

# Semiparametric robust mean estimations based on the orderliness of quantile averages

Tuban Lee

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## Hodges–Lehmann inequality and $\gamma$ - $U$ -orderliness

The Hodges–Lehmann estimator stands out as a unique robust location estimator due to its definition being substantially dissimilar from conventional  $L$ -estimators,  $R$ -estimators, and  $M$ -estimators. In their landmark paper, *Estimates of location based on rank tests*, Hodges and Lehmann (1) proposed two methods for computing the H-L estimator: the Wilcoxon score  $R$ -estimator and the median of pairwise means. The Wilcoxon score  $R$ -estimator is a location estimator based on signed-rank test, or  $R$ -estimator, (1) and was later independently discovered by Sen (1963) (2, 3). However, the median of pairwise means is a generalized  $L$ -statistic and a trimmed  $U$ -statistic, as classified by Serfling in his novel conceptualized study in 1984 (4). Serfling further advanced the understanding by generalizing the H-L kernel as  $hl_k(x_1, \dots, x_k) = \frac{1}{k} \sum_{i=1}^k x_i$ , where  $k \in \mathbb{N}$  (4). Here, the weighted H-L kernel is defined as  $whl_k(x_1, \dots, x_k) = \frac{\sum_{i=1}^k x_i \mathbf{w}_i}{\sum_{i=1}^k \mathbf{w}_i}$ , where  $\mathbf{w}_i$ s are the weights applied to each element.

By using the weighted H-L kernel and the  $L$ -estimator, it is now clear that the Hodges–Lehmann estimator is an  $LL$ -statistic, the definition of which is provided as follows:

$$LL_{k,\epsilon,\gamma,n} := L_{\epsilon_0,\gamma,n} \left( \text{sort} \left( (whl_k(X_{N_1}, \dots, X_{N_k}))_{N=1}^{\binom{n}{k}} \right) \right),$$

where  $L_{\epsilon_0,\gamma,n}(Y)$  represents the  $\epsilon_0, \gamma$ - $L$ -estimator that uses the sorted sequence,  $\text{sort} \left( (whl_k(X_{N_1}, \dots, X_{N_k}))_{N=1}^{\binom{n}{k}} \right)$ , as input. The upper asymptotic breakdown point of  $LL_{k,\epsilon,\gamma}$  is  $\epsilon = 1 - (1 - \epsilon_0)^{\frac{1}{k}}$ , as proven in DSSM II. There are two ways to adjust the breakdown point: either by setting  $k$  as a constant and adjusting  $\epsilon_0$ , or by setting  $\epsilon_0$  as a constant and adjusting  $k$ . In the above definition,  $k$  is discrete, but the bootstrap method can be applied to ensure the continuity of  $k$ , also making the breakdown point continuous. Specifically, if  $k \in \mathbb{R}$ , let the bootstrap size be denoted by  $b$ , then first sampling the original sample  $(1 - k + [k])b$  times with each sample size of  $[k]$ , and then subsequently sampling  $(1 - [k] + k)b$  times with each sample size of  $[k]$ ,  $(1 - k + [k])b \in \mathbb{N}$ ,  $(1 - [k] + k)b \in \mathbb{N}$ . The corresponding kernels are computed separately, and the pooled sorted sequence is used as the input for the  $L$ -estimator. Let  $\mathbf{S}_k$  represent the sorted sequence. Indeed, for any finite sample,  $X$ , when  $k = n$ ,  $\mathbf{S}_k$  becomes a single point,  $whl_{k=n}(X_1, \dots, X_n)$ . When  $\mathbf{w}_i = 1$ , the minimum of  $\mathbf{S}_k$  is  $\frac{1}{k} \sum_{i=1}^k X_i$ , due to the property of order statistics. The maximum of  $\mathbf{S}_k$  is  $\frac{1}{k} \sum_{i=1}^k X_{n-i+1}$ . The monotonicity of the order statistics implies the monotonicity of the extrema with respect to  $k$ , i.e., the support of  $\mathbf{S}_k$  shrinks monotonically. For

