



ON THE IMPACT OF APPROXIMATION ERRORS ON EXTREME QUANTILE ESTIMATION WITH APPLICATIONS TO FUNCTIONAL DATA ANALYSIS

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Agenda of the presentation

Univariate Extreme Value Theory

Impact of Approximation Errors

Extreme Quantile Estimation for L^p -Norms

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What is Extreme Value Theory?

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- Extreme quantile estimation
- Tail probability estimation
- Estimation of the endpoint of a given distribution

Maximum Domain of Attraction

Definition

Let Y_1, \dots, Y_n be i.i.d. observations of a random variable Y . If there exist sequences $a_n > 0$ and $b_n \in \mathbb{R}$, and a random variable G with a nondegenerate distribution such that

$$\frac{\max(Y_1, \dots, Y_n) - b_n}{a_n} \xrightarrow{\mathcal{D}} G, \quad n \rightarrow \infty,$$

we say that Y belongs to the maximum domain of attraction of G , and denote $Y \in \text{MDA}(G)$.

Extreme Value Index

Theorem (Fisher and Tippett 1928; Gnedenko 1943)

Up to location and scale, the distribution of $G = G_\gamma$ is characterized by the parameter γ , called the extreme value index. That is, the distribution of G_γ is of the type

$$F_{G_\gamma}(x) = \begin{cases} \exp\left(-(1 + \gamma x)^{-1/\gamma}\right), & 1 + \gamma x > 0 \quad \text{if } \gamma \neq 0, \\ \exp(-e^{-x}), & x \in \mathbb{R} \quad \text{if } \gamma = 0. \end{cases}$$

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In the case $\gamma > 0$ the type of G_γ is Fréchet,

$$\Phi_\gamma(x) = \begin{cases} 0, & x \leq 0 \\ \exp(-x^{-1/\gamma}), & x > 0. \end{cases}$$

Tail Quantile Function

Define tail quantile function corresponding to distribution F by

$$U(t) = F^{\leftarrow} \left(1 - \frac{1}{t} \right), \quad t > 1,$$

where we denote left-continuous inverse of a nondecreasing function by $f^{\leftarrow}(y) = \inf \{x \in \mathbb{R} : f(x) \geq y\}$.

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That is, $U(1/p)$ is the $(1 - p)$ -quantile.

Definition (Regular variation)

A Lebesgue measurable function $f : \mathbb{R}^+ \rightarrow \mathbb{R}$ that is eventually positive is regularly varying with index $\alpha \in \mathbb{R}$ if for all $x > 0$,

$$\lim_{t \rightarrow \infty} \frac{f(tx)}{f(t)} = x^\alpha.$$

Then we denote $f \in RV_\alpha$. Furthermore, we say that a function f is slowly varying if $f \in RV_0$.

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Intuition:

$$f \in RV_\alpha \iff f(x) = L(x)x^\alpha, \quad L \in RV_0.$$

We also have

$$\lim_{x \rightarrow \infty} x^{-\varepsilon} L(x) = 0, \quad \forall \varepsilon > 0.$$

Construction of an Extreme Quantile Estimator

Theorem ((Gnedenko 1943; de Haan 1970))

Let $\gamma > 0$. We have

$$Y \in \text{MDA}(G_\gamma) \iff 1 - F \in RV_{-1/\gamma} \iff U \in RV_\gamma.$$

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Choose $t = n/k$ and $x = k/(np)$ to get the approximation

$$U\left(\frac{1}{p}\right) \approx U\left(\frac{n}{k}\right) \left(\frac{k}{np}\right)^\gamma.$$

Extreme Quantile Estimation

Suppose $\mathbf{Y} = (Y_1, \dots, Y_n)$ is an i.i.d. sample of $Y \in \text{MDA}(\mathbf{G}_\gamma)$, $\gamma > 0$. Denote order statistics corresponding to the sample \mathbf{Y} by $\mathbf{Y}_{1,n} \leq \dots \leq \mathbf{Y}_{n,n}$. Then an estimator for the extreme $(1 - p)$ -quantile $x_p = U(1/p)$ can be given as

$$\hat{x}_p(\mathbf{Y}) = \mathbf{Y}_{n-k,n} \left(\frac{k}{np} \right)^{\hat{\gamma}(\mathbf{Y})},$$

where $\hat{\gamma}$ is an estimator for the extreme value index γ .

