

Extrema of Branching Brownian Motion in \mathbb{R}^d

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Joint works with Julien Berestycki, Bastien Mallein, Eyal Lubetzky, and Ofer Zeitouni.

Paradigmatic model in the study of extrema of log-correlated fields– see Ofer's talk from 9/1.

- Random matrix theory
- Statistics of Riemann zeta function
- GFF and GMC
- Cover times of random walks
- PDEs (F-KPP equation)
- ...

Model Definition

Fix the dimension $d \geq 1$.

- Start: a single particle v at 0 performs Brownian motion in \mathbb{R}^d (iid 1d BM's in each coordinate)

$$X_s^{(v)} = (W_s^{1,(v)}, \dots, W_s^{d,(v)}) \in \mathbb{R}^d$$

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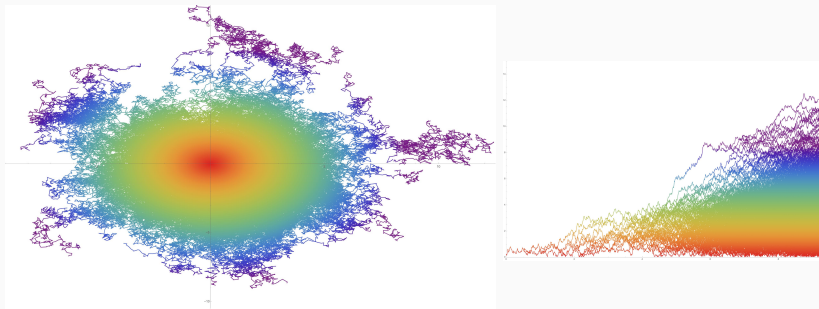


Fig: 2D BBM (left) and its modulus as a function of time (right)

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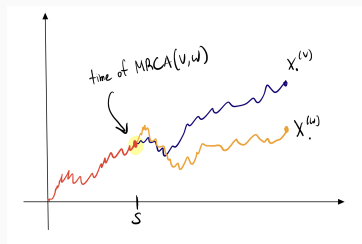
- After an $\exp(1)$ distributed time, the particle splits into **two** particles, which perform independent (d -dim) BM's from that point forward and carry their own exponential clocks
- Repeat.

Notation.

- Let $N_t :=$ set of particles at time t .
- $X_t^{(v)} :=$ the d -dim BM path of v .

Quick facts.

- $\mathbb{E}[N_t] = e^t$
- For coordinate indices $i, j \in \{1, \dots, d\}$, $\text{Cov}(X_t^{(v)}(i), X_t^{(w)}(j)) =$ time of the most recent common ancestor of v and w



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- **Bramson**: found centering term $m_t(1) = \sqrt{2}t - \frac{3}{2\sqrt{2}} \log t$, and showed $R_t^* - m_t(1)$ converges in law via connection to F-KPP equation.

Theorem (Bramson '77, '83)

$\lim_{t \rightarrow \infty} \mathbb{P}(R_t^* - m_t(1) \leq y) = w(y)$, where $\frac{1}{2}w'' + \sqrt{2}w' + w^2 - w = 0$.

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- **Idea from physics**: the distribution of the max. of log-correlated fields should still resemble classical (iid) extreme value distributions
- **Lalley-Selke**: characterization of the limiting law as a *randomly shifted Gumbel*, where the random shift comes from the behavior of the particles at the beginning of the process (more on this later).

Theorem (Lalley-Selke '87)

There exists a random variable Z , called the derivative martingale, and a constant $C > 0$ such that

$$\lim_{t \rightarrow \infty} \mathbb{P}(R_t^* - m_t(1) \leq y) = \mathbb{E} \left[\exp \left(- e^{-\sqrt{2}(y - CZ)} \right) \right], \quad \forall y \in \mathbb{R}.$$

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What about the point process formed by all particles “near the maximum”: the **extremal point process**?

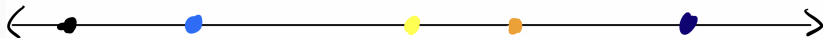
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- The limit was identified independently by Aidekon-Berestycki-Brunet-Shi and Arguin-Bovier-Kistler as a **randomly shifted, decorated Poisson point process**
- The shift is given by the log of the derivative martingale Z .

Theorem (ABBS/ABK 2011)

Let $\sum_{i \in \mathbb{N}} \delta_{\eta_i}$ have law $\text{PPP}(C\sqrt{2}e^{-\sqrt{2}x} dx)$. Let $\{\mathcal{D}^{(i)}\}_{i \in \mathbb{N}}$ be a family of iid point processes with an explicit “decoration law.” Then \mathcal{E}_t converges in law as $t \rightarrow \infty$ to