unequal  $\mathbf{w}_i$ s, the shrinkage of the support of  $\mathbf{S}_k$  might not be strictly monotonic, but the general trend remains, since all  $LL$ -statistics converge to the same point, as  $k \rightarrow n$ . Therefore, if  $\frac{\sum_{i=1}^n X_i \mathbf{w}_i}{\sum_{i=1}^n \mathbf{w}_i}$  approaches the population mean when  $n \rightarrow \infty$ , all  $LL$ -statistics based on such consistent kernel function approach the population mean as  $k \rightarrow \infty$ . For example, if  $whl_k = \text{BM}_{\nu,\epsilon_k,n=k}$ ,  $\nu \ll \epsilon_k^{-1}$ ,  $\epsilon_k \rightarrow 0$ , such kernel function is consistent. These cases are termed the  $LL$ -mean ( $LLM_{k,\epsilon,\gamma,n}$ ). By substituting the  $WA_{\epsilon_0,\gamma,n}$  for the  $L_{\epsilon_0,\gamma,n}$  in  $LL$ -statistic, the resulting statistic is referred to as the weighted  $L$ -statistic ( $WL_{k,\epsilon,\gamma,n}$ ). The case having a consistent kernel function is termed as the weighted  $L$ -mean ( $WLM_{k,\epsilon,\gamma,n}$ ). The  $w_i = 1$  case of  $WLM_{k,\epsilon,\gamma,n}$  is termed the weighted Hodges–Lehmann mean ( $WHLM_{k,\epsilon,\gamma,n}$ ). The  $WHLM_{k=1,\epsilon,\gamma,n}$  is the weighted average. If  $k \geq 2$  and the  $WA$  in  $WHLM$  is set as  $TM_{\epsilon_0}$ , it is called the trimmed H-L mean (Figure ??,  $k = 2$ ,  $\epsilon_0 = \frac{15}{64}$ ). The  $THLM_{k=2,\epsilon,\gamma=1,n}$  appears similar to the Wilcoxon's one-sample statistic investigated by Saleh in 1976 (5), which involves first censoring the sample, and then computing the mean of the number of events that the pairwise mean is greater than zero. The  $THLM_{k=2,\epsilon=1-(1-\frac{1}{2})^{\frac{1}{2}},\gamma=1,n}$  is the Hodges–Lehmann estimator, or more generally, a special case of the median Hodges–Lehmann mean ( $mHLM_{k,n}$ ).  $mHLM_{k,n}$  is asymptotically equivalent to the  $\text{MoM}_{k,b=\frac{n}{k},n}$  as discussed previously. Therefore, it is possible to define a series of location estimators, analogous to the  $WHLM$ , based on  $\text{MoM}$ . For example, the  $\gamma$ -median of means,  $\gamma\text{moM}_{k,b=\frac{n}{k},n}$ , is defined by replacing the median in  $\text{MoM}_{k,b=\frac{n}{k},n}$  with the  $\gamma$ -median.

The  $hl_k$  kernel distribution, denoted as  $F_{hl_k}$ , can be defined as the probability distribution of the sorted sequence  $\text{sort} \left( (hl_k(X_{N_1}, \dots, X_{N_k}))_{N=1}^{\binom{n}{k}} \right)$ . For any real value  $y$ , the cdf of the  $hl_k$  kernel distribution is given by:  $F_{hl_k}(y) = \text{Pr}(Y_i \leq y)$ , where  $Y_i$  represents an individual element from the sorted sequence. The overall  $hl_k$  kernel distributions possess a two-dimensional structure, encompassing  $n$  kernel distributions with varying  $k$  values, from 1 to  $n$ , where one dimension is inherent to each individual kernel distribution, while the other is formed by the alignment of the same percentiles across all kernel distributions. As  $k$  increases, all percentiles converge to  $\bar{X}$ , leading to the concept of  $\gamma$ - $U$ -orderliness:

$$(\forall k_2 \geq k_1 \geq 1, \gamma mHLM_{k_2,\epsilon=1-(\frac{\gamma}{1+\gamma})^{\frac{1}{k_2}},\gamma} \geq \gamma mHLM_{k_1,\epsilon=1-(\frac{\gamma}{1+\gamma})^{\frac{1}{k_1}},\gamma}) \vee$$

$$(\forall k_2 \geq k_1 \geq 1, \gamma mHLM_{k_2,\epsilon=1-(\frac{\gamma}{1+\gamma})^{\frac{1}{k_2}},\gamma} \leq \gamma mHLM_{k_1,\epsilon=1-(\frac{\gamma}{1+\gamma})^{\frac{1}{k_1}},\gamma}),$$

where  $\gamma mHLM_k$  sets the  $WA$  in  $WHLM$  as  $\gamma$ -median, with  $\gamma$  being constant. The direction of the inequality depends

