Asymptotic Properties of the Hill Estimator

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Abstract

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Preface

I want to thank Professor Pirjo Professori and my instructor Dr Alan Advisor for their good and poor guidance.

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Eddie E. A. Engineer

Contents

Symbols and abbreviations

Symbols

$x^* = \sup\{x : F(x) < 1\}$	right endpoint of the distribution
γ	extreme value index
$F^{\leftarrow}(y) = \inf\{x : F(x) \geq y\}$	left-continuous inverse
U	left-continuous inverse of $\frac{1}{1-F}$
$\mathbb{1}(p) = \begin{cases} 1, \text{if p is true} \\ 0, \text{otherwise} \end{cases}$	indicator fuction
$X_{i,n}$	ith order statistic
λ	Lebesque measure
$\limsup A_n = \bigcap_{k=1}^{\infty} \bigcup_{n=k}^{\infty} A_n$	limit supremum of a sequence of sets A_n
$f \in RV_\alpha$	f is an regularly varying function with index α
G	extreme value distribution
$f \in D(G_\gamma)$	f is in the maximum domain of attraction of G

Abbreviations

cdf	cumulative distribution function
i.d.d.	independent and identically distributed
a.s.	almost surely

1 Introduction

2 Backround

2.1 Fisher-Tippett-Gnedenko Theorem and Domains of Attraction

First approach to study the behavior of extreme events could be to find limiting distribution of the sample maxima $M_n = \max(X_1, X_2, ..., X_n)$. Here $X_1, X_2, ..., X_n$ are i.d.d. random variables from cdf F_X. Function for the cdf of M_n can be easily derived, since $X_1, X_2, ..., X_3$ are i.d.d.

$$P(\max(X_1, X_2, ..., X_n) \leq x) = P(X_1 \leq x, X_2 \leq x, ..., X_n \leq x) = \\ P(X_1 \leq x)P(X_2 \leq x)...P(X_n \leq x) = F^n(x).$$

Now it can be shown that this approach is not very useful since

$$\lim_{n\to\infty} F^n(x) = \begin{cases} 0, x < x^* \\ 1, x \geq x^*. \end{cases}$$

To achieve a nondegerate distribution it is necessary to normalize the sample maxima M_n. After normalization a nondegenate distribution is gained as stated in the Fisher-Tippett-Gnedenko Theorem [2].

Theorem 2.1. *There exists real constants $a_n > 0$ and $b_n \in \mathbb{R}$ such that*

$$\lim_{n\to\infty} F^n(a_n x + b_n) = G_\gamma(ax + b), \tag{1}$$

where

$$G_\gamma(x) = \begin{cases} \exp(-(1 + \gamma x)^{-\frac{1}{\gamma}}), \gamma \neq 0 \\ \exp(-e^{-x}), \gamma = 0, \end{cases}$$

for all x with $1 + \gamma x > 0$ where $\gamma \in \mathbb{R}$.

If F fullfills the equation 1 for some $\gamma \in \mathbb{R}$ then it is said that F is in the maximum domain of attraction of G_γ i.e. $F \in D(G_\gamma)$. Considering the Hill estimator we are especially interested in the case $F \in D(G_{\gamma>0})$. It turns out that $F \in D(G_{\gamma>0})$ is equivalent to the fact that function $1 - F$ is regularly varying with index $-\frac{1}{\gamma}$. [2]

Theorem 2.2. *Cdf F is in the maximum domain of attraction of the extreme value distribution G_γ with $\gamma > 0$ if and only if $x^* = \infty$ and*

$$\lim_{t\to\infty} \frac{1 - F(tx)}{1 - F(t)} = x^{-\frac{1}{\gamma}}, x > 0. \tag{2}$$

In addition, condition 2 can be written in different form with the U function [2].

Corollary 2.3. *Condition 2 is equivalent to*

$$\lim_{t\to\infty} \frac{U(tx)}{U(t)} = x^\gamma, x > 0. \tag{3}$$

Above equation implies that U is regularly varying with index γ if $F \in D(G_{\gamma>0})$.

