

$$a) \quad \frac{1}{N} S_N \xrightarrow{N \rightarrow \infty} \mu_1 \quad \text{provided } \mu_1 \text{ exists,}$$

in the following precise sense:

$$\lim_{N \rightarrow \infty} \text{Prob} \left[ \left| \frac{1}{N} S_N - \mu_1 \right| > \varepsilon \right] = 0 \quad \text{for any } \varepsilon > 0$$

a more similar formulation. In the following we are interested in the fluctuations of  $S_N$  around its mean.

### a) Central limit theorem (CLT)

Assume for simplicity that  $\mu_1 = 0$ , and that  $\sigma^2 < \infty$ . Then the CLT states that the distribution of the RV

$$Z_N = \frac{1}{\sqrt{N}} S_N = \frac{1}{\sqrt{N}} \sum_{i=1}^N X_i$$

becomes Gaussian for  $N \rightarrow \infty$ ,

$$f_N(z) \xrightarrow{N \rightarrow \infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-z^2/2\sigma^2}$$

Proof:  $G_{Z_N}(k) = \langle e^{ikX/\sqrt{N}} \rangle_x^N = G_X(k/\sqrt{N})^N$

$$\Rightarrow \ln G_{Z_N}(k) = N \underbrace{\ln G_X(k/\sqrt{N})}$$

$$\approx 1 - \frac{1}{2} \sigma^2 \frac{k^2}{N} + \frac{1}{6} \frac{\kappa_3}{N^{3/2}} (ik)^3 + \dots$$

$$\Rightarrow \lim_{N \rightarrow \infty} \ln G_{Z_N}(k) = -\frac{1}{2} \sigma^2 k^2$$

and all higher cumulants vanish under this scaling. □

## b) Lévy laws

What happens if  $\sigma^2 = \infty$ , e.g. if Pareto

$$f(x) \sim |x|^{-(\alpha+1)}, \quad |x| \rightarrow \infty$$

with  $\alpha < 2$ ?

Consider for example the Cauchy distribution

$$f(x) = \frac{1}{\pi} \frac{c}{c^2 + x^2}$$

$$\Rightarrow G_X(k) = e^{-c|k|} \approx 1 - c|k|, \quad k \rightarrow 0$$

Define now  $Z_H = \frac{1}{N} \sum_{i=1}^H X_i = \frac{1}{N} S_H$

$$\Rightarrow G_{Z_H}(k) = \left( e^{-c \frac{|k|}{N}} \right)^H = e^{-c|k|}$$

$\Rightarrow$  Cauchy distribution is a stable law, which is invariant under addition & rescaling of RV's. In contrast to the CLT case,

- $G_X(k)$  is non-analytic at  $k=0$ , which
- requires a different scaling of  $S_N$ .

This picture generalizes to any  $\alpha < 2$ ; assuming for now that  $f(x) = f(-x)$ , we have

(i)  $G_X(k) \approx 1 - c|k|^\alpha, \quad |k| \rightarrow 0$

(ii) Rescaling  $Z_H = \frac{1}{N^{1/\alpha}} S_H \xrightarrow{H \rightarrow \infty} Z$  with

(iii)  $f(z) = L_{\alpha,0}(z) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dk e^{-ikz} e^{-c|k|^\alpha}$

symmetric Lévy law.

In the general, asymmetric case one has to distinguish between  $1 < \alpha < 2$  and  $0 < \alpha < 1$ :

$$\left. \begin{array}{ll} \underline{1 < \alpha < 2:} & Z_H = \frac{1}{N^{1/\alpha}} (S_H - \mu_H N) \\ \underline{0 < \alpha < 1:} & Z_H = \frac{1}{N^{1/\alpha}} S_H \end{array} \right\}$$

converges to RV with pdf

$$L_{\alpha, \beta}(z) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dk e^{-izk} e^{-c|k|^{\alpha} (1 + i\beta \operatorname{sgn}(k) \tan \frac{\pi\alpha}{2})}$$

$$\beta = \frac{C_+ - C_-}{C_+ + C_-}, \quad f(x) \sim \begin{cases} C_- |x|^{-(\alpha+1)} & x \rightarrow -\infty \\ C_+ |x|^{-(\alpha+1)} & x \rightarrow \infty \end{cases}$$

