

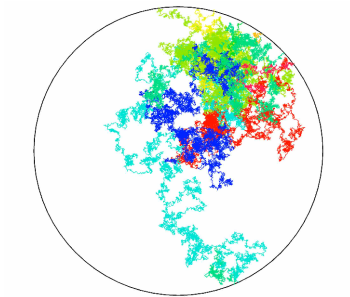
CRITICAL BEHAVIOUR OF BRANCHING  
DIFFUSIONS IN BOUNDED DOMAINS  
THE FOURTH BATH-PARIS BRANCHING STRUCTURES MEETING

Ellen Powell

28th June 2016



# BRANCHING DIFFUSIONS IN A DOMAIN



- $D \subset \mathbb{R}^d$  bounded,  $C^1$  domain.
- Start BBM at  $x \in D$ . Particles killed upon hitting the boundary.

Simulation by Henry Jackson.

# NOTATIONS

$\beta$  = branching rate.

$(X_1^t, \dots, X_{N_t}^t)$  = system at time  $t$ .

# EXTINCTION (BBM WITH BINARY BRANCHING)

## PHASE TRANSITION (SEVAST'YANOV 1958, WATANABE 1965)

There exists a critical value  $\lambda$  of the branching parameter  $\beta$  s.t.

- $\beta \leq \lambda \Rightarrow$  a.s. extinction
- $\beta > \lambda \Rightarrow$  survival with positive probability.

$\lambda$  is the first eigenvalue of  $-\frac{1}{2}\Delta$  on  $D$ .

# SURVIVAL PROBABILITIES

- Survival probability =  $\mathbb{P}_x(N_t > 0)$ .
- Decays exponentially in subcritical case.
- Critical case?

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GALTON-WATSON CASE (KOLMOGOROV 1938, MIERMONT 2008 )

Critical GW and multitype GW processes *with finite variance* have

$$\mathbb{P}(N_n > 0) \sim c/n$$

as  $n \rightarrow \infty$ .

# MAIN RESULTS (BBM WITH BINARY BRANCHING)

## THEOREM (P. 2015)

In the critical case  $\beta = \lambda$ , for all  $x \in D$  we have

$$\mathbb{P}_x(N_t > 0) \sim \frac{1}{t} \times \frac{\varphi(x)}{\lambda \int_D \varphi(y)^3 dy}$$

as  $t \rightarrow \infty$ .

$\varphi$  is the first eigenfunction of  $-\frac{1}{2}\Delta$  on  $D$ , normalised to have unit  $L^2$  norm.

# MAIN RESULTS (BBM WITH BINARY BRANCHING)

## THEOREM (P. 2015)

For any measurable  $E \subset D$ , if  $N_t^E$  is the number of particles in  $E$  at time  $t$ , we have

$$\left( \frac{N_t^E}{t} \mid N_t > 0 \right) \rightarrow Z$$

in distribution as  $t \rightarrow \infty$ , where  $Z$  is an exponential random variable with mean

$$\lambda \langle \varphi, \mathbf{1}_E \rangle_{L^2(D)} \int_D \varphi^3.$$



# MAIN RESULTS (BBM WITH BINARY BRANCHING)

## COROLLARY

Let

$$\mu_t := \frac{1}{N_t} \sum_{i=1}^{N_t} \delta_{X_t^i}$$

be the uniform distribution on all particles alive at time  $t$ , given survival. Then, for each measurable  $E \subset D$ , we have that

$$\mu_t(E) \rightarrow \mu(E)$$

in distribution, and hence in probability, as  $t \rightarrow \infty$ , where

$$\mu(E) = \frac{\int_E \varphi(x) dx}{\int_D \varphi(x) dx}.$$

# NOTATIONS

$A =$  offspring distribution - mean  $m$ .

$L =$  generator.

Assume:  $D$  is  $C^1$ ,  $\mathbb{E}[A^3] < \infty$  and  $L$  is uniformly elliptic and self-adjoint with smooth coefficients.

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Assume:  $D$  is  $C^1$ ,  $\mathbb{E}[A^3] < \infty$  and  $L$  is uniformly elliptic and self-adjoint with smooth coefficients.

BBM with binary branching:  $A \equiv 2$ ,  $L = \frac{1}{2}\Delta$ .

# EXTINCTION (GENERAL CASE)

## PHASE TRANSITION (SEVAST'YANOV 1958, WATANABE 1965)

There exists a critical value  $\frac{\lambda}{m-1}$  of the branching parameter  $\beta$  s.t.

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## THEOREM (P. 2015)

In the critical case  $\beta = \frac{\lambda}{m-1}$ , for all  $x \in D$  we have

$$\mathbb{P}_x(N_t > 0) \sim \frac{1}{t} \times \frac{2(m-1)\varphi(x)}{\lambda(\mathbb{E}[A^2] - \mathbb{E}[A]) \int_D \varphi(y)^3 dy}$$

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$$\frac{\lambda (\mathbb{E}[A^2] - \mathbb{E}[A]) \langle \varphi, \mathbf{1}_E \rangle_{L^2(D)} \int_D \varphi^3}{2(m-1)}.$$

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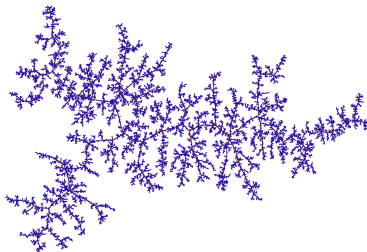
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# SCALING LIMIT



Simulation by Igor Kortchemski.

- What does the conditioned tree look like?
- **Conjecture:** It converges (with appropriate rescaling) to the CRT.
- Work in progress!