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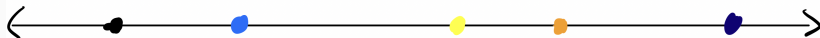
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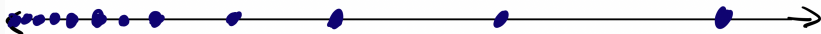
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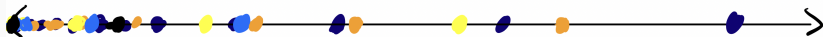
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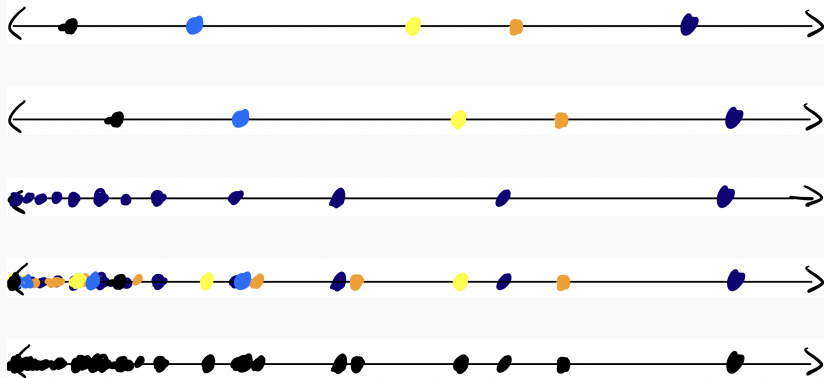
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- Lots of further work: extending convergence to include genealogical info (Bovier-Hartung 2016), structure of extreme level sets (Cortines-Hartung-Louidor 2017), etc.

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Theorem (K.-Lubetzky-Zeitouni 2021)

Let $m_t := \sqrt{2}t + \frac{d-4}{2\sqrt{2}} \log t$. There exists a non-degenerate, positive random variable Z_∞ and a constant $C_d > 0$ such that

$$\lim_{t \rightarrow \infty} \mathbb{P}(R_t^* \leq m_t + y) = \mathbb{E} \left[\exp \left(-C_d e^{-\sqrt{2}(y - \frac{1}{\sqrt{2}} \log Z_\infty)} \right) \right], \quad \forall y \in \mathbb{R}.$$

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Previous work:

- Biggins '95: $R_t^*/\sqrt{2}t \rightarrow 1$ a.s.
- Mallein 2015: $\{R_t^* - m_t\}_{t>0}$ is tight.

The (branching) Bessel process and the Girsanov transform

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Girsanov transform from Bessel to BM

$$dP^R|_{\mathcal{F}_t} = \underbrace{\left(\frac{W_t}{W_0}\right)^{\frac{d-1}{2}}}_{\text{start/endpoint dependence}} \underbrace{\exp\left(\int_0^t \frac{c_d}{W_u^2} du\right) \mathbb{1}_{\{W_u > 0, u \in [0, t]\}}}_{\text{pathwise dependence}} dP^W|_{\mathcal{F}_t},$$

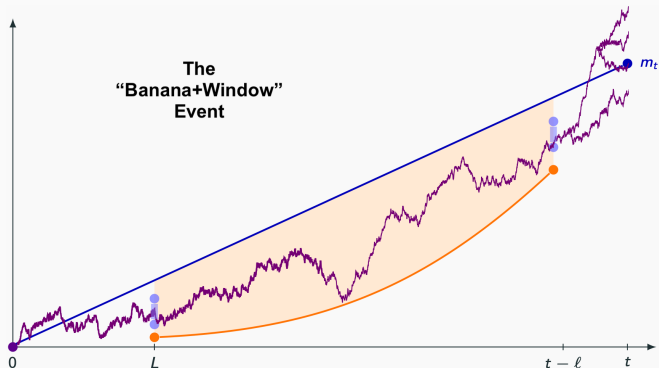
where $c_d > 0$ for $d \geq 3$ and $c_d < 0$ for $d = 2$.

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Extremal particle trajectories

W.h.p., all particles $v \in N_t$ that reach height m_t at time t did the following:

- at time L , passed through the “window” $\sqrt{2}L - [L^{1/6}, L^{2/3}]$
- at time $t - \ell$, passed through the “window” $\frac{m_t}{t}(t - \ell) - [\ell^{1/3}, \ell^{2/3}]$
- on $[L, t - \ell]$, stayed within the “banana”

Proof of Main Result

Say we have a particle $v \in N_L$ such that $R_L^{(v)} = r \in \sqrt{2}L - [L^{1/6}, L^{2/3}]$.

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- (1) The fact that this asymptotic has **no t -dependence** means that $m_t := \sqrt{2}t + \frac{d-4}{2\sqrt{2}} \log t$ is the right centering term!

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We show that, on the Banana+Window event, at most one $u \in N_{t-L-\ell}$ produces a descendant that exceeds height m_t . Done via a “modified” second moment method, inspired by the work of Bramson-Ding-Zeitouni (2013) establishing convergence of the re-centered maximum of the 2d discrete GFF.

