

Branching random walk in random environment

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joint work with Piotr Miłoś

ENS, DMA

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Plan

- 1 The branching random walk in random environment
- 2 The random walk in random environment
- 3 Brownian motion above a Brownian curve

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Description of the process

Let $(\mathcal{L}_n, n \geq 0)$ be an i.i.d. sequence of point processes distributions on \mathbb{R} .

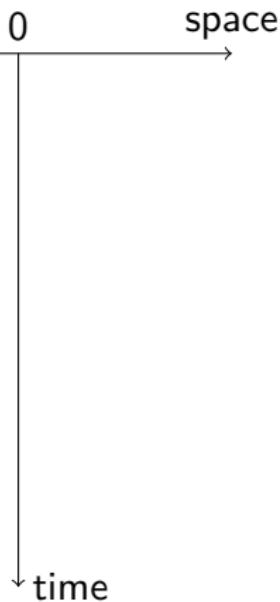


Description

- An individual alive at time 0.
- Gives birth to children around its current position.
- Each child then reproduces independently.
- Every new generation reproduces independently.
- We take interest in the maximal displacement.

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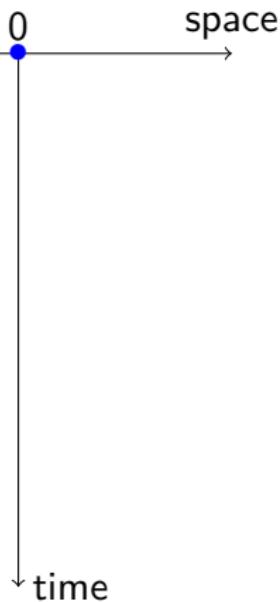


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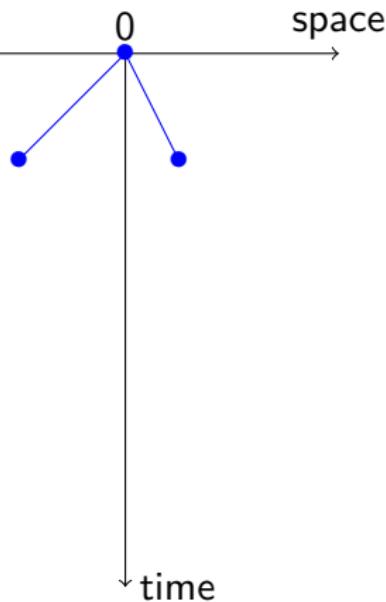


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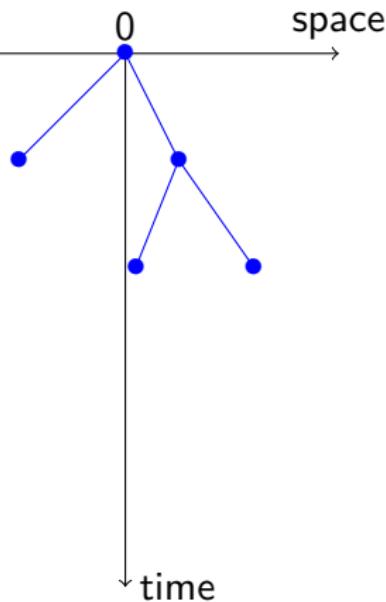


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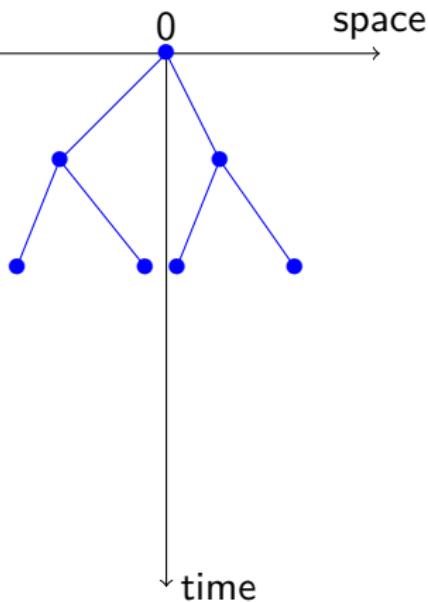


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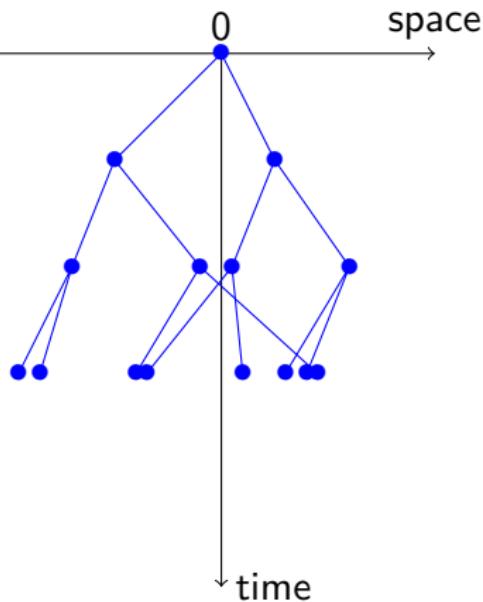


