Supporting Information for

Near-consistent robust estimations of moments for unimodal distributions

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Theorem 0.1. $\psi_k\left(x_1=\lambda x_1+\mu,\cdots,x_k=\lambda x_k+\mu\right)=\lambda^k\psi_k\left(x_1,\cdots,x_k\right)$.

Proof. ψ_k can be divided into k groups. From 1st to $k-1$th group, the gth group has $\binom{k}{g}\binom{g}{1}$ terms having the form $(-1)^{g+1}\frac{1}{k-g+1}x_{i_1}^{k-g+1}\ldots x_{i_g}$. The final kth group is the term $(-1)^{k-1}(k-1)\,x_1\cdots x_k$. Let $x_{i_1}=x_1$, $k\neq g$, the gth group of ψ_k has $\binom{k-l}{g-l}$ terms having the form $(-1)^{g+1}\frac{1}{k-g+1}x_1^{k-g+1}\,x_2\cdots x_l x_{i_1}\cdots x_{i_{g-l}}$, where $x_1,\ x_2,\cdots,x_l$ are fixed, $x_{i_1},\cdots,x_{i_{g-l}}$ are selected such that $i_1,\cdots,\ i_{g-l}\neq 1,2,\cdots,l$. Let $\Psi_k\left(x_1,x_2,\cdots,x_l,x_{i_1},\cdots,x_{i_{g-l}}\right)=(\lambda x_1+\mu)^{k-g+1}(\lambda x_2+\mu)\cdots(\lambda x_l+\mu)(\lambda x_{i_1}+\mu)\cdots\left(\lambda x_{i_{g-l}}+\mu\right)$, the first group of Ψ_k is $\lambda^k x_1\cdots x_l x_{i_1}\cdots x_{i_{g-l}}$, the hth group of Ψ_k, $h>1$, has $\binom{k-g+1}{k-h-l+2}$ terms having the form $\lambda^{k-h+1}\mu^{h-1}x_1^{k-h-l+2}x_2\cdots x_l$. Transforming ψ_k by Ψ_k, then combing all terms with $\lambda^{k-h+1}\mu^{h-1}x_1^{k-h-l+2}x_2\cdots x_l$, $x_1^{k-h-l+2}\neq x_1$, the summed coefficient is $S1_l=\sum_{g=l}^{h+l-1}(-1)^{g+1}\frac{1}{k-g+1}\binom{k-g+1}{k-h-l+2}\binom{k-l}{g-l}=\sum_{g=l}^{h+l-1}(-1)^{g+1}\frac{(k-l)!}{(h+l-g-1)!(k-h-l+2)!(g-l)!}=0$, since the summation is starting from l, ending at $h+l-1$, the first term includes the factor $g-l=0$, the final term includes the factor $h+l-g-1=0$, the terms in the middle are also zero due to the factorial property.

