

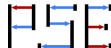
Extremal Processes of Branching Brownian Motions

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with Louis-Pierre Arguin, Nicola Kistler
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hausdorff center for mathematics



PROBABILISTIC STRUCTURES
IN EVOLUTION
DFG SPP 1590

Plan

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- 1 Gaussian processes on trees
- 2 Branching Brownian motion
- 3 The extremal process of BBM
- 4 Variable speed BBM
- 5 Universality

Motivation

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This is too hard in general, but we will look at a setting where these questions have a chance to be answered. **Branching Brownian motion** is at the heart of this setting.

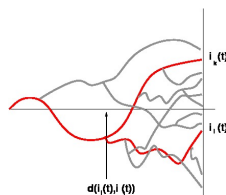
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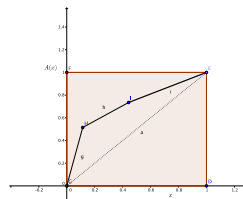
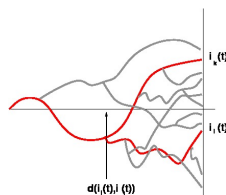


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- For fixed time horizon t , define **Gaussian process**, $(x_k^t(s), k \leq n(t), s \leq t)$, with covariance

$$\mathbb{E}x_k^t(r)x_\ell^t(s) = tA(t^{-1}d(\mathbf{i}_k(r), \mathbf{i}_\ell(s)))$$

for $A : [0, 1] \rightarrow [0, 1]$, increasing.

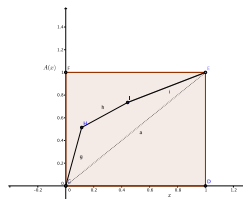
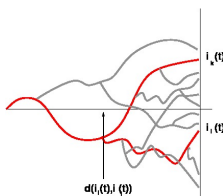


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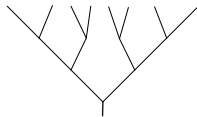


Can be constructed as time change of **branching Brownian motion**

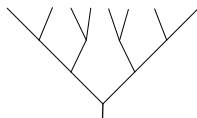
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Binary tree, branching at integer times

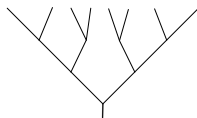


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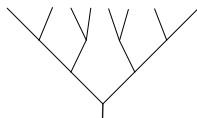
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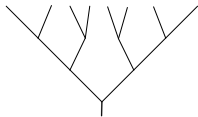
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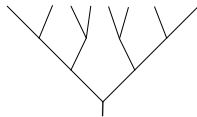
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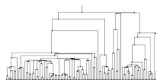


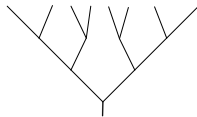
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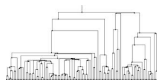
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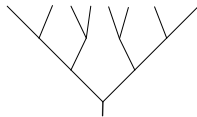
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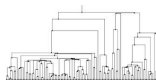
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- General A : **variable speed BBM** [Derrida-Spohn '88, Fang-Zeitouni '12]



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- Is there a limiting **extremal process**, \mathcal{P} , such that

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- $$\sum_{k \leq n(t)} \delta_{u_t^{-1}(x_k(t))} \rightarrow \text{PPP}\left(\frac{1}{4\pi} e^{-\sqrt{2}x} dx\right)$$

where $\text{PPP}(\mu)$ denotes the **Poisson Point Process** with intensity μ .

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Note in particular that as long as $A(s) \leq s$, for all $s \leq 1$, then $\bar{A}(s) = s$, and the order of the maximum is the same as in the REM.

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Note the special role of the linear function $A(s) = s$

Branching Brownian motion

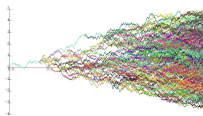


(BBM) is a classical object in probability, combining the standard models of **random motion** and **random genealogies** into one: Each particle of the Galton-Watson process performs Brownian motion independently of any other. This produces an immersion of the Galton-Watson process in space.

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Picture by **Matt Roberts**, Bath

BBM is the canonical model of a spatial branching process.