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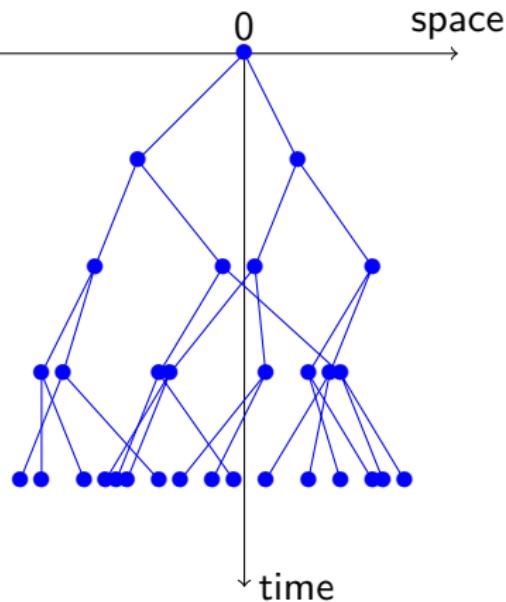


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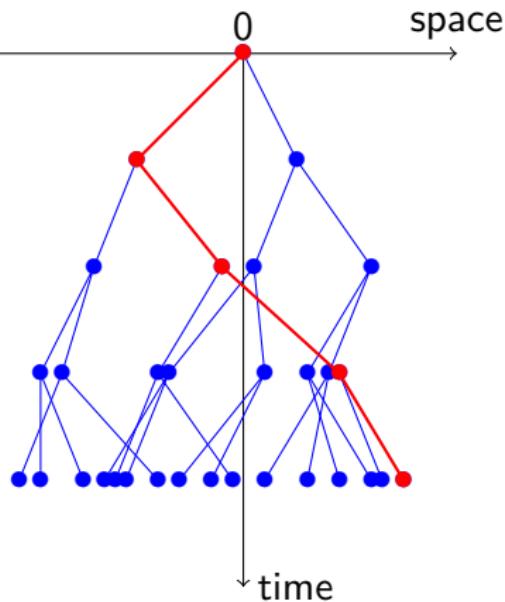


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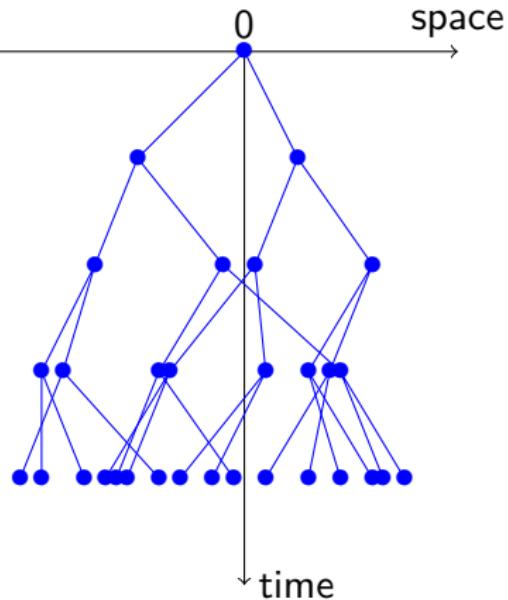
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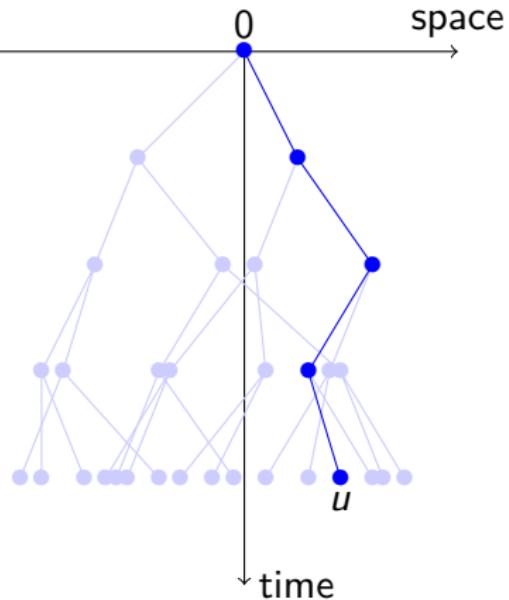
Some notation



Notation

- Let u be an individual.
- $V(u)$: position of u .
- $|u|$: generation of u .
- u_k : ancestor of u at time k .
- M_n : position of the rightmost individual at time n .

