

Branching random walks: speed and entropy

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- A black and white photograph of three pieces of chalk lying on a dark, textured surface. The chalk pieces are arranged diagonally from the top right towards the bottom left. The piece in the foreground is the most prominent, showing its cylindrical shape and some surface texture. The other two pieces are partially visible behind it.
- ▶ **BRW: Branching random walks**
 - ▶ **Empirical distributions**
 - ▶ **Speed and displacement**
 - ▶ **Entropy**

Joint research with



Robin Kaiser



Jérémie Brioussel

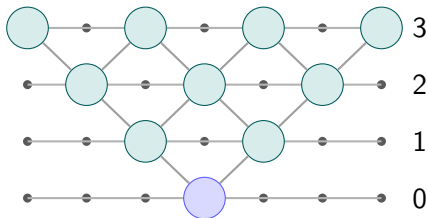


Martin Klötzer

Branching random walks BRW

BRW combines two mechanisms:

- 1 each particle branches according to π ;
- 2 each child does a random walk on G .



State space: infinite graph G .

For this talk the state space is regular tree $\mathbb{T}_d$ (or $\mathbb{Z}^d$).

Branching process

Generation 0

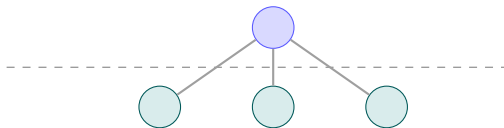


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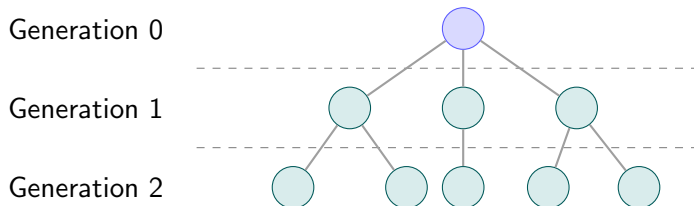
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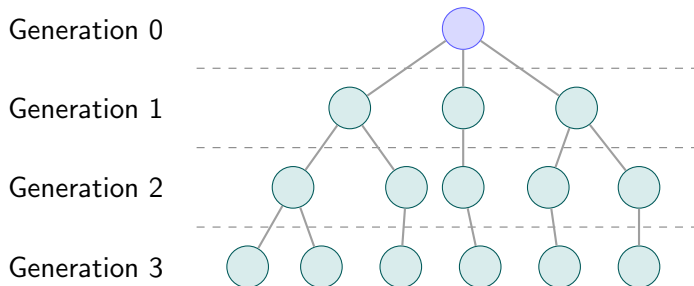
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- Produces k children with distribution $\pi(k)$ and then it dies.

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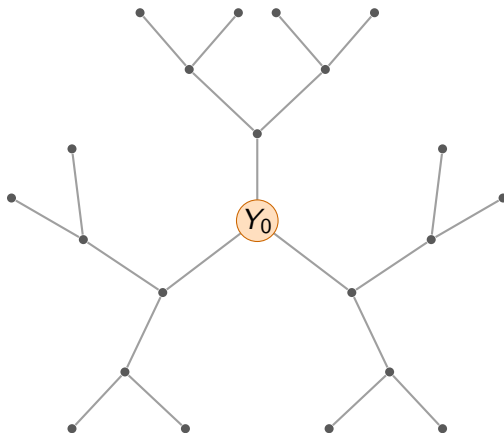
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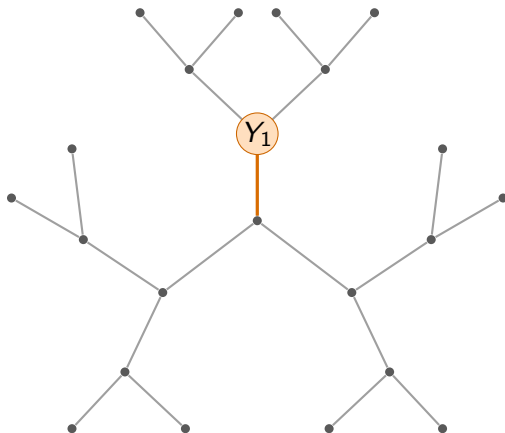
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- Produces k children with distribution $\pi(k)$ and then it dies.
- Each new particle branches independently and then it dies.
- The genealogy is built generation by generation.
- **Z_n = number of particles** in the n -th generation.