2.2 Regularly Varying Functions

In section 2.1 we saw that if $F \in D(G_{\gamma>0})$ then U is regularly varying function. Regularly varying functions have some useful properties that are needed to prove the consistency of the Hill estimator. Let's define regularly varying functions properly [2]:

Definition 2.4. *A Lebesque measurable function $f : \mathbb{R}^+ \to \mathbb{R}$ that is eventually positive is regularly varying if for some index $\alpha \in \mathbb{R}$,*

$$\lim_{x\to\infty} \frac{f(tx)}{f(t)} = x^{\alpha}, \quad x > 0. \tag{4}$$

If function f is regularly varying with index $\alpha = 0$ then f is called slowly varying. For a slowly varying function the limit relation 4 can be written in different form with function $F = \log f(e^x)$:

$$\lim_{t\to\infty} F(t+x) - F(x) = 0. \tag{5}$$

The above argument is true, since

$$F(t+x) - F(t) = \log f(e^{t+x}) - \log f(e^t) = \log \left(\underbrace{\frac{f(e^t e^x)}{f(e^t)}}_{\to 1} \right) \to 0$$

as $t \to \infty$. The alternative form for slow variation 5 is used in the proof of the uniform convergence.

Theorem 2.5. *If $f \in RV_\alpha$ then the convergence in the equation 4 is uniform .*

$$\lim_{t\to\infty} \sup_{x\in[a,b]} \left| \frac{f(tx)}{f(t)} - x^{\alpha} \right| = 0,$$

for $0 < a < b < \infty$.

Furthermore, the lemma below is neccessary for the proof of the theorem 2.5.

Lemma 2.6 (Fatou's lemma for sets)**.** *For a sequence of Lebesque measurable sets A_n:*

$$\lambda(\limsup A_n) \geq \limsup \lambda(A_n)$$

if $\lambda(\bigcup_{n=k}^{\infty} A_n) < \infty$ for some $k \geq 1$.

Here the lemma 2.6 is called "Fatou's lemma for sets" because it is actually a special case of Fatou's lemma [1]. So the above lemma can be proved directly from the Fatou's lemma but we represent a different proof.

Proof. By the monotocity of measure we have $\lambda(\bigcup_{n=k}^{\infty} A_n) \geq \lambda(A_j), j \geq k$. This implies that

$$\lambda(\bigcup_{n=k}^{\infty} A_n) \geq \sup_{j\geq k} \lambda(A_j)$$
$$\Rightarrow \lim_{n\to\infty} \lambda(\bigcup_{n=k}^{\infty} A_n) \geq \lim_{n\to\infty} \sup_{j\geq k} \lambda(A_j). \tag{6}$$

The $\limsup A_n$ can be written as

$$\lambda(\limsup A_n) = \lambda(\bigcap_{k=1}^{\infty} \bigcup_{n=k}^{\infty} A_n) = \lim_{k\to\infty} \lambda(\bigcup_{n=k}^{\infty} A_n) \tag{7}$$

by the downwards uniform convergence theorem [1]. Now by combining equations 6 and 7 we get the result. ☐

Proof. For the proof it can be assumed that $\alpha = 0$. If this isn't the case replace $f(x)$ by $f(x)x^{-\alpha}$. Suppose there exists sequences $t_n \to \infty$, $x_n \to 0$ as $n \to \infty$ such that

$$\left|\frac{f(t_n x_n)}{f(t_n)} - 1\right| > \delta$$

for all $n \in \mathbb{N}$ and some $\delta > 0$. An equivalent condition can be formulated with function $F(x) = \log f(e^x)$(see equation 5):