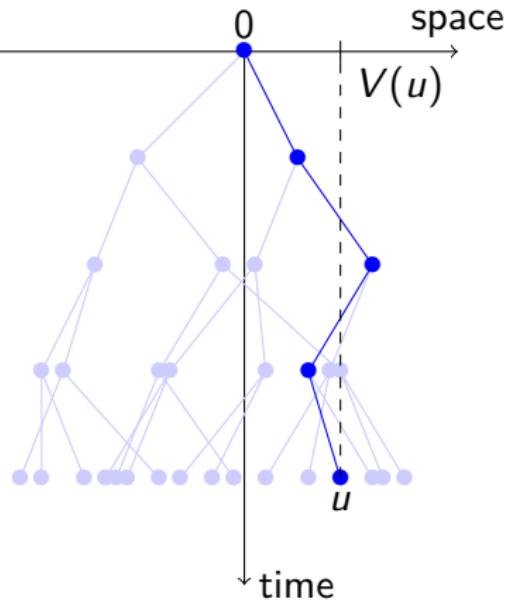
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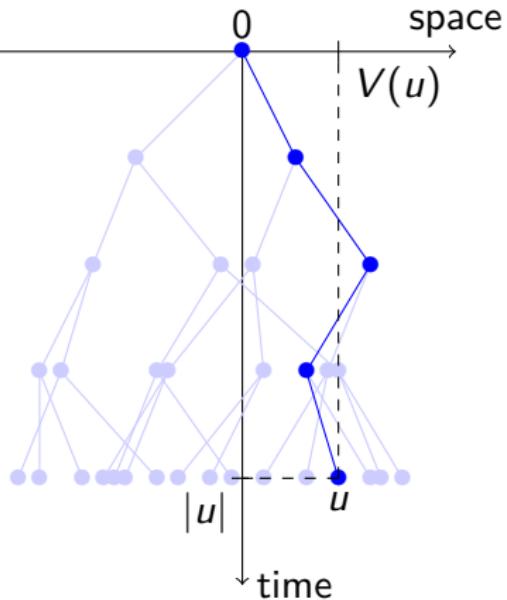
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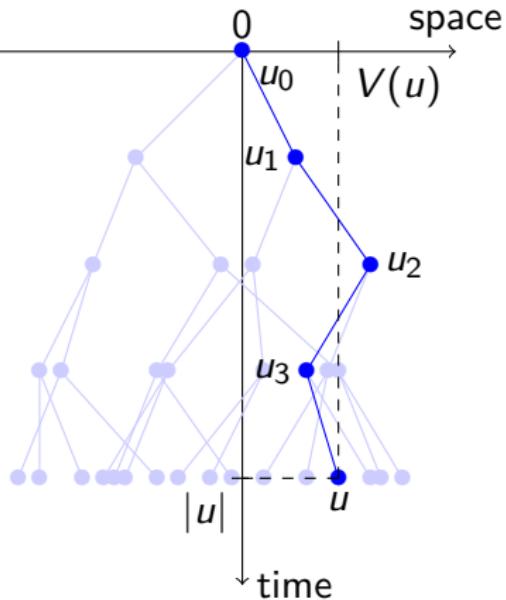
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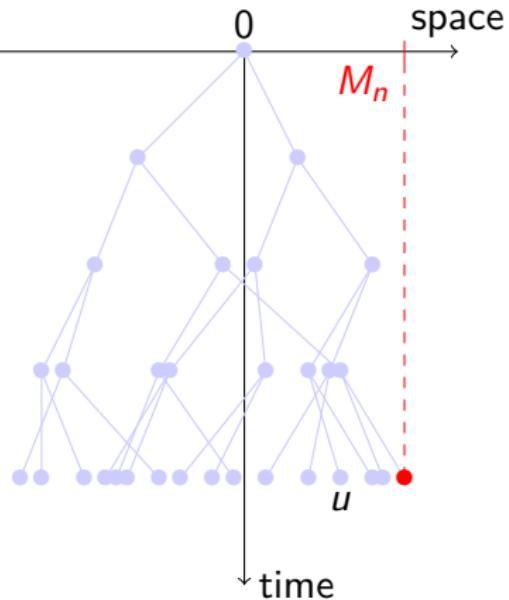