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One of the simplest **reaction-diffusion equations** is the Fisher-Kolmogorov-Petrovsky-Piscounov (F-KPP) equation:

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Fischer used this equation to model the evolution of biological populations. It accounts for:

- **birth:** v ,
- **death:** $-v^2$,
- **diffusive migration:** $\partial_x^2 v$.



F-KPP equation and BBM



F-KPP equation and BBM

Lemma (McKeane '75, Ikeda, Nagasawa, Watanabe '69)

Let $f : \mathbb{R} \rightarrow [0, 1]$ and $\{x_k(t) : k \leq n(t)\}$ BBM.

$$u(t, x) = \mathbb{E} \left[\prod_{k=1}^{n(t)} f(x - x_k(t)) \right]$$

Then $v \equiv 1 - u$ is the solution of the F-KPP equation with initial condition $v(0, x) = 1 - f(x)$.

Travelling waves





Travelling waves

Theorem (Bramson '78)

The equation

$$\frac{1}{2}\omega'' + \sqrt{2}\omega' - \omega^2 + \omega = 0.$$

has a unique solution satisfying $0 < \omega(x) < 1$, $\omega(x) \rightarrow 0$, as $x \rightarrow +\infty$, and $\omega(x) \rightarrow 1$, as $x \rightarrow -\infty$, up to translation, i.e. if ω, ω' are two solutions, then there exists $a \in \mathbb{R}$ s.t. $\omega'(x) = \omega(x + a)$.



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For suitable initial conditions,

$$u(t, x + m(t)) \rightarrow \omega(x),$$

where $m(t) = \sqrt{2}t - \frac{3}{2\sqrt{2}} \ln t$, where ω is one of the stationary solutions.

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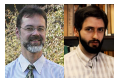
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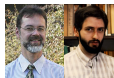
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In particular, it gives Bramson's celebrated result

$$\lim_{t \rightarrow \infty} \mathbb{P}(\max_{k \leq n(t)} x_k(t) - m(t) \leq x) = \omega(x)$$

The derivative martingale





The derivative martingale

Lalley-Sellke, 1987: $\omega(x)$ is random shift of Gumbel-distribution

$$\omega(x) = \mathbb{E} \left[e^{-CZ e^{-\sqrt{2}x}} \right], \quad (*)$$



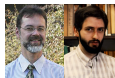
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$Z \stackrel{(d)}{=} \lim_{t \rightarrow \infty} Z(t)$, where $Z(t)$ is the **derivative martingale**,

$$Z(t) = \sum_{k \leq n(t)} \{\sqrt{2}t - x_k(t)\} e^{-\sqrt{2}\{\sqrt{2}t - x_k(t)\}}$$



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The form $(*)$ seems universal, but Z is particular.

For the REM on the GW tree $(*)$ holds with Z a standard exponential.

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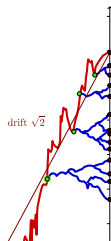
Poisson Point Process: $\mathcal{P}_Z = \sum_{i \in \mathbb{N}} \delta_{p_i} \equiv \text{PPP} \left(CZe^{-\sqrt{2}x} dx \right)$

Cluster process:

$$\Delta(t) \equiv \sum_k \delta_{x_k(t) - \max_{j \leq n(t)} x_j(t)}.$$

conditioned on the event $\{ \max_{j \leq n(t)} x_j(t) > \sqrt{2}t \}$
converges in law to point process, Δ .

[Chauvin, Rouault '90]



$$\mathcal{E} \equiv \sum_{i,j \in \mathbb{N}} \delta_{p_i + \Delta_j^{(i)}}, \quad \Delta^{(i)} \text{ iid copies of } \Delta$$

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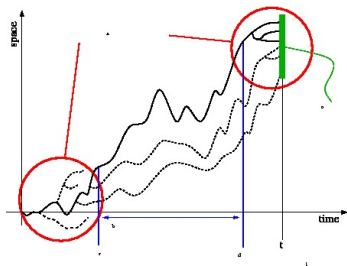
Theorem (Arguin-B-Kistler '11, Aidékon, Brunet, Berestycki, Shi '11)

The point process $\mathcal{E}_t \equiv \sum_{i=1}^{n(t)} \delta_{x_i(t)-m(t)} \rightarrow \mathcal{E}$.