$$|F(t_n + x_n) - F(t_n)| > \delta \tag{8}$$

with possibly different x_n, t_n and δ. Let's define sets

$$Y_{1,n} = \left\{ y \in J : |F(t_n + y) - F(t_n)| > \frac{\delta}{2} \right\},$$
$$Y_{2,n} = \left\{ y \in J : |F(t_n + x_n) - F(t_n + y)| > \frac{\delta}{2} \right\} \quad \text{and}$$
$$Z_n = \left\{ z : |F(t_n + x_n) - F(t_n + x_n - z)| > \frac{\delta}{2}, x_n - z \in J \right\}$$
$$= \{z : x_n - z \in Y_{2,n}\}$$

where $J \subset \mathbb{R}$ is a finite interval. Next we will prove that if the equation 8 holds then pointwise convergence $\lim_{t\to\infty} F(t + x_0) - F(t) = 0$ cannot hold. Pointwise convergence does not hold if some x_0 is included in infinitely many $Y_{1,n}$. Reason for this is that

$$n \geq n_\varepsilon \Rightarrow |F(t + x_0) - F(t)| < \varepsilon, \forall\varepsilon > 0, \exists n_\varepsilon \in \mathbb{N} \tag{9}$$

cannot hold if x_0 is included in infinitely many $Y_{1,n}$. This can be noticed by comparing equation 9 and the condition of $Y_{1,n}$. Similarly if x_0 is included in infinitely many Z_n then pointwise convergence cannot hold, since the condition in Z_n can be written as

$$\left| F(\underbrace{t_n + x_n}_{=u_n}) - F(\underbrace{t_n + x_n}_{=u_n} \overbrace{-z}^{=x_0}) \right| > \frac{\delta}{2}$$
$$\Leftrightarrow |F(u_n + x_0) - F(u_n)| > \frac{\delta}{2}$$

where $u_n \to \infty$.

Notice that $Y_{1,n} \cup Y_{2,n} = J$, since by the equation 8 and triangle inequality we have

$$\begin{aligned}\delta < |F(t_n + x_n) - F(t_n)| &= |(F(t_n + x_n) - F(t_n + y)) + (F(t_n + y) - F(t_n))| \\ &\leq |(F(t_n + x_n) - F(t_n + y))| + |(F(t_n + y) - F(t_n))| \\ \Rightarrow |(F(t_n + x_n) - F(t_n + y))| &> \frac{\delta}{2} \vee |(F(t_n + y) - F(t_n))| > \frac{\delta}{2}.\end{aligned}$$

Additionally $Y_{1,n}$, $Y_{2,n}$ and J are measurable sets. So by subadditivity of the Lebesque measure we have $\lambda(Y_{1,n}) \geq \frac{\lambda(J)}{2} \vee \lambda(Y_{2,n}) \geq \frac{\lambda(J)}{2}$. By the translation property of the Lebesque measure $\lambda(Z_n) = \lambda(Y_{2,n})$ holds. Thus $\lambda(Y_{1,n}) \geq \frac{\lambda(J)}{2} \vee \lambda(Z_n) \geq \frac{\lambda(J)}{2}$ infinitely often. All $Y_{1,n}$ are subsets of finite interval since $Y_{1,n} \subset J$ for all n. Similarly all Z_n are subset of a finite interval since $x_n \to 0$. Now we can use lemma 2.6:

$$\lambda(\limsup Y_{1,n}) \geq \limsup \lambda(Y_{1,n}) \geq \frac{\lambda(J)}{2} \quad \vee$$
$$\lambda(\limsup Z_n) \geq \limsup \lambda(Z_n) \geq \frac{\lambda(J)}{2}.$$

Since at least one of the measures $\lambda(\limsup Y_{1,n})$ or $\lambda(\limsup Z_n)$ is greater than zero, we have some x_0 that is contained in infinitely many $Y_{1,n}$ or Z_n. This was the desired contradiction. □

With uniform convergence it can be proved that all the regularly varying functions are in certain form:

Theorem 2.7 (Karamata's representation theorem)**.** *If $f \in RV_\alpha$ then there exists measurable functions $a : \mathbb{R} \to \mathbb{R}^+$ and $c : \mathbb{R} \to \mathbb{R}^+$ with*

$$\lim_{t\to\infty} c(t) = c_0 \text{ and } \lim_{t\to\infty} a(t) = \alpha$$

and $t_0 \in \mathbb{R}^+$ such that for $t > t_0$

$$f(t) = c(t) \exp\left(\int_{t_0}^{t} \frac{a(s)}{s} ds\right) \tag{10}$$

Conversely, if 10 holds, then $f \in RV_\alpha$.