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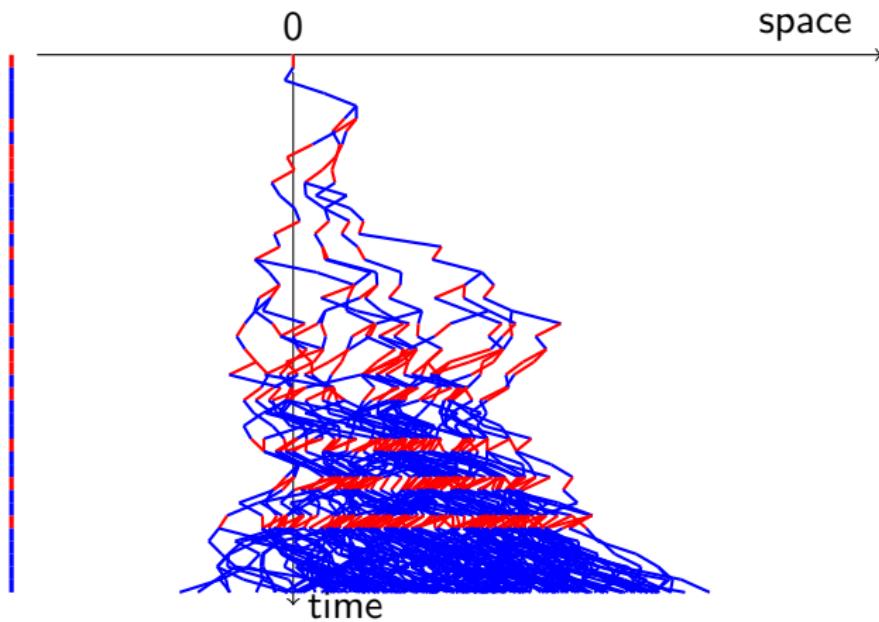
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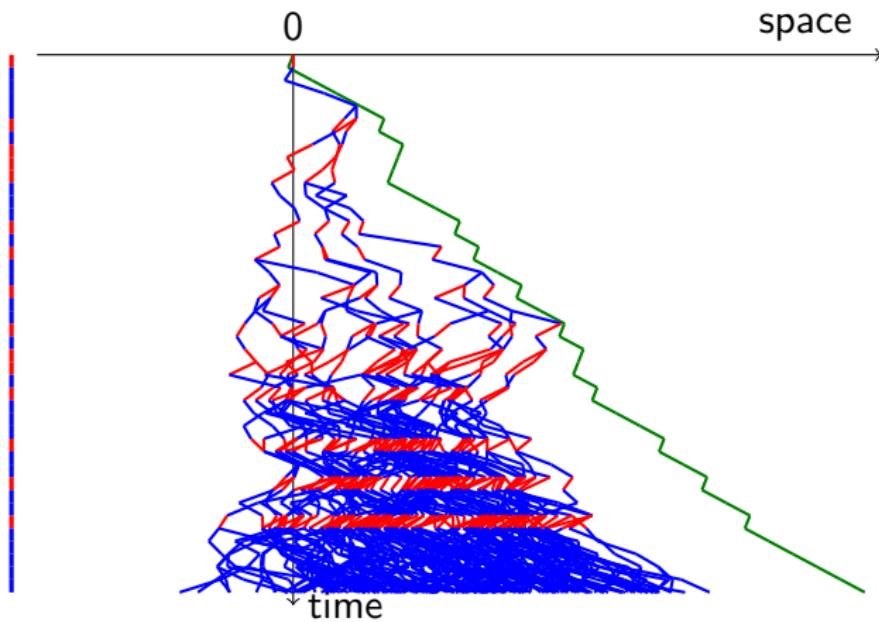
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Example of a branching random walk in random environment



