

Semiparametric robust mean estimations based on the orderliness of quantile averages

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Hodges–Lehmann inequality and γ - 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 ϵ_0, γ - 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 ϵ_0 , or by setting ϵ_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 ($WLM_{k,\epsilon,\gamma,n}$). 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_{ϵ_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 MoM . For example, the γ -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 γ -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: $F_{hl_k}(y) = \Pr(Y_i \leq y)$, 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 γ - 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 γ -median, with γ being constant. The direction of the inequality depends

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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 γ - U -orderliness when $\gamma = 1$. When $\gamma \in \{0, \infty\}$, the γ - U -orderliness is valid for any distribution as previously shown. If $\gamma \notin \{0, \infty\}$, analytically proving the validity of the γ - 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, $f_{hl_2, \text{exp}}(x) = 4\lambda^{-2}xe^{-2\lambda^{-1}x}$, λ 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 γ - U -orderliness is bounded under certain assumptions, as shown below.

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

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

Proof. Denote the mean of each block as $\hat{\mu}_i$, $1 \leq i \leq b$. Observe that the event $\left\{\gamma \text{moM}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right\}$ necessitates the condition that there are at least $b(1 - \frac{\gamma}{1+\gamma})$ of $\hat{\mu}_i$ s larger than μ by more than $\frac{t\sigma}{\sqrt{k}}$, i.e., $\left\{\gamma \text{moM}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right\} \subset \left\{\sum_{i=1}^b \mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} \geq b(1 - \frac{\gamma}{1+\gamma})\right\}$, where $\mathbf{1}_A$ is the indicator of event A . Assuming a finite second central moment, σ^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, according to the aforementioned inclusion relation, the one-sided Chebeshev's inequality and the one-sided Hoeffding's inequality, $\mathbb{P}\left(\gamma \text{moM}_{k, b=\frac{n}{k}, n} - \mu > \frac{t\sigma}{\sqrt{k}}\right) \leq \mathbb{P}\left(\sum_{i=1}^b \mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} \geq b(1 - \frac{\gamma}{1+\gamma})\right) = \mathbb{P}\left(\frac{1}{b} \sum_{i=1}^b \left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}} - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right) \geq \left(1 - \frac{\gamma}{1+\gamma}\right) - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right) \leq e^{-2b\left(\left(1 - \frac{\gamma}{1+\gamma}\right) - \mathbb{E}\left(\mathbf{1}_{(\hat{\mu}_i - \mu) > \frac{t\sigma}{\sqrt{k}}}\right)\right)^2} = e^{-2b\left(1 - \frac{\gamma}{1+\gamma} - \frac{\sigma^2}{k\sigma^2 + t^2\sigma^2}\right)^2} = e^{-2b\left(\frac{1}{1+\gamma} - \frac{1}{k+t^2}\right)^2}.$

Theorem .2. *Let $B(k, \gamma, t, n) = e^{-\frac{2n}{k}\left(\frac{1}{1+\gamma} - \frac{1}{k+t^2}\right)^2}$. If $n \in \mathbb{N}$, $\gamma \geq 0$, $0 \leq t^2 < \gamma + 1$, and $\gamma - t^2 + 1 \leq k \leq \frac{1}{2}\sqrt{9\gamma^2 + 18\gamma - 8\gamma t^2 - 8t^2 + 9} + \frac{1}{2}(3\gamma - 2t^2 + 3)$, B is monotonic decreasing with respect to k .*

Proof. Since $\frac{\partial B}{\partial k} = \left(\frac{2n\left(\frac{1}{\gamma+1} - \frac{1}{k+t^2}\right)^2}{k^2} - \frac{4n\left(\frac{1}{\gamma+1} - \frac{1}{k+t^2}\right)}{k(k+t^2)^2}\right)$

$$e^{-\frac{2n\left(\frac{1}{\gamma+1} - \frac{1}{k+t^2}\right)^2}{k^2}} \quad \text{and} \quad n \in \mathbb{N}, \quad \frac{\partial B}{\partial k} \leq 0 \quad \Leftrightarrow$$

$$\frac{2n\left(\frac{1}{\gamma+1} - \frac{1}{k+t^2}\right)^2}{k^2} - \frac{4n\left(\frac{1}{\gamma+1} - \frac{1}{k+t^2}\right)}{k(k+t^2)^2} \leq 0 \quad \Leftrightarrow$$

$$\frac{2n(-\gamma+k+t^2-1)(k^2-3(\gamma+1)k+2kt^2+t^2(-\gamma+t^2-1))}{(\gamma+1)^2k^2(k+t^2)^3} \leq 0 \quad \Leftrightarrow$$