The Hill Estimator (Hill 1975; Mason 1982)

Suppose $\mathbf{Y} = (Y_1, \dots, Y_n)$ is an i.i.d. sample of $Y \in \text{MDA}(G_\gamma)$, $\gamma > 0$. The Hill estimator is defined as

$$\hat{\gamma}_H(\mathbf{Y}) = \frac{1}{k} \sum_{i=0}^{k-1} \ln \left(\frac{\mathbf{Y}_{n-i,n}}{\mathbf{Y}_{n-k,n}} \right).$$

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If additionally as $n \rightarrow \infty$, $k = k_n \rightarrow \infty$, $k/n \rightarrow 0$, then

$$\hat{\gamma}_H(\mathbf{Y}) \xrightarrow{\mathbb{P}} \gamma, \quad n \rightarrow \infty.$$

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The General Framework

- What if instead of the sample \mathbf{Y} , only approximations $\hat{\mathbf{Y}} = (\hat{Y}_1, \dots, \hat{Y}_n)$ are available?

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- How the approximation error affects the asymptotics?
- \Rightarrow Useful approach in multivariate and infinite dimensional settings:
 - Let $X \in \mathbb{S}$ be a random object, where, e.g., $\mathbb{S} = \mathbb{R}^d$ or $\mathbb{S} = L^p([0, 1]^d)$.
 - Let $g : \mathbb{S} \rightarrow \mathbb{R}$ be some suitable map.
 - Apply extreme value theory to $g(X)$.

Approximated L^p -Norms

- Let $X \in L^p([0, 1]^d)$, and let X_1, \dots, X_n be i.i.d. copies of X .
- We wish to estimate extreme value index and extreme quantiles corresponding to $\|X\|_p \in \text{MDA}(G_\gamma)$, $\gamma > 0$.

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- In practice we never observe X_1, \dots, X_n .
- Approximate norms with Riemann sums or Monte Carlo integration.
- Use approximated norms \hat{Y}_i in the estimation.
- As the estimator of the extreme value index we choose the Hill estimator

$$\hat{\gamma}(\hat{\mathbf{Y}}) = \frac{1}{k} \sum_{i=0}^{k-1} \ln \left(\frac{\hat{\mathbf{Y}}_{n-i,n}}{\hat{\mathbf{Y}}_{n-k,n}} \right).$$

Draft of the Main Result

Let $\gamma > 0$. Let Y_1, \dots, Y_n be i.i.d. copies of $Y \in \text{MDA}(G_\gamma)$ and $\hat{\mathbf{Y}} = (\hat{Y}_1, \dots, \hat{Y}_n)$ the corresponding approximations. Denote errors by $E_i = |\hat{Y}_i - Y_i|$. If

$$\sqrt{k} \frac{\mathbf{E}_{n,n}}{U_Y(n/k)} \xrightarrow{\mathbb{P}} 0, \quad n \rightarrow \infty,$$

then

$$\sqrt{k} \left(\hat{\gamma}(\hat{\mathbf{Y}}) - \gamma \right) \quad \text{and} \quad \frac{\sqrt{k}}{\ln(k/(np))} \left(\frac{\hat{x}_p(\hat{\mathbf{Y}})}{U(1/p)} - 1 \right)$$

are asymptotically normally distributed under the standard assumptions (second-order condition, rate for $p = p_n$, $k = k_n \rightarrow \infty$, $k/n \rightarrow 0$, as $n \rightarrow \infty$).

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