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Additional notation

We write $\mathbb{E}_{\mathcal{L}}[\cdot] = \mathbf{E}[\cdot | \mathcal{L}_1, \mathcal{L}_2, \dots]$ and L_n a point process with law \mathcal{L}_n .

Log-Laplace transform of \mathcal{L}_n

$$\forall \phi > 0, \kappa_n(\phi) = \log \mathbf{E} \left[\sum_{\ell \in L_n} e^{\phi \ell} \right].$$

Critical parameter

We set $K(\phi) = \mathbf{E}(\kappa_1(\phi))$. We assume there exists $\theta > 0$ such that

$$\theta K'(\theta) - K(\theta) = 0.$$

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Boundary of the branching random walk

From now on, we assume that θ is the critical parameter of the branching random walk.

Boundary of the branching random walk

For any $n \in \mathbb{N}$, we write $F_n = \sum_{j=1}^n \kappa_j(\theta)/\theta$.

Observations

The process $(F_n, n \geq 0)$ is a random walk that depend only on the environment $(\mathcal{L}_n, n \geq 1)$.

We have $\lim_{n \rightarrow +\infty} \frac{F_n}{n} = \frac{K(\theta)}{\theta} = K'(\theta)$.

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The maximal displacement

Theorem

We assume there exists $\theta > 0$ such that $\theta K'(\theta) - K(\theta) = 0$. We write

$$F_n = \sum_{j=1}^n \frac{\kappa_j(\theta)}{\theta}, \quad \sigma_Q^2 = \theta^2 \mathbf{E} [\kappa_1''(\theta)] \quad \text{and} \quad \sigma_A^2 = \mathbf{Var} [\theta \kappa_1'(\theta) - \kappa_1(\theta)].$$

Let $m_n = \inf\{y \in \mathbb{R} : \mathbb{P}_{\mathcal{L}}(M_n \geq y) = 1/2\}$, we have

$$m_n = F_n - \phi \log n + o_{\mathbb{P}}(\log n) \quad \text{and} \quad M_n = F_n - \phi \log n + o_{\mathbb{P}}(\log n),$$

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Many-to-one lemma

We write $\mu_n((-\infty, x]) = \mathbb{E}_{\mathcal{L}} \left[\sum_{\ell \in L_n} e^{\theta \ell - \kappa_n(\theta)} \mathbf{1}_{\{\ell \leq x\}} \right]$, and we set X_n a random variable with law μ_n .

Definition

The sequence $(\mu_n, n \in \mathbb{N})$ is a sequence of i.i.d. random probability distributions on \mathbb{R} .

The process $S_n = X_1 + X_2 + \cdots + X_n$ is a random walk with random environment $(\mu_n, n \in \mathbb{N})$.

Lemma (Many-to-one lemma)

Let f be a measurable positive function, we have

$$\mathbb{E}_{\mathcal{L}} \left[\sum_{|u|=n} f(V(u_j), j \leq n) \right] = \mathbb{E}_{\mathcal{L}} \left[e^{-\theta(S_n - F_n)} f(S_j, j \leq n) \right].$$

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We compute the number of individuals crossing for the first time
 $k \mapsto F_k + x$:

$$\begin{aligned} & \mathbb{E}_{\mathcal{L}} \left[\sum_{u \in \mathbb{T}} \mathbf{1}_{\{V(u) > F_{|u|} + x\}} \mathbf{1}_{\{V(u_j) \leq F_j + x, j < |u|\}} \right] \\ &= \sum_{n \geq 1} \mathbb{E}_{\mathcal{L}} \left[\sum_{|u|=n} \mathbf{1}_{\{V(u) > F_n + x\}} \mathbf{1}_{\{V(u_j) \leq F_j + x, j < n\}} \right] \\ &= \sum_{n \geq 1} \mathbb{E}_{\mathcal{L}} \left[e^{-\theta(S_n - F_n)} \mathbf{1}_{\{S_n > F_n + x\}} \mathbf{1}_{\{S_j < F_j + x, j < n\}} \right] \\ &\leq e^{-\theta x} \sum_{n \geq 1} \mathbb{P}_{\mathcal{L}} [S_n > F_n + x, S_j < F_j + x, j < n] \\ &\leq e^{-\theta x}. \end{aligned}$$

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Upper bound for the maximal displacement

We compute the number of individuals who, while staying below the curve $k \mapsto F_k + x$, are at time n larger than $F_n - \lambda \log n$.

$$\begin{aligned} & \mathbb{E}_{\mathcal{L}} \left[\sum_{|u|=n} \mathbf{1}_{\{V(u) \geq F_n - \lambda \log n\}} \mathbf{1}_{\{V(u_j) \leq F_j + x, j \leq n\}} \right] \\ &= \mathbb{E}_{\mathcal{L}} \left[e^{\theta(S_n - F_n)} \mathbf{1}_{\{S_n - F_n \geq -\lambda \log n\}} \mathbf{1}_{\{S_j - F_j \leq x, j \leq n\}} \right] \\ &\approx n^{\theta \lambda} \mathbb{P}_{\mathcal{L}} (S_n - F_n \geq -\lambda \log n, S_j - F_j \leq x, j \leq n). \end{aligned}$$

To conclude, we need to compute the asymptotic behaviour of

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$$\begin{aligned} & \mathbb{E}_{\mathcal{L}} \left[\sum_{|u|=n} \mathbf{1}_{\{V(u) \geq F_n - \lambda \log n\}} \mathbf{1}_{\{V(u_j) \leq F_j + x, j \leq n\}} \right] \\ &= \mathbb{E}_{\mathcal{L}} \left[e^{\theta(S_n - F_n)} \mathbf{1}_{\{S_n - F_n \geq -\lambda \log n\}} \mathbf{1}_{\{S_j - F_j \leq x, j \leq n\}} \right] \\ &\approx n^{\theta \lambda} \mathbb{P}_{\mathcal{L}} (S_n - F_n \geq -\lambda \log n, S_j - F_j \leq x, j \leq n). \end{aligned}$$

To conclude, we need to compute the asymptotic behaviour of

$$\mathbb{P}_{\mathcal{L}} (S_n - F_n \geq -\lambda \log n, S_j - F_j \leq x, j \leq n).$$

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Persistence exponent for the random walk in random environment

Let S be a random walk in random environment.