Random walk on a tree $\mathbb{T}_d$



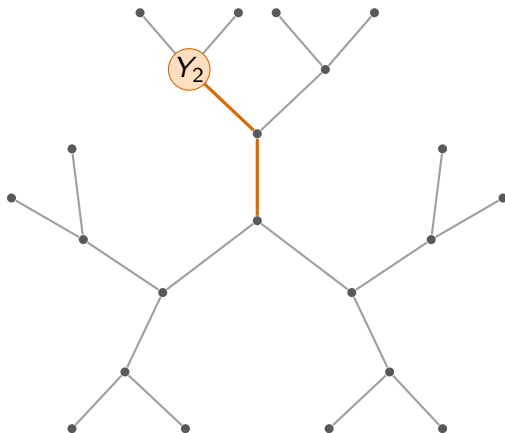
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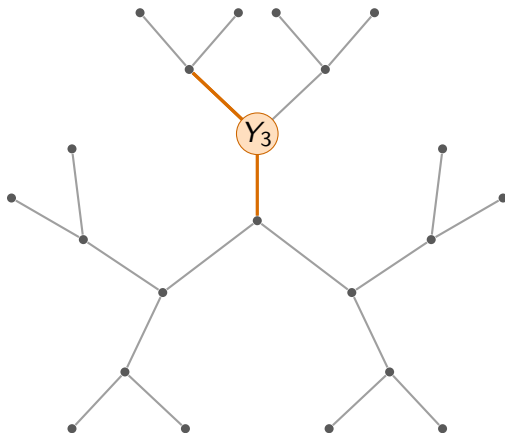
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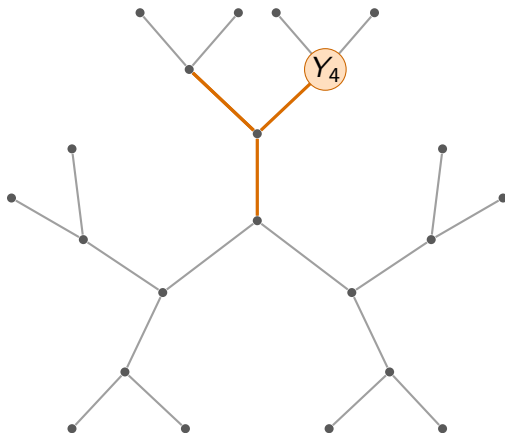
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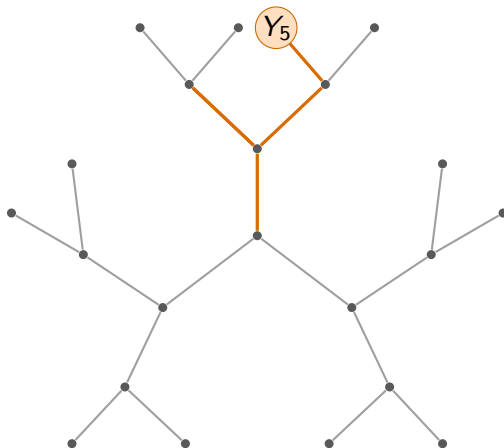
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- Kesten-Stigum [1966]

$$\frac{Z_n}{\rho^n} \rightarrow W \text{ almost surely and } \mathbb{P}[W > 0] = 1.$$

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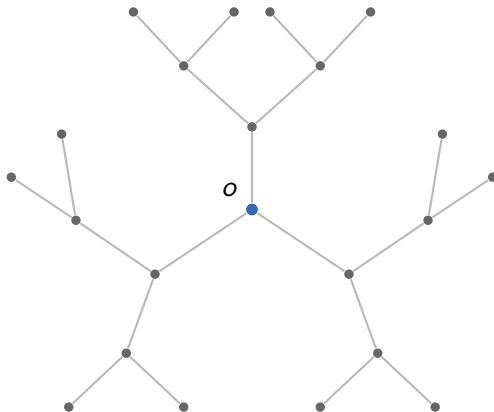
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For $n \geq 0$ let $M_n : V \rightarrow \mathbb{N}$ random population at time n ; for $x \in V$

$M_n(x) := \#$ individuals at vertex x at time n

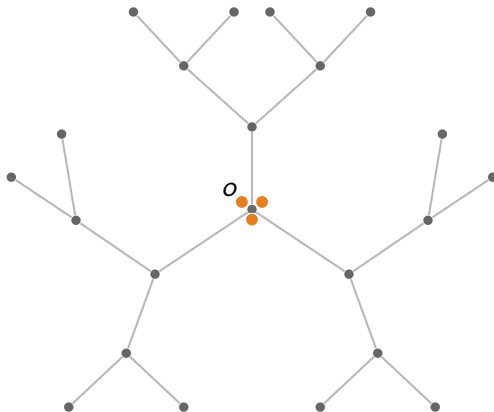
$$M_n = \sum_{x \in V} M_n(x) \delta_x \quad \text{measure on } G$$