For the proof of the above theorem following lemma is needed.

Lemma 2.8. *Suppose $f \in RV_\alpha$. There exists $t_0 > 0$ such that $f(t)$ is positive and locally bounded for $t \geq t_0$. If $\alpha \geq -1$ then*

$$\lim_{t\to\infty} \frac{tf(t)}{\int_{t_0}^{t} f(s)ds} = \alpha + 1. \tag{11}$$

If $\alpha < -1$ or $\alpha = -1$ and $\int_0^\infty ds < \infty$, then

$$\lim_{t\to\infty} \frac{tf(t)}{\int_{t}^{\infty} f(s)ds} = -\alpha - 1. \tag{12}$$

Conversely, if 11 holds for $-1 \leq \alpha < \infty$ or 12 holds for $-\infty < \alpha < -1$, then $f \in RV_\alpha$.

Next we prove the above lemma.

Proof. □

3 Hill Estimator

3.1 Consistency

The following theorem states that Hill estimator is consistent i.e. estimator converges in probability to extreme value index. [2]

Theorem 3.1. *Let $X_1, X_2, ...$ be i.d.d. variables with cdf F_X. Suppose $F_X \in D(G_\gamma)$ with $\gamma > 0$. Then as $n \to \infty$, $k = k(n) \to \infty$, $\frac{k}{n} \to 0$,*

$$\hat{\gamma}_H \xrightarrow{p} \gamma.$$

For the proof of the above theorem following lemmas are needed, firstly the Renyi's representation [3].

Lemma 3.2. *If $E_1, E_2, ...$ are i.d.d. random variables from the standard exponential distribution and $E_{1,n} \leq E_{2,n} \leq ... \leq E_{n,n}$ then for $k \leq n$ we have*

$$\Big(E_{1,n}, E_{2,n}, ..., E_{k,n}\Big) \stackrel{d}{=} \left(\frac{E_1^*}{n}, \frac{E_1^*}{n} + \frac{E_2^*}{n-1}, ..., \frac{E_1^*}{n} + \frac{E_2^*}{n-1} + ... + \frac{E_k^*}{n-k+1}\right),$$

where $E_1^*, E_2^*, ...$ are i.d.d. random variables from standard exponential distribution.

Secondly the lemma about the order statistics of Pareto distribution is necessary [2].

Lemma 3.3. *Let $Y_1, Y_2, ...$ be i.d.d. random variables from Pareto distribution $F_Y(y) = 1 - \frac{1}{y}$, $y \geq 0$ and let $Y_{1,n} \geq Y_{2,n} \geq ... \geq Y_{n,n}$ be the nth order statistics. Then with such $k = k(n)$ that $k \to \infty$, $\frac{k}{n} \to 0$ as $n \to \infty$,*

$$\lim_{n\to\infty} Y_{n-k,n} = \infty \quad a.s.$$

Last lemma we need says that U(Y) is equal in distribution to X, where Y is random variable from Pareto distribution and X is random variable from some distribution F_X.

Lemma 3.4. *Let Y be random variable from Pareto distribution $F_Y = 1 - \frac{1}{y}$, $y \geq 0$ Let X be random variable with cdf F_X then $U(Y) \stackrel{d}{=} X$.*

Next we prove the lemma 3.3. Proof of the lemma 3.2 is omitted here.