Theorem

We assume that $\mathbf{E}(S_1) = 0$ and there exists $\lambda > 0$ and $C > 0$ such that

$$\mathbf{E} \left(e^{\lambda |X_1|} \right) < +\infty \quad \text{et} \quad \mathbb{E}_{\mathcal{L}} \left(e^{\lambda |X_1 - \mathbb{E}_{\mathcal{L}}(X_1)|} \right) \leq C \quad p.s.$$

There exists $\gamma \geq 1/2$ such that

$$-\frac{1}{\log n} \log \mathbb{P}_{\mu} (S_j \geq -\log n, j \leq n) = \gamma \quad p.s.$$

Thus $\mathbb{P}_{\mu} (S_j \geq -\log n, j \leq n) \approx n^{-\gamma}$ a.s.

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From random walk to Brownian motion I

We set $E_j = S_j - \mathbb{E}_{\mathcal{L}}(S_j)$ and $M_j = -\mathbb{E}_{\mathcal{L}}(S_j)$. We have

$$\mathbb{P}_\mu(S_j \geq -\log n, j \leq n) = \mathbb{P}_\mu(E_j \geq M_j - \log n, j \leq n).$$

Notation

Set $\sigma_A^2 = \mathbf{Var}(M_1) = \mathbf{Var}(\mathbb{E}_{\mathcal{L}}(X_1))$ and $\sigma_Q^2 = \mathbf{E}(E_1^2) = \mathbf{E}(\mathbf{Var}_\mu(X_1))$.

Sakhanenko inequalities

- As M is a random walk, there exists a Brownian motion W such that $|M_j - \sigma_A W_j| \lesssim \log n$.
- Conditionally on \mathcal{L} and W , E is the sum of i.i.d. centred random variables, there exists a Brownian motion B such that $|E_j - \sigma_Q B_j| \lesssim \log n$.

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Therefore, we have

$$\mathbb{P}_\mu(S_j \geq -\log n, j \leq n) \approx \mathbf{P}(\sigma_Q B_s \geq \sigma_A W_s - \log n, s \leq n | W) \quad \text{a.s.}$$

Thus $\gamma = \gamma(\sigma_A/\sigma_Q)$, where we define

$$\gamma(\beta) = \lim_{t \rightarrow +\infty} -\frac{1}{\log t} \log \mathbf{P}(B_s \geq \beta W_s - 1, s \leq t | W).$$

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Brownian motion above a Brownian curve

- 1 The branching random walk in random environment
- 2 The random walk in random environment
- 3 Brownian motion above a Brownian curve

Brownian motion above a Brownian curve

Let B and W be two independent Brownian motions.

Theorem

There exists a convex pair function γ such that for all $\beta \in \mathbb{R}$,

$$\lim_{t \rightarrow +\infty} \frac{1}{\log t} \log \mathbf{P}(B_s + 1 \geq \beta W_s, s \leq t | W) = -\gamma(\beta) \quad p.s.$$

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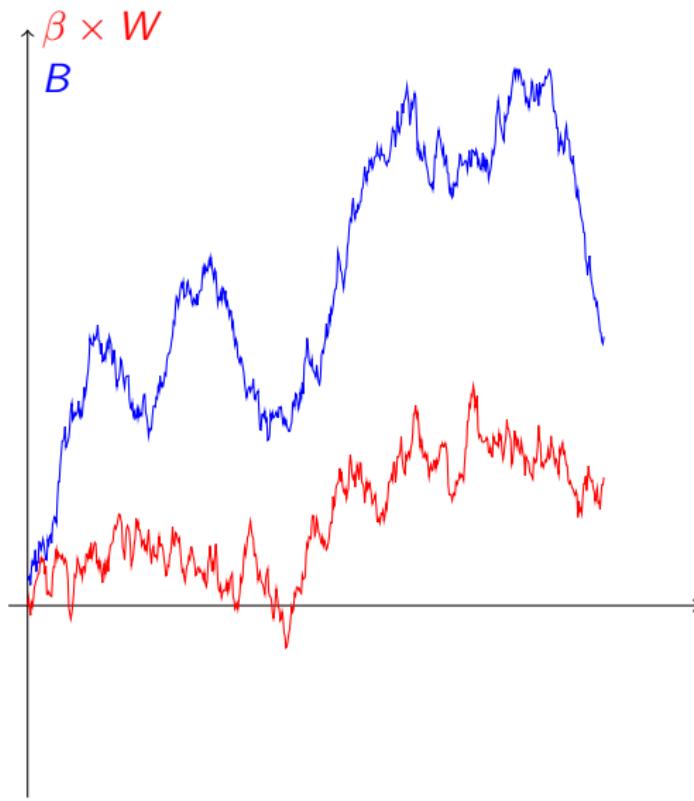
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Properties of γ

