

d) Applications: Lévy RV's with $\alpha < 1$

Recall that for Lévy RV's with $\alpha < 1$ the typical value of

$$S_N = \sum_{i=1}^N X_i \sim N^{1/\alpha} \Rightarrow N$$

On the other hand we have now shown that

$$X_{\max} = \max\{X_1, \dots, X_N\} \sim N^{1/\alpha}$$

\Rightarrow typically $X_{\max}/S_N = O(1)$, i.e. the largest RV is of the same order as the sum.

To quantify this statement consider the participation ratios

$$w_N^i = \frac{X_i}{S_N} \in [0, 1] \quad \text{identically distr. but not independent!}$$

then it can be shown that the moments $\langle w_N^k \rangle$, $k \geq 2$, have a finite limit for $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} \langle w_N^k \rangle = \frac{\Gamma(k-\alpha)}{\Gamma(k)\Gamma(1-\alpha)} \quad \begin{array}{l} 0 < \alpha < 1 \\ 0 < \alpha < 1 \\ k \geq 2 \end{array}$$

(Derrida, 1994)

\Rightarrow Problem

Also, note that

$$\sum_{i=1}^H W_i^k \leq W_{max}^{k-1}$$

Proof: Induction

and hence

$$\langle W_{max}^{k-1} \rangle \geq \langle W_H^k \rangle > 0 \text{ for } H \rightarrow \infty.$$

It follows that $W_{max} > 0$ with non-zero probability for $H \rightarrow \infty$

e) The peaks-over-threshold approach

For applications it is inconvenient to estimate the extreme value parameters from $X_{(n-k)}$, since one has only a single observation per sample. Here we consider instead all events above some threshold u , and study the limit $u \rightarrow s_+$, where s_+ is the upper limit of the support of $F(x)$ ($s_+ = \infty$ for unbounded RV's).

Define the excess probability

$$P_u(x) = \text{Prob}[X > u+x \mid X > u] = \\ = \frac{1 - F(u+x)}{1 - F(u)}, \quad x \geq 0$$

so that $1 - P_u$ is a distribution function on $[0, \infty]$. Consider some examples:

(i) exponential: $F(x) = 1 - e^{-x} \Rightarrow P_u(x) = e^{-x}$ }
independent of u

(ii) Gaussian: $1 - F(x) \approx \frac{1}{x} \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, \quad x \rightarrow \infty$

$$\Rightarrow P_u(x) = \frac{u}{u+x} \exp\left[-\frac{1}{2}(x+u)^2 + \frac{1}{2}u^2\right] = \\ = \frac{u}{u+x} \exp\left[-\frac{1}{2}x^2 - ux\right]$$

so $\lim_{u \rightarrow \infty} P_u(x) = 0$ for any x . To get a non-dependent limit we define $y = ux$

$$\Rightarrow P_u(y) = \frac{u^2}{u^2 + y} \exp\left[-\frac{y^2}{u^2} - y\right] \xrightarrow{u \rightarrow \infty} \underline{e^{-y}}$$

(iii) Pareto: $F(x) = 1 - x^{-\alpha}$, $x \gg 1$

$$\Rightarrow P_u(x) = \left(\frac{u}{u+x}\right)^\alpha \xrightarrow{u \rightarrow \infty} 1$$

In this case the appropriate rescaling is $\underline{y = x/u}$

$$\Rightarrow P_u(y) = \left(\frac{u}{u+uy}\right)^\alpha = \left(\frac{1}{1+y}\right)^\alpha \quad \text{indep. of } u.$$

(iv) Uniform: $F(x) = x$, $x \in [0, 1]$

$$\Rightarrow P_u = \frac{1 - (u+x)}{1-u} = 1 - \frac{x}{1-u}$$

which should converge for $u \rightarrow 1$. Clearly the rescaling is $y = x/(1-u) \Rightarrow P_u(y) = 1 - y$.