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Interpretation:

p_i : positions of maxima of clusters with recent common ancestors.

$\Delta^{(i)}$: positions of members of clusters seen from their maximal one

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$$\mathbb{E} \left[\exp \left(- \int \phi(y) \mathcal{E}_t(dy) \right) \right] \rightarrow \mathbb{E} [\exp(-C(\phi)Z)]$$

for any $\phi \in \mathcal{C}_c(\mathbb{R})$ non-negative, where

$$C(\phi) = \lim_{t \rightarrow \infty} \sqrt{\frac{2}{\pi}} \int_0^\infty (1 - u(t, y + \sqrt{2t})) y e^{\sqrt{2}y} dy$$

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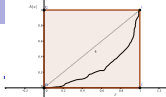
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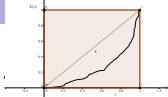
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Then show that the limit is the Laplace functional of the process \mathcal{E} described above.

Variable speed BBM.....below the straight line...

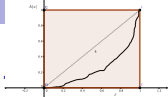




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Theorem (B-Hartung '13,'14)

Assume that $A(x) < x, \forall x \in (0, 1), A'(0) = a^2 < 1, A'(1) = b^2 > 1$.

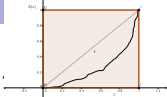


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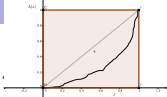
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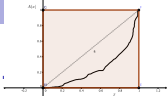
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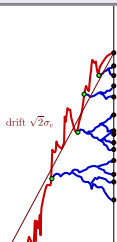
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$$\tilde{m}(t) \equiv \sqrt{2}t - \frac{1}{2\sqrt{2}} \ln t.$$

p_i : e the atoms of a $\text{PPP}(C(b)Y_a e^{-\sqrt{2}x} dx)$,

Δ : are as in BBM but with the conditioning on the event $\{\max_k x_k(t) \geq \sqrt{2}bt\}$.



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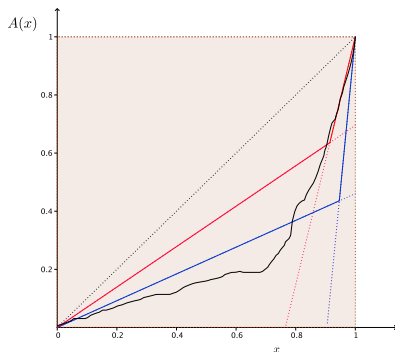
$$Y_s \equiv \sum_{i=1}^{n(s)} e^{-s(1+\sigma_1^2) + \sqrt{2}x_i(s)}$$
- Asymptotics of solutions of the FKPP equation at **very** large values ahead of the travelling wave.

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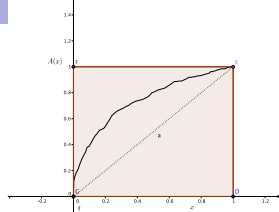
Elements of the proof:

2) Gaussian comparison for general A :

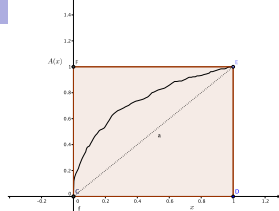
Use comparison for Laplace functionals with two-speed process; only good approximation of covariance near 0 and 1 needed.



Above the straight line

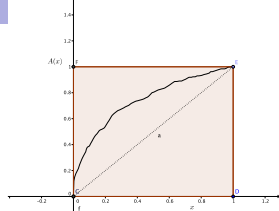


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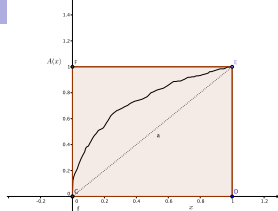
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- If A is **piecewise linear**, it is quite easy to get the full picture:
Cascade of BBM processes.
- If A is strictly concave, Fang and Zeitouni '12 and Maillard and Zeitouni '13 have shown that the correct rescaling is

$$m(t) = C_\sigma t - D_\sigma t^{1/3} - \sigma^2(1) \ln t$$

(with explicit constants C_σ and D_σ) but there are no explicit limit laws or limit processes available.

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- **Statistics of zeros of Riemann zeta-function** [Fyodorov, Keating '12]

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Thank you for your attention!



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