$$(-\gamma+k+t^2-1)(k^2-3(\gamma+1)k+2kt^2+t^2(-\gamma+t^2-1)) \leq 0. \quad \text{When the factors are expanded, it yields a cubic inequality in terms of } k: k^3+k^2(3t^2-4(\gamma+1))+3k(\gamma-t^2+1)^2+t^2(\gamma-t^2+1)^2 \leq 0. \quad \text{Assuming } 0 \leq t^2 < \gamma+1 \text{ and } \gamma \geq 0,$$

$$\text{using the factored form and subsequently applying the quadratic formula, the inequality is valid if } \gamma - t^2 + 1 \leq k \leq \frac{1}{2}\sqrt{9\gamma^2 + 18\gamma - 8\gamma t^2 - 8t^2 + 9} + \frac{1}{2}(3\gamma - 2t^2 + 3). \quad \square$$

$$\text{Let } X \text{ be a random variable and } \bar{Y} = \frac{1}{k}(Y_1 + \dots + Y_k) \text{ be the average of } k \text{ independent, identically distributed copies of } X. \text{ Applying the variance operation gives: } \text{Var}(\bar{Y}) = \text{Var}\left(\frac{1}{k}(Y_1 + \dots + Y_k)\right) = \frac{1}{k^2}(\text{Var}(Y_1) + \dots + \text{Var}(Y_k)) = \frac{1}{k^2}(k\sigma^2) = \frac{\sigma^2}{k}, \text{ since the variance operation is a linear operator for independent variables, and the variance of a scaled random variable is the square of the scale times the variance of the variable, i.e., } \text{Var}(cX) = E[(cX - E[cX])^2] = E[(cX - cE[X])^2] = E[c^2(X - E[X])^2] = c^2E[(X - E[X])^2] = c^2\text{Var}(X). \text{ Thus, the standard deviation of the } hl_k \text{ kernel distribution, asymptotically, is } \frac{\sigma}{\sqrt{k}}. \text{ By utilizing the asymptotic bias bound of any quantile for any continuous distribution with a finite second central moment, } \sigma^2, (6), \text{ a conservative asymptotic bias bound of } \gamma \text{moM}_{k, b=\frac{n}{k}} \text{ can be established as } \gamma \text{moM}_{k, b=\frac{n}{k}} - \mu \leq \sqrt{\frac{\gamma}{1-\frac{\gamma}{1+\gamma}}} \sigma_{hl_k} = \sqrt{\frac{\gamma}{k}} \sigma. \text{ That implies in Theorem .1, } t < \sqrt{\gamma}, \text{ so when } \gamma = 1, \text{ the upper bound of } k, \text{ subject to the monotonic decreasing constraint, is } 2 + \sqrt{5} < \frac{1}{2}\sqrt{9 + 18 - 8t^2 - 8t^2 + 9} + \frac{1}{2}(3 - 2t^2 + 3) \leq 6, \text{ the lower bound is } 1 < 2 - t^2 \leq 2. \text{ These analyses elucidate a surprising result: although the conservative asymptotic bound of } \text{MoM}_{k, b=\frac{n}{k}} \text{ is monotonic with respect to } k, \text{ its concentration bound is optimal when } k \in (2 + \sqrt{5}, 6].$$

Then consider the structure within each individual hl_k kernel distribution. The sorted sequence \mathbf{S}_k , when $k = n - 1$, has n elements and the corresponding hl_k kernel distribution can be seen as a location-scale transformation of the original distribution, so the corresponding hl_k kernel distribution is ν th γ -ordered if and only if the original distribution is ν th γ -ordered according to Theorem ?? . Analytically 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 decreasing, 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 (7, 8). Theorem ?? implies that the violation of ν th γ -orderliness within the hl_k kernel distribution is also bounded, and the bound monotonically shrinks as k increases because the bound is in unit of the standard deviation of the

164 hl_k kernel distribution. If all hl_k kernel distributions are ν th
 165 γ -ordered and the distribution itself is ν th γ -ordered and γ - U -
 166 ordered, then the distribution is called ν th γ - U -ordered. The
 167 following theorems highlight the significance of γ -symmetric
 168 distributions.

169 **Theorem .3.** Any γ -symmetric distribution is ν th γ - U -
 170 ordered, provided that the γ is the same.

171 *Proof.* □

172 The succeeding theorem shows that the whl_k kernel distri-
 173 bution is invariably a location-scale distribution if the original
 174 distribution belongs to a location-scale family with the same
 175 location and scale parameters.