BRW: $(M_n)_{n \in \mathbb{N}}$ sequence of random populations



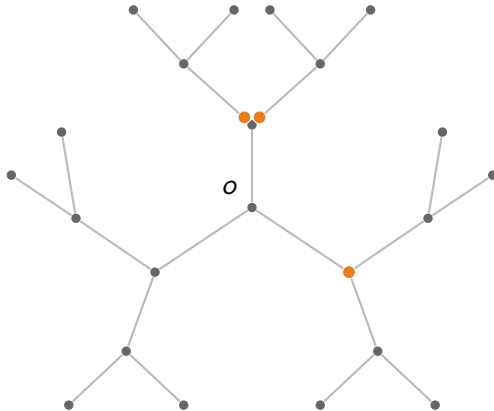
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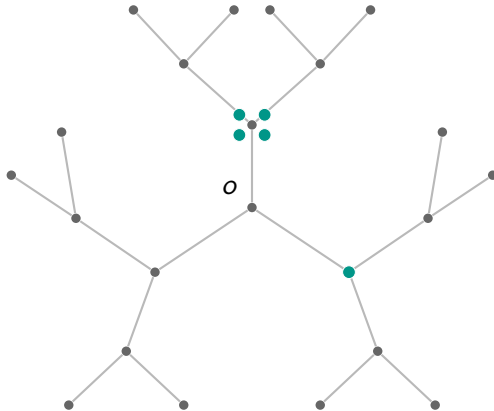
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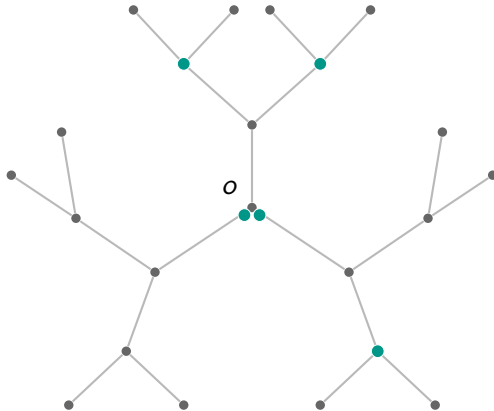
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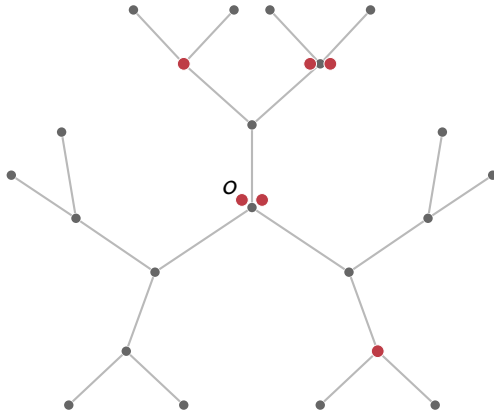
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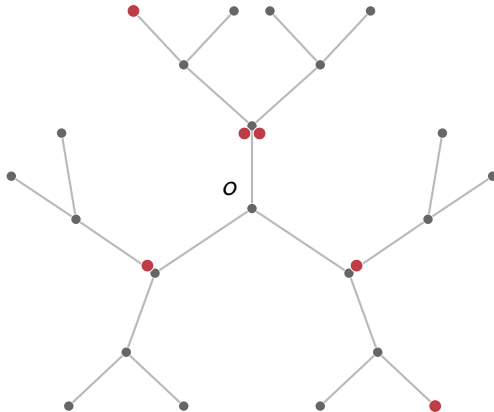
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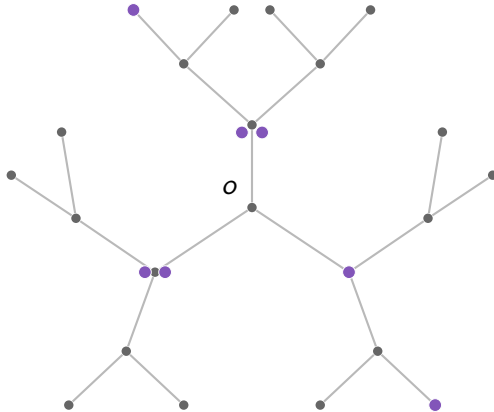
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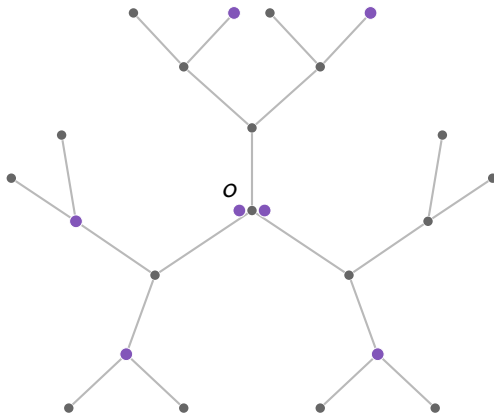
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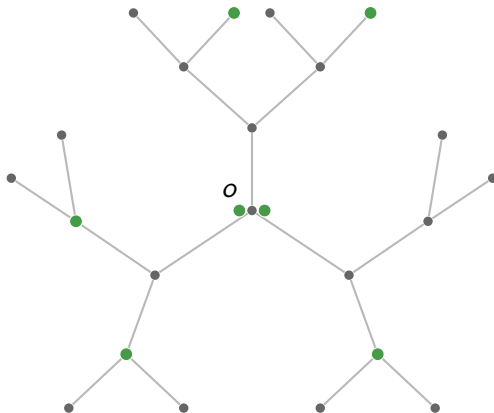
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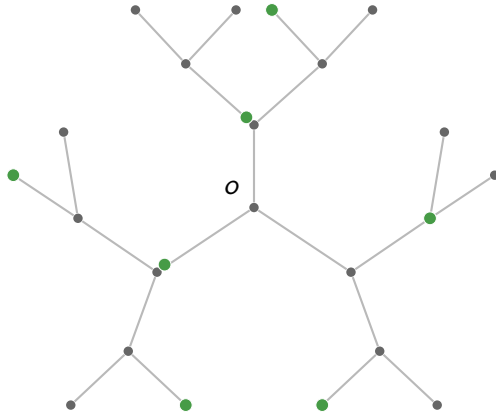
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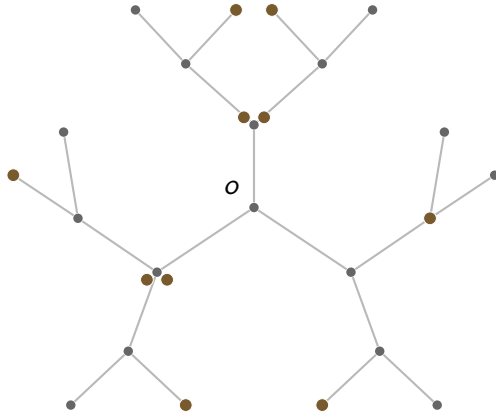
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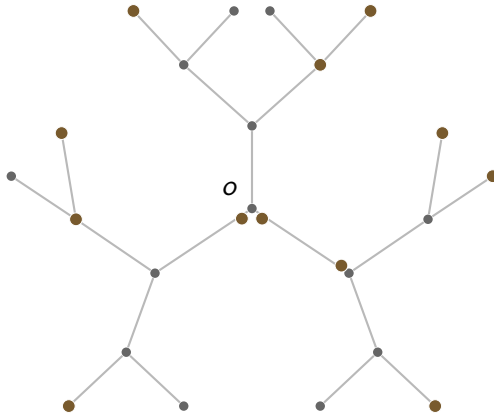
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 - **Transience:** every finite subset of G visited finitely many times a.s. by the BRW.
 - **Recurrence:** every finite subset of G visited ∞ often a.s.