Another possible choice is letting one of $x_{i_2}\ldots x_{i_g}$ equal to x_1, the gth group of ψ_k has $(k-h)\binom{h-1}{g-k+h-1}$ terms having the form $(-1)^{g+1}\frac{1}{k-g+1}x_1x_2\ldots x_j^{k-g+1}\ldots x_{k-h+1}x_{i_1}\ldots x_{i_{g-k+h-1}}$, provided that $k\neq g$, $2\leq j\leq k-h+1$, where $x_1,\ldots,x_{k-h+1}$ are fixed, x_j^{k-g+1} and $x_{i_1},\cdots,x_{i_{g-k+h-1}}$ are selected. Transforming these terms by $\Psi_k\left(x_1,x_2,\ldots,x_j,\ldots,x_{k-h+1},x_{i_1},\ldots,x_{i_{g-k+h-1}}\right)$ $=(\lambda x_1+\mu)(\lambda x_2+\mu)\cdots(\lambda x_j+\mu)^{k-g+1}\cdots(\lambda x_{k-h+1}+\mu)(\lambda x_{i_1}+\mu)\cdots\left(\lambda x_{i_{g-k+h-1}}+\mu\right)$, then, there are $k-g+1$ terms having the form $\lambda^{k-h+1}\mu^{h-1}x_1x_2\ldots x_{k-h+1}$. So, the combined result is $(-1)^{g+1}(k-h)\binom{h-1}{g-k+h-1}\lambda^{k-h+1}\mu^{h-1}x_1x_2\ldots x_{k-h+1}$. Transforming the final kth group of ψ_k by Ψ_k, then, there is one term having the form $(-1)^{k-1}(k-1)\,\lambda^{k-h+1}\mu^{h-1}x_1x_2\ldots x_{k-h+1}$. Another possible combination is that the gth group of ψ_k contains $(g-k+h-1)\binom{h-1}{g-k+h-1}$ terms having the form $(-1)^{g+1}\frac{1}{k-g+1}$ $x_1x_2\ldots x_{k-h+1}x_{i_1}\ldots x_{i_j}^{k-g+1}\ldots x_{i_{g-k+h-1}}$, there is only one term having the form $\lambda^{k-h+1}\mu^{h-1}x_1x_2\ldots x_{k-h+1}$. The above summation $S1_l$ should also be included, i.e., $x_1^{k-h-l+2}=x_1$, $k=h+l-1$, so, combing all terms with $\lambda^{k-h+1}\mu^{h-1}x_1x_2\ldots x_{k-h+1}$, according to the binomial theorem, the summed coefficient is $S2_l=\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}\left(k-h+1+\frac{g-k+h-1}{k-g+1}\right)+(-1)^{k-1}(k-1)=(k-h+1)\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}+\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}\left(\frac{g-k+h-1}{k-g+1}\right)+(-1)^{k-1}(k-1)=(-1)^k(k-h+1)+(h-2)(-1)^k+(-1)^{k-1}(k-1)=0$. The summation identities are $\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}=(-1)^k$ and $\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}\left(\frac{g-k+h-1}{k-g+1}\right)=(h-2)(-1)^k$. These two summation identities are proven in Lemma 0.2 and 0.3. The result is the same if replacing x_1 with x_i, where i is from 2 to k, and replacing x_l with other x_i. Thus, all terms including μ can be canceled out. The proof is complete by noticing that the remaining part is $\lambda^k\psi_k\left(x_1,\cdots,x_k\right)$. □

Lemma 0.2. $\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}=(-1)^k$.

Proof. Let $u=k-h+1$, then the above identity becomes $\sum_{g=u}^{k-1}(-1)^{g+1}\binom{k-u}{g-u}=(-1)^k$. Then, by deducing,

$$\begin{aligned}\sum_{g=u}^{k-1}(-1)^{g+1}\binom{k-u}{g-u}&=\sum_{i=0}^{k-u-1}(-1)^{i+u+1}\binom{k-u}{i} && \text{(Substitute } i=g-u\text{)}\\&=(-1)^{k+2}+\sum_{i=0}^{k-u}(-1)^{i+u+1}\binom{k-u}{i}\\&=(-1)^{k+2}+(-1)^{u+1}\sum_{i=0}^{k-u}(-1)^{i}\binom{k-u}{i}\\&=(-1)^k && \text{(Apply the alternating sum identity),}\end{aligned}$$

the proof is complete.

□

Lemma 0.3. $\sum_{g=k-h+1}^{k-1}(-1)^{g+1}\binom{h-1}{g-k+h-1}\left(\frac{g-k+h-1}{k-g+1}\right)=(h-2)(-1)^k$.

Proof. Let $u=k-h+1$, then the above identity becomes $\sum_{g=u}^{k-1}(-1)^{g+1}\binom{k-u}{g-u-1}=(-1)^k(k-u-1)$. Then by deducing,

$$
\begin{aligned}
\sum_{g=u}^{k-1}(-1)^{g+1}\binom{k-u}{g-u-1} &= \sum_{i=-1}^{k-u-2}(-1)^{u+i+2}\binom{k-u}{i} && \text{(Substitute } i=g-u-1\text{)} \\
&= \sum_{i=0}^{k-u}(-1)^{u+i+2}\binom{k-u}{i} - \sum_{i=k-u-1}^{k-u}(-1)^{u+i+2}\binom{k-u}{i} && \text{(Apply the alternating sum identity)} \\
&= -\sum_{i=k-u-1}^{k-u}(-1)^{u+i+2}\binom{k-u}{i} \\
&= (-1)^{k+2}\binom{k-u}{k-u-1} + (-1)^{k+3}\binom{k-u}{k-u} \\
&= (-1)^{k+2}(k-u) + (-1)^{k+3} \\
&= (-1)^{k+2}(k-u-1),
\end{aligned}
$$

the proof is complete.