# FKPP EQUATION

**Key Tool:** Let

$$u(x, t) = \mathbb{P}_x(N_t > 0).$$

Then  $u$  satisfies the **FKPP equation**:

$$\frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + \lambda(u - u^2)$$

in  $D$  with correct boundary/initial conditions.

# HEURISTICS

$$\text{Reminder: } \frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + \lambda(u - u^2).$$

Write

$$u(x, t) = \sum_i a_i(t) \varphi_i(x); \quad a_i(t) = \int_D u(x, t) \varphi_i(x) dx.$$

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IBP  $\Rightarrow$

$$\frac{da_i}{dt} = \int_D (-\lambda_i u + \lambda(u - u^2)) \varphi_i(x) dx.$$

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$$\frac{da_i}{dt} = (\lambda - \lambda_i) a_i(t) - \lambda \int_D u^2(x, t) \varphi_i(x) dx \text{ for } i \geq 2.$$

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**Guess:**  $u(x, t) \sim a_1(t) \varphi(x).$



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**Guess:**  $u(x, t) \sim a_1(t) \varphi(x)$ .

Sadly, doesn't quite work.

# HEURISTICS

$$\text{Reminder: } \frac{da_1}{dt} = -\lambda \int_D u^2(x, t) \varphi(x) dx.$$

Suppose  $u(x, t) \sim a_1(t)\varphi(x)$ . Then

$$\frac{da_1}{dt} \sim -a_1^2 \times \lambda \int_D \varphi(x)^3 dx.$$

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Easy to prove:

$$a_1(t) \sim \frac{1}{t} \times \frac{1}{\lambda \int_D \varphi(y)^3}.$$

# MARTINGALES

**Goal:**  $u(x, t) \sim a_1(t)\varphi(x)$ .

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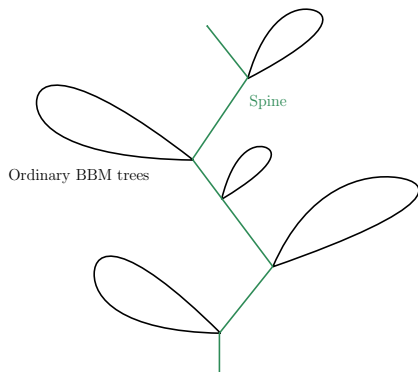
**Goal:**  $u(x, t) \sim a_1(t)\varphi(x)$ .

**Key tool:**

$$M_t = \sum_{i=1}^{N_t} \varphi(X_t^i)$$

is a martingale.

# CHANGE OF MEASURE - CRITICAL CASE



No extinction under  $\mathbb{Q}_x$  (new measure).

- Change measure by 
$$\frac{M_t}{\mathbb{E}_x[M_t]} = \frac{\sum_i \varphi(X_i^t)}{\varphi(x)}.$$
- Spine particle is BM conditioned to remain in  $D$ .
- Branches at rate  $2\lambda$ .
- Offspring are ordinary BBM processes.

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Reminder: want  $\mathbb{P}_x(N_t > 0) \sim a_1(t)\varphi(x)$ .

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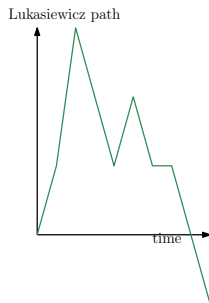
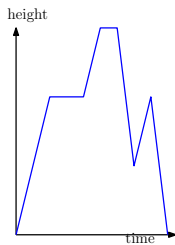
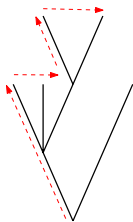
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So  $\mathbb{P}_x(N_t > 0) \sim c(t)\varphi(x)$  as  $t \rightarrow \infty$ , and  $c(t) \sim a_1(t)$ .

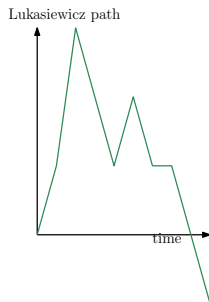
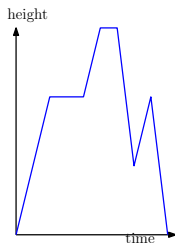
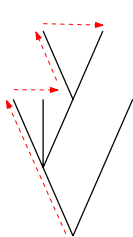
# CONDITIONED RESULTS

- Asymptotic for survival probability.
- Many-to-few Lemma.
- Method of Moments.

# SCALING LIMIT

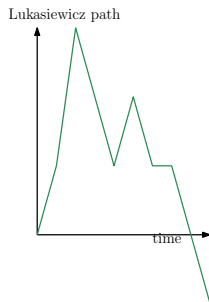
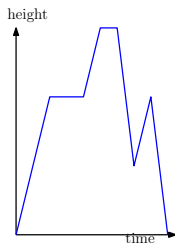
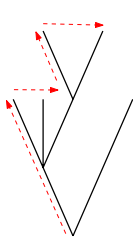


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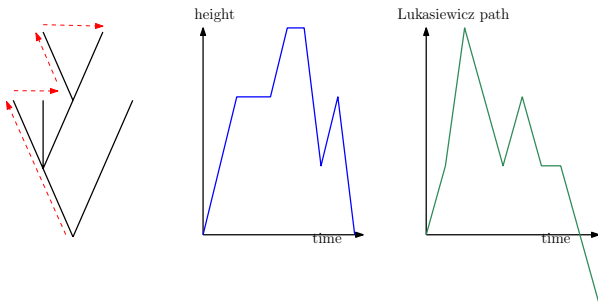
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- **GW case:** connect height function with random walk.
- **BBM case:** connect height function with martingale.



THANKS FOR LISTENING!