Phase transitions for BRW

Transience/recurrence phase transition for BRW occurs at $1/r$:
Benjamini-Peres (1996), Gantert-Müller (2007)

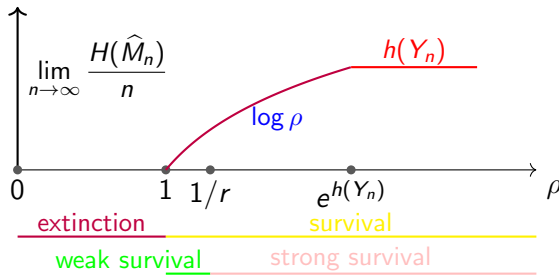
- $\rho \leq \frac{1}{r}$: BRW is **transient** (**extinction** if $\rho \leq 1$ and **weak survival** if $\rho \in (1, \frac{1}{r}]$).
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Aim of this talk: existence of a third phase transition!



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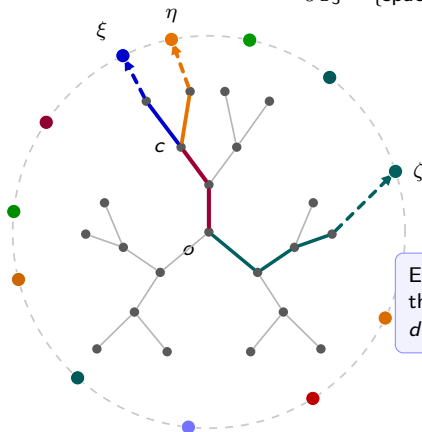
Theorem: [Candellero-Hutchcroft, Kaimanovich-Woess 2023]

Let (M_n) be supercritical BRW on G with $L \log L$ condition and transient underlying random walk. Then, **almost surely** (for almost all realizations of BRW)

$\hat{M}_n = \frac{M_n}{Z_n}$ converges **weakly** to a random measure on ∂G .

