

Tutorials 2 – Probability (2)

1 Large deviations

Consider N i.i.d. random variables distributed according to the law $p(x) = \frac{1}{2}e^{-|x|}$. In the large N limit, the distribution of the sum of N such random variables exhibits the scaling form

$$P_N(s) \underset{N \rightarrow \infty}{\sim} e^{-N\Phi(s/N)} \quad \text{where } \Phi(y) = \max_k \{ky - W(k)\} \quad (1)$$

is the large deviation function (Cramér theorem). Here $W(k) = \ln \langle e^{kX} \rangle$. Compute the large deviation function $\Phi(y)$. Compare to the exact distribution (related to the MacDonald function)

$$P_{n+1}(s) = \frac{1}{2\sqrt{\pi}n!} \left| \frac{s}{2} \right|^{n+1/2} K_{n+\frac{1}{2}}(s) = \frac{e^{-|s|}}{2^{2n+1}n!} \sum_{m=0}^n \frac{(n+m)!}{m!(n-m)!} (2|s|)^{n-m}. \quad (2)$$

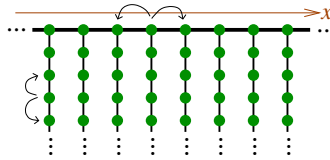
2 Random trap model

We consider a particle jumping from trap to trap along a line. The traps have regular positions. At step $\alpha \in \mathbb{N}$, the particle is trapped during a random time τ_α , and eventually jumps on one of the two neighbouring traps with probability $1/2$ (hence we describe here a symmetric random walk with waiting times). After a time (fixed) t , the particle has performed N jumps (N is random) and is typically at distance $x_t \sim N^{1/2}$. In order to find the scaling between t and N , we rather consider a *fixed* number of jumps N , thus the time t is a random quantity, given by the sum of trapping times

$$t = \sum_{\alpha=1}^N \tau_\alpha. \quad (3)$$

The trapping times τ_α 's are i.i.d. random variables with distribution $\psi(\tau)$. We assume the power law tail $\psi(\tau) \sim \tau^{-1-\mu}$ for $\tau \rightarrow \infty$, with $\mu > 0$.

- 1/ Discuss how t scales with N , depending on μ .
- 2/ Deduce the nature of the random walk.
- 3/ **Diffusion along the skeleton of a comb** : We consider a regular random walk between the nearest neighbour sites of a comb (figure).



In one dimension, the probability of *first* return to the starting point is $\psi(\tau) \sim \tau^{-3/2}$. We denote by x_t the position of the particle along the skeleton. Deduce how x_t scales with time.

3 Random variables with power law distribution

In the lectures, we have extended the central limit theorem to the case of i.i.d. random variables with a symmetric power law distribution $p(x) \sim |x|^{-1-\mu}$ for $\mu \in]0, 2[$. However, in general, $p(x)$ can be asymmetric : the power law tails for $x \rightarrow \pm\infty$ have same exponents but different weights, $p(x) \sim \frac{1+\beta \operatorname{sign}(x)}{|x|^{1+\mu}}$ with $\beta \in [-1, +1]$ the asymmetry parameter. We denote $P_N(s)$ the distribution of the sum of N such i.i.d. random variables.

1/ For $\mu > 1$, argue that the distribution presents the scaling form

$$P_N(s) \underset{N \rightarrow \infty}{\simeq} \frac{1}{N^\alpha} F\left(\frac{s - c N^\theta}{N^\alpha}\right) \quad (4)$$

What are c and the two exponents α and θ ?

2/ What is the corresponding form for $\mu \in]0, 1[$?

3/ We discuss the **marginal case** for $\mu = 1$. The stable Lévy laws are characterized by two indices, the tail exponent μ and the asymmetry parameter $\beta \in [-1, +1]$ ($\beta = 0$ for the symmetric case). For $\mu = 1$, the characteristic function is

$$\widehat{\mathcal{L}}_{1,\beta}(k) = e^{-|k| \left[1 - \frac{2i\beta}{\pi} \operatorname{sign}(k) \ln |k|\right]} \quad (5)$$

a) Deduce $\mathcal{L}_{1,0}(x)$.

b) We now consider the asymmetric case. Consider N i.i.d. random variables distributed according to the Lévy law $p(x) = \mathcal{L}_{1,\beta}(x)$. Check the stability of $\mathcal{L}_{1,\beta}(x)$ against convolution. Express the distribution $P_N(s)$ in terms of $\mathcal{L}_{1,\beta}(x)$.

c) Consider now a more general case where the distribution differs from $\mathcal{L}_{1,\beta}(x)$, but presents similar tails $p(x) \propto \frac{1+\beta \operatorname{sign}(x)}{x^2}$ for $x \rightarrow \pm\infty$ (with different weights at $\pm\infty$). Discuss $P_N(s)$.

4/ Being imaginative, propose the scaling form corresponding to a power law tail $p(x) \sim |x|^{-3}$.

4 Extreme statistics for Gaussian random variable

We consider N i.i.d. Gaussian random variables with distribution

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \quad (6)$$

The aim is to study the distribution of the maximum M_N of N such variables.

1/ Express the cumulative distribution $F(x) = \int_{-\infty}^x dt f(t)$ in terms of the complementary error function $\operatorname{erfc}(z) \stackrel{\text{def}}{=} \frac{2}{\sqrt{\pi}} \int_z^{+\infty} dt e^{-t^2}$. Get the asymptotic behaviour of $\operatorname{erfc}(z)$ (for $z \rightarrow +\infty$).

2/ We recall that the typical position a_N of the maximum of N variables is given by $F(a_N) = 1 - \frac{1}{N}$. Recover that $a_N \approx \sqrt{2 \ln N}$ for the Gaussian case and find the next correction.

3/ Express $\Phi_N(x) = \operatorname{Proba}\{M_N < x\}$, the cumulative distribution of the maximum, in terms of $F(x)$.

4/ Show that $1/b_N \stackrel{\text{def}}{=} \frac{da_N}{d \ln N} \simeq a_N$ for Gaussian variables. Given that $F(x) \simeq 1 - \frac{1}{N} e^{-(x-a_N)/b_N}$ in the neighbourhood of a_N , recover the Gumbel law.

5/ Large deviations : Compare $\Phi_N(x = a_N + b_N y)$ for $x \sim a_N$ [i.e. $y \sim \mathcal{O}(1)$] and for $x \gg a_N$.