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Proof of main result:

$$\mathbb{P}(R_t^* \leq m_t + y) = \mathbb{E}\left[\prod_{v \in N_L} \mathbb{P}_{R_L^{(v)}}(R_{t-L}^* \leq m_t + y)\right] = \mathbb{E}\left[\prod_{v \in N_L} (1 - \mathbb{P}_{R_L^{(v)}}(R_{t-L}^* > m_t + y))\right]$$

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Proof of main result:

$$\begin{aligned}\mathbb{P}(R_t^* \leq m_t + y) &= \mathbb{E}\left[\prod_{v \in N_L} \mathbb{P}_{R_L^{(v)}}(R_{t-L}^* \leq m_t + y)\right] = \mathbb{E}\left[\prod_{v \in N_L} (1 - \mathbb{P}_{R_L^{(v)}}(R_{t-L}^* > m_t + y))\right] \\ &\approx \mathbb{E}\left[\prod_{v \in N_L} (1 - C_d f(R_L^{(v)})) e^{-y\sqrt{2}}\right]\end{aligned}$$

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- Note the LHS has no L dependence, while the RHS has no t dependence \Rightarrow both sides converge!

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- Note the LHS has no L dependence, while the RHS has no t dependence \Rightarrow both sides converge!
- Z_∞ is the limit in distribution of $\sum_{v \in N_L} f(R_L^{(v)})$. Convergence in \mathbb{P} forthcoming work with J. Berestycki, B. Mallein.

Interpretation of Z_∞ by Lalley-Selke

Theorem (Berestycki-K.-Lubetzky-Mallein-Zeitouni 2021)

$$\mathbb{P}(R_t^* - m_t \leq y \mid \mathcal{F}_L) \xrightarrow[t \rightarrow \infty, L \rightarrow \infty]{p} \exp(-C_d Z_\infty e^{-\sqrt{2}y})$$

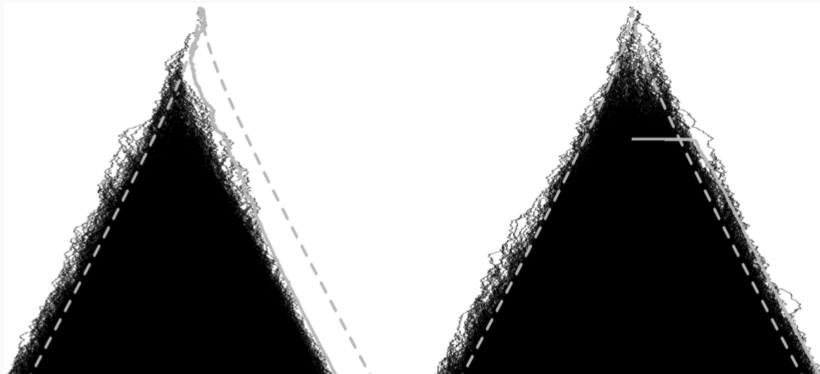


Figure 2: Left: initial particles veer to the left. Right: initial particles veer far to the right. In both pictures, we see how the initial behavior permanently shifts the maximum. (Image from Éric Brunet).

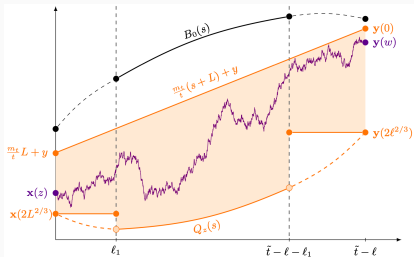
Main Results: The Extremal Point Process in \mathbb{R}^d

- Stasiński, Berestycki, and Mallein (2020) constructed a random measure $D_\infty(\cdot)$ on \mathbb{S}^{d-1} , which is the a.s., a.e. limit of an “angular” derivative martingale. So, Z_∞ and $D_\infty(\mathbb{S}^{d-1})$ have the same law.
- D_∞ is a.s. absolutely continuous wrt Leb.
- It turns out that $\sum_{v \in N_L} f(R_L^{(v)})$ converges in probability to $c_d D_\infty(\mathbb{S}^{d-1})$, for some constant $c_d > 0$.
- Let the point process $\sum_{i=1}^{\infty} \delta_{(\eta_i, \theta_i)}$ on $\mathbb{R} \times \mathbb{S}^{d-1}$ have law $\text{PPP}\left(\bar{c}_d D_\infty(\mathbb{S}^{d-1}) e^{-\sqrt{2}x} dx \times \frac{D_\infty(\theta)}{D_\infty(\mathbb{S}^{d-1})} d\theta\right)$.
- Let $\mathcal{E}_t := \sum_{v \in N_t} \delta_{(\|X_t\| - m_t, X_t / \|X_t\|)}$ denote the extremal point process of BBM in dimension d .

Theorem

Let $\{\mathcal{D}^{(i)}\}_{i \in \mathbb{N}}$ be a collection of iid point processes with the same law as the decorations from the 1D BBM case. Then \mathcal{E}_t converges in law as $t \rightarrow \infty$ to

$$\mathcal{E} := \sum_{i \in \mathbb{N}} \sum_{\xi_j \in \mathcal{D}^{(i)}} \delta_{(\eta_i + \xi_j, \theta_i)}$$



Thank you!