Explicit expressions for the limit laws exist only for  $\alpha = 1, \beta = 0$  (Cauchy) and  $\alpha = \frac{1}{2}, \beta = 1$ :

$$L_{\frac{1}{2}, 1}(z) = \begin{cases} \frac{c}{\sqrt{2\pi}} z^{-3/2} e^{-c^2/2z} & z > 0 \\ 0 & z < 0 \end{cases}$$

Remark: Power law distributions with  $\alpha > 2$   
display higher order singularities in  $G_X(k)$ .

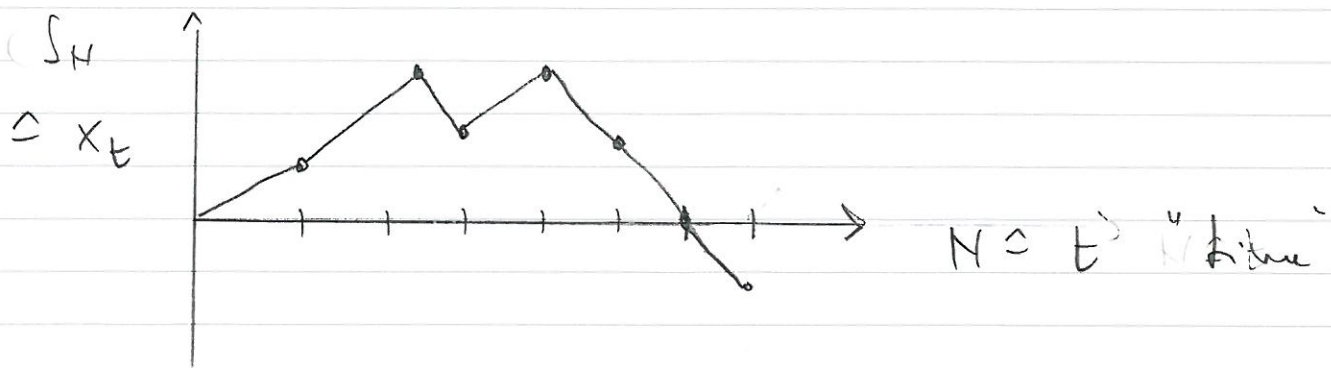
Example:  $f(x) = \frac{2C^3}{\pi (x^2 + C^2)^2} \quad (\alpha = 3)$

$$\Rightarrow G_X(k) = (1 + C|k|) e^{-C|k|} \approx 1 - \frac{1}{2} C^2 k^2 + \frac{C^3}{3} |k|^3 + \dots$$

$\sim |k|^\alpha$

### c) Random walks and Lévy Flight

let  $S_N = \sum_{i=1}^N X_i$  with  $X_i$  i.i.d. from a symmetric distribution. Then  $S_N$  can be interpreted as the position of a one-dimensional random walk (RW):



Generalization to d dimensions:

$$\vec{R}_N = \sum_{i=1}^N \vec{r}_i, \quad \vec{r}_i = (x_1, \dots, x_d), \quad x_i \text{ i.i.d., symmetric.}$$

Two cases: (i)  $\langle X_i^2 \rangle = \sigma^2 < \infty$

$\Rightarrow$  CLT states that  $\frac{1}{\sqrt{N}} \vec{R}_N \xrightarrow{N \rightarrow \infty} \text{Gaussian,}$

$$\langle |\vec{R}_N|^2 \rangle \approx d \sigma^2 N \quad \text{standard diffusion}$$

(ii)  $\langle X_i^2 \rangle = \infty$ ,  $f(x) \sim x^{-(\alpha+1)}$  with  $\alpha < 2$

$\Rightarrow N^{-1/\alpha} \vec{R}_N \xrightarrow{N \rightarrow \infty} \text{Lévy law, which}$

implies that typically,

$$|\vec{R}_N| \sim N^{1/\alpha} \quad \text{super diffusive, } \frac{1}{\alpha} > \frac{1}{2}.$$

But note that the mean square displacement does not exist.