These examples illustrate the limit theorem of Balkema / de Haan¹⁾ (1974) and Pickands (1975):

¹⁾ "Residual life time at great age"

Suppose a function $a(u)$ exists such that

$$\lim_{u \rightarrow S_+} P_u(a(u)y) = H(y)$$

exists and is non-degenerate. Then H belongs to the one-parameter family of generalized Pareto distributions (GPD)

$$\underline{H_\gamma(y) = (1 + \gamma y)^{-1/\gamma}}, \quad 1 + \gamma y > 0$$

and $H_0(y) = e^{-y}$.

Note that $H_\gamma = -\ln G_\gamma$, and the domains of attraction are the same in both cases.

Application: Fitness distributions in experimental evolution
(Rokhsar et al., 2008)
based on Orr (2003)

5° Theory of records

Let X_i be a sequence of continuous, i.i.d. RV.

X_k is a ^(Upper) record if $X_k = \max(X_1, \dots, X_k)$.

By symmetry

$$\text{Prob}[X_k = \max(X_1, \dots, X_k)] = \frac{1}{k}$$

\Rightarrow number of records $H(n)$ up to time n :

$$\langle H(n) \rangle = \sum_{k=1}^n \frac{1}{k} \approx \ln(n) + 0.5772 \dots$$

Ex: Weather records (Glick)

For $n = 100$, we have $\langle H(n) \rangle \approx 5.2$

a) The distribution of the number of records

(H. Glick, Amer. Math. Monthly 85, 2
(1978))

Rényi representation: (1962)

Define RV's Y_k through

$$Y_k = \begin{cases} 1 & X_k \text{ is a record} \\ 0 & \text{else} \end{cases}$$

then clearly $\langle Y_k \rangle = \frac{1}{k}$.

Correlations: let $j > i$, then

$$\langle Y_i Y_j \rangle = \text{Prob} [X_i = \max(X_1, \dots, X_i) \text{ and } X_j = \max(X_1, \dots, X_j)] =$$

(split into independent events)

$$= \text{Prob} [X_i = \max(X_1, \dots, X_i)] \times$$

$$\times \text{Prob} [X_j = \max(X_{i+1}, \dots, X_j)] \times$$

$$\times \text{Prob} [\max(X_1, \dots, X_i) < \max(X_{i+1}, \dots, X_j)]$$

$$= \max(X_1, \dots, X_j) \text{ occurs in } \{X_{i+1}, \dots, X_j\}$$

$$= \frac{1}{i} \cdot \frac{1}{j-i} \cdot \frac{j-i}{j} = \frac{1}{i} \cdot \frac{1}{j} = \langle Y_i \rangle \langle Y_j \rangle$$

This allows to compute the variance of

$$H(n) = \sum_{i=1}^n Y_i$$

$$\langle H(n)^2 \rangle = \sum_{i=1}^n \sum_{j=1}^n \langle Y_i Y_j \rangle = \sum_{i=1}^n \frac{1}{i} +$$

$$+ \langle H(n) \rangle^2 - \sum_{i=1}^n \left(\frac{1}{i} \right)^2$$

$$\Rightarrow \langle H(n)^2 \rangle - \langle H(n) \rangle^2 = \sum_{i=1}^n \left(\frac{1}{i} - \frac{1}{i^2} \right)$$

$$\xrightarrow{n \rightarrow \infty} \ln(n) + 0.5772 - \frac{\pi^2}{6} = \ln(n) - 1.07$$

$$\Rightarrow \lim_{n \rightarrow \infty} \frac{\langle H^2 \rangle - \langle H \rangle^2}{\langle H \rangle} = 1 \quad \text{Poisson-like}$$

In the same way it can be shown that the X_k are independent, and asymptotically

$$\text{Prob} [H(n) = M] \rightarrow \frac{1}{n} \frac{(\ln(n))^M}{M!}$$

log-Poisson distribution

(b.) Record times

Denote by R_k the time of the k -th record, with $R_1 = 1$ by convention.