□

Theorem 0.4. *Given a U-statistic associated with a symmetric kernel of degree k. Then, assuming that as $n \to \infty$, k is a constant, the upper breakdown point of the weighted U-statistic is $1-(1-\epsilon)^{\frac{1}{k}}$, where ϵ is the upper breakdown point of the corresponding weighted L-statistic.*

Proof. Suppose m arbitrary large contaminants are added to the sample. The fraction of bad values in the sample can be represented as $\epsilon_{U_k} = \frac{m}{n+m}$, where n denotes the original number of data points that remain unaffected. In the kernel distribution, $\binom{n}{k}$ out of a total of $\binom{n+m}{k}$ points are not corrupted. Then, the breakdown can be avoided if the following inequality holds

$$
\binom{n}{k} > \left(\frac{1}{\epsilon}-1\right) \times \left(\binom{n+m}{k} - \binom{n}{k}\right).
$$

Since ϵ is the upper breakdown point of the corresponding weighted L-statistic, $\frac{1}{1+\gamma} \geq \epsilon \geq 0$,

$$
\frac{1}{1-\epsilon} > \frac{\binom{n+m}{k}}{\binom{n}{k}} = \frac{(n+m)(n+m-1)\dots(n+m-k+1)}{n(n-1)\dots(n-k+1)}.
$$

Assuming $n \to \infty$, k is a constant, $\lim_{n\to\infty}\left(\frac{n+m-k+1}{n-k+1}\right) = \frac{n+m}{n}$, then the above inequality does not hold when $\frac{n+m}{n} \geq \left(\frac{1}{1-\epsilon}\right)^{\frac{1}{k}}$. So, the upper asymptotic breakdown point of the weighted U-statistic is $\epsilon_{U_k} = \frac{m}{n+m} = 1 - \frac{n}{n+m} = 1-(1-\epsilon)^{\frac{1}{k}}$. □

Methods

A. SWLs in invariant moments. For invariant means, $m\text{HLM}_{k=4,\epsilon\approx 0.159,n}$, $\text{WHLM}_{k=4,\epsilon=\frac{1}{16},n}$, $\text{THLM}_{k=4,\epsilon=\frac{1}{16},n}$, $\text{BM}_{\epsilon=\frac{1}{16},n}$, $\text{SQM}_{\epsilon=\frac{1}{16},n}$, $\text{BM}_{\nu=2,\epsilon=\frac{1}{16},n}$, $\text{WM}_{\epsilon=\frac{1}{16},n}$, $\text{BWM}_{\epsilon=\frac{1}{16},n}$, and $\text{TM}_{\epsilon=\frac{1}{16},n}$ were used. For invariant second central moments, $m\text{HLM}_{k=4,\epsilon\approx 0.159,n}$, $\text{WHLM}_{k=4,\epsilon=\frac{31}{256},n}$, $\text{THLM}_{k=4,\epsilon=\frac{31}{256},n}$, $\text{BM}_{\epsilon=\frac{31}{256},n}$, $\text{SQM}_{\epsilon=\frac{31}{256},n}$, $\text{BM}_{\nu=2,\epsilon=\frac{31}{256},n}$, $\text{WM}_{\epsilon=\frac{31}{256},n}$, $\text{BWM}_{\epsilon=\frac{31}{256},n}$, and $\text{TM}_{\epsilon=\frac{31}{256},n}$ were used. For all SWAs, the sorted sample was divided into 9 blocks, 8 blocks are the same as those in $\text{BM}_{\epsilon=\frac{1}{8},n}$, the weight of the middle block is always 1 to ensure the continuity of the breakdown points, i.e., one additional block is added and the size is $\frac{1}{32}$ of the sample size. This strategy will also be used in the following SWAs. For invariant third central moments, $m\text{HLM}_{k=3,\epsilon\approx 0.206,n}$, $\text{WHLM}_{k=3,\epsilon=\frac{721}{4096},n}$, $\text{THLM}_{k=3,\epsilon=\frac{721}{4096},n}$, $\text{SQM}_{\epsilon=\frac{721}{4096},n}$, $\text{BM}_{\nu=2,\epsilon=\frac{721}{4096},n}$, $\text{WM}_{\epsilon=\frac{721}{4096},n}$, $\text{BWM}_{\epsilon=\frac{721}{4096},n}$, and $\text{TM}_{\epsilon=\frac{721}{4096},n}$ were used. For invariant fourth central moments, $m\text{HLM}_{k=2,\epsilon\approx 0.293,n}$, $\text{WHLM}_{k=2,\epsilon=\frac{14911}{65536},n}$, $\text{THLM}_{k=2,\epsilon=\frac{14911}{65536},n}$, $\text{SQM}_{\epsilon=\frac{14911}{65536},n}$, $\text{WM}_{\epsilon=\frac{14911}{65536},n}$, $\text{BWM}_{\epsilon=\frac{14911}{65536},n}$, and $\text{TM}_{\epsilon=\frac{14911}{65536},n}$ were used.