End compactification of $\mathbb{T}_3$

$$\partial\mathbb{T}_3 = \{\text{space of ends}\} = \{\text{infinite rays}\}$$



Ends ξ and η agree on $[0, c]$
 then split: $d(\xi, \eta) = 2^{-|c|}$.
 d metric on $\hat{\mathbb{T}}_3$

$$\hat{\mathbb{T}}_3 = \mathbb{T}_3 \cup \partial\mathbb{T}_3: \text{vertices plus infinite rays.}$$

$w = [w_0, w_1, \dots] \rightarrow \xi$ if length common initial segment $\rightarrow \infty$.

Quantitative behaviour of empirical distributions

$\hat{M}_n = \frac{M_n}{Z_n}$ empirical distributions of the BRW on G .

Questions (Kaimanovich-Woess [2023])

Empirical versions of limit theorems for BRW:

- **Speed:** random walk has speed ℓ , does the whole cloud of particle move with the same speed?
- **CLT for $\hat{M}_n$:** if speed of a random walk has Gaussian fluctuations, does the BRW cloud inherit the fluctuations?
- **Entropy:** If we know the entropy of the underlying random walk, what can we say about the entropy of $\hat{M}_n$?

Average speed and CLT for the empirical distributions

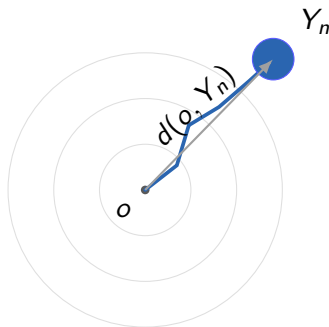
Underlying random walk: Let $(Y_n)_{n \geq 0}$ be a transient random walk on G started at o .

Rate of escape/Speed

$$\ell = \lim_{n \rightarrow \infty} \frac{d(o, Y_n)}{n}.$$

For the CLT part, assume that for some $\sigma > 0$,

$$\frac{d(o, Y_n) - \ell n}{\sigma \sqrt{n}} \xrightarrow{n \rightarrow \infty} \mathcal{N}(0, 1).$$



the distance from o grows linearly $\asymp \ell n$, with possible Gaussian fluctuations

Speed of the empirical cloud of particles

Define the normalized average speed (displacement)

$$D_n := \frac{1}{n} \int d(o, x) d\hat{M}_n(x) = \frac{1}{nZ_n} \sum_{x \in G} d(o, x) M_n(x).$$

Theorem: [Kaiser-Klötzer-Sava-Huss 2026]

Empirical rate of escape on transitive graphs G : if random walk (Y_n) has speed $\ell = \lim_{n \rightarrow \infty} \frac{d(o, Y_n)}{n}$ (almost sure limit), and offspring distribution with $\pi(0) = 0$, $\rho > 1$, and finite second moment, then

$$D_n \xrightarrow[n \rightarrow \infty]{a.s.} \ell.$$

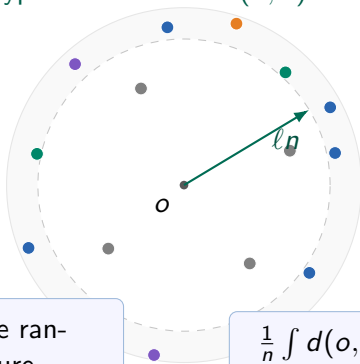
Equivalently, on the survival event where $W > 0$,

$$\frac{1}{n\rho^n} \sum_{x \in G} d(o, x) M_n(x) \xrightarrow[n \rightarrow \infty]{a.s.} \ell W.$$

Picture of the speed theorem

BRW cloud travels at the same linear speed as one random walk;
random factor is the martingale limit W when normalizing by ρ^n .

typical radial shell $d(o, x) \approx \ell n$



$\hat{M}_n$ is a finite random measure.

$$\frac{1}{n} \int d(o, x) d\hat{M}_n(x) \rightarrow \ell.$$

Stam-type CLT on $\mathbb{Z}$

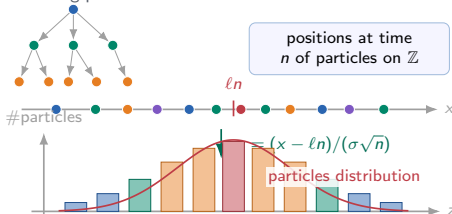
Stam [1966], Biggins [1988]

BRW on $\mathbb{Z}$ with speed ℓ and variance σ^2 , for each $y \in \mathbb{R}$,

$$\frac{1}{\rho^n} Z_n((-\infty, \ell n + \sigma \sqrt{n} y]) \rightarrow W\Phi(y)$$

- center at the drift ℓn ;
- rescale $\sqrt{n}$;
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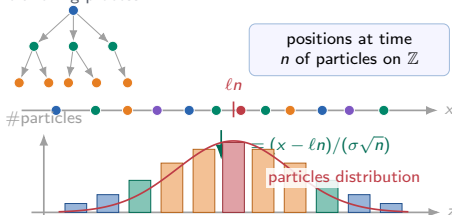
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branching process



CLT for empirical distributions $\hat{M}_n = \frac{M_n}{Z_n}$ of BRW on $\mathbb{T}_d$?