Symmetry

As $W \stackrel{(d)}{=} -W$, we have

$$(\mathbf{P}(B_s + 1 \geq \beta W_s, s \leq t | W))_{t \geq 0} \stackrel{(d)}{=} (\mathbf{P}(B_s + 1 \geq -\beta W_s, s \leq t | W))_{t \geq 0},$$

thus $\gamma(\beta) = \gamma(-\beta)$.

Lower bound

By Jensen inequality,

$$\mathbf{E}[-\log \mathbf{P}(B_s + 1 \geq \beta W_s, s \leq t | W)] \geq -\log \mathbf{P}(B_s + 1 \geq \beta W_s, s \leq t),$$

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The Gaussian random variables being log-concave, we have

$$\mathbf{P}(B_s \geq f(s), s \leq t) \mathbf{P}(B_s \geq g(s), s \leq t) \leq \mathbf{P}\left(B_s \geq \frac{f(s)+g(s)}{2}, s \leq t\right)^2.$$

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By similar arguments, $\beta \mapsto \gamma(\sqrt{|\beta|})$ is convex.

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Existence of γ |

Let $X_t = e^{-t/2}(1 + B_{e^t - 1})$ et $Y_t = e^{-t/2}W_{e^t - 1}$.

X and Y are two independent Ornstein-Uhlenbeck processes, moreover:

$$\mathbf{P}(B_s + 1 \geq \beta W_s, s \leq t | W) = \mathbf{P}(X_s \geq \beta Y_s, s \leq \log t | Y).$$

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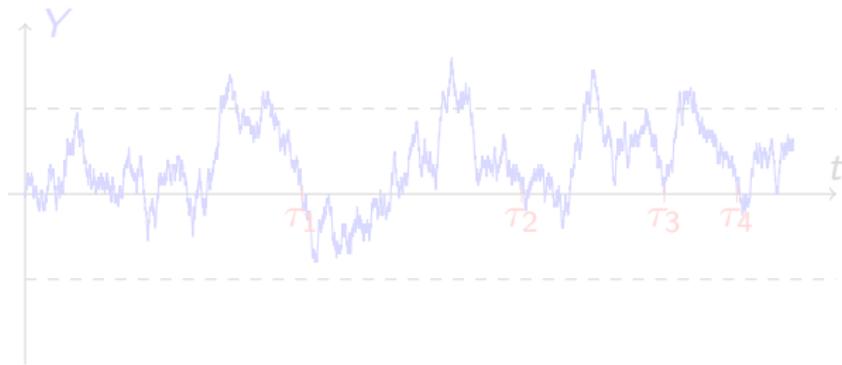
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We set $\tau_0 = 0$ and

$$\tau_{k+1} = \inf \{t \geq \tau_k : Y_t = 0, \exists s \in [\tau_k, t] : |Y_s| = 1\}.$$



