

b) The limit theorem (Fisher & Tippett, 1928;
Gnedenko, 1943)

Suppose there is a sequence of constants a_N, b_N with $a_N > 0$, and that the RV

$$Y_N = \frac{X_{\max}(N) - b_N}{a_N}$$

has a non-degenerate distribution for $N \rightarrow \infty$,
i.e. that the limit

$$\lim_{N \rightarrow \infty} F(a_N y + b_N)^N = G(y)$$

exists and is non-degenerate. Then G
belongs to the one-parameter family

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

with $\gamma \in \mathbb{R}$. In the case $\gamma = 0$

$$G_0(y) = \exp(-e^{-y})$$

γ is called the extreme value index.
In the explicit examples we found that

- (i) exponential: $b_H = \ln H$, $a_H = 1$, $\gamma = 0$
- (ii) unbounded: $b_H = 1 - \frac{1}{H}$, $a_H = \frac{1}{H}$, $\gamma = -1$
- (iii) Pareto: $b_H = 0$, $a_H = H^{1/\alpha}$, $\gamma = \frac{1}{\alpha}$

In general one distinguishes three classes of extreme value distributions:

$\gamma > 0$: Fréchet, unbounded with power law tail

$\gamma = 0$: Gumbel, unbounded¹⁾ with decay faster than a power law¹⁾ or bounded

$\gamma < 0$: Weibull, bounded support with power law behavior at the boundary.

We derive G_γ using a renormalization approach (Berthou, Györfi, 2010).

The combination of maximization, shift & rescaling defines an RG transformation on F ,

$$\underline{[\hat{R}_N F](x) = F^N(a_N x + b_N)} \quad \text{RG}$$

Setting $N = p^n$ we can perform the transformation iteratively by applying $\hat{R}_p$ n times, $\hat{R}_N = (\hat{R}_p)^n$. This suggests to use a "time scale" s that is linear in n by defining $s = \ln N$ and

$$F(x, s) = [\hat{R}_{e^s} F](x), \quad F(x, 0) = F(x)$$

abuse of notation!

"parent distribution"

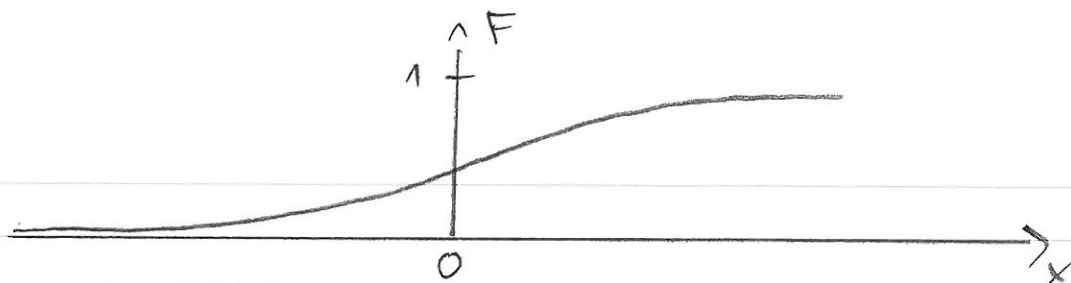
Moreover, for convenience we write

$$\underline{F(x, s) = \exp(-e^{-g(x, s)})}, \quad F(x) = \exp(-e^{-g(x)})$$

Similarly $a_N = a_{e^s} = a(s)$, $b_N = b(s)$.

We fix $a(s), b(s)$ through the requirement that **RG** tends to a non-degenerate limit

in $N \rightarrow \infty$:



$\Rightarrow$ require that $F(0, s) = 1/e$, $\partial_x F(0, s) = 1/e \quad \forall s$
(or some other number)

With $\partial_x F = \partial_x g \cdot e^{-g} = e^{-g}$ this implies

$$\underline{g(0, s) = 0, \quad \partial_x g(0, s) = 1} \quad (1)$$

In this notation **RC** reads

$$F(x, s) = F(a(s)x + b(s))e^s$$

$$\begin{aligned} \Rightarrow \underline{g(x, s)} &= -\ln(-\ln F(x, s)) = -\ln(e^s(-\ln F(ax+b))) \\ &= -s - \ln(-\ln F(ax+b)) \\ &= \underline{g(a(s)x + b(s)) - s} \quad (2) \end{aligned}$$