What about the set of particles in $\mathbb{T}_d$ in BRW that deviate at most of order $\sqrt{n}$ from the average speed ℓn ?

$$A_n(a, b) = \left\{ x \in G : a \leq \frac{d(o, x) - \ell n}{\sigma \sqrt{n}} \leq b \right\}.$$

CLT for the empirical distributions $\hat{M}_n = \frac{M_n}{Z_n}$

For $a < b$, define the radial CLT window

$$A_n(a, b) = \left\{ x \in G : a \leq \frac{d(o, x) - \ell n}{\sigma \sqrt{n}} \leq b \right\}.$$

Theorem: [Kaiser-Klötzer-Sava-Huss 2026]

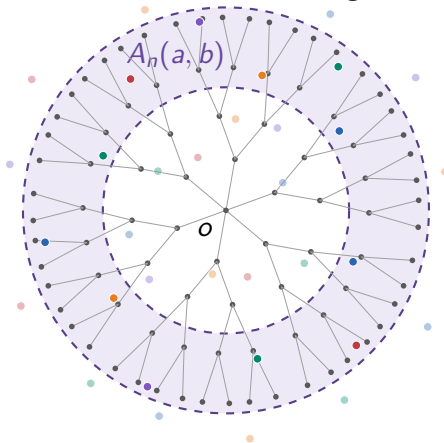
Empirical CLT for BRW: If the underlying random walk (Y_n) satisfies a CLT (and $\rho > 1$ and finite second moment for π)

$$\frac{d(o, Y_n) - \ell n}{\sigma \sqrt{n}} \xrightarrow[n \rightarrow \infty]{} \mathcal{N}(0, 1),$$

then the empirical rescaled radial empirical distributions converge weakly in probability to $W\mathcal{N}(0, 1)$:

$$\frac{1}{\rho^n} M_n(A_n(a, b)) \xrightarrow[n \rightarrow \infty]{\mathbb{P}} W(\Phi(b) - \Phi(a)).$$

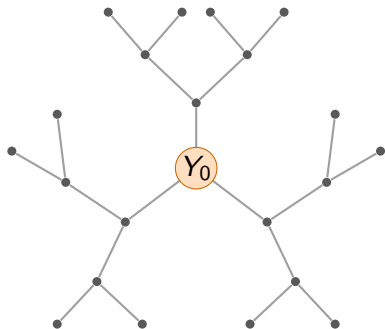
Empirical CLT for branching random walks



Shell between $r_a = \ell n + \sigma\sqrt{n}a$ and $r_b = \ell n + \sigma\sqrt{n}b$.

Many particles lie outside the shell; only particles in the shell contribute to $\hat{M}_n(A_n(a, b))$.

Asymptotic entropy $h(Y_n)$ of random walk Y_n

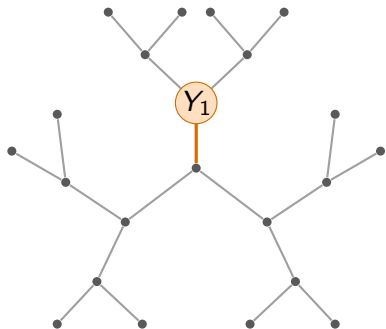


- **Entropy:** how many vertices are plausible locations of Y_n ?

Meaning of $h(Y_n)$

$e^{nh(Y_n)}$ is the exponential growth rate of the part of the tree explored by the walk.