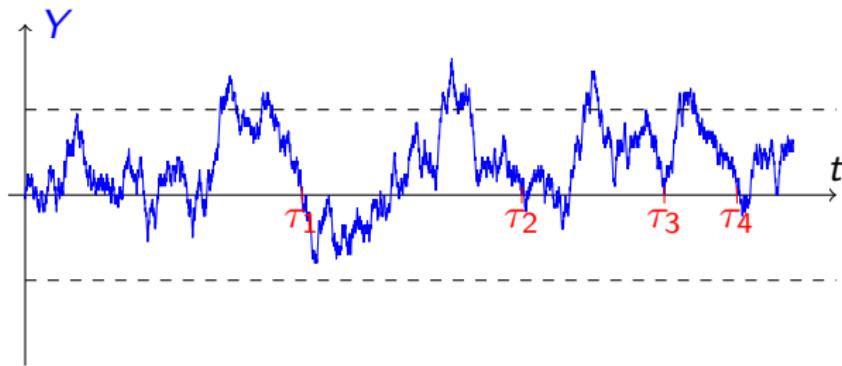
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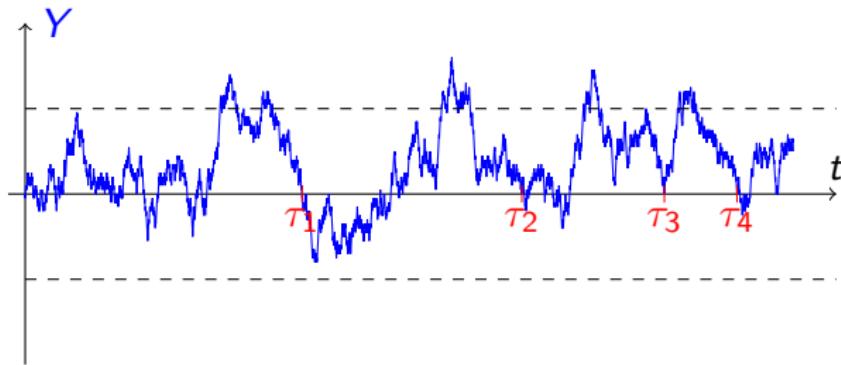
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By the Markov property, we have

- $p_{0,m+n} \geq p_{0,m} + p_{m,m+n}$;
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- $\mathbf{E}(|p_{0,1}|) < +\infty$.

Kingman's subadditive ergodic theorem

We have

$$\lim_{n \rightarrow +\infty} \frac{p_{0,n}}{n} = -\tilde{\gamma}(\beta) > -\infty \quad \text{p.s.}$$

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We set $q_n = \log \mathbf{P}(X_s \geq \beta Y_s, s \leq \tau_n | Y)$. Observe that $q_n \geq p_n$.

FKG inequality

By FKG inequality for the Brownian motion, we have

$$q_n + \log \mathbf{P}(X_{\tau_n} \geq 1 | Y) \leq p_n.$$

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For all $\tau_n \leq t \leq \tau_{n+1}$,

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The γ function

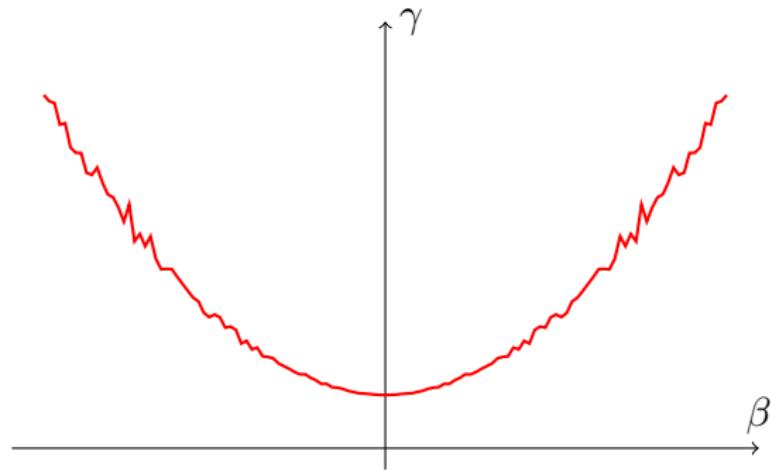


Figure : An approximation of $\mathbf{E}[-\log \mathbf{P}(B_s \geq \beta W_s - 1, s \leq 1000)]$.

The γ function

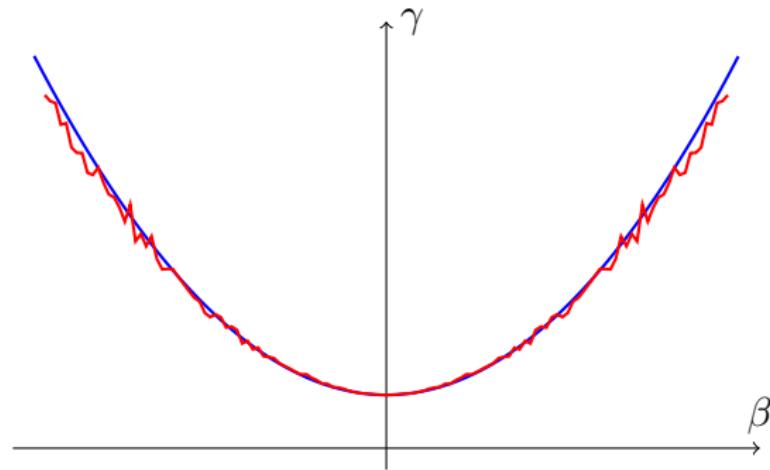


Figure : An approximation of $\mathbf{E}[-\log \mathbf{P}(B_s \geq \beta W_s - 1, s \leq 1000)]$.