Proof. Let us assume that $Y_{n-k,n} < r$ for some $r > 0$ infinitely often. In other words

$$\frac{k}{n} = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}(Y_i > Y_{n-k,n}) > \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}(Y_i > r).$$

Now the left side of the equation converges to zero, since

$$\lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}(Y_i > Y_{n-k,n}) = \lim_{n\to\infty} \frac{k}{n} = 0.$$

But the right side converges to $1/r$ almost surely, since

$$\frac{1}{n} \sum_{i=1}^{n} \mathbb{1}(Y_i > r) \xrightarrow{a.s} P(Y_i > r) = 1 - F_Y(r) = \frac{1}{r}$$

by the strong law of large numbers [4]. So the assumption cannot hold which implies that

$$P(\lim_{n\to\infty} Y_{n-k,n} = \infty) = 1.$$

□

Now we prove the last lemma 3.4 that is needed for the proof of theorem 3.1

Proof. Let's study the condition $U(Y) \leq a, a \in \mathbb{R}$.

$$\begin{aligned} &U(Y) \leq a \\ \Leftrightarrow \inf &\Big\{x : \frac{1}{1 - F_X(x)} \geq Y\Big\} \leq a \\ \Leftrightarrow \inf &\Big\{x : 1 - \frac{1}{Y} \leq F_X(x)\Big\} \leq a \end{aligned} \tag{13}$$

Let $S = \Big\{x : 1 - \frac{1}{Y} \leq F_X(x)\Big\}$ and $b = \inf S$. Notice that F is increasing and right-continuous, since F is a cdf. So S is an interval of form $[b, \infty)$ or (b, ∞), since F is increasing. Let's define a sequence $x_n = b + \frac{1}{n}, n \in \mathbb{N}$. Notice that $x_n \to b$ and $x_n \in S$ for all n. Now right-continuity implies that $b \in S$ i.e S is an interval $[b, \infty)$. Additionally $a \in S$ since $a \geq b$ so a satisfies the condition $1 - \frac{1}{Y} \leq F(a)$. Therefore the equation 13 implies

$$U(Y) \leq a \Leftrightarrow 1 - \frac{1}{Y} \leq F_X(a) \Leftrightarrow Y \leq \frac{1}{1 - F(a)},$$

So now from the cdf of U(Y) we have

$$\begin{aligned} F_{U(Y)} = P(U(Y) \leq x) = P\Big(Y \leq \frac{1}{1 - F_X(x)}\Big) &= F_Y\Big(\frac{1}{1 - F_X(x)}\Big) \\ &= 1 - \Big(\frac{1}{1 - F_X(x)}\Big)^{-1} = F_X(x). \end{aligned}$$

□

Now we are equipped to prove the theorem 3.1.

Proof. $F \in D(G_{\gamma>0})$ is equivalent to the fact that $U \in RV_\gamma$ i.e.

$$\lim_{t\to\infty} \frac{U(tx)}{U(t)} = x^\gamma.$$

From the uniform convergence of the regularly varying functions follows that for $x > 1$ and $t \geq t_0$,

$$(1-\varepsilon)x^{\gamma-\delta} < \frac{U(tx)}{U(t)} < (1+\varepsilon)x^{\gamma+\delta},$$

for all $\varepsilon > 0$ and $\delta > 0$. By taking natural logarithm from both sides of the equation above, it can be written as

$$\begin{aligned} \log(1-\varepsilon) + (\gamma-\delta)\log(x) &< \log(U(tx)) - \log(U(t)) \\ &< \log(1+\varepsilon) + (\gamma+\delta)\log(x). \end{aligned} \tag{14}$$