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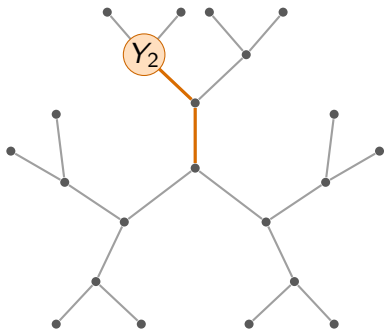
- **Entropy:** how many vertices are plausible locations of Y_n ?
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$$H(Y_n) = - \sum_{x \in \mathbb{T}_d} p_n(x) \log p_n(x).$$

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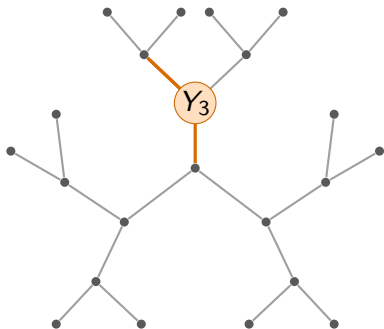
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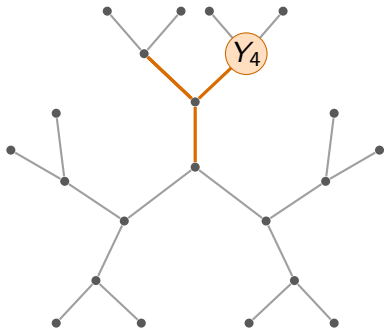
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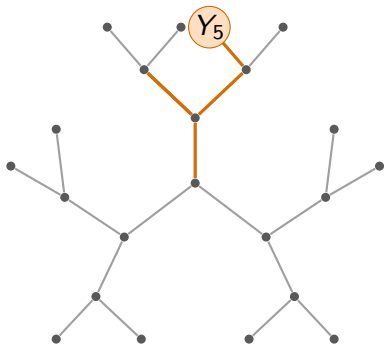
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Example: simple walk on the 3-regular tree

For the simple random walk on $\mathbb{T}_3$, the distance from the root behaves like a biased walk on $\mathbb{N}$.

Speed

Away from the root, one edge goes back and two edges go forward. Hence the distance has drift

$$\frac{2}{3} - \frac{1}{3} = \frac{1}{3}, \quad d(0, Y_n) \approx \frac{n}{3}.$$

Asymptotic entropy

The ball of radius r has about 2^r vertices, so typical sites at time n occupy roughly

$$2^{n/3} = e^{(n/3) \log 2}$$

positions. Thus

$$h(Y_n) = \frac{1}{3} \log 2.$$

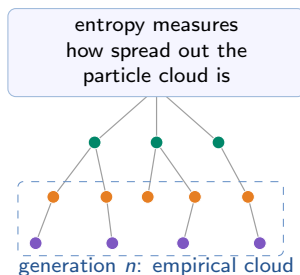
Entropy of the empirical distributions

For a branching random walk on G ,
the empirical distribution at time n is

$$\hat{M}_n(x) = \frac{M_n(x)}{Z_n}.$$

Its Shannon entropy is

$$H(\hat{M}_n) = - \sum_{x \in G} \hat{M}_n(x) \log \hat{M}_n(x).$$



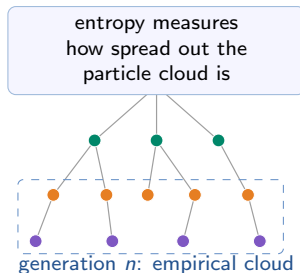
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Question

Does the limit

$$\lim_{n \rightarrow \infty} \frac{H(\hat{M}_n)}{n}$$

exist almost surely, and what is its value?

Phase transition for the entropy

Theorem: [Brieussel-Klötzer-Sava-Huss 2026+]

Under assumptions ($h(Y_n) < \infty$, $\pi(0) = 0$, $\rho > 1$, π second moment)

$$\lim_{n \rightarrow \infty} \frac{H(\hat{M}_n)}{n} = \begin{cases} \log \rho, & \rho \leq e^{h(Y_n)}, \\ h(Y_n), & \rho > e^{h(Y_n)}, \end{cases} \quad \text{almost surely.}$$

Equivalently $\lim_{n \rightarrow \infty} \frac{H(\hat{M}_n)}{n} = \min\{\log \rho, h(Y_n)\}$.