B. d value calibration. Asymptotic d values for the invariant central moments for the exponential distribution were approximated by a quasi-Monte Carlo study (1, 2) based on generating a large quasi-random sample with sample size 1.8 million from the exponential distribution and quasi-subsampling the sample $1.8k$ million times to approximate the distributions of the kernels of the corresponding U-statistics, then computing the binomial kth central moment (Bkm), median kth central moment (mkm), and corresponding quantiles, finally obtained by the formulae $d_{rkm} = \frac{km_{bs} - \text{B}km_{bs}}{\text{B}km_{bs} - mkm_{bs}}$ and $d_{qkm} = \frac{pkm_{bs} - p\text{B}km_{bs}}{p\text{B}km_{bs} - \frac{1}{2}}$, where $p\text{B}km = \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}_{X_i \leq (\text{B}km_{bs})}$, $pkm = \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}_{X_i \leq (km_{bs})}$, bs indicates the quasi-bootstrap moments. The accuracy of the estimates was verified by comparing the quasi-bootstrap central moments to their asymptotic values, yielding errors of ≈ 0.0003, ≈ 0.001, and ≈ 0.03 for the second, third, and fourth central moments, respectively. The sample standard deviation of the kernel distributions for these moments are 2.234, 9.627, and 60.064, respectively, resulting in standardized errors for the biases that were all smaller than 0.001, thus ensuring the accuracy implied in the number of significant digits of the values in Table 1. For invariant mean, the procedure is the same, just without quasi-bootstrap. The calculations of invariant moments using other symmetric weighted L-statistics were performed analogously by substituting of the appropriate values.

For finite sample, the d values were estimated using 1000 pseudorandom samples with sample size $n = 5400$ with a quasi-bootstrap size of 18000. To estimate the errors of d value estimations under finite sample size, first consider the first order Taylor approximation of the d value function, $d = \frac{x_1 - x_2}{x_2 - x_3} \approx d^0 + \frac{\partial d}{\partial x_1}x_1 + \frac{\partial d}{\partial x_2}x_2 + \frac{\partial d}{\partial x_3}x_3$. Then, by applying Bienaymé's identity, the variance of d can be approximated by $\sigma_d^2 \approx \left|\frac{\partial d}{\partial x_1}\right|^2 \sigma_{x_1}^2 + \left|\frac{\partial d}{\partial x_2}\right|^2 \sigma_{x_2}^2 + \left|\frac{\partial d}{\partial x_3}\right|^2 \sigma_{x_3}^2 + 2\left|\frac{\partial d}{\partial x_1}\right|\left|\frac{\partial d}{\partial x_2}\right| Cov\left(X_1, X_2\right) + 2\left|\frac{\partial d}{\partial x_1}\right|\left|\frac{\partial d}{\partial x_3}\right| Cov\left(X_1, X_3\right) + 2\left|\frac{\partial d}{\partial x_2}\right|\left|\frac{\partial d}{\partial x_3}\right| Cov\left(X_2, X_3\right) = \left|\frac{1}{x_2 - x_3}\right|^2 \sigma_{x_1}^2 + \left|-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right|^2 \sigma_{x_2}^2 + \left|\frac{x_1 - x_2}{(x_2 - x_3)^2}\right|^2 \sigma_{x_3}^2 + 2\left|\frac{1}{x_2 - x_3}\right|\left|-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right| Cov\left(X_1, X_2\right) + 2\left|\frac{1}{x_2 - x_3}\right|\left|\frac{x_1 - x_2}{(x_2 - x_3)^2}\right| Cov\left(X_1, X_3\right) + 2\left|-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right|\left|\frac{x_1 - x_2}{(x_2 - x_3)^2}\right| Cov\left(X_2, X_3\right)$. Since for the recombined mean, $\sigma_{x_1}^2 = 0$, so, $\sigma_{d_{rm}}^2 \approx \left|-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right|^2 \sigma_{x_2}^2 + \left|\frac{x_1 - x_2}{(x_2 - x_3)^2}\right|^2 \sigma_{x_3}^2 + 2\left(-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right)\left(\frac{x_1 - x_2}{(x_2 - x_3)^2}\right) Cov\left(X_2, X_3\right)$, where x_1 is the expected value, x_2 is the weighted average used, x_3 is the median. For quantile mean, since $\sigma_{x_3}^2 = 0$, $\sigma_{d_{qm}}^2 \approx \left|\frac{1}{x_2 - x_3}\right|^2 \sigma_{x_1}^2 + \left|-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right|^2 \sigma_{x_2}^2 + 2\left(\frac{1}{x_2 - x_3}\right)\left(-\frac{x_1 - x_2}{(x_2 - x_3)^2} - \frac{1}{x_2 - x_3}\right) Cov\left(X_1, X_2\right)$, where x_1 is the percentile of the expected value, x_2 is the percentile of the weighted average used, x_3 is the percentile of median, $\frac{1}{2}$. Finally, the errors were estimated by the corresponding sample statistics. The results of error estimation were included in the SI Dataset S1.

