percentiles. Furthermore, while the bounds confirm
105 that the Winsorized mean and median of means outperform
106 the trimmed mean (6, 7, 17, 19) in worst-case performance,
107 the complexity of bound analysis makes it difficult to achieve a
108 complete and intuitive understanding of these results. Also, a
109 clear explanation for the average performance of them remains
110 elusive. The aim of this paper is to define a series of semi-
111 parametric models using the signs of derivatives, reveal their
112 elegant interrelations and connections to parametric models,
113 and show that by exploiting these models, a set of sophisti-
114 cated mean estimators can be deduced, which exhibit strong
115 robustness to departures from assumptions.

116 Quantile average and weighted average

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

$$SWA_{\epsilon, n} := \frac{\sum_{i=1}^{\lceil \frac{n}{2} \rceil} \frac{X_i + X_{n-i+1}}{2} w_i}{\sum_{i=1}^{\lceil \frac{n}{2} \rceil} w_i},$$

where w_i s are the weights applied to the symmetric quantile
averages according to the definition of the corresponding L -
estimators. 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 asymmet-
ric case, there are two possible definitions for the ϵ, γ -quantile
average (QA(ϵ, γ, n)), i.e.,

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

and

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

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 essen-
tially 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

$$WA_{\epsilon, \gamma, n} := \frac{\int_{\epsilon_0=0}^{\frac{1}{1+\gamma}} QA(\epsilon_0, \gamma, n) w_{\epsilon_0}}{\int_{\epsilon_0=0}^{\frac{1}{1+\gamma}} w_{\epsilon_0}}.$$

For instance, the ϵ, γ -trimmed mean ($TM_{\epsilon, \gamma, n}$) is a weighted
average with a left trim size of γn and a right trim size of $n\epsilon$,
where $w_{\epsilon_0} = \begin{cases} 0, & \epsilon_0 < \epsilon \\ 1, & \epsilon_0 \geq \epsilon \end{cases}$. According to this definition, even
 $\gamma n \notin \mathbb{N}$ or $n\epsilon \notin \mathbb{N}$, the TM computation remains unaltered
since it is based on the empirical quantile function. However,
considering the computational cost, here, the solution to the
decimal issue in WA, in most cases, is the same as that in SM,
unless specified otherwise.

Data Availability. Data for Figure ?? are given in SI Dataset
S1. All codes have been deposited in [GitHub](#).

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