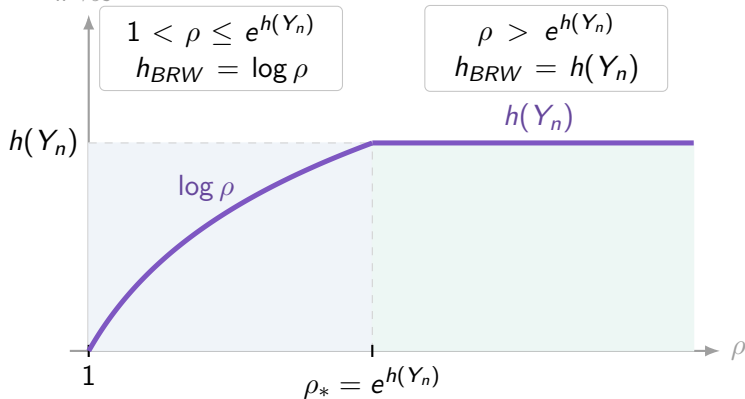
The critical value is

$$\rho_* = e^{h(Y_n)}.$$

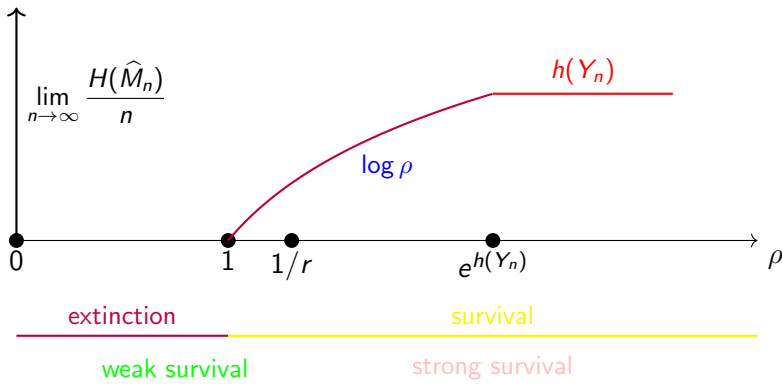
Below ρ_* , population is too small to probe the random-walk distribution;
above ρ_* , it is large enough to recover the random-walk entropy rate.

Picture of the phase transition

$$h_{BRW} = \lim_{n \rightarrow \infty} H(\hat{M}_n)/n$$



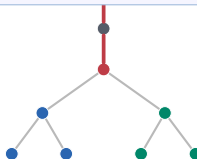
3 phase transitions in branching random walks



BRW is harder than independent random walkers

- BRW particles share long ancestral paths.
- Atypical early particles can create many descendants.
- Standard subadditive tools do not directly apply to $H(\hat{M}_n)$.
- One must control whole lineages, not only endpoints.

shared ancestry creates correlations



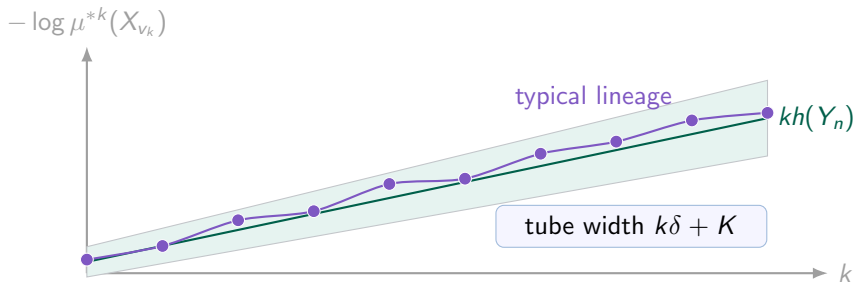
Key proof idea: the entropic tube

For a typical random-walk path, (μ is the step distribution of (Y_n))

$$-\log \mu^{*k}(Y_k) \approx kh(Y_n).$$

Restrict attention to particles whose whole ancestral trajectory stays in this typical window:

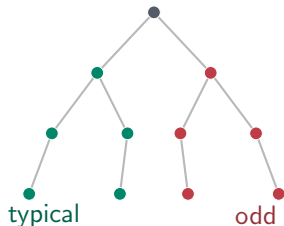
$$\text{Ent}_{n,\delta,K} := \{ \forall k \leq n : |-\log \mu^{*k}(Y_k) - kh(Y_n)| \leq k\delta + K \}.$$



Typical and odd particles

Partition of generation n

- Typ_n : particles whose ancestral paths stay inside the entropic tube.
- Odd_n : particles whose ancestral paths exit the tube.



We prove

$$\frac{\#\text{Typ}_n}{\rho^n} \rightarrow W^{\text{typ}}, \quad \frac{\#\text{Odd}_n}{\rho^n} \rightarrow W^{\text{odd}}.$$

As the tube is widened, $W^{\text{typ}} \rightarrow W$ and $W^{\text{odd}} \rightarrow 0$.

Good sites and collision control

The proof then studies how many typical particles may coalesce at the same vertex

Small- ρ regime

When $\rho \leq e^{h(Y_n)}$, typical particles do not cluster too much:

$$M_n^{\text{typ}}(x) \leq (1 + c)^n$$

for most of the typical mass.
This forces entropy rate $\log \rho$.

Large- ρ regime

When $\rho > e^{h(Y_n)}$, for most typical mass,

$$M_n^{\text{typ}}(x) \lesssim \rho^n e^{-n(h(\mu) - \varepsilon)}.$$

The empirical profile approximates the random-walk entropy scale.

The estimates rely on second-moment bounds for typical-particle overlaps, using the branching time of pairs.

Questions

- Second order estimates for the asymptotic entropy of the empirical distributions of BRW?
- Why is entropy important for understanding the non-trivial behaviour of branching random walks at infinity?

THANK YOU!