C. AAB, AB, and SSE. The computations of ABs and AABs for invariant central moments were described in the Main Text. The SSE was computed by approximating the sampling distribution with 1000 pseudorandom samples for $n = 5400$ and 30 pseudorandom samples for $n = 1.8 \times 10^6$. Common random numbers were used for better comparison. Analogous to the asymptotic bias, the scaled standard error can be standardized, averaged, and weighted. It should be noted that, in Table 1, for symmetric distributions, the generalized Gaussian, the standard errors were used for location and asymmetry estimators, since when the mean value is close to zero, the scaled standard error will approach infinity and therefore be too sensitive to small changes. The errors of AB and SSE were estimated by $se\left(\bar{x}\right) = \frac{\sigma}{\sqrt{n}} \approx \frac{usb}{\sqrt{n}}$, $se\left(sd\right) \approx \frac{1}{2\sigma} se\left(var\right) = \sqrt{\frac{\mu_4}{4n\sigma^2} - \frac{n-3}{4n(n-1)}\sigma^2} \approx \sqrt{\frac{fm}{4nvar} - \frac{n-3}{4n(n-1)}var}$, where usb is unbiased standard deviation of the sampling distribution with normality assumption (3). The computational methods used for two-parameter distributions were identical. The computations of invariant moments were described in the Main Text. The results of error estimation were also included in the SI Dataset S1.

D. The impact of bootstrap size on variance. The study of the impact of the bootstrap size, from $n = 1.8 \times 10^2$ to $n = 1.8 \times 10^4$, on the variance for the exponential distribution was done the same as above.

E. Comparisons to M-estimator and percentile estimator. Within the same kurtosis range and four two-parametric distributions (except the generalized Gaussian distribution, since the logarithmic function does not produce results for negative values) as the above, the percentile estimators were computed using the method proposed by Marks (2005) (4) (consistent for the Weibull distribution) and the parameter setting proposed by Boudt, Caliskan, and Croux (2011) (5). The results were then transformed to the first four moments to compute AABs. The robust M-estimators were also computed in the same way using the methods proposed by Huber (6) (consistent for the Gaussian distribution) and He and Fung (1999) (7) (consistent for the Weibull distribution). Bisection is used to find the solution of the key equation in (7), while the results from the percentile estimator were used as initial values (-0.3 and +0.3).

F. Maximum asymptotic biases. For simplicity, a brute force approach was used to estimate the maximum biases of SWLs and SWkms for five unimodal distributions. A wide range was set to roughly estimate the parameter ranges in which the maximum bias might occur (the corresponding maximum kurtoses are all larger than 500). Then, the parameter range was broken to 100 parts, combining with the above results for AAB estimations, the maximum of both was determined to be very close to the true maximum. Pseudo-maximum bias was described in the Main Text.

The brute force approach is generally valid, i.e., the maximum is the global maximum, not local maximum, even when the the corresponding maximum kurtosis is finite. Because all five distributions here have the property that, as the kurtosis of the distribution increases to infinity, the standardized biases of SWAs approach zero.