176 **Theorem .4.** $whl_k(x_1 = \lambda x_1 + \mu, \dots, x_k = \lambda x_k + \mu) =$
 177 $\lambda whl_k(x_1, \dots, x_k) + \mu.$

178 *Proof.* $whl_k(x_1 = \lambda x_1 + \mu, \dots, x_k = \lambda x_k + \mu) =$
 179 $\frac{\sum_{i=1}^k (\lambda x_i + \mu) w_i}{\sum_{i=1}^k w_i} = \frac{\sum_{i=1}^k \lambda x_i w_i + \sum_{i=1}^k \mu w_i}{\sum_{i=1}^k w_i} = \lambda \frac{\sum_{i=1}^k x_i w_i}{\sum_{i=1}^k w_i} +$
 180 $\frac{\sum_{i=1}^k \mu w_i}{\sum_{i=1}^k w_i} = \lambda \frac{\sum_{i=1}^k x_i w_i}{\sum_{i=1}^k w_i} + \mu = \lambda whl_k(x_1, \dots, x_k) + \mu. \quad \square$

181 According to Theorem .4, the γ -weighted inequality for a
 182 right-skewed distribution can be modified as $\forall 0 \leq \epsilon_{01} \leq \epsilon_{02} \leq$
 183 $\frac{1}{1+\gamma}$, $WLM_{k, \epsilon=1-(1-\epsilon_{01})^{\frac{1}{k}, \gamma}} \geq WLM_{k, \epsilon=1-(1-\epsilon_{02})^{\frac{1}{k}, \gamma}}$, which
 184 holds the same rationale as the γ -weighted inequality defined
 185 in the last section. If the ν th γ -orderliness is valid for the
 186 whl_k kernel distribution, then all results in the last section can
 187 be directly implemented. From that, the binomial H-L mean
 188 (set the WA as BM) can be constructed (Figure ??), while its
 189 maximum breakdown point is ≈ 0.065 if $\nu = 3$. A compar-
 190 ison of the biases of $BM_{\nu=3, \epsilon=\frac{1}{8}}$, $SQM_{\epsilon=\frac{1}{8}}$, $THLM_{k=2, \epsilon=\frac{1}{8}}$,
 191 $WHLM_{k=2, \epsilon=\frac{1}{8}}$, $MHLM_{k=\frac{2 \ln(2) - \ln(3)}{3 \ln(2) - \ln(7)}, \epsilon=\frac{1}{8}}$ (midhinge
 192 H-L mean), $mHLM_{k=\frac{\ln(2)}{3 \ln(2) - \ln(7)}, \epsilon=\frac{1}{8}}$, $THLM_{k=5, \epsilon=\frac{1}{8}}$,
 193 and $WHLM_{k=5, \epsilon=\frac{1}{8}}$ is appropriate (Figure ??, SI
 194 Dataset S1), given their same breakdown points, with
 195 $mHLM_{k=\frac{\ln(2)}{3 \ln(2) - \ln(7)}, \epsilon=\frac{1}{8}}$ exhibiting the smallest biases. This
 196 result align with Devroye et al. (2016)'s seminal work that
 197 MoM is nearly optimal with regards to concentration bounds
 198 for heavy-tailed distributions (9).

199 In 1958, Richtmyer introduced the concept of quasi-Monte
 200 Carlo simulation that utilizes low-discrepancy sequences, re-
 201 sulting in a significant reduction in computational expenses
 202 for large sample simulation (10).

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

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- 208 1. J Hodges Jr, E Lehmann, Estimates of location based on rank tests. *The Annals Math. Stat.*
 209 **34**, 598–611 (1963).
- 210 2. PK Sen, On the estimation of relative potency in dilution (-direct) assays by distribution-free
 211 methods. *Biometrics* pp. 532–552 (1963).
- 212 3. M Ghosh, MJ Schell, PK Sen, A conversation with pranab kumar sen. *Stat. Sci.* pp. 548–564
 213 (2008).
- 214 4. RJ Serfling, Generalized l-, m-, and r-statistics. *The Annals Stat.* **12**, 76–86 (1984).
- 215 5. A Ehsanes Saleh, Hodges-lehmann estimate of the location parameter in censored samples.
 216 *Annals Inst. Stat. Math.* **28**, 235–247 (1976).

6. L Li, H Shao, R Wang, J Yang, Worst-case range value-at-risk with partial information. *SIAM J.*
 217 *on Financial Math.* **9**, 190–218 (2018). 218
7. J Hodges, E Lehmann, Matching in paired comparisons. *The Annals Math. Stat.* **25**, 787–791
 219 (1954). 220
8. K Chung, Sur les lois de probabilité unimodales. *COMPTE RENDUS HEBDOMADAIRES*
 221 *DES SEANCES DE L ACADEMIE DES SCIENCES* **236**, 583–584 (1953). 222
9. L Devroye, M Lerasle, G Lugosi, RI Oliveira, Sub-gaussian mean estimators. *The Annals Stat.*
 223 **44**, 2695–2725 (2016). 224
10. RD Richtmyer, A non-random sampling method, based on congruences, for" monte carlo"
 225 problems, (New York Univ., New York. Atomic Energy Commission Computing and Applied ...),
 226 Technical report (1958). 227