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<sup>1</sup>To whom correspondence should be addressed. E-mail: tl@biomathematics.org

on the relative magnitudes of  $\gamma m \text{HLM}_{k=1, \epsilon, \gamma} = \gamma m$  and  $\gamma m \text{HLM}_{k=\infty, \epsilon, \gamma} = \mu$ . The Hodges-Lehmann inequality can be defined as a special case of the  $\gamma$ - $U$ -orderliness when  $\gamma = 1$ . When  $\gamma \in \{0, \infty\}$ , the  $\gamma$ - $U$ -orderliness is valid for any distribution as previously shown. If  $\gamma \notin \{0, \infty\}$ , analytically proving the validity of the  $\gamma$ - $U$ -orderliness for a parametric distribution is pretty challenging. As an example, 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  $\int_0^{\text{H-L}} (f_{hl_2}(s)) ds = \frac{1}{2}$ . For the exponential distribution,  $f_{hl_2, exp}(x) = 4\lambda^{-2}xe^{-2\lambda^{-1}x}$ ,  $\lambda$  is a scale parameter,  $E[\text{H-L}] = \frac{-W_{-1}(-\frac{1}{2e})-1}{2}\lambda \approx 0.839\lambda$ , where  $W_{-1}$  is a branch of the Lambert  $W$  function which cannot be expressed in terms of elementary functions. However, the violation of the  $\gamma$ - $U$ -orderliness is bounded under certain assumptions, as shown below.

**Theorem 1.** *For any distribution with a finite second central moment,  $\sigma^2$ , the following concentration bound can be established for the  $\gamma$ -median of means,*

$$\mathbb{P}\left(\gamma m \text{M}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right) \leq e^{-\frac{2n}{k}\left(\frac{1}{1+\gamma} - \frac{1}{k+t^2}\right)^2}.$$

*Proof.* Denote the mean of each block as  $\hat{\mu}_i$ ,  $1 \leq i \leq b$ . Observe that the event  $\left\{\gamma m \text{M}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right\}$  necessitates the condition that there are at least  $b(1 - \frac{\gamma}{1+\gamma})$  of  $\hat{\mu}_i$ s larger than  $\mu$  by more than  $\frac{t\sigma}{\sqrt{k}}$ , i.e.,  $\left\{\gamma m \text{M}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right\} \subset \left\{\sum_{i=1}^b \mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} \geq b\left(1 - \frac{\gamma}{1+\gamma}\right)\right\}$ , where  $\mathbf{1}_A$  is the indicator of event  $A$ . Assuming a finite second central moment,  $\sigma^2$ , it follows from one-sided Chebeshev's inequality that  $\mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right) = \mathbb{P}\left((\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}\right) \leq \frac{\sigma^2}{k\sigma^2 + t^2\sigma^2}$ . Given that  $\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} \in [0, 1]$  are independent and identically distributed random variables, by one-sided Hoeffding's inequality,  $\mathbb{P}\left(\gamma m \text{M}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right) \leq \mathbb{P}\left(\sum_{i=1}^b \mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} \geq b\left(1 - \frac{\gamma}{1+\gamma}\right)\right) = \mathbb{P}\left(\frac{1}{b} \sum_{i=1}^b \left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right) \geq \left(1 - \frac{\gamma}{1+\gamma}\right) - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right) \leq e^{-2b\left(\left(1 - \frac{\gamma}{1+\gamma}\right) - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right)^2} \leq e^{-2b\left(1 - \frac{\gamma}{1+\gamma} - \frac{\sigma^2}{k\sigma^2 + t^2\sigma^2}\right)^2} = e^{-2b\left(\frac{1}{1+\gamma} - \frac{1}{k+t^2}\right)^2}.$   $\square$

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

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1. J Hodges Jr, E Lehmann, Estimates of location based on rank tests. *The Annals Math. Stat.* **34**, 598–611 (1963).

2. PK Sen, On the estimation of relative potency in dilution (-direct) assays by distribution-free methods. *Biometrics* pp. 532–552 (1963).
3. M Ghosh, MJ Schell, PK Sen, A conversation with pranab kumar sen. *Stat. Sci.* pp. 548–564 (2008).
4. RJ Serfling, Generalized l-, m-, and r-statistics. *The Annals Stat.* **12**, 76–86 (1984).
5. A Ehsanes Saleh, Hodges-lehmann estimate of the location parameter in censored samples. *Annals Inst. Stat. Math.* **28**, 235–247 (1976).