For example, for the Perato distribution,

$$B_{\mathrm{SQA}}(\epsilon, \alpha) = \frac{\frac{1}{2}\left(x_m\left(1-\epsilon\right)^{-\frac{1}{\alpha}} + x_m \epsilon^{-\frac{1}{\alpha}}\right) - \frac{\alpha x_m}{\alpha - 1}}{\sqrt{\frac{\alpha {x_m}^2}{(1-\alpha)^2(\alpha-2)}}}.$$

$$\lim_{\alpha\to 2} B_{\mathrm{SQA}}(\epsilon,\alpha) = \lim_{\alpha\to 2} \frac{\frac{1}{2}\left(x_m(1-\epsilon)^{-\frac{1}{\alpha}} + x_m\epsilon^{-\frac{1}{\alpha}}\right)}{\sqrt{\frac{\alpha x_m{}^2}{(1-\alpha)^2(\alpha-2)}}} - \frac{\frac{\alpha x_m}{\alpha-1}}{\sqrt{\frac{\alpha x_m{}^2}{(1-\alpha)^2(\alpha-2)}}} = \lim_{\alpha\to 2} \frac{\frac{1}{2}\left(\frac{1}{\sqrt{\epsilon}} + \frac{1}{\sqrt{1-\epsilon}}\right)}{\sqrt{\frac{\alpha}{(1-\alpha)^2(\alpha-2)}}} + \lim_{\alpha\to 2} \frac{-\alpha}{\sqrt{\frac{\alpha}{(\alpha-2)}}} = 0.$$

In the previous article, it is proven that when the kurtoses of the distributions approach infinity, all the five parametric distributions will be ordered, that means the SWAs based on the orderliness will follow the mean-SWA-median inequality, thus, proving the limits of the ratios between μ and σ, as well as m and σ is enough.

For example, for the Weibull distribution, the ratio of μ and σ is $\lim_{\alpha\to 0} \frac{\Gamma\left(1+\frac{1}{\alpha}\right)}{\sqrt{\Gamma\left(\frac{\alpha+2}{\alpha}\right)}} = \lim_{\alpha\to 0} \frac{\left(1+\frac{1}{\alpha}-1\right)!}{\sqrt{\left(\frac{\alpha+2}{\alpha}-1\right)!}} = \lim_{\alpha\to 0} \frac{\left(\frac{1}{\alpha}\right)!}{\sqrt{\left(2\times\frac{1}{\alpha}\right)!}} = 0$, the ratio of m and σ is $\lim_{\alpha\to 0} \frac{\sqrt[\alpha]{\ln(2)}}{\sqrt{\Gamma\left(\frac{\alpha+2}{\alpha}\right)}} = \lim_{\alpha\to 0} \frac{0}{\sqrt{\Gamma\left(\frac{\alpha+2}{\alpha}\right)}} = 0$.

Similarly, for the gamma distribution, the ratio of μ and σ is $\lim_{\alpha\to 0} \frac{\alpha}{\sqrt{\alpha}} = \lim_{\alpha\to 0} \frac{1}{\sqrt{\alpha}} = 0$, the ratio of m and σ is $\lim_{\alpha\to 0} \frac{P^{-1}\left(\alpha,\frac{1}{2}\right)}{\sqrt{\alpha}} = 0$ (8).

The lognormal distribution is the same, the ratio of μ and σ is $\lim_{\sigma\to\infty} \frac{e^{\mu+\frac{\sigma^2}{2}}}{\sqrt{\left(e^{\sigma^2}-1\right)e^{2\mu+\sigma^2}}} = \lim_{\sigma\to\infty} \frac{e^{\mu+\frac{\sigma^2}{2}}}{\sqrt{e^{2\mu+2\sigma^2}}} = \lim_{\sigma\to\infty} \frac{e^{\frac{\sigma^2}{2}}}{e^{\sigma^2}} = 0$, the ratio of m and σ is $\lim_{\sigma\to\infty} \frac{e^{\mu}}{\sqrt{\left(e^{\sigma^2}-1\right)e^{2\mu+\sigma^2}}} = 0$.

As demonstrated, the growth rate of the standard deviation greatly exceeds that of the mean and that of the median. This phenomenon is closely tied to the Taylor's law and is more widespread than these examples suggest.

SI Dataset S1 (dataset_one.xlsx)

Raw data of Table 1 in the Main Text.

References

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