To determine $a(s)$ and $b(s)$ we insert (2) in (1):

$$g(0, s) = g(b(s)) - s = 0 \quad \Rightarrow \underline{b(s) = g^{-1}(s)} \quad (3)$$

$$\partial_x g(x, s) = a(s) g'(a(s)x + b(s)) \stackrel{(1)}{=} 1 \quad \text{at } x=0$$

$$\Rightarrow \underline{a(s) = 1/g'(b(s))} \quad (4)$$

To derive a flow equation for $g(x,s)$ we take the derivative of (2) w.r.t. s :

$$\partial_s g(x,s) = (\dot{a}x + \dot{b}) g'(ax+b) - 1$$

To determine $\dot{a}$, $\dot{b}$ we use (3), (4):

$$\left. \begin{aligned} \frac{d}{ds} g(b(s)) &= 1 \Rightarrow \dot{b} = \frac{1}{g'(b(s))} = a \\ \dot{a} &= \frac{d}{ds} \left(\frac{1}{g'(b(s))} \right) = - \frac{1}{g'(b(s))^2} g''(b(s)) \dot{b} \end{aligned} \right\}$$

$$\Rightarrow \frac{\dot{a}}{a} = - \frac{g''(b(s))}{g'(b(s))^2} := \delta(s)$$

Moreover from $\partial_x g(x,s) = 1$ we have

$$g'(ax+b) = \frac{1}{a} \partial_x g(x,s)$$

$$\begin{aligned} \Rightarrow \underline{\partial_s g(x,s)} &= \frac{\dot{a}x + \dot{b}}{a} \partial_x g(x,s) - 1 = \\ &= \underline{(1 + \delta x) \partial_x g(x,s) - 1} \end{aligned}$$

an autonomous eq. for $g(x,s)$, with all information about the parent distribution contained in $\delta(s)$.

Fixed point: $\gamma(s) = \gamma = \text{const.}$, $\partial_s g = 0$

$$\Rightarrow (1 + \gamma x) \frac{d}{dx} g^*(x) = 1, \quad g^*(0) = 0$$

$$\Rightarrow g^*(x) = \int_0^x \frac{dx'}{1 + \gamma x'} = \frac{1}{\gamma} \ln(1 + \gamma x)$$

Transforming back to the original distribution we have

$$\underline{F^*(x) = e^{-e^{-g^*(x)}} = e^{-(1+\gamma x)^{-1/\gamma}} = G_\gamma(x) \quad \square}$$

Examples:

(i) Exponential: $F(x) = 1 - e^{-x}$

$$\Rightarrow g(x) = -\ln(-\ln F(x)) = -\ln(\underbrace{-\ln(1 - e^{-x})}_{\approx e^{-x}}) \approx x$$

$$\Rightarrow g'' = 0, \quad \underline{\gamma = 0}. \quad \text{The scale parameters are}$$

$$b(s) = g''(s) = 0 = \ln 1, \quad a(s) = b = 1.$$

(ii) Pareto: $F(x) = 1 - x^{-\alpha} \Rightarrow g(x) \approx \alpha \ln x$

$$\Rightarrow g' = \frac{\alpha}{x}, \quad g'' = -\frac{\alpha}{x^2} \Rightarrow \underline{\gamma = -\frac{g''}{(g')^2} = 1/\alpha}.$$

(iii) uniform:
$$\left. \begin{aligned} F(x) &= x, & g(x) &= -\ln \ln(1/x) \\ b(s) &= e^{-e^{-s}} \rightarrow 1, & s &\rightarrow \infty \end{aligned} \right\}$$

$$\Rightarrow g'(x) = \frac{1}{x \ln(1/x)}, \quad g'' = -\frac{1}{x^2 \ln(1/x)} + \frac{1}{x^2 \ln(1/x)^2}$$

$$\Rightarrow \gamma = -\frac{g''}{(g')^2} \Big|_{x=1} = -1$$

(iv) Gaussian:
$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

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

$$\Rightarrow g(x) = -\ln(-\ln F) \approx \frac{x^2}{2} + \ln x + \frac{1}{2} \ln(2\pi)$$

$$g' = x + \frac{1}{x}, \quad g'' = 1 - \frac{1}{x^2}$$

$$\Rightarrow \gamma = -\frac{g''}{(g')^2} \approx -\frac{1}{x^2} \rightarrow \underline{0}, \quad x \rightarrow \infty.$$