RW's with  $\alpha < 2$  are also called Lévy flights.

### Examples:

- (i) Two-dimensional Lorentz gas
- (ii) Living polymers
- (iii) Foraging behavior in animals
- (iv) Stock prices

(ii) Living polymers (Ott et al., PRL 65, 2201, 1990)

"Living polymers" are chains of micelles that break up & recombine to produce a stationary length distribution

$$f(l) = l_0^{-2} l e^{-l/l_0}$$

A tracer particle on a polymer of length  $l$  diffuses with diffusion constant

$$D(l) = D_0 (l_0/l)^\gamma \sim l^{-\gamma}, \quad \gamma \approx 2.15$$

$\Rightarrow$  distance covered during time  $\tau^*$  between two breakup/recombination events is

$$\underline{r(l) = \sqrt{D(l) \tau^*} \sim l^{-\gamma/2}}, \quad l \sim r^{-2/\gamma}$$

$$\begin{aligned} \Rightarrow \underline{f(r)} &\sim \frac{dl}{dr} f(l) \sim r^{-\left(\frac{2}{\gamma}+1\right)} r^{-\frac{2}{\gamma}} \underbrace{e^{-l/l_0}}_{\rightarrow 1, r \rightarrow \infty} \\ &\sim \underline{r^{-\left(\frac{4}{\gamma}+1\right)}} \end{aligned}$$

$\Rightarrow$  Lévy-flight with  $\alpha = \frac{4}{\gamma} \approx 1.86 < 2$ .

(iii) Foraging behavior of animalsViswanathan et al., Nature 381, 413 (1996)

Find a power law distribution of flight times of wandering albatross with  $\alpha \approx 1$ .

This finding was subsequently revisited & questioned by the same group (Edwards et al., Nature 449, 1044, 2007).

(iv) Stock prices

Let  $S_N = \sum_{i=1}^N X_i$  be a detrended stock price,

$X_i$  price increments at high temporal resolution.

Then the distribution of the  $X_i$  is a

truncated power law

$$f(x) = C |x|^{-(\alpha+1)} e^{-|x|/\xi}, \quad \alpha \approx 1.4$$

(Mantegna, Stanley, Nature 376, 46, 1995)

This implies a crossover in  $S_N$  from Lévy-behavior at short times to Gaussian behavior at long times.

## Estimate of the crossover time:

- variance of  $X$  is

$$\begin{aligned} \sigma^2 = \langle x^2 \rangle &= \int dx |x|^{1-\alpha} e^{-|x|/\xi} \\ &\sim \int dx x^{1-\alpha} \sim \xi^{(2-\alpha)} \end{aligned} \quad \left. \vphantom{\int dx x^{1-\alpha} \sim \xi^{(2-\alpha)}} \right\}$$

- Thus

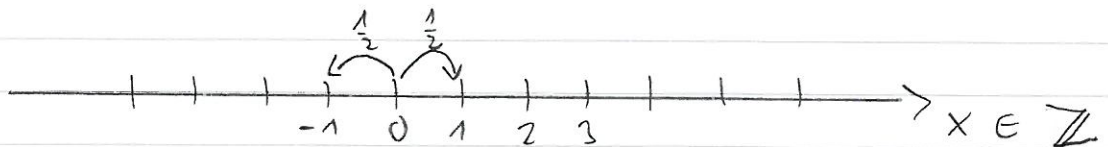
$$S_H \sim \begin{cases} N^{1/\alpha} & \text{short times} \\ \sqrt{\xi^{(2-\alpha)} N} & \text{long times} \end{cases}$$

$$\Rightarrow \text{crossover at } \xi^{(2-\alpha)} N \sim N^{2/\alpha} \Rightarrow \underline{N_x \sim \xi^\alpha}$$

Detailed analysis: I. Kopov, PRE 52, 1157, 1995

## d) Subdiffusion and continuous time RW's

Consider RW on a (one-dim.) lattice:



$\Rightarrow$  displacement after  $n$  steps is  $\langle x_n^2 \rangle = n$ .