\Rightarrow a "point process" on \mathbb{N}

(i) Time of the second record:

$$\begin{aligned} \text{Prob} [R_2 > n] &= \text{Prob} [X_1 = \max(X_1, \dots, X_n)] = \\ &= \frac{1}{n} \end{aligned}$$

$$\Rightarrow \text{Prob} [R_2 = n] = \text{Prob} [R_2 > n-1] -$$

$$- \text{Prob} [R_2 > n] = \frac{1}{n-1} - \frac{1}{n} = \frac{1}{n(n-1)}, \quad n \geq 2$$

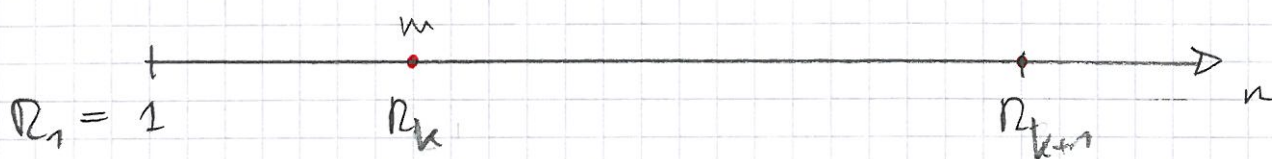
$$\sim \frac{1}{n^2}, \quad n \rightarrow \infty$$

⇒ R_2 has a fat tail with $\alpha = 1$.

In particular, $\langle R_2 \rangle = \infty$. ⇒ $\langle R_k \rangle = \infty$
∀ k .

(ii) Successive record times

Suppose the record time R_k is given. Where does record $k+1$ occur?



$$\begin{aligned} & \text{Prob}[R_k / R_{k+1} < \frac{m}{n} \mid R_k = m] = \\ & = \text{Prob}[R_{k+1} > n \mid R_k = m] = \\ & = \text{Prob}[\max\{X_1, \dots, X_n\} = \max\{X_1, \dots, X_m\}] = \\ & = m/n \text{ by symmetry} \end{aligned}$$

⇒ $R_k / R_{k+1} \approx$ uniform RV on $[0, 1]$.

⊗ Theorem: (Shorrock, 1972; Resnick, 1973)

The ratios $R_k / R_{k+1}, R_{k+1} / R_{k+2}, \dots$ are asymptotically independent uniform RV's.

$$\Rightarrow R_k \approx \prod_{j=2}^k (1/\xi_j), \quad \xi_j \text{ uniform RV}$$

$$\Rightarrow \ln R_k \approx \sum_{j=2}^k \ln(1/\xi_j) = \sum_{j=2}^k z_j, \quad \xi_j = e^{-z_j}$$

The distribution of z_j is

$$P(z_j) = \left| \frac{ds_j}{dz_j} \right| = e^{-z_j}$$

$\Rightarrow z_j$ are independent exponential RV's w. mean 1

$$\Rightarrow \langle \ln R_k \rangle \approx k$$

$$\Rightarrow \underline{R_k \sim e^k} \text{ typically}$$

Theorem (Rényi, 1962)

$$\lim_{k \rightarrow \infty} \langle \ln R_k \rangle / k = 1 \text{ with probability } 1$$

(iii) Conditional expectations

What is the statistics of R_k , given R_{k+1} (backward in "time") or R_{k-1} (forward in "time")?

The representation \otimes implies

$$\underline{\langle R_k | R_{k+1} \rangle} = \langle s_{k+1} \rangle \cdot R_{k+1} = \underline{\frac{1}{2} R_{k+1}}$$

but

$$\underline{\langle R_k | R_{k-1} \rangle} = \langle 1/s_k \rangle \cdot R_{k-1} = \underline{\infty}$$

More precisely:

$$\begin{aligned} \text{Prob} [R_k > n | R_{k-1}] &= \text{Prob} [1/s_k > n/R_{k-1}] \\ &= \text{Prob} [s_k < R_{k-1}/n] = \frac{R_{k-1}}{n} \end{aligned}$$

$$\Rightarrow \text{Prob} [R_k = u \mid R_{k-1}] \approx \frac{R_{k-1}}{n^2}$$

the same qualitative behavior as for $k=2$.

[Faint handwritten notes, possibly describing a process or model]