If $Y_1, Y_2, ...$ are i.d.d random variables from Pareto distribution with cdf $F_Y(y) = 1 - \frac{1}{y}$ then $U(Y_i) \stackrel{d}{=} X_i$ as stated in lemma 3.4. Hence it is sufficient to prove the result for $\hat{\gamma}_H = \frac{1}{k}\sum_{i=0}^{k-1} \log(U(Y_{n-i,n})) - \log(U(Y_{n-k,n}))$. For $t = Y_{n-k,n}$ and $x = \frac{Y_{n-i,n}}{Y_{n-k,n}}$ equation 14 has the form

$$\begin{aligned} \log(1-\varepsilon) + (\gamma-\delta)\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right) &< \log(U(Y_{n-i,n})) - \log(U(Y_{n-k,n})) \\ &< \log(1+\varepsilon) + (\gamma+\delta)\log(\frac{Y_{n-i,n}}{Y_{n-k,n}}). \end{aligned} \tag{15}$$

Notice that we can replace t with $Y_{n-k,n}$ because we can always find some n_0 such that $Y_{n_0-k,n_0} \geq t_0$ according to lemma 3.3. Furthermore, $Y_{n-i,n}$ is greater than $Y_{n-k,n}$ always when $i < k$. Therefore x can be replaced with $\frac{Y_{n-i,n}}{Y_{n-k,n}}$.

Equation 15 applies for every $i = 0, 1, 2, ..., k-1$. Thus we can write

$$\begin{aligned} \log(1-\varepsilon) + (\gamma-\delta)\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right) &< \frac{1}{k}\sum_{i=0}^{k-1}\log(U(Y_{n-i,n})) - \log(U(Y_{n-k,n})) \\ &< \log(1+\varepsilon) + (\gamma+\delta)\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right). \end{aligned}$$

The term in the middle is the hill estimator $\hat{\gamma}_H$, hence above becomes

$$\begin{aligned} \log(1-\varepsilon) + (\gamma-\delta)\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right) &< \hat{\gamma}_H \\ &< \log(1+\varepsilon) + (\gamma+\delta)\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right). \end{aligned}$$

Now it is sufficient to only prove that

$$\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right)\xrightarrow{p}1.$$

$\log(Y_i)$ has a standard exponential distribution, since

$$F_{\log(Y_i)}(x)=P(\log(Y_i)<x)=P(e^{\log(Y_i)}<e^x)=P(Y_i<e^x)=F_Y(e^x)=1-e^{-x}.$$

Therefore we can write

$$\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right)=\frac{1}{k}\sum_{i=0}^{k-1}E_{n-i,n}-E_{n-k,n},$$

where $E_1, E_2, ...$ are i.d.d. random variables from standard exponential distribution. Now Renyi's representation 3.2 implies

$$\begin{aligned}
&\left\{E_{n-i,n}-E_{n-k,n}\right\}_{i=0}^{k-1}\\
\stackrel{d}{=}&\left\{\left(\frac{E_1^*}{n}+\frac{E_2^*}{n-1}+...+\frac{E_{n-(i+1)}^*}{n-(n-(i+1))+1}+\frac{E_{n-i}^*}{n-(n-i)+1}\right)\right.\\
&\left.-\left(\frac{E_1^*}{n}+\frac{E_2^*}{n-1}+...+\frac{E_{n-k}^*}{n-(n-k)+1}\right)\right\}_{i=0}^{k-1}\\
=&\left\{\frac{E_{n-i}^*}{i+1}+\frac{E_{n-(i+1)}^*}{i+2}+...+\frac{E_{n-(k-2)}^*}{k-1}+\frac{E_{n-(k-1)}^*}{k}\right\}_{i=0}^{k-1}\\
\stackrel{d}{=}&\left\{E_{k-i,k}\right\}_{i=0}^{k-1}.
\end{aligned}$$

Consequently we have

$$\frac{1}{k}\sum_{i=0}^{k-1}\log\left(\frac{Y_{n-i,n}}{Y_{n-k,n}}\right)\stackrel{d}{=}\frac{1}{k}\sum_{i=0}^{k-1}E_{k-i,k}=\frac{1}{k}\sum_{i=0}^{k-1}E_i\xrightarrow{p}E[E_i]=1$$

by the weak law of large numbers [4]. Notice that the expected value of a standard exponential is one.

□

3.2 Simulations

4 Conclusions

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Appendix