Gumbel class

The scale parameter $b(s)$ is the solution of

$$g(b) = \frac{b^2}{2} + \ln b + \frac{1}{2} \ln(2\pi) = s \Rightarrow \underline{b \approx \sqrt{2s}}$$

to leading order.

$$\Rightarrow a(s) = \dot{b} = \frac{1}{\sqrt{2s}} \rightarrow 0, s \rightarrow \infty.$$

In the original variables this implies

$$Y_H = \frac{X_{\max}(H) - \sqrt{2 \ln H}}{\frac{1}{\sqrt{2 \ln H}}}$$

$\Rightarrow$ typical value $\sqrt{2 \ln H}$ ¹⁾ with fluctuations
 $\sim \frac{1}{\sqrt{2 \ln H}}$, Gumbel distributed.

1) more precise: $(2 \ln H - \ln \ln H - \ln 4\pi)^{1/2} = \ln H$

c) Application: Random energy model

N spins, 2^N configurations with energies drawn randomly from Gaussian distribution

$$f(E) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-E^2/2\sigma^2}, \quad \langle E \rangle = 0.$$

Then the expected value of the ground state is determined by

$$\frac{E_{\min}(H) + \sqrt{2\sigma^2 \ln 2^H}}{\frac{1}{\sqrt{2\sigma^2 \ln 2^H}}} = \gamma_E$$

but note that
 there are corrections
 to $\ln H$

mean of
 Gumbel distr.

$$\Rightarrow \underline{E_{\text{min}}(N) \approx -\sqrt{2\hbar^2 \sigma^2 N}}$$

In order for the ground state energy to be extensive we need $\sigma^2 \sim N \Rightarrow$ set $\sigma^2 = N$.
Then we know that

$$\underline{\lim_{\beta \rightarrow \infty} \left(-\frac{1}{\beta} \langle \ln Z_N(\beta) \rangle \right) = E_{\text{min}}(N) = -\sqrt{2\hbar^2} N}$$

For comparison we compute the "unrelated" free energy

$$\mathcal{F}_N^{\text{un}}(\beta) = -\frac{1}{\beta} \ln \langle Z_N(\beta) \rangle$$

We have

$$\langle Z_N(\beta) \rangle = \left\langle \sum_{i=1}^{2^N} e^{-\beta E_i} \right\rangle = 2^N \langle e^{-\beta E_i} \rangle$$

$$\begin{aligned} \langle e^{-\beta E_i} \rangle &= \int_{-\infty}^{\infty} dE \frac{1}{\sqrt{2i\pi N}} e^{-E^2/2N} e^{-\beta E} \\ &= e^{\frac{N}{2} \beta^2} \end{aligned}$$

$$\Rightarrow \mathcal{F}_N(\beta) = -\frac{1}{\beta} \left(N \ln 2 + \frac{N}{2} \beta^2 \right) =$$

$$= -N \left(\frac{\ln 2}{\beta} + \frac{\beta}{2} \right) = \underline{-N \left(\ln 2 \cdot T + \frac{1}{2T} \right)} \quad (k_B = 1)$$

$\Rightarrow \mathcal{F}_H^{\text{an}}(\beta) \rightarrow -\infty$ as $\beta \rightarrow \infty$, whereas the true free energy cannot be smaller than E_{min} .

We can also compute the annealed entropy:

$$S_H^{\text{an}} = - \frac{\partial \mathcal{F}_H^{\text{an}}}{\partial T} = N \ln 2 - \frac{N}{2T^2} = 0$$

at $\underline{T_c = 1/\sqrt{2 \ln 2}}$. At this temperature the annealed free energy is

$$\underline{\mathcal{F}_H^{\text{an}}(T_c) = -N \sqrt{2 \ln 2} = E_{\text{min}}(N)}$$

$\Rightarrow$ at $T = T_c$ the system freezes into the ground state