In the continuous time RW (CTRW) the walker waits a random waiting time  $\tau$

between two jumps, with pdf  $\psi(\tau)$ .

Two cases:

$$(i) \quad \langle \tau \rangle < \infty \Rightarrow \langle x(t)^2 \rangle \approx \frac{t}{\langle \tau \rangle} \quad \left. \vphantom{\langle \tau \rangle} \right\} \text{various diffusion}$$

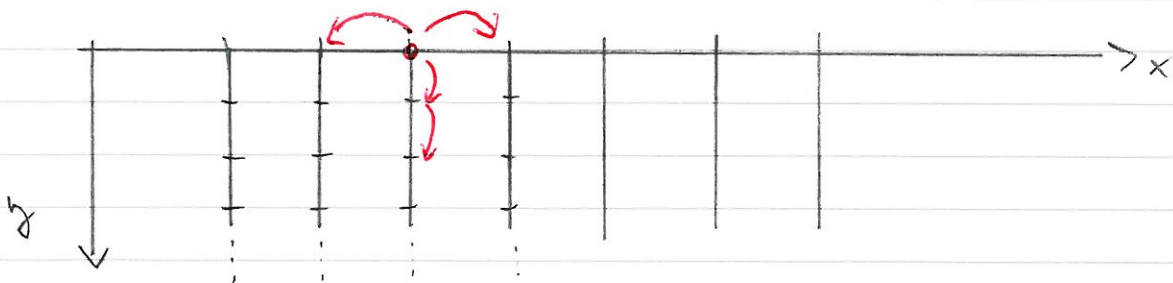
$$(ii) \quad \langle \tau \rangle = \infty, \text{ e.g. } \psi(\tau) \sim \tau^{-(\alpha+1)} \text{ with } \underline{\alpha < 1}$$

Then the time elapsed after  $n$  hops is a Lévy variable

$$t_n = \sum_{i=1}^n \tau_i \sim n^{1/\alpha} \gg n$$

$$\Rightarrow \underline{x_n^2 \sim n \sim t^\alpha \ll t} \quad \underline{\text{subdiffusion}}$$

Example: Diffusion in combs (Havlin, Ben-Avraham 1987)



pdf of return times to  $y=0$  is  $\psi(\tau) \sim \tau^{-3/2}$

$$\Rightarrow \underline{x_t^2 \sim t^{1/2}}$$

In the most general CTRW, jump lengths are drawn from pdf  $f(x)$  and waiting times from pdf  $\psi(\tau)$ . Then if

$$\left. \begin{aligned} f(x) &\sim x^{-(\alpha_x+1)}, \quad \psi(\tau) \sim \tau^{-(\alpha_\tau+1)} \\ \alpha_x &< 2, \quad \alpha_\tau < 1 \end{aligned} \right\}$$

We can estimate

$$\left. \begin{aligned} X_t^2 &\sim n^{1/\alpha_x}, \quad n \sim t^{\alpha_\tau} \\ \Rightarrow X_t^2 &\sim n^{\alpha_\tau/\alpha_x} \end{aligned} \right\}$$

but the computation of the distribution of  $x$  is quite non-trivial.

### 3° Large deviations

Motivation: Consider binomial RV

$$X = \begin{cases} 1 & \text{prob. } p \text{ "success"} \\ 0 & \text{prob. } 1-p \text{ "failure"} \end{cases}$$

$$\Rightarrow \mu_1 = \frac{1}{2}, \quad \sigma^